Chapter 1: Framing, context, methods

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Executive Summary

The IPCC 6th Assessment Report assessing information that is relevant for the knowledge needs of a world that is rapidly changing, in terms of the physical climate system and the international processes set in place to address the changes and resulting challenges. The Paris Agreement set a long-term goal to hold the increase in the global average temperature to “well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5°C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change”. Together with a range of related international processes and initiatives, such as the Sustainable Development Goals, the Sendai Framework for Disaster Risk Reduction, the Global Framework of the Climate Services, and the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, the Paris Agreement forms a key framing for the present report. A consistent risk framework is adopted across the 6th Assessment Report. {1.2, 1.2.2, 1.2.4}

The IPCC 5th Assessment Report (AR5) concluded that warming of the climate system is unequivocal. Since the AR5, multiple concurrent changes have continued throughout the physical climate system, including increasing global mean surface temperature, loss of glacial mass, sea level rise, increasing ocean heat content, changes to global precipitation patterns, and rising greenhouse gas concentrations. Many of these changes occur at rates and magnitudes beyond what can be attributed to natural variability. The rapid changes to the physical climate system represent a key framing for the present report. The changes presently observed are significant even when considering a long time frame such as the last two millennia. Multiple independent lines of evidence, reaching from the recent observational era back to the mid Pliocene (3.6 million years BP), indicate the unique nature of the present, global scale rate of change, even when seen in the context of a million year period. {1.2.1}

Understanding of essential features of the climate system is robust and well established. The major natural forcings governing the climate system have been known since the early 20th century. The possibility of anthropogenic climate change was proposed in the 19th century, and major anthropogenic forcings (primarily heat-trapping gases and aerosols) were established by the mid-1970s. Since systematic scientific assessments began in the late 1970s, anthropogenic climate change has evolved from a hypothesis to a fact. Climate change projections made since the 1980s are generally in good agreement with the amplitude and pattern of subsequent observed temperature change. {1.3}

Capabilities to observe across the breadth of the physical climate system continue to improve and expand, but recent and/or pending losses in key observational systems underscore the vulnerability of some classes of climate observations. Progress in climate science relies on the quality and quantity of observations from a range of platforms: surface-based instrumental measurements, aircraft observations, satellite-based retrievals, in-situ measurements and palaeoclimatic records. Overall, observational coverage of the climate system is as good for the AR6 as it was for the AR5, with notable improvements in some areas, but also some emerging risks of loss of coverage or continuity. In addition to the reduced coverage of certain satellite products, surface station networks, and radiosonde launches, paleoclimate archives such as corals, tropical ice cores, and trees are rapidly disappearing owing to a host of anthropogenic pressures, including high temperatures caused by anthropogenic climate change (*high confidence*) {1.4.1}

New reanalyses have been developed with various combinations of increased resolution, extended records, more consistent data assimilation, and/or a full representation of the coupled atmosphere-ocean system. Reanalysis datasets provide gridded output, physical consistency across variables (within the limitations of the forecast model used), information about variables that are not directly observed, and information at locations that are unobserved. {1.4.2}

Climate models have been further improved since the AR5, with more Earth system models that represent biogeochemical cycles and more high resolution models that capture small-scale processes and extremes. Improved constraints on cloud and carbon cycle feedbacks have been deduced from observations since AR5 and these in turn constrain climate sensitivity and future projections. {1.4.3}

New tools and advanced techniques are available to more rapidly and comprehensively evaluate climate and Earth system models, attribute observed changes, and constrain the ranges of key Earth system variables. There is now a host of methods to attribute change in events, impacts, and even adaptive measures. Newly developed evaluation tools ensure traceability and reproducibility of the results from model evaluation and analysis. Moreover, the emerging use of machine learning in climate science complements classical model evaluation approaches and provides new insights on the dynamics of the climate system. Large ensembles of climate model simulations have supported improved understanding of the relative roles of internal variability and forced change in the climate system. {1.4.4; 1.4.5; 1.5.5}

Regional climate change is emphasized in AR6 and throughout this Working Group I report. A unified set of land and ocean regions is introduced. These regions are semi-continental domains defined in terms of characteristic climate and environmental features, as recognized from the assessed literature. Particular aspects of climate change are also addressed in this report by higher-resolution, specialized domains called typological regions such as monsoon regions, mountains, megacities, etc. {1.5.2; 1.8}

The early industrial period (1850-1900) is used as an approximation for pre-industrial global temperatures. In terms of radiative forcing, “pre-industrial” refers to the period around 1750 when large-scale natural forcings (solar irradiance, astronomical factors, and volcanic activity) were similar to the modern period. It is *likely* (*medium confidence*) that some anthropogenic warming occurred before 1850; the magnitude of this warming is between 0.0-0.1°C. {1.5.3}

In addition to internal variability, uncertainties in projections of the physical climate system stem from a number of sources. These include (a) the actual future trajectory of radiative forcing, which depends on sociotechnical change (including climate policy) and natural events such as volcanic eruptions, and (b) how the climate will respond to that specific trajectory**.** A third source of uncertainty regards “unknown unknowns”, or possible aspects of climatic behavior not yet identified or accounted for. {1.5.4}

In AR6 scenarios, future temperature levels and cumulative carbon emissions are used as dimensions of integration within and across the three IPCC Working Groups. A new set of emission and concentration scenarios, the Shared Socioeconomic Pathways (SSPs), is used to synthesize knowledge across the physical sciences, impact and adaptation and mitigation research. Two additional ‘dimensions of integration’ are global mean temperature levels as well as a categorization of emission scenarios or geophysical impacts in relation to their cumulative carbon emissions. The SSP scenarios cover lower levels of warming compared to previous Assessment Reports, including scenarios consistent with a 1.5°C warming in line with the lower climate target envisaged in the Paris Agreement {1.6}

Reducing key knowledge gaps via the integration of knowledge across disciplines will accelerate climate understanding. A better understanding of climate processes and phenomena leads to better informed risk assessment, and it is therefore important to identify areas primed for rapid advances. {1.7}

1.1 Chapter preview

The Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) now marks more than 30 years of global international collaboration to describe and understand one of the defining challenges of the 21st century and beyond: human-induced climate change. Since the inception of the IPCC in 1990, our understanding of the physical science basis of climate change has much advanced, and the amount and quality of direct observations and information from palaeoclimate archives has substantially increased. Climate model capabilities have evolved in line with the increased computational capacities of the world's supercomputers, understanding of individual processes has improved, and there is more realistic treatment of interactions among the components of the climate system. At the same time, some key assessment conclusions from previous IPCC reports remained practically unchanged, indicating the robustness of our understanding around the primary causes and consequences of anthropogenic climate change.

The role of the IPCC is to assess on a comprehensive, objective, open and transparent basis the scientific, technical and socio-economic information relevant to understanding the risks of human-induced climate change, its potential impacts and options for adaptation and mitigation. Starting from the work on the First Assessment Report (FAR) published in 1990, the IPCC Assessments have been structured into three Working Groups. Working Group I (WGI) assesses the physical science basis of climate change, Working Group II (WGII) assesses associated impacts, vulnerability and adaptation to climate change, and Working Group III (WGIII) assesses mitigation response options. The volume of knowledge and also the cross-linkages between the three Working Groups has evolved over time.

As part of the AR6 cycle from 2017 to 2022, the IPCC is preparing the set of the three Working Group reports plus three targeted Special Reports and, finally, the Synthesis Report. The three AR6 Special Reports cover the topics of “Global Warming of 1.5°C”, “Climate Change and Land” and the “The Ocean and Cryosphere in a Changing Climate” and are, for the first time in the IPCC, coordinated across all three Working Groups.

This chapter provides the introduction to the WGI contribution to the AR6. The main purposes of the Chapter are: 1) to frame AR6 in the current global context with a focus on international climate governance frameworks, 2) to set the scene for the assessment and to place it in the context of ongoing global changes, the history of climate science and the evolution from previous IPCC assessments, including the Special Reports prepared as part of this Assessment Cycle, 3) to describe key concepts, approaches, and methods used in this assessment.

The Chapter comprises eight sections. The present state of Earth’s climate, in the context of observed long-term changes and variations caused by natural and anthropogenic drivers, as well as the international climate change governance structure, which serves as context to the present assessment, are described in section 1.2. The evolution of knowledge about climate change and the development of earlier IPCC assessments is presented in Section 1.3. New developments in observations, reanalyses, modelling capabilities and techniques since AR5 are discussed in Section 1.4. Approaches, methods, and key concepts of this assessment are introduced in Section 1.5. The three main ‘dimensions of integration’ across Working Groups in the AR6, i.e. scenarios, temperature levels and cumulative carbon emissions, are described in Section 1.6. The Chapter closes with a discussion of opportunities and gaps in knowledge integration in Section 1.7, before presenting the structure and chapter organization of the overall WGI AR6 report in Section 1.8.

1.2 The global context of the present assessment

The context of the IPCC 6th Assessment cycle is different from those of its predecessors. Numerous, substantial changes have been observed across the physical climate system, many of which can be attributed to anthropogenic influences, with impacts on natural and human systems. Governments and societies are responding to these changes and deciding on specific courses of action to mitigate and adapt to anthropogenic climate change.

This section summarizes key elements of this context. Starting by illustrating the changing state of the climate system, as presently observed and in a longer term context (1.2.1). Then, summarizing ongoing processes in international governance that form part of the wider context of the AR6 process (1.2.2), and changes to the wider perceptions of climate change and climate science (1.2.3). Finally, approaches and rationale that are different in the present assessment cycle, relative to past IPCC assessment cycles, are introduced (1.2.4): The risk framing, the possibility of abrupt climate change, and the usage of narratives and storylines.

1.2.1 The changing state of the physical climate system

The starting point for the present report is the context of rapid, ongoing changes in the physical climate system, increased monitoring capability, and improved knowledge. In 2013, the WGI contribution to the IPCC AR5 (AR5WGI) concluded that “warming of the climate system is unequivocal,” and since the 1950s, many of the observed changes are unprecedented over decades to millennia (IPCC, 2013b)

Since AR5, changes to the state of the physical climate system have continued, and, in places, accelerated. Details of these changes are assessed in full in the coming chapters. Ongoing changes are illustrated through key large-scale observables and shown in relation to the longer-term evolution of the climate.

1.2.1.1 Change across multiple indicators

The physical climate system comprises all components and processes that combine to form weather and climate. Broadly speaking the physical climate system is divided into five realms: The atmosphere, the land surface, the cryosphere, the oceans and the biosphere. Figure 1.1 shows these components of the climate system, highlights a set of related indicators of rapidly evolving changes, and links to their full assessment in subsequent chapters. The climate change ‘rosette’ shows year-to-year variability, as deviations from their mean (see caption), illustrating that many components of the climate system have now been altered outside of their natural range of interannual variability. Here, natural variability is estimated from the observed record, but in Section 1.2.1.2, variability in longer records is also discussed.

[Note: The following discussion uses earlier datasets as placeholders and will be updated for the Second Order Draft based]

Atmospheric concentrations of a range of greenhouse gases are increasing, notably carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). These observed changes are consistent with known anthropogenic emissions, when accounting for observed and inferred uptake by the oceans and biosphere respectively. Presently, the global mean CO_2 concentration is increasing by [*XX*] ppm per year. Figure 1.1 (wedges a and b), shows the evolution of global mean surface temperature (GMST) since 1850, and the concentration of CO_2 at Mauna Loa since 1959.

Both the atmosphere and the land surface are undergoing rapid changes. Most notably, the global mean surface temperature has increased by [*XX*] °C since [*YYYY*] and is presently increasing at a rate of 0.17 °C per decade [SR15].

Precipitation patterns are also changing, but with a different regional pattern than surface temperature. Figure 1.1 (wedge c) shows the evolution of annual mean precipitation over land in five latitude bands (shown is the [*XXX*] series of observations, available for the period [*19XX-201X*]). [*Considering changing this to a time series of ocean surface pH.*]

The cryosphere, which comprises all frozen parts of the globe, including terrestrial snow, permafrost, sea ice, glaciers, and the massive ice sheets covering Greenland and Antarctica, is also undergoing rapid changes. Globally, glaciers have been continuously losing mass for the last century; presently their mass balance is at *[-XXX*] Gt/year. See Figure 1.1 (wedge d).

In the oceans as well, changes have progressed beyond year-to-year variability. Notably, the averaged heat content of the oceans down to [*700, 2000*] meters is steadily increasing, presently at a rate of [*XX*] GJ/year (Figure 1.1, wedge e). The global mean sea level is rising at the rate of [*XX*] mm/year over [*19XX-20XX*] (Figure 1.1, wedge f), and this rate has itself increased, from [*XX*] mm/yr over [*19XX-19XX*].

Figure 1.1 presents examples of datasets illustrating recent changes. Overall, the current conditions are such that s one of marked, ongoing and concurrent changes to many components of the physical climate system. These changes, and many others, will be further presented in the coming chapters, together with a rigorous assessment of the recent supporting literature.

[START FIGURE 1.1 HERE]

Figure 1.1: The changing state of the physical climate system. Left: Schematic of the components of the climate system, and examples of how key physical observables are changing. Right: Each wedge of the rosette shows annual means of one variable, from 1850 (center) out to 2017 (outer circle). Grey indicates missing data. [To be updated for SOD. All data plotted so far temporary, taken predominantly from AR5.]

[END FIGURE 1.1 HERE]

1.2.1.2 Change across multiple timescales

Information from paleoclimate archives provides an essential long-term context for the anthropogenic climate change of the past 150 years and the projected changes in the 21st century and beyond (Masson-Delmotte et al., 2013). Figure 1.2 shows reconstructions of three key indicators of change over the past 800,000 years, comprising eight complete glacial-interglacial cycles (EPICA Community Members, 2004). The dominant 100,000-year cycles are characterized by natural CO_2 variations between 174 ppm and 299 ppm (±1.3 ppm), as measured directly in air trapped in ice at Dome Concordia, Antarctica (Bereiter et al., 2015; Lüthi et al., 2008), reconstructed global average surface temperature variations relative to 1850-1900 between -7°C to +2°C (Snyder, 2016), and sea level changes from about-126 m to +1.85 m (Bintanja and van de Wal, 2008) [*range to be reviewed in the SOD to ensure consistency with Chapter 9*]. The ranges represent roughly the amplitudes of natural variations for the last 800,000 years, prior to greenhouse gas emissions caused by human activity, although more precise estimates are available for shorter time periods (ref. Chapter 9 and SROCC).

[START FIGURE 1.2 HERE]

Figure 1.2: Long-term context of anthropogenic climate change based on selected paleoclimatic reconstructions over the past 800,000 years for three key indicators: atmospheric CO_2 concentrations, global mean surface temperature, and sea level. **a)** Measurements of CO_2 in air enclosed in Antarctic ice cores (Lüthi et al., 2008; MacFarling Meure et al., 2006) and direct air measurements (Dlugokenky and Tans, 2019) (Keeling et al., 1976). Inferred CO_2 concentrations for the RCPs are indicated by the bars on the right side of the figure and taken from Zickfeld et al. (2013). Reconstruction of global average surface air temperature based on a combination of several marine paleoclimate proxies and PMIP model simulations (Snyder, 2016). Observed temperature changes since 1850 are from the HadCRUT4 dataset, re-referenced to 1850-1900; bars indicate the projected ranges of warming derived from CMIP5 simulations (IPCC, 2013b) Sea level changes reconstructed from oxygen isotope measurements on several ocean sediment cores (Bintanja and van de Wal, 2008, re-referenced to 1850-1900). The observed sea level record is from

Jevrejeva et al. (2014); projections are based on a combination of CMIP5 ensembles and process-based models (IPCC, 2013b). [PLACEHOLDER: projections are based on CMIP5. They will be replaced by CMIP6 in the SOD; uncertainties will be added to the paleoclimate reconstructions in the SOD. Also, SLR projections will likely use Spratt and Lisiecki (2016) (re-referenced to 1850-1900) for the SOD instead of Bintanja and van de Wal (2008).

[END FIGURE 1.2 HERE]

Paleoclimate reconstructions also shed light on the causes of these variations, revealing processes that need to be considered when projecting climate change. The records presented in Figure 1.2 show that sustained changes in global mean temperature of a few degrees Celsius cause increases in sea level by several tens of meters, rising rapidly over several millennia at the end of ice ages (Bintanja and van de Wal, 2008). Seen against this background, ongoing present-day warming represents a commitment to long-term sea level rise and many other impacts (Clark et al., 2016; Fischer et al., 2018; Pfister and Stocker, 2016).

The records also show centennial- to millennial-scale variations, particularly during the ice ages, which indicate rapid or abrupt changes of the Atlantic Meridional Overturning Circulation and the occurance of a bipolar seesaw (Members WAIS Divide Project et al., 2015; Pedro et al., 2018; Stocker and Johnsen, 2003). This process suggests that instabilities and irreversible changes could be triggered in the future if critical thresholds are passed (ref. Section 1.2.4.2). High-resolution paleoclimate data also confirm the synchronicity between changes in greenhouse gas concentrations and global mean temperature (Members WAIS Divide Project et al., 2015; Parrenin et al., 2013). This underlines the important role of greenhouse gases as one driver of climate change in the past.

The values derived from direct instrumental observations and ice core CO_2 data since 1850 CE, combined with the paleoclimate record, are in Figure 1.2. By the first decade of the 20th century, CO_2 concentrations had already outside the reconstructed range of natural variation over the past 800,000 years, while global average temperature and sea level were higher than today during several interglacials across that period. Projections of these three indicators for the end of the 21st century, however, show that for all but the mitigation scenario RCP2.6 (IPCC, 2013b) (ref. Section 1.6) , these global-scale indicators will rapidly move out of their long-term natural range within the next few decades. Detection and attribution studies of climate change (ref. Section 1.5.3), in particular of global mean temperature and sea level, have long demonstrated that the anthropogenic increase of greenhouse gas concentrations is the dominant cause for this development (Bindoff et al., 2013; Slangen et al., 2014; Stott et al., 2000) (ref. Section 1.5).

The rate, scale, and magnitude of anthropogenic changes in the climate system since the mid-20th century support the concept of an Anthropocene epoch, in other words, an era in which human activity is altering Earth systems on a magtude and scale similar to geophysical forces, leaving measureable traces which will remain in the permanent geological record (SR1.5). Such changes include not only climate change itself, but also a sixth mass extinction of species, rapid ocean acidification due to uptake of anthropogenic carbon dioxide, and massive destruction of tropical forests (Crutzen and Stoermer, 2000; Scholes et al., 2018; Steffen et al., 2007, 2018; Zalasiewicz et al., 2017, Steffen et al., 2017).

1.2.2 International governance to address challenges posed by climate change

Since a wide range of human impacts on our environment have emerged, various previously independent international agendas have become more closely integrated. These developments recognize how strongly climate change, disaster risk, global development, and human well-being are interconnected. This section summarizes key ongoing international governance processes that form the context of this report, and which have shaped its assessment approach.

The Paris Agreement was agreed to at the 21st Conferences of Parties to the UN Framework Convention on Climate Change in December 2015 (UNFCCC, 2015) aims at strengthening the global response to climate change in the context of sustainable development and efforts to eradicate poverty. The Paris agreement sets a long-term goal to limit global average temperature to "well below 2°C above pre-industrial levels, and to pursue efforts to limit the temperature increase to 1.5°C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change." The Paris agreement will be implemented from 2020 onwards. It addresses both mitigating and adapting to climate change, as well as loss and damage, finance, technology transfer, capacity-building and education (UNFCCC, 2015).

In the near term (2031–2050), the Paris agreement calls for emission reduction pledges through Nationally Determined Contributions (NDCs) (e.g. Geng et al., 2018; Rogelj et al., 2016; Winkler et al., 2017). Pledges of many lower-income countries, whose emissions may increase as their populations and affluence grow, are conditional on international financial and technical assistance (Rose et al., 2017). Also the majority of countries, particularly developing countries, include an adaptation component in their NDCs (Kato and Ellis, 2016). Article 4 of the Paris Agreement specifies that NDCs are to be updated every five years and successive NDCs are to be informed by the global stocktake specified in Article 14 of the Paris Agreement (see Cross-Chapter Box 1.1).

The IPCC will inform the global stocktake through the series of reports prepared for its Sixth Assessment cycle. The AR6 cycle will end with the publication of the Synthesis Report in 2022, with its outcomes expected to contribute the global stocktaking process planned for 2023 and then every five years (e.g. Schleussner et al. 2016, Cross-Chapter Box 1.1).

The 2030 Agenda for Sustainable Development 'Transforming our World' (UNGA, 2015) was agreed to in September 2015 at the UN General Assembly and the Addis Ababa Action Agenda in July 2015 to support their implementation. **The Sustainable Development Goals (SDGs)** adopted in support of the new 2030 Agenda urge nations to "take the bold and transformative steps which are urgently needed to shift the world onto a sustainable and resilient path." The seventeen goals are integrated, indivisible and balanced between the economic, social, and environmental dimensions of sustainable development: to support people, prosperity, peace, partnership, and the planet (UNGA, 2015). Goal 13, "Action for Climate Change," deals explicitly with climate change, establishing several targets to implement "urgent action to address climate change and its impacts". Most other SDGs are also tightly linked to climate and climate change.

AR6 comes in the context of post UN 2030 Agenda and new literature linking sustainable development to climate (e.g. Nunan, 2017). The IPCC Special Report on Global Warming of 1.5°C was prepared in the context of strengthening the global response to the threat of climate change, sustainable development and efforts to eradicate poverty (SR1.5 2018).

The Special Report on Ocean and Cryosphere in a Changing Climate (SROCC), in exploring the impacts of changes of physical and biogeochemical properties and processes on marine environment in conjunction with non-climate drivers, will provide valuable information for the achievement of for example the SDG 14 (Life below water). The Special Report on Climate Change and Land (SRLCC) assess synergies and trade-offs of response options that affect sustainable development, linked to SDG 15 (Life on land). Finally, SDG 11 (sustainable cities and communities) and SDG 7 (affordable and clean energy) are addressed in Chapter 6 of this report and are also connected to the New Urban Agenda (see below).

The New Urban Agenda was established in 2016 in Quito as an outcome of the UN Conference on Housing and Sustainable Development to contribute to the 2030 Agenda for "sustainable cities and communities" (United Nations, 2017). It envisages cities that "adopt and implement disaster risk reduction and management, reduce vulnerability, build resilience and responsiveness to natural and human-made hazards and foster mitigation of and adaptation to climate change." The assembly committed to undertake various climate actions, consistent with the goals of the Paris Agreement, to reduce emissions of greenhouse gases from all sectors, and, in particular, to manage and minimize short-lived climate forcers (SLCFs). AR6 evaluates the consequences of increasing urbanisation — particularly in developing countries — and the contribution of megacities to SLCF emissions and the impacts of these emissions on climate (see Chapter 6).

The Sendai Framework for Disaster Risk Reduction (SFDRR) 2015-2030 (UNISDR, 2015), successor to the Hyogo Framework for Action (HFA), is a voluntary pathway to reduce risks associated with disasters of all scales, frequencies, and onset rates caused by natural or manmade hazards. Disaster risk reduction (DRR), climate change, and sustainable development are tightly linked (Forino et al., 2015; Kelman, 2015, 2017; McBean, 2012). As a result, a more holistic picture of climate change adaptation with DRR integration (Forino et al., 2015) and of climate change mitigation with pollution prevention is needed in the broader context of sustainable development (Kelman, 2017). Therefore, AR6 adopts a risk and solution-oriented framing (see section 1.2.4.1, Risk Framing) that calls for a multidisciplinary approach and Cross-Working Group coordination in order to ensure integrative discussions of major scientific issues associated with integrative risk management and sustainable solutions (IPCC, 2017).

The Global Framework for Climate Services (GFCS) was established by the World Meteorological Organisation (WMO) and partners in 2009 to provide science-based information for risk management and adaptation to climate change (Hewitt et al., 2017a; Trenberth et al., 2016). The GFCS intends to “guide the development and application of science-based climate information and services in support of decision making in climate sensitive sectors”, in particular for five priority areas: Agriculture and Food Security, Disaster Risk Reduction, Energy, Health, and Water (WMO, 2014b, Lúcio and Grasso, 2016). Multiple initiatives have been proposed to deliver climate services (Brasseur and Gallardo, 2016). Climate services support the National Adaptation Plan (NAP) process, established by the UNFCCC as a way to facilitate adaptation in Least Developed Countries (LDCs; WMO, 2016) and can play a major role in achieving the SDGs (WMO, 2017). In AR5, climate services were somewhat addressed in WGII (Jones, 2014). With links between WGI and WGII becoming stronger, and a greater focus in WGI on regional information to feed into WGII, the WGI IPCC AR6 assessment provides an assessment of regional information methods (Chapter 10), projections at regional level (Atlas) that can form the basis for critical hazard indicators (Chapter 12) and for some basic climate services. The current landscape of climate services (including GFCS) is assessed in detail in Chapter 12 (Section 12.6).

The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), established in 2012, builds on the IPCC model “to strengthen knowledge foundations for better policy through science, for the conservation and sustainable use of biodiversity, long-term human well-being and sustainable development.” Due to the strong linkages between biodiversity and climate (e.g. Pecl et al., 2017), UNFCCC and the Convention on Biological Diversity (CBD) have invited Climate Change and Biodiversity communities to further collaborate, in particular through IPCC and IPBES assessments cycles, and have committed for strengthened and more coherent implementation under the Convention on Biological Diversity and UNFCCC (CBD, 2018). In that context, the IPBES future work programme plans to address the nexus between climate change and food systems. In turn, the IPCC Special Report on Climate Change and Land (2019) will assess in particular feedbacks on the climate system created by changes in biodiversity.

This evolving governance context challenges the IPCC to produce an assessment report that can provide the necessary information for future actions in a more integrative manner. This requires more common frameworks to be adopted across the three WGs. For the WGI contribution, this means providing relevant information for both adaptation and mitigation of climate change. This challenge has translated into a change in the WGI structure compared to previous assessments, which will be further explained in Section 1.2.4.

[START CROSS-CHAPTER BOX 1.1 HERE]

Cross-Chapter Box 1.1: The WGI AR6 Contribution and its Relevance for the Global Stocktake

The IPCC AR6 will prominently inform the global stocktake through relevant assessment information from the series of AR6 Special Reports (SR1.5, SROCC and SRCCL), the individual Working Group contributions to the AR6 and ultimately the AR6 SYR. This box aims to serve as the entry point to the WGI contributions to the global stocktake. Cross-Chapter Box 1.1, Table 1 lists topics and related key assessment findings from the WGI assessment and provides a brief explanation of their potential relevance for the global stocktake. Pointers to the relevant chapter and sections are also provided.

Article 14 of the Paris Agreement provides for a **periodic global stocktake "of the implementation of this Agreement to assess the collective progress towards achieving the purpose of this Agreement and its long-term goals.**" This stocktake should be done in a "comprehensive and facilitative manner, considering mitigation, adaptation and the means of implementation and support, and in the light of equity and the best available science". The first global stocktake is due in 2023, and then every five years thereafter, unless otherwise decided by the Conference of the Parties, the decision-making body of the UN Framework Convention on Climate Change (UNFCCC), serving as the meeting of the Parties to the Paris Agreement (CMA). The CMA oversees the implementation of the Paris Agreement and takes decisions to promote its effective implementation (https://unfccc.int/topics/science/workstreams/global-stocktake-referred-to-in-article-14-of-the-paris-agreement).

To take stock of the implementation of the Paris Agreement and to assess the collective progress, the global stocktake will consider the thematic areas of "mitigation, adaptation and means of implementation and support, noting, in this context, that the global stocktake may take into account, as appropriate, efforts related to its work that: (i) address the social and economic consequences and impacts of response measures and; (ii) avert, minimize and address loss and damage associated with the adverse effects of climate change; (paragraph 6 of decision -/CMA.1 in FCCC/CP/2018/L.16[1]).

The purpose and long-term goals towards which the "collective progress" shall be assessed as part of the global stocktake are different across those thematic areas and have not yet been specified by Parties. For ***mitigation***, the long-term goals will include Art. 2.1 (a) of the Paris Agreement, referring to the "well below 2°C" and "1.5°C" temperature increases above pre-industrial levels - as well as in Art. 4.1, in which the Paris Agreement states "Parties aim to reach global peaking of greenhouse gas emissions as soon as possible, recognizing that peaking will take longer for developing country Parties, and to undertake rapid reductions thereafter in accordance with best available science, so as to achieve a balance between anthropogenic emissions by sources and removals by sinks of greenhouse gases in the second half of this century, on the basis of equity, and in the context of sustainable development and efforts to eradicate poverty". For ***adaptation***, Art. 2 1(b) of the Paris Agreement sets the aim of "Increasing the ability to adapt to the adverse impacts of climate change and foster climate resilience and low greenhouse gas emissions development, in a manner that does not threaten food production"; and Art. 7 of the Agreement further establishes "the global goal on adaptation of enhancing adaptive capacity, strengthening resilience and reducing vulnerability to climate change, with a view to contributing to sustainable development and ensuring an adequate adaptation response in the context of the temperature goal referred to in Article 2". On the "means of implementation and support" thematic area, the long-terms goals will likely include Art 2.1(c), which sets the aim of "making finance flows consistent with a pathway towards low greenhouse gas emissions and climate resilient development", and relevant goals under the Paris Agreement related to finance, technology and capacity-building. Other goals might also be identified in relation to response measures and loss and damage.

The sources of input that the global stocktake envisages to consider explicitly include the "latest reports of the Intergovernmental Panel on Climate Change" as a central source of information, as confirmed recently (paragraph 36 in -/CMA.1 in FCCC/CP/2018/L.16, pursuant decision 1/CP.21, paragraph 99 of the adoption of the Paris Agreement in FCCC/CP/2015/10/Add.1[2]). In fact, the Subsidiary Body on Scientific and Technical Advice explicitly "encouraged the IPCC to pay particular attention to the first global stocktake when scoping the Sixth Assessment Report, taking into account that the global stocktake will assess collective progress towards achieving the purpose of the Paris Agreement and its long-term goals in a comprehensive and facilitative manner, considering mitigation, adaptation and the means of implementation and support, in the light of equity and the best available science". (paragraph 52 of FCCC/SBSTA/2016/4[3]).

The type of information that the global stocktake in its assessments of the progress towards the purpose and goals of the Paris Agreement is explicitly seeking - at a collective level - has been described by UNFCCC

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[1] available at: https://unfccc.int/sites/default/files/resource/FCCC_CP_2018_L.16.pdf

[2] available at: https://unfccc.int/resource/docs/2015/cop21/eng/10a01.pdf

[3] available at: https://unfccc.int/sites/default/files/resource/docs/2016/sbsta/eng/04.pdf

parties in paragraph 36 of -/CMA.1 in FCCC/CP/2018/L.16. Cognizant of the complementary contributions of other Special Reports and IPCC Working Group contributions, the areas where the WGI assessment is particularly relavant are:

(a) The state of greenhouse gas emissions by sources and removals by sinks, including information that would allow to discuss long-term low greenhouse gas emission development strategies (Art. 4, paragraph 15 of the Paris Agreement) (paragraph 36 (b) of -/CMA.1 in FCCC/CP/2018/L.16).
(b) Information that allows to put the overall effect of nationally determined contributions and overall progress made by Parties towards the implementation of their nationally determined contributions and long-term plans into the context of the Paris Agreement's purpose and goals (paragraph 36 (b)).
(c) Information that enhances understanding of loss and damage associated with the adverse effects of climate change (paragraph 36 (e)).

[START CROSS-CHAPTER BOX 1.1, TABLE 1 HERE]

Cross-Chapter Box 1.1, Table 1: Working Group I (WGI) assessment findings and their relevance for the global stocktake. The table combines information assessed in this report that could potentially be relevant for the global stocktake process. Section 1 "State of the Climate" is focused on the state of the climate, understanding of historical and current emission balances, any biogeophysical Earth System changes that can pose challenges for adaptation, and methodologies, like attribution of extreme events. Section 2 "Future Projections" is focused on future projections in the context of the Paris Agreement's long term 1.5°C, 2.0°C goals and the progress towards net-zero greenhouse gas emission. Note: We include here only information covered in the WGI contribution to the AR6. Working Groups II and III will cover further relevant information in their contributions to the AR6. The overarching synthesis will be part of the AR6 Synthesis Report.

Section 1: State of the Climate			
Topic	**Question**	**Chapter/ Section**	**Potential Relevance**
Changing state of the climate system (Chapter 2)	How much warming did we observe in global-mean surface air temperatures since pre-industrial or early-industrial times?	2.3.1.1	The knowledge about the current warming relative to pre-industrial levels allows us an understanding of the distance towards the Paris Agreement goal of keeping global-mean temperatures well below 2°C or pursue best efforts to limit warming to 1.5°C.
	By how much are the oceans warming?	2.3.3.1	Warming oceans can affect marine life (e.g. coral bleaching) and also are among the main contributors to long-term sea level rise (thermosteric expansion). Also, knowing the heat uptake of the oceans helps to better project future warming.
	How did the sea ice extent change in recent decades in both the Arctic and Antarctic?	2.3.2.1.1, 2.3.2.1.2 9	Sea ice extent can affect polar life, influences heat exchange between the atmosphere and oceans. Sea ice extent is also related to complex dynamical changes in atmospheric flows.
	Are mountain glaciers across the globe shrinking? By how much?	2.3.2.3 9 9.5.2.2/4	Mountain glaciers often feed downstream river systems during the melting period, can be an important source for freshwater. Changing river discharge can pose adaptation challenges. Melting

			mountain glaciers are among the main contributors to observed global-mean sea level rise.
	How much did atmospheric CO_2 concentrations increase since the pre-industrial period?	2.2.4	The main human influence on the climate is via combustion of fossil fuels and land-use change related CO_2 emissions and the related increase of the greenhouse gas CO_2 concentrations since the pre-industrial period. An understanding of historical fossil fuel emissions and of the carbon cycle interactions that led to observed CO_2 concentrations is crucial for better estimates of future CO_2 emissions in line with the Paris Agreement's long-term goals.
	How much did sea level rise in the past centuries?	2.3.3.3 9	Sea level rise is a comparatively slow consequence of a warming world with potential multi-meter increases over hundreds of years. The current sea level change (both rising and lowering) around the coastlines of the world can have strong impacts on storm surge flooding, coastal erosion etc., posing coastal adaptation challenges.
	How much did the oceans acidify already?	2.3.4.3	Ocean acidification is affecting marine life, especially organisms that build calciferous shells and structures (e.g. coral reefs) as they can disintegrate/dissolve in too acidic waters. In addition to ocean warming, this poses adaptation challenges for oceanic food supply and ecosystems.
Human influence on the climate system (Chapter 3)	How much of the observed warming since since pre-industrial or early-industrial times was due to anthropogenic influences?	3.3.1	To monitor progress towards the Paris Agreement's long-term goals it is important to know how much of the observed warming (see above) is due to human activities. Chapter 3 will provide an estimate of human-induced warming in global mean near-surface air temperature for the decade 2010-2019, relative to the agreed early-industrial period of 1850-1900, taken as proxy for warming since the pre-industrial period, with associated uncertainties, derived using a detection and attribution approach. This estimate can be compared with observed estimates of warming for the same decade reported in Chapter 2, and can be used to calculate remaining carbon budgets consistent with remaining below these temperature thresholds by Chapter 5.
Global carbon and other biogeochemical cycles and feedbacks (Chapter 5)	How well do we understand historical cumulative carbon emissions, the increase of atmospheric carbon and uptakes on land and in oceans?	5.2.2, in particular 5.2.2.6	A key part of our understanding of climate change to date is a consolidated understanding of historical emissions of carbon-dioxide and how the carbon cycle has contributed to redistribute these emissions among the various reservoirs in the Earth system. This historical perspective of the emissions of the most dominant anthropogenic greenhouse gas is critical to put in perspective any estimates of the remaining carbon budget consistent with limiting warming to 1.5°C or 2°C. Understanding of the historical carbon budget also

			allows us to realize that anthropogenic carbon-dioxide emissions do not disappear from the active carbon cycle over timescales of centuries, but are merely redistributed.
	What are historical and contemporary greenhouse gas emissions levels and the associated projected future atmospheric concentrations?	5.1.1, atmospheric concentrations; 5.2.2, 5.2.3, 5.2.4, annual emissions of CO_2, CH_4, and N_2O.	Contemporary trends of greenhouse gas emissions allow us to inform where we are today. Combined with historical and current atmospheric concentrations of these greenhouse gases, this is essential to understand that the rates at which atmospheric concentrations are currently changing are unprecedented in the past 800 thousand years.
Linking global to regional climate change (Chapter 10)	State of the regional climate and attribution of a number of forcings and drivers	10.2, observational uncertainty; 10.4/10.6 examples of challenges to formulate regional climate messages for the present	Robust and reliable estimates of current regional climate is challenging due to the large uncertainties associated with observations in many regions of the planet, the limitations of current climate models and tools that are particularly relevant at regional spatial scales (e.g. urban climates) and the difficulty to build coherent narratives that convey understandable and usable regional climate messages.
Weather and climate extreme events in a changing climate (Chapter 11)	State of extreme events.	11	The current state of weather and climate extreme events in the context of historical changes is important to assess the challenges related to climate impacts that go beyond the adaptive capacities of various regions. Also, methodologies and uncertainties related to the attribution of these weather and climate extreme events to human-induced climate change and various drivers could be important for a deeper understanding on these issues.
Atlas	Current observations of regional temperatures, precipitation means and extremes and various other climate indicators.	Atlas	Current observations of mean climate or relevant hazard or extreme indices at current global-mean temperature levels - and comparison with historical observations.
Other potential information sources complementing the IPCC WGI contribution to the global stocktake	Climate Indicators by WMO		The World Meteorological Organization (WMO), in conjunction with partner organizations including the Global Climate Observing System (GCOS) and the World Climate Research Programme (WCRP), has developed a set of Essential Climate Variables for tracking changes in the physical climate system (Williams and Eggleston, 2017). Those indicators are global mean surface temperature, ocean heat content, Arctic and Antarctic sea ice extent, glacial mass balance, globally averaged atmospheric CO_2 concentrations, sea level, and ocean acidification. The global stocktake is expected to be one of the

			major applications for this set of indicators, alongside more frequent monitoring, such as through WMO's annual State of the Climate reports. The WMO's chosen set of indicators is intended to capture the widest possible picture of climate change whilst still keeping the number of indicators to a manageable level. The criteria that WMO has used for shortlisting indicators are relevance, representativeness, traceability, timeliness and data adequacy. Whilst some indicators, such as global mean surface temperature and sea ice extent, are available in close to real time, others, such as glacial mass balance and globally averaged atmospheric CO_2 concentrations, can be 12 months or more in arrears.
Section 2: Future Projections			
Topic	**Question**	**Chapter/ Section**	**Potential Relevance**
Future global climate: scenario-based projections and near-term information (Chapter 4)	What are projected key climate indices under low, medium and high emission scenarios in the near-term, i.e. the next 20 years?	4.3, 4.4, FAQ 4.1	Much of the near-term information allows us to sketch the climate adaptation challenges for the next decades as well as the opportunities to reduce climate change by pursuing lower emission scenarios.
	If lower emission scenarios are pursued, what are the differences in climate over the 21st century compared to emission scenarios where no additional climate policies are implemented?	4.6	The new generation of scenarios spans the response space from very low emission scenarios (SSP1-1.9) under the assumption of climate policy implementation to very high emission scenarios that are projected in the absence of climate policies (SSP3-7.0 or SSP5-8.5). The climate differences between those future high emission scenarios and those compatible with the Paris Agreement's long-term targets can help inform about differences in corresponding adaptation challenges.
	How much confidence can we have in the ensembles of climate model projections and what are the techniques to derive a range of future global and	Box 4.1	The scientific literature provides new insights regarding ensemble evaluation and weighting that can lead to more appropriate projection ranges, which take into account the skill of climate models and interdependencies among them. These techniques have a strong relevance to quantifying future uncertainties, for example regarding the likelihood with which the various scenarios would exceed the Paris Agreement's long-term goals of 1.5°C or 2°C.

	regional climate changes?		
	When greenhouse gas emissions are reduced, what changes will we see and when?	FAQ 4.2	The understanding the response to a change of anthropogenic emissions is important to estimate an appropriate scale and timing of mitigation compatible with the Paris Agreement's long-term targets.
Global carbon and other biogeochemical cycles and feedbacks (Chapter 5)	What is the remaining carbon budget that is consistent with the Paris Agreement's long-term objectives?	5.5; 5.5.1, TCRE; 5.5.2, remaining carbon budget.	The remaining carbon budget provides an estimate of how much CO_2 can still be emitted into the atmosphere by human activities while keeping global warming to a specific temperature limit. It thus provides key geophysical information about emissions limits consistent with limiting global warming to well below 2 °C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5 °C. Remaining carbon budgets should be seen in context of historical CO_2 emissions to date. The concept of the transient climate response to cumulative emissions of carbon-dioxide (TCRE) indicates that one tonne of carbon-dioxide has the same incremental effect on global warming irrespective of whether it is emitted in the past, today or in the future.
Short-lived climate forcers (Chapter 6)	How important are reductions in short-lived climate forcers compared to the reduction of CO_2 and other long-lived greenhouse gases?	6.1.4	Short-lived climate forcers play an important role in the anthropogenic effect on climate change. Many aerosol species tend to cool the climate and their reduction leads to an unmasking of greenhouse gas induced warming. On the other hand, many shorter lived species themselves exert a warming effect, including black carbon and also methane, the second most important anthropogenic greenhouse gas (in terms of current radiative forcing). Thus, strategies to limit future climate change need to undertake a mix of mitigation strategies and the question is how important are reduction in short-lived climate pollutants, often driven by additional clean air policy objectives, compared to the reduction of CO_2 and other long-lived greenhouse gases.
	What are the co-benefits of and co-challenges of climate mitigation?	6.1.4	The reduction of fossil-fuel related emissions often goes hand in hand with a reduction of air pollutants, like aerosols. Those reductions in air pollutants can accrue co-benefits in terms of increased air quality and improved human health and could be factored into a response strategy to climate change.
The Earth's energy budget, climate feedbacks, and climate sensitivity (Chapter 7)	What is the Transient Climate Response and what does it tell us about expected warming over the 21st century under various scenarios?	7.5.7	The transient climate response is a is a measure of the strength of climate feedbacks and the timescale of ocean heat uptake.
	Equilibrium Climate Sensitivity	7.5.7	The Equilibrium Climate Sensitivity (ECS) has summarized our understanding for decades of how sensitive the Earth's climate system is to elevated

			CO_2 concentrations. The higher the ECS, the lower are the greenhouse gas emissions that are consistent with the Paris Agreement's long-term targets.
	Earth's energy imbalance	7.2.2	The Earth's energy imbalance indicates how far the Earth's climate is from a temperature equilibrium with the current level of greenhouse gas concentrations, aerosols and other forcers. An energy imbalance indicates that one can expect additional warming before the Earth climate is in equilibrium with the current level of radiative forcing.
	How can mitigation action in relation to different greenhouse gases be compared in relation to their effect of Earth's climate?	7.7	To compare the relative climate benefit of mitigating the emission of 1 tonne of CO_2versus 1 tonne of methane or other greenhouse gas, the Global Warming Potential is used to compare the relative merit of reducing various gases. Various approaches can theoretically be taken to create an optimal mix of mitigation action across shorter lived, longer lived greenhouse gases and CO_2.
Water Cycle Changes (Chapter 8)	Total atmospheric moisture	8.2.1.1.1, global hydrological sensitivity; 8.2.1.2, physical linkages temperature-moisture, 8.3.1.2, observational evidence; 8.4.1.2, projected changes.	Changes in the water cycle, in particular in regional precipitation - both in terms of extremes and long-term averages are important to estimate adaptation challenges. In terms of measuring the effects of climate change/global warming on the water cycle, atmospheric moisture content is a fundamental quantity.
	Large-scale changes in P-E (Precipitation minus Evaporation) and surface salinity	8.2, Physical drivers; 8.3.1.1.1/2, observational evidence; 8.4.1.1 projections.	Changes in surface P-E arise from changes in atmospheric moisture, atmospheric circulation (convergence zones, storm tracks, regional monsoons etc), changes to local and regional surface radiative budgets, changes in evaporation efficiency and surface water availability. P-E over oceans is closely related to ocean surface salinity, while P-E over land is closely related to surface water availabilit and to drought occurrence. Hence, this projected indicator over land is important to estimate food production and water supply adaptation challenges.
Ocean, cryosphere, and sea level change (Chapter 9)	What are the expected sea level changes in a changing climate?	9.6, 9.6.3.4	Unlike many regional climate impacts, sea level change over this century is not approximately linearly related to global-mean temperature levels. That is because of the long-time scales with ocean heat uptake, glacier melt, solid ice discharge and surface mass balances of ice sheets adapt to a change in temperatures.
	How are the mountain glacier	9.5 9.5.2.5	Mountain glaciers provide source and temporary storage of freshwater for drinking water and energy

	melt rates expected to develop in regions that are currently dependent on this seasonal freshwater supply?		systems in many regions of the world. Projected global glacier loss in line with the Paris Agreement's long-term temperature targets of well-below 2°C and 1.5°C are key to assess minimal adaptation challenges on various timescales.
Linking global to regional climate change (Chapter 10)	Capacities and limitations in the provision of regional climate information for adaptation as one of the components of the global stocktake	10.3, methodologies; 10.4, cases illustrating attribution to drivers; 10.5, construction of regional climate messages.	Adaptation challenges are predominantly local, even if globally interlinked. Thus, the methodologies, relative merits and challenges in the production of regional climate information for adaptation purposes can be a key information input to the global stocktake regarding adaptation discussions. Regions are considered in the chapter without any a priori boundaries and cover any subcontinental area where climate adaptation decisions are made by climate-vulnerable sectors. Regional climate messages are built upon a number of tools (GCMs, RCMs, empirical models, observations, contextual information, model selection, narratives) that have relative merits and limitations.
Weather and climate extreme events in a changing climate (Chapter 11)	Projection of weather and climate extreme events under various scenarios.	11	A key research frontier relates to the projection and attribution of weather and climate extreme events in the near-, mid and longer term and regional occurrence of extreme events under various future scenarios. This can be of relevance for both the examination of adaptation challenges and loss and damage aspects.
Climate change information for regional impact and for risk assessment (Chapter 12)	Changes in hazards relevant to impacts that feed into 'Reasons for Concern' at the warming levels of the Paris Agreement's long-term temperature goals and other levels.	12.5.2	Synthesis information on projected changes in hazards relevant to impacts that feed into different 'Reasons for Concern' (assessed by WGII, Chapter 16). Where possible, an explicit transfer function between different warming levels from the pre-industrial baseline and indices quantifying characteristics of these hazards is provided, or the difficulties in doing so documented. Those hazard indices will include Arctic Sea Ice Extent in September (ref Chapter 4); Global average change in ocean acidification (ref Chapter 5); Global SST annual averages (ref Atlas); Surface mass balance of glaciers or Snow Cover (ref Chapter 9); Ice volume change for WAIS and GIS, (ref Chapter 9); AMOC strength (ref Chapter 4); Amplitude and variance of ENSO mode (Nino3.4 index) (ref Chapter 4).
Atlas	Region-by-region assessments	Atlas	Future projections of mean climate or relevant hazard or extreme indices at both 1.5°C and 2.0°C. This projected regional information is inter alia important under adaptation considerations of the global stocktake.

[END CROSS-CHAPTER BOX 1.1, TABLE 1 HERE]

[END CROSS-CHAPTER BOX 1.1 HERE]

1.2.3 Climate, science, and societies: perceptions, values, and ethics

Values and ethics play critical roles in climate understanding. Science can answer questions about *what, how,* and *why*: how and why Earth's climate is changing (IPCC WGI), how climate change may affect human societies and natural systems (WGII), how societies might adapt (WGII), and how it might be mitigated (WGIII). By contrast, science can offer no response to questions of *value* or *importance*, such as which courses of action are best or of highest priority. Answers to those questions depend on what people judge to be good and bad, right and wrong, important and unimportant. Some values are widely shared, but others vary considerably across cultures, groups, and individuals; one key example is the differing human value of "subsistence" carbon emissions — those needed for simple survival — versus the "luxury" emissions of wealthy people and nations (Agarwal and Narain, 2012; Jasanoff, 2010). Values are reflected in ethics, or moral principles and rules of conduct, as well as in social norms, political rhetoric, and decision-making. They also have powerful effects on perceptions of climate change and on literacy about climate science. Although few high-quality trans-national surveys exist, they show that in many countries education is the strongest predictor of climate change perceptions (Lee et al., 2015). However, values are also strong influences, in some cases (e.g. the USA and UK) dominating education and knowledge as predictors of attitudes (McCright and Dunlap, 2011; Whitmarsh, 2011).

The international governance efforts and strengthening the response to climate change necessitates that leaders, policymakers, and the broader public have literacy in the causes, effects, and possible future course of climate change. Achieving this is complicated by the fact that scientific knowledge adds to, and interacts with, other understandings of weather and climate built up in diverse world cultures over centuries (Hulme, 2009, 2018; Nakashima et al., 2012). These localized understandings contrast with the vast geographical and temporal scales of climate science (Green et al., 2010; Jasanoff, 2010; Orlove et al., 2010). Political cultures also give rise to geographical variations in how climate science knowledge is interpreted, used, and challenged (Jasanoff, 2011; Mahony, 2014, 2015). Furthermore, climate change itself is not uniform: some regions face steady, readily observable change, while others experience high variability that masks underlying trends. Short-term temperature trends, such as cold spells or warm days, have been shown to influence public concern (Bohr, 2017; Hamilton and Stampone, 2013; Zaval et al., 2014).

Against this background, ethical practice requires that scientists take special care when communicating findings and uncertainties that inform high-stakes decisions. In some cases evidence is sufficient to assign a precise probability to a conclusion, but often uncertainty is deeper and will be more accurately characterized in alternative ways (Kandlikar et al., 2005). To achieve this, the IPCC uses standardised calibrated language of likelihood and confidence to communicate the outcomes of the assessment (see Box 1.1). Yet even with calibrated language, the choice of category (e.g. *likely* vs. *very likely*) may itself be uncertain. Further, this calibrated language does not prevent confusion or misunderstandings. Studies show that even when shown IPCC uncertainty guidance, lay readers systematically underestimate the intended level of certainty; indicating numerical ranges alongside likelihood terminology, and allowing for narrower (more precise) ranges when appropriate, could help to reduce confusion in public communication (Budescu et al., 2014).

Media coverage of climate change plays a major role in climate perception and literacy (Brulle et al., 2012; Jaspal and Nerlich, 2014). While research into media reporting on climate change has expanded, research remains largely focused on Western countries (Schäfer and Schlichting, 2014). In the USA, analyses of television network news show that climate change receives minimal attention, is most often framed in a political context, and largely fails to draw appropriate linkages between climate change and some types of extreme weather events (Hassol et al., 2016). In five EU countries, television coverage of AR5 used 'disaster' and 'opportunity' as its principal themes; it virtually ignored the "explicit risk" frame, introduced by WGII (Painter, 2015) and now extended by the cross-WG AR6 risk framework (see Section 1.2.4.1). This is important considering that framing studies have confirmed that the way climate change is presented to people has a significant and differential impact on the quality of their responses (Dewulf, 2013)d. For example, when framed as a catastrophe (e.g., Hine et al., 2015), associated with local identities (Sapiains et al., 2016), or as a social justice issue (Howell, 2013), people have different types of reactions. Similarly, audience segmentation studies have shown how responses to climate change vary between groups of people with different, although not necessarily opposed, views on this phenomenon (e.g., Detenber et al., 2016; Sherley et al., 2014). In Brazil two studies have shown the influence of mass media on the high level of public climate change concern in this country (Dayrell, 2019; Rodas and Giulio., 2017).

Social media platforms have dramatically altered the mass-media landscape, bringing about a shift from unidirectional transfer of information and ideas to more fluid, multi-directional flows (Pearce et al., 2019). Climate science remains well-represented and prominent on social media. For example, in studies of Twitter reactions to the AR5, “settled science” was the most dominant theme and professional media organizations were the most linked-to sources (Newman, 2017; O’Neill et al., 2015). Social media suffer from well known problems, such as incivility that inhibits consensus-building and “filter bubbles” that restrict interactions to those with broadly similar views (Anderson and Huntington, 2017). However, at certain moments (such as at the release of the AR5 WGI report), Twitter studies have found that more mixed, highly-connected groups existed, within which members were less polarized (Pearce et al., 2014; Williams et al., 2015). Thus, social media platforms may in some circumstances support dialogic approaches to climate communication.

Science itself strives for an ethic of honesty, objectivity, and openness, though it does not always succeed (Medicine et al., 2009). In its theories and results, science values such features as predictive accuracy, explanatory power, falsifiability, and replicability (Kuhn, 1977; Popper, 1959). Practices embodying these scientific values include peer review, publication, model intercomparison projects (MIPs), and multiple groups analysing the same problems and data; in recent decades, open data and open code have facilitated greater independent scrutiny of published results.

Whether and how societal, political, and personal values should influence science continues to be debated. While such *contextual* values (Longino, 1990) can bias research, they can also play positive roles, especially in decision-relevant science when stakeholder values are taken into account in a transparent way (Douglas, 2009; Elliott, 2017). Some climate science questions are deemed a higher priority for investigation, or expressed in particular ways, because of their societal relevance; one example is the question of how the effects of a 1.5 °C warming would differ from 2 °C (Hoegh-Guldberg et al., 2018). Likewise, particular model outputs — such as projected precipitation in a specific region or sea level rise — are sometimes prioritized in model improvement efforts because of their practical relevance for specific groups of people (Intemann, 2015; Winsberg, 2018). Groups whose interests do not influence research and modelling priorities may thus receive less attention in support their climate-related decisions (Parker and Winsberg, 2018).

1.2.4 New approaches in the WGI AR6 report

The assessment approach, scope, and structure of the WGI AR6 have been shaped by the twin contexts of the changing climate system and the evolving political and societal responses. As a result of the scoping process, the WGI contribution to the AR6 is focused on results and understanding relevant to the global stocktake, as well as to adaptation, mitigation, and impacts at both global and regional scales. The report builds on the conclusions of previous IPCC assessments, and on the possibilities for integration along topics resulting from the maturation of climate science since AR5 and across multiple lines of evidence.

Based on this rationale, some changes in the structure of WGI AR6 have ben introduced. The new structure is designed to strengthen the assessment of climate information for regions and thus provide greater relevance for policymakers and to enhance links with WGII and WGIII (see also Section 1.8). Earlier reports divided topics along boundaries between modern observations, paleoclimatic data, and understanding from models. In contrast, the AR6 outline is structured around topics such as large-scale climate changes (Chapters 2-4), climate processes (Chapters 5-9), and regional climate information (Chapters 10-12 and Atlas). This approach aims at a greater visibility for key knowledge developments relevant for policymakers, particularly for the global stocktake and for regional adaptation planning based on a risk management framework.

Some Chapters integrate research elements such as observations, paleoclimate information, and modelling approaches. Two subjects presented separately in AR5, paleoclimate and model evaluation, are distributed among multiple Chapters. Observations, detection and attribution, and future projections are also distributed over multiple Chapters. This approach provides closer integration of different research elements in each Chapter.

Regional information provision is enhanced in this report, with an emphasis on the role of variability. The single regional chapter in the AR5 has been expanded to three chapters in AR6. The assessment on extreme events, distributed across multiple Chapters in the AR5, while there is a dedicated Chapter 11 in this report. The Atlas of global and regional climate projection was included as an Annex in the AR5; instead, the Atlas in this report involves the assessment of regional climate change and will include an interactive web-based product. This enhancement of regional assessment, together with a common framework of risk, enables a strong and consistent link between the WGI, WGII as well as WGIII AR6 reports. A more detailed description of the structure of this report may be found in Section 1.8.

1.2.4.1 Risk framing

Although climate change can potentially have both positive or adverse consequences for human or ecological systems, a major focus has been on understanding and assessing the adverse consequences. This focus stems directly from the UNFCCC, which states in its preamble: "*Acknowledging* that change in the Earth's climate and its adverse effects are a common concern of humankind". Furthermore, Article 2 declares that the ultimate goal of the convention is to "…. prevent dangerous anthropogenic interference with the climate system". This emphasis has led to the development of a common risk framework in order to assess such adverse consequences.

Risks to human and natural systems result from the interactions of climate-related hazards (including extreme weather and climate events) with exposure to and vulnerability to those hazards. Impacts generally refer to effects on lives; livelihoods; health and wellbeing; ecosystems and species; economic, social and cultural assets; services (including ecosystem services); and infrastructure. Impacts may be referred to as consequences or outcomes and can be adverse or beneficial. Risk can however also result from responses to climate change (adaptation and mitigation).

Evolution of the risk framework in IPCC assessments. The IPCC Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation SREX (IPCC, 2012) integrated climate science, climate impacts, adaptation and disaster risk management in the context of changing climate in response to the Hyogo Framework for Action (predecessor of SFDRR) and subsequent United Nations statements. AR5 WGII further explored the emergent risks and key vulnerabilities to climate change by analysing the "interaction of the changing physical characteristics of the climate system with evolving characteristics of socioeconomic and biological systems (exposure and vulnerability) to produce risk." SREX and subsequently AR5 WGII moved from a notion of climate change adaptation based upon vulnerability to one based on risk (Connelly et al., 2018). This concept of risk combines the language of probability and consequences with a focus on spatial relationships between hazard, exposure and vulnerability.

WGII AR5 assessed that in order to reduce risk, effective adaptation should include actions with co-benefits for other objectives or effective risk reduction and adaptation strategies that consider the dynamics of vulnerability and exposure and their linkages with socioeconomic processes, sustainable development, and climate change. Strategies should therefore include actions with co-benefits for other objectives. Organizations bridging science and decision making, including climate services, can play an important role in the communication, transfer, and development of climate-related knowledge, including translation, engagement, and knowledge exchange (Field et al., 2014). The risk framework has then also been used in the IPCC special reports following AR5. IPCC SR1.5 builds upon SREX Chapter 3, AR5 WGI and new relevant literature to assess hazards associated with global and regional climate changes when the globally averaged surface temperature is 1.5°C above the pre-industrial baseline versus 2°C or higher levels of warming. IPCC SR1.5 added to the framework the concept of "climate resilient pathways", illustrated as an iterative process of effectively reducing risk through pathways that combine adaptation and mitigation in a synergistic manner (IPCC, 2019).

[*Placeholder: include SROCC and SRCCL discussion*].

Risk concept in AR6. The conceptual risk framework is an integral element of the AR6. The risk framework is wider than the concept of "hazard-exposure-vulnerability" defined in SREX and AR5. The framework also encompasses risks related to climate policies (adaptation, mitigation, investment). A cross-Working Group process has been underway as part of the AR6 to develop a common risk definition and is presented in Cross-Chapter Box 1.2.

In WGI, the risk concept is related to climate change impacts and builds upon the concept first developed in the IPCC SREX (IPCC, 2012), which focused particularly on the negative consequences of hazards and disaster risk. The risk framework was then also adopted by IPCC AR5 WGII Ch19 (Oppenheimer et al., 2014), which refers more generally to the characteristics of climate change and its effects on geophysical systems. This conceptual risk framing can be applied across timescales and across spatial scales in the context of different regional and sectoral aspects. In the IPCC risk framework, the dynamic interaction between hazards, exposure and vulnerability determines risk. These elements are driven by both climate and socioeconomic processes. Climate influences mainly hazards, (although not exclusively) through a combination of natural climate variability and anthropogenic climate change.

Integrating adaptation in line with the Paris Agreement and SDGs into planning and decision making (including incremental and transformational adjustments) can promote synergies with development and disaster risk reduction and environmental quality (IPCC 2018). The AR6 risk framework builds on WGII AR5, which assessed the potential for reducing risks through both adaptation and mitigation (Oppenheimer et al, 2014). The Shared Socioeconomic Pathways (SSPs, see section 1.6) describe characteristics of a set of global reference futures. They are designed to promote more integrated assessments of climate change and its impacts by linking them to adaption, mitigation, and sustainable development. They will be used in AR6 and interpreted in the light of the large body of literature that has become available since the publication of AR5 (O'Neill et al., 2017c; Riahi et al., 2017a; Rogelj et al., 2018).

Some post-AR5 literature has critically discussed the IPCC risk framework. Arven and Renn (2015) point out the need for moving beyond the probability-based perspectives on risk and have proposed alternative definitions of risk, focusing mainly on consequences and uncertainties. The IPCC risk framework and associated terminology has since been revised and the updated definitions are provided in Cross-Chapter Box 1.2. Sutton (2018) proposes to include unlikely but high impact risks (Figure 1.3).

The reasons for concern framework. The Reasons for Concern (RFC) framework, used by WGII since IPCC TAR and also in post AR5 Special reports (SR1.5, SROCC and SRCCL) is a classification framework that compiles key risks across regions and sectors. Key risks have potentially severe impacts related to implications of warming and adaptation limits for the society, the economy and the environment, relevant to Article 2 of the UNFCCC. The RFC framework aggregates risks in five categories as a function of global mean temperature: (1) risks to unique and threatened systems, (2) risks associated with extreme weather events, (3) risks associated with the distribution of impacts, (4) risks associated with global aggregate impacts and (5) risks associated with large-scale singular events. AR5 assessed literature related to each of the RFCs, taking into account the socio-economic development pathway (Oppenheimer et al. 2014) to risk associated with each RFC. The SR1.5 builds upon AR5 but with a focus on the consequences of 1.5ºC of warming compared to 2°C and consequently develops RFC diagrams only up to 2.5ºC. It also accounts for the rate and timing of impacts when assessing RFC 1 and 5. In addition, the RFC framework was broadened in SR1.5 to include new and more specific evaluation of certain natural, managed and human systems. By adopting a common risk framework across working groups, the contribution of WGI is explicitly integrated into the assessments of the RFCs.

Multiple lines of evidence show that there has been a substantial increase since AR5 in the levels of risk associated with four of the five Reasons for Concern (RFCs) for global warming levels of up to 2°C (IPCC, 2018). The key risks identified in AR5-WGII-SPM that follow, all of which are identified with *high confidence*, span sectors and regions. Each of these key risks contributes to one or more RFCs (IPCC, 2014).

Post-AR5 literature (e.g. O'Neill et al., 2017) calls for the extension of the RFC framework in AR6 to consider complementary climate change metrics, individual risk assessments and better inclusion of socio ecological vulnerabilities in addition to the impacts on physical and ecological systems.

The WGI contribution to the risk framework focuses primarily on the assessment of hazards (see Cross-Chapter Box 1.2) and how these are changing under anthropogenic climate change. Chapter 12 forms the direct handshake to WGII by assessing climate-related hazards for different regions and sectors and relating those to essential climate variables and climate extreme indices as assessed in other chapters. The rate of change and the intensity of climate-related hazards is related to the emission pathways and corresponding mitigation policies as assessed by WGIII.

[START CROSS-CHAPTER BOX 1.2 HERE]

Cross-Chapter Box 1.2: Risk Framing in IPCC AR6

Since its inception, the UNFCCC has seen climate change as a risk to human and ecological systems, as stated in its preamble: "Acknowledging that change in the Earth's climate and its adverse effects are a common concern of humankind".

In order to assess those adverse effects, the IPCC has long addressed the understanding of the physical climate change, its impacts and mitigation options as a risk. However, up to now, there was no common framework to assess risk, that could then be applied with the specificities of each Working Group.

A cross-Working Group process has been underway as part of the AR6 to develop a common risk definition. The resulting definition is as follows:

Risk: The potential for adverse consequences for human or ecological systems, recognizing the diversity of values and objectives associated with such systems. In the context of climate change, risks can arise from potential impacts of climate change as well as human responses to climate change. Relevant adverse consequences include those on lives, livelihoods, health and wellbeing, economic, social and cultural assets and investments, infrastructure, services (including ecosystem services), ecosystems and species.

In the context of climate change impacts, risks result from dynamic interactions between climate-related hazards with the exposure and vulnerability of the affected human or ecological system to the hazards. Hazards, exposure and vulnerability may each be subject to uncertainty in terms of magnitude and likelihood of occurrence, and each may change over time and space due to socio-economic changes and human decision-making (see also risk management, adaptation, mitigation).

In the context of climate change responses, risks result from the potential for such responses not achieving the intended objective(s), or from potential trade-offs with, or negative side-effects on, other societal objectives, such as the Sustainable Development Goals (see also risk trade-off). Risks can arise for example from uncertainty in implementation, effectiveness or outcomes of climate policy, climate-related investments, technology development or adoption, and system transitions.

Risk management: Plans, actions, strategies or policies to reduce the likelihood and/or magnitude of adverse potential consequences, based on assessed or perceived risks (see also risk assessment, risk perception, risk transfer).

The following definitions of key concepts are included within the definition of risk:

Exposure: The presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected.

Vulnerability: The propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt. It also includes structural, economic, social, or cultural assets in places and settings that could be adversely affected. A broad set of factors such as wealth, social status, and gender determine vulnerability and exposure to climate-related risk.

Hazard: The potential occurrence of a natural or human-induced physical event or trend or physical impact that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems, and environmental resources. In this report, the term hazard usually refers to climate-related physical events or trends or their physical impacts. Relevant to WGI (and further discussed in Chapter 12), the definition of 'hazards' includes both trends and extreme events,' impact' for AR6 in general, is a specific intersection of hazard, vulnerability, and exposure within a sector.

Impacts: Effects on natural and human systems. In this report, the term impacts is used primarily to refer to the effects on society and ecosystems of extreme weather and climate events and of climate change. Impacts generally refer to effects on lives, livelihoods, health, ecosystems, economies, societies, cultures, services, and infrastructure due to the interaction of climate changes or hazardous climate events occurring within a specific time period and the vulnerability of an exposed society or ecosystem. Impacts are also referred to as consequences and outcomes. The impacts of climate change on geophysical systems, including floods, droughts, and sea level rise, are a subset of impacts called physical impacts.

In the context of climate change impacts, risks result from dynamic interactions between climate-related hazards with the exposure and vulnerability of the affected human or ecological system to the hazards. Hazards, exposure and vulnerability may each be subject to uncertainty in terms of likelihood of occurrence and magnitude. Each of these may change over time and space as a result of socio-economic changes and human decision-making (risk management). Examples of risks include those arising from potential impacts on lives, livelihoods, health and wellbeing, ecosystems and species, economic, social and cultural assets, services (including ecosystem services), and infrastructure (e.g. risk of heat-related deaths). But adverse consequences can also arise as human responses to climate change (e.g. risk of wind turbines harming birds.

It is recognized that much of the literature assessed within WGI talks about risk when evaluating impacts on physical system, such as floods for example. In the context of the IPCC, such studies assess the «frequency and or magnitude of flood events », and risk only applies if an explicit assessment to humans is included (exposure or vulnerability).

Risk is intrinsically related to uncertainty, and since its beginning, the IPCC has developed a consistent treatment and communication of scientific uncertainty (see Box 1.1).

Some post-AR5 literature has critically discussed the earlier IPCC risk framework. Arven and Renn (2015) point out the need for moving beyond the probability-based perspectives on risk and have proposed alternative definitions of risk, focusing mainly on consequences and uncertainties (Box 1.1 and Section 1.2.4.2).

[START CROSS-CHAPTER BOX 1.2, FIGURE 1. HERE]

Cross-Chapter Box 1.2, Figure 1: Schematic of the Risk Framework used in AR6. Risk results from the interaction between hazards, exposure and vulnerability. Vulnerability and exposure are mainly driven by socioeconomic processes. Climate mainly influences hazards through natural climate variability as well as anthropogenic climate change. Risk can be reduced via adaptation and mitigation, thereby constructing resilience.

[END CROSS-CHAPTER BOX 1.2, FIGURE 1. HERE]

[END CROSS-CHAPTER BOX 1.2 HERE]

1.2.4.2 Abrupt climate change, tipping points, and surprises

A key aspect of risk is the potential for abrupt climate change, defined in this report as one that occurs much faster than the rate of change of the external climate forcing. In some cases, abrupt change occurs because the current state becomes unstable, such that the subsequent rate of change is actually independent of the forcing. We refer to this class of abrupt climate change a “tipping point” (Lenton et al., 2008).

There is evidence of abrupt changes and tipping points in Earth System Models (ESM) projections (Drijfhout et al., 2015). Tipping points occur in narrow regions of parameter space (e.g. CO_2 concentration or temperature increase), and for specific climate background states. This makes them difficult to predict using mechanistic ESMs. Tipping points may show up in one model but not in others, or even in one specific run with a given model, but not in other runs. In such cases, a probability of tipping could be estimated in principle, but this would require many more ESM simulations than are typically available. In some cases, it is possible to detect forthcoming tipping points through time-series analysis that identifies reduced resilience to perturbations as the tipping point is approached (e.g. ‘critical slowing-down’, Scheffer et al., 2012)

Many proposed climate tipping points are actually bifurcation points, where transitions from one (equilibrium) state to another occur. These tipping points will display hysteresis (sometimes called path-dependence or irreversibility) if there are regions of parameter space where multiple stable states exist. A well-known example is multi-states and hysteresis in the ocean’s thermohaline circulation in response to changes in freshwater input from rainfall and ice-sheet melt (Rahmstorf et al., 2005). Transitions from one state to another can also be prompted by stochastic perturbations (such as climate extremes) which force the system outside of its current basin of attraction – this is called noise-induced tipping (Ashwin et al., 2012). For example, the tropical forest dieback seen in some ESM projections is accelerated by longer and more frequent droughts over tropical land (Good et al., 2013).

The tipping point concept is most commonly framed for systems in which the forcing changes relatively slowly. However, this is not the case for most scenarios of anthropogenic forcing projected for the 21st century. Systems with inertia struggle to keep up with rapidly-increasing forcing, which can lead to the failure of early warning signals, and also the possibility of rate-induced tipping – when a fast positive feedback overwhelms a slow negative feedback (e.g. the “compost bomb”; Wieczorek et al., 2011) — or even temporarily overshooting a bifurcation point without provoking tipping (Ritchie et al., 2019).

Many of the tipping points discussed in this report (see, e.g., Sections 4.7.2, 5.4.5, 8.6) would have severe local impacts relevant to the concept of dangerous climate change. There is also evidence of abrupt change and tipping points in the palaeoclimate record (Dakos et al., 2008). Some of these are associated with significant changes in the global climate, most notably deglaciations in the Quaternary and rapid warming at the end of the Palaeocene (Bowen et al., 2015). Such events changed the planetary climate for tens to hundreds of thousands of years, but at a rate that is actually much slower than projected anthropogenic climate change over the coming century.

“Surprises” are a class of risks involving very unlikely but well-understood events, on the one hand, and “unknown unknowns,” or events that cannot be predicted with current understanding, on the other. Examples of the former include a series of major volcanic eruptions or a large-scale nuclear war, either of which would cause substantial planetary cooling (Mills et al., 2014; Robock et al., 2007). An example of the latter is unexpected biological epidemics, such as the massive infestation of pine bark beetles that is currently devastating North American conifer forests, which may cause large-scale, irreversible changes in ecological regimes with feedback effects on climate (Bentz et al., 2010). In this context Sutton (2018) proposes to include unlikely but high impact risks as an integral part of the WGI assessment.

[START Figure 1.3 HERE]

Figure 1.3: A schematic representation of how climate change risk depends on equilibrium climate sensitivity (ECS). (a) A possible likelihood distribution consistent with the IPCC AR5 assessment that “Equilibrium climate sensitivity is likely in the range 1.5 to 4.5°C (high confidence), extremely unlikely less than 1°C (high confidence) and very unlikely greater than 6°C (medium confidence)”. (b) A schematic illustration of the fact that, for a given emissions scenario, the cost of impacts and adaptation rises very rapidly (shown here as an exponential damage function) with ECS. (c) In this example, the resultant risk (quantified here as likelihood × impact) is highest for high ECS values. The precise shape of the risk curve is dependent on assumptions about the shape of the likelihood and damage functions at high sensitivity (Weitzman, 2011). Figure and caption taken from Sutton (2018) [To be updated]

[END Figure 1.3 HERE]

1.2.4.3 Narratives and Storylines

As societies are increasingly experiencing the impacts of climate change related events, the climate science community is solicited to develop climate information tailored for regions and sectors. In this context, the traditional form in which scientists, including the IPCC, communicate information including a description of the uncertainties as well as confidence on the understanding of a given event or a projection (and associated probabilities) is often insufficient for the purpose of decision-making (e.g., Howarth and Painter, 2016, see also 1.2.4.1).

Recognizing these limitations, the use of narratives or storylines approaches have emerged, aiming to build a cohesive picture of a climate message that moves beyond the presentation of data and figures (Dessai et al., 2018; Fløttum and Gjerstad, 2017; Moezzi et al., 2017; Scott et al., 2018). Up to now these two terms have been used somewhat interchangeable in the literature, and also in somewhat different contexts.

On the one hand, narratives or storylines have been used in the context of socio-economic scenarios (scenario-storylines) that form the basis for deriving greenhouse gas emission scenarios as forcing for climate model simulations projecting future climate change and for vulnerability and impact assessment (SRES report, O’Neill et al., 2017c). On the other hand, storylines are used to give a qualitative and internally consistent description of past or future event (event-storyline), and have recently been defined as "a physically self-consistent unfolding of past events, or of plausible future events or pathways" (Shepherd et al., 2018) and used as such for example in IPCC SR1.5 (Ch 3, Box 8). Earlier uses include the compound phrasing of “narrative storylines” (Schneider, 2001) through to more recent transdisciplinary narrative framing approaches (Scott et al., 2018) or storylines linking atmospheric processes (Zappa and Shepherd, 2017), as an alternative approach to represent uncertainty. Hazeleger et al. (2015) suggested using “tales of future weather” (stories or narratives of observed high-impact events under climate change) to relate to users and their experiences. In summary, narratives or storylines are used to describe future socio-economic developments, as a means to represent uncertainty when deriving the physical conext of a past or future event, and finally as a tool for more effective communicating climate information.

Nevertheless, although the motivation and communication purpose of “scenario-storylines” and “event-storyline” might differ, both are similar in the sense that they are a qualitative approach for internally consistent descriptions of scientific results with the aim to enhance knowledge-integration in decision-making contexts.

Currently the IPCC glossary defines narratives as a “qualitative descriptions of plausible future world evolutions, describing the characteristics, general logic and developments underlying a particular quantitative set of scenarios. Narratives are also referred to in the literature as “storylines”.”

In this report a storyline approach can be found in Chapter 4 for discussion high-level of global warming projections. Chapter 10, Chapter 12 and the Atlas focus on the role of narratives and storylines for communication purposes, and also propose a distinction between the two terms. Chapter 11 uses a storyline approach for discussing low-probability high-impact extreme events (section 11.10). Scenario-storylines are further discussed in section 1.6.1 of this chapter.

1.3 History of climate understanding

Chapter 1 of the Working Group I (WGI) contribution to the AR4 (2007) provided a comprehensive overview of the history of climate knowledge. This section summarizes some of the important milestones and adds new discussions of the more recent history, including the IPCC era. It introduces the treatment of uncertainty and calibrated uncertainty language used in IPCC reports. Finally, it presents key findings from AR5 and the post-AR5 IPCC Special Reports, and compares projections from previous reports with recent observations. The Appendix to this chapter summarizes the principal findings of all six IPCC assessment reports, including the present one.

1.3.1 Climate science before 1950

Modern climate science combines aspects of meteorology, oceanography, geography, geology, ecology, chemistry, hydrology, glaciology, and geophysics, as well as other disciplines. It coalesced as a separate field of study in the mid-20th century. Scientists first developed theories of anthropogenic climate change in the 19th century, but these were not systematically explored until after World War II. This section reviews major lines of work contributing to its emergence.

Observations. Observing patterns of weather and climate is an ancient practice, as evidenced by descriptions and typologies of climatic regions in many cultures and literatures. Instrumental weather observation dates to the invention of thermometers and barometers in the 16th and 17th centuries. Several synoptic observing networks were established in 17th century Eurasia, but none endured more than two decades (Cassidy, 1985; Khrgian and Hardin, 1970; Nebeker, 1995). Isolines and other graphical techniques for representing synoptic measurements were invented in the early 19th century (Humboldt, 1817). By the mid-19th century, semi-standardized naval logs provided records of winds, ocean currents, precipitation, and air and sea surface temperatures, and low-resolution seasonal climatologies (long-term means) had already been prepared for much of the globe (Dove and Sabine, 1853; Maury, 1855, 1860; Maury and United States Naval Observatory, 1849). The five-zone Köppen climate classification, developed in 1884, remains in use today (Belda et al., 2014). It was even used as a diagnostic tool for climate models (Lohmann et al., 1993) and to describe climate changes (Chen and Chen, 2013). Peruvian fishermen first identified the El Niño phenomenon; related global teleconnections were noted in the late 19th century, and the atmospheric Southern Oscillation was first described in the 1920s (Cushman, 2004). Japanese meteorologist, Wasaburo Ooishi, discovered the jet stream in the 1920s using pilot balloons (Lewis, 2003).

Synoptic meteorology began in the 1840s with the spread of the electric telegraph. Telegraph operators transmitted weather data at no cost, establishing a crucial tradition of free exchange of data. 19th-century national weather services developed networks of surface stations and issued weather forecasts starting in 1861; recognizing the value of shared data and standards, they created the International Meteorological Organization (IMO) in 1873. A patchy data-sharing network reached all continents except Antarctica by 1900. Regular collection of climatological data for the world began in 1905 with the Réseau Mondial (Great Britain Meteorological Office and Shaw, 1920), and the similar collections *World Weather Records* (Clayton, 1927) and *Monthly Climatic Data for the World* (est. 1948) have been published continuously since their founding.

Palaeoclimate perspectives. With the gradual acceptance of “deep time” in the 19th century came investigation of fossils, geological strata, and other evidence pointing to large periodic shifts in Earth’s climate, from ice ages to much warmer periods, across hundreds of millions of years. Orbital theories of long-term climatic change, first suggested by Herschel around 1830, entered the literature starting with Croll

(1864, 1885). The interacting periodicities of orbital eccentricity, axial tilt, and axial precession were theorized in the early 20th century (Milankovich, 1920), but were not definitively linked to ice age cycles until decades later (Broecker et al., 1968; Emiliani, 1978). The reconstruction of more recent climate variability and change began in the 1800s, with the recovery of tree rings, ice cores, and lake sediments for early paleoclimate investigation. By the early 20th century, laboratory research had begun using tree rings to measure precipitation and the possible influence of sunspots on climatic change (Douglass, 1914, 1919, 1922). The advent of radiocarbon dating in the 1940s (Arnold and Libby, 1949) would usher in an era of rapid progress in paleoclimatology.

Understanding the climate system. The fact that climate is a globally interconnected system has been known since ancient times. The English word "climate" derives from the Greek root *klima* ("inclination"), a reference to the angle of incidence of the sun's rays at different latitudes, a key cause of climatic differences. Ocean currents and prevailing winds were well known to ancient mariners of many cultures, such as the Polynesian islanders who navigated vast distances of open ocean (Genz et al., 2009). Scientific theories of climate begin with Halley (1686), who articulated a theory of vertical circulation in the tropics to explain the trade winds. Hadley (1735) improved on Halley's explanation by including the Earth's rotation as well as solar heating; these large-scale tropical circulatory patterns are known today as Hadley cells. Ferrel (1856) added the Coriolis force to existing theory, describing and explaining the major structures of the global circulation. 19th-century scientists also established the main physical principles governing Earth's temperature. By 1822, the principle of radiative equilibrium (the balance between incoming solar radiation and the energy Earth re-radiates into space) had been articulated, and the atmosphere's role in retaining heat had been likened to a *serre*, or greenhouse (Fleming, 1998; Fourier, 1822).

Before computers, models of climate were conceptual, analog, or mathematical. Conceptual models, such as those of Hadley and Ferrel, explained major climatic features and processes in qualitative terms. Analogue "dishpan" models simulated atmospheric circulatory patterns by means of rotating cylinders or globes filled with viscous fluids and exposed to a heat source. Mathematical models applied basic physical principles, such as radiative equilibrium or the Coriolis force, expressed in equations. Arrhenius (1896), seeking the cause of ice ages, developed a 2-dimensional mathematical model of radiative transfer. In the early 1900s Bjerknes extended the Navier-Stokes equations of fluid dynamics to the atmosphere, creating the mathematical basis for a three-dimensional model of the global circulation (Bjerknes, 1906; Bjerknes et al., 1910). During World War I, Richardson developed a system for numerical weather prediction based on these equations (Richardson, 1922). When his attempt to apply his own method failed dramatically, meteorologists turned away from numerical modeling until after World War II (Nebeker, 1995).

Human and natural drivers. The first to measure the heat-absorbing capacity of carbon dioxide was Eunice Foote (1856), though her contribution was ignored until very recently. By the late 1850s, spectrophotometers permitted direct measurements of the radiative activity of gases. Water vapor, ozone, carbon dioxide, and certain hydrocarbons were found to absorb longwave radiation emitted from the ground, the principal mechanism of the greenhouse effect (Tyndall, 1861). Investigators established the major elements of the geochemical carbon cycle on geological time scales: volcanic outgassing, coal formation, rock weathering, deep-sea sedimentation, and oceanic absorption (Chamberlin, 1897, 1898; Ekholm, 1901). Some speculated that variations in solar activity, such as the 17th-century "Maunder minimum" when few sunspots or aurorae were observed, might affect short-term weather or climate (Weart, Discovery of Global Warming, 2018 web version). Scientists speculatively linked volcanic aerosols to ice ages in the 1890s (Dörries, 2006; Humphreys, 1913).

In the 1890s Högbom estimated that worldwide coal combustion of about 500 megatonnes per annum had already completely offset the natural absorption of CO_2 by silicate rock weathering (Berner, 1995; Crawford, 1997). Arrhenius (1896) found that a doubling of carbon dioxide would produce a 5-6°C warming, but in 1900 new measurements seemed to rule out CO_2 as a greenhouse gas due to overlap with the absorption bands of water vapor (Angström, 1900; Anonymous, 1901). Nonetheless, as coal combustion reached 900 megatonnes per annum, Arrhenius wrote that anthropogenic carbon dioxide might eventually warm the planet (Arrhenius and Borns, 1908). However, Hann's *Handbook of Climatology* — the field's standard textbook for 50 years — dismissed the carbon dioxide theory based on Angström's result (Hann, 1883; Hann and Ward, 1903), and most scientists treated carbon dioxide as irrelevant to climate until after WWII (Edwards, 2010a; Fleming, 1998). More sensitive instruments later revealed Angström's conclusion to be false. Analysing records from 147 stations around the globe, Callendar accurately calculated atmospheric warming over land at 0.3-0.4°C from 1890-1935 (Callendar, 1938; Hawkins and Jones, 2013). He attributed about half of this warming to anthropogenic CO_2 (see Figure 1.4).

[START FIGURE 1.4 HERE]

Figure 1.4: G.S. Callendar's graph of global temperatures from 147 surface stations, 1880-1934. Top: ten-year moving departures from the mean of 1901-1930 (Callendar, 1938). The dashed line represents his estimate of the "CO_2 effect" on temperature rise. Bottom: annual departures from the 1901-1930 mean.

[START FIGURE 1.4 HERE]

1.3.2 Climate understanding matures: 1950-1990

Between 1950 and 1990, climate science matured into an interdisciplinary field. By the 1970s, consistent projections of substantial anthropogenic climate change led to growing concern and increasing policy uptake, including convening a World Climate Conference (1979). Preparations for negotiating the UN Framework Convention on Climate Change (UNFCCC, 1992) began in the late 1980s, with the first IPCC assessment (1990) being prepared to support those negotiations and a Second World Climate Conference (1990).

Observations. Globally coordinated efforts produced major advances in observing systems after World War II. The World Meteorological Organization (WMO), an intergovernmental body under United Nations auspices, was founded in 1951. The WMO worked to standardize weather observations internationally and expand observing networks. By 1968 it had established the World Weather Watch, the institutional and technological base for modern global weather forecasting.

Meteorologists participated centrally in the 1957-58 International Geophysical Year (IGY), which featured globally coordinated observations of the atmosphere and oceans. The World Data Centres for Meteorology inaugurated for the IGY remain key climatological data repositories. Carbon dioxide monitoring stations, first established in Antarctica and at Mauna Loa, Hawaii, during the IGY, have tracked the increase in atmospheric CO_2 concentrations from 315 ppmv in 1958 to 410 ppmv in 2018. New island and Antarctic observing stations established during the IGY made it possible to confirm the Southern Annular Mode (also known by other names, including "high latitude mode" and "Antarctic Oscillation") as the principal mechanism of climate variability in the southern hemisphere (Karoly et al., 1996; Kidson, 1999; Rogers and van Loon, 1982).

Until the 1950s, little data was collected systematically at altitude, apart from at mountain summits. Starting in the 1920s, some military and commercial aircraft carried meteorographs. In the 1950s, fallout from nuclear weapons tests was used opportunistically as an atmospheric tracer, providing more detailed understanding of circulation in the stratosphere (Machta, 2002). Bomb radiocarbon (14C) also provided insight into the carbon cycle as it moved from the atmosphere into the biosphere, oceans, and soils (Broecker and Olson, 1960). However, the upper troposphere and stratosphere were not observed on a continuous basis until radiosonde networks emerged in the 1950s (Stickler et al., 2010).

Satellite observing systems added crucial new data sources starting around 1960. In polar orbits, satellites can observe the entire planet twice daily with a single instrument. In 1959 infrared radiometers returned the first measurements of both incoming solar radiation and outgoing longwave radiation. Since 1978, microwave radiometers have provided indirect measures of temperature, humidity, ozone, and liquid water. Satellite remote sensing revolutionized studies of the cryosphere, particularly near the poles where conditions make surface observations very difficult. Satellite mapping and measurement of snow cover began in 1966, with land and sea ice observations following in the mid-1970s.

Earth's oceans store the vast majority of heat retained by the planet and play a major role in the climate system. In addition to temperature, pressure, and other meteorological variables, military and merchant ships measured sea surface temperature (SST), a major variable in climate studies. Both natural radiocarbon and radionuclides from nuclear weapons tests provided tracers that helped establish circulatory patterns, especially in the deep ocean (Broecker et al., 1960, 1980). Marine observations for the globe were first assembled in the mid-1980s in the International Comprehensive Ocean-Atmosphere Data Set (ICOADS; Woodruff et al., 1987, 2005). Sea level was historically measured by onshore tide gauges, but due to numerous sources of error and limited spatial distribution, these are valuable mainly for measuring long-term change. Satellite radar altimetry can measure sea level and ocean circulation from space at much higher spatial and temporal resolutions, but after the brief SeaSat mission in 1978, was not deployed operationally until the TOPEX/Poseidon missions of the 1990s (Katsaros and Brown, 1991). Ocean surface and subsurface data collection efforts expanded in the 1980s with the Tropical Ocean Global Experiment (TOGA), which eventually deployed 70 moored buoys (Gould, 2003).

Palaeoclimate perspectives. Palaeoclimatology covers a wide range of temporal scales, ranging from the historical past to geological deep time (millions of years). Historical climatology aids near-term palaeoclimate reconstructions using media such as diaries, almanacs, and merchant accounts that describe climate-related events as frosts, flowers, harvests, droughts, famines, and grain prices. Meticulous records by Chinese scholars and government workers, for example, have permitted detailed reconstructions of China's climate back to 1000 AD, and even beyond (Ge et al., 2008; Louie and Liu, 2003). Climatic phenomena such as the Little Ice Age and the Medieval Climate Anomaly were originally proposed using data from historical records from across Europe (Lamb, 1965, 1995; Le Roy Ladurie, 1967).

Most palaeoclimate research relies on climate proxy data generated from geological archives. Among the few direct sources of observations about ancient climates are tiny air bubbles trapped in ice cores; these can be sampled, providing direct evidence of past atmospheric composition (including CO_2 levels). Climate research using ice cores began in the 1950s, with oxygen-18 isotope in precipitation serving as a proxy marker for temperature (Dansgaard, 1954). Cores were taken in Greenland, Antarctica, and various Arctic locations during the 1957-58 International Geophysical Year, but palaeoclimate reconstructions were first published a decade later on an almost 100,000-year core taken at Camp Century, Greenland (Dansgaard et al., 1969; Langway Jr, 2008). Subsequent ice cores from Dome C in East Antarctica have extended this climatic record to 800,000 years (Jouzel, 2013).

In the 1950s, glacial-interglacial cycles were observed in deep-sea sediment cores using oxygen isotope ratios (Emiliani, 1955). The same technique was later combined with magnetic stratigraphy to establish 22 glacial-interglacial cycles over the past 870,000 years (Shackleton and Opdyke, 1973), confirming the Milankovitch theory of orbital cycles as a key driver of natural climate change (Hays et al., 1976). Beginning in the 1970s and continuing through the 1980s, global reconstructions of sea-surface temperature were developed from hundreds of deep-sea sediment cores (McIntyre et al., 1976), providing the first quantitative constraints for model simulations of ice age climates (e.g. Rind and Peteet, 1985).

Major volcanic eruptions, which can cause pronounced global cooling lasting 1-3 years, are recorded in ash layers within ice cores and sediment layers. Starting in the 1960s, long-term changes in solar irradiance were reconstructed from combinations of sunspot and aural observations, radiocarbon captured in tree wood, 10Be in ice cores, and other indicators (Eddy, 1976; Stuiver, 1965). By the 1980s, other palaeoclimate archives, including loess deposits, corals, pollen, tree rings, ice cores, lake sediments, and marine sediments, were also contributing to past climate reconstructions, with temporal resolutions as high as monthly, in the case of corals (Bradley, 2015; Jones et al., 2009).

Human and natural drivers. The major anthropogenic driver of climate change is greenhouse gases, with aerosols and land use change playing significant secondary roles. Carbon dioxide's key role in climate was re-established following World War II. Studies established that the oceanic carbon sink absorbed some, but not all anthropogenic CO_2, thus accounting for its buildup in the atmosphere as well as for ocean acidification. Revelle and Suess (1957) famously described fossil fuel emissions as a "large scale geophysical experiment," in which "within a few centuries we are returning to the atmosphere and oceans the concentrated organic carbon stored in sedimentary rocks over hundreds of millions of years". The 1960s saw increasing attention to other radiatively active gases, especially ozone (Manabe and Möller, 1961; Plass, 1961). Methane, nitrous oxide, and chlorofluorocarbons were not considered systematically until the 1970s, when anthropogenic increases in those gases were first noted (Rasmussen and Khalil, 1981) . The US Climatic Impact Assessment Program (CIAP) of the early 1970s found that proposed fleets of supersonic aircraft, flying in the stratosphere, would cause substantial depletion of the ozone layer (10-20 percent or more) and possible aerosol cooling, stimulating efforts to understand and to model stratospheric circulation, atmospheric chemistry, and aerosol radiative effects (Mormino et al., 1975).

Natural drivers on decadal to centennial time scales include volcanoes, changes in solar irradiance, and natural carbon sources and sinks. In the 1960-1990 period, volcanic activity of the recent past was traced via historical records and quantified through observations of major eruptions by aircraft, satellites, and other instruments (Dörries, 2006). Detailed global measurements of surface-level solar irradiance were first conducted during the IGY (Landsberg, 1961), while top-of-atmosphere irradiance has been measured by satellites since 1959 (House et al., 1986). Investigation of the carbon cycle was extended to the biosphere and soils as well as the atmosphere, oceans, and marine sediments, with the ultimate goal of quantifying all natural and anthropogenic carbon sources and sinks (Broecker and Olson, 1960).

Understanding and attributing climate change. With the arrival of digital computers in the 1950s, mathematical models could be built to simulate climatic processes and climate change. A crude proof-of-concept climate simulation was created in 1956 (Phillips, 1956), and several laboratories devoted to climate modelling emerged in the 1960s. By 1975, numerous laboratories had created general circulation models (GCMs) for climate research. Rapid increases in computer power enabled higher resolutions and longer model runs, and the inclusion of more physical processes. Of the latter, heat exchange between the oceans and the atmosphere was the most essential. The first coupled ocean-atmosphere model (OAGCM) with realistic topography appeared in 1975 (Bryan et al., 1975; Manabe et al., 1975). Over time, modelers introduced more physical processes, including aerosols, atmospheric chemistry, sea ice, and snow, into climate models (see Table 1.2). At the same time, research continued on zero- , one- , and two-dimensional models, which provided constraints on the more complex GCMs.

Laboratory measurements, simpler models, and GCMs all supported the possibility of significant surface warming as carbon emissions increased. From 1931-1980, most estimates of equilibrium climate sensitivity fell into the 2-4°C range (see Edwards, 2010, p. 182). The detection of an anthropogenic warming "signal" against the backdrop of natural variability was achieved in the 1990s. Nonetheless, the relatively consistent results from measurements and models supported a series of policy reports flagging "inadvertent climate modification" as a potential future policy concern (Conservation Foundation, 1963; Panel on Weather and Climate Modification, 1966; Tukey et al., 1965). By 1970, the potential impacts of climate change on human societies were being studied as inputs to the 1972 UN Conference on the Human Environment (Study of Critical Environmental Problems, 1970; Study of Man's Impact on Climate, 1971).

Projections of future climate change. General circulation modelling matured in the 1970s. By 1979, responding to mounting concern, the US National Research Council (NRC) reported on the "best present understanding of the carbon dioxide/climate issue for the benefit of policymakers." The NRC evaluated results from GCMs, radiative-convective models, and energy-balance models. The report estimated climate sensitivity at 3°±1.5°C, stating the most likely range as 2-3.5°C, based on "consistent and mutually supporting" model results (National Research Council; Ad Hoc Study Group on Carbon Dioxide and Climate, 1979).

Throughout the 1980s, increasing attention to the climate change issue drove multidisciplinary research, seeking more detailed understanding of regional effects, human and environmental impacts, and mitigation strategies. Ecology, glaciology, hydrology, and atmospheric chemistry joined the list of contributing natural sciences. Analysts developed integrated assessment models (IAMs) to study how human activity influences climate change, how societies might be affected, and how they might respond (Rotmans, 1990). Numerous organizations at both national and international levels began to assess the physical science of climate change, as well as the risks to human and natural systems (Bolin, 2007).

The World Climate Conference held in 1979 issued an “appeal to nations” for “urgently necessary” research on climate, leading to establishment of the World Climate Research Program (WCRP) under joint auspices of the WMO, ICSU, and UNESCO. The WCRP immediately called for an “international board” to address “all scientific aspects of the CO_2 question” (Global Atmospheric Research Programme and World Climate Research Programme, 1980). As part of the ICSU Scientific Committee on Problems of the Environment (SCOPE), scientists from 29 nations contributed to an evaluation of potential ecological effects of greenhouse warming (Bolin et al., 1986). An International Geosphere-Biosphere Programme (IGBP), also under ICSU, was established in 1987. As negotiations toward the UN Framework Convention on Climate Change (FCCC) proceeded in the latter half of the 1980s, the IPCC was founded in 1988 to assess scientific understanding of the climate system. It issued its first report in 1990.

Table 1.1 provides equilibrium climate sensitivity (ECS) estimates from all major assessments since 1979. The more recent assessments emphasize additional ways of estimating climate responses, including transient response and palaeoclimate reconstructions of ECS. The table shows that despite some variation in the range of GCM results, expert assessment of the likely range of climate sensitivity has hardly changed since 1979.

[START TABLE 1.1 HERE]

Table 1.1: Estimates of equilibrium climate sensitivity (ECS), transient climate response (TCR), and "best guess" global temperature increase for CO2 doubling from successive assessment reports. ECS is defined as the globally averaged surface air temperature response to instantaneous CO2 doubling after the modeled climate has reached equilibrium. TCR is defined as the globally averaged surface air temperature change at the time of CO2 doubling in a scenario of concentration increasing at 1% per year. Early TCR results were discussed in the IPCC’s Supplementary Report (1992, Chapter B2) and the Second Assessment Report (A. Kattenberg et al., 1995), but no range was formally assessed until the Third Assessment Report (Houghton et al., 2001). Transient response is a more realistic measure of the actual climate system’s near-term response to gradually increasing CO2, but over longer periods of time, equilibrium must eventually be reached. When transient response simulations are continued (at doubled CO2) until they reach equilibrium, their range of results is similar to that of ECS simulations.

Assessment	Range of GCM results (°C)	Estimated range of ECS (°C)	"Best guess" ECS (°C)	Estimated range of TCR (°C)
NAS 1979 (National Research Council; Ad Hoc Study Group on Carbon Dioxide and Climate, 1979)	2.0-3.5	1.5-4.5	3.0	
NAS 1983 (National Research Council & Carbon Dioxide Assessment Committee, 1983)	2.0-3.5	1.5-4.5	3.0	
Villach 1985 (World Climate Programme, International Council of Scientific Unions, United Nations Environment Programme, & World Meteorological Organization, 1986)	1.5-5.5	1.5-4.5	3.0	
IPCC FAR 1990	1.9-5.2	1.5-4.5	2.5	
IPCC 1992 Supplementary Report (J T Houghton, Callander, & Varney, 1992)	1.7-5.4	1.5-4.5	2.5	not given
IPCC 1994 Radiative Forcing report (John Theodore Houghton et al., 1995)	not given	1.5-4.5	2.5	
IPCC SAR 1995	1.9-5.2	1.5-4.5	2.5	not given
IPCC TAR 2001	2.0-5.1	1.5-4.5	2.5	1.1-3.1
IPCC AR4 2007	2.1-4.4	2.0-4.5	3.0	1.0-3.0
IPCC AR5 2013	2.0-4.5	1.5-4.5	not given	1.0-2.5
IPCC AR6 2021 – fill in when available	Fill in	Fill in	Fill in	

[END TABLE 1.1 HERE]

1.3.3 Climate science and global change, 1990-present: the IPCC era

Since 1990, numerous national science agencies, academic researchers, and international and intergovernmental scientific organizations — many of them newly established — have contributed to increased understanding of the climate system and to projections of future climate change. IPCC assessments consider data and understanding as published in the peer-reviewed scientific literature. IPCC reports undergo one of the most exhaustive, open, and rigorous review and revision processes ever designed for science assessments; the assessment and review process itself has undergone intensive scrutiny and multiple revisions in response to critique (Mach et al., 2016; Shapiro et al., 2010).

Observations. Increasing confidence in an unprecedented warming trend in both atmosphere and oceans is based on a large and growing body of observational evidence. New organizations and networks were established to coordinate and standardize climate-related observing systems on a global scale. These include the Global Ocean Observing System (GOOS, est. 1991), the Global Climate Observing System (GCOS, est. 1992), the Global Historical Climatology Network (GHCN, est. 1992), the Global Earth Observing System of Systems (GEOSS, est. 2005), and the Global Cryosphere Watch (est. 2011). As a result, most but not all observing systems have experienced improvement in consistency and coverage since 1990 (see Section 1.4).

Data on surface temperature have been repeatedly extended, refined, and evaluated. Global land-ocean surface datasets, first developed in the 1980s by three independent groups (NOAA, NASA GISS, and HadCRU), introduced numerous new methods for quality control, adjustment, and error analysis (Hansen et al., 2010; Morice et al., 2012; Vose et al., 2012). A new, independently developed land surface dataset for 1753-2011 used novel adjustment techniques and data from over 36,000 thermometer sites (Muller et al., 2013; Rohde et al., 2013), and agrees closely with the three established datasets.

Data sources for the vertical dimension — principally radiosondes and satellites — have evolved considerably since 1990. New methods for spatial and temporal homogenization of radiosonde records, using comparisons with reanalyses and with neighboring stations, were introduced in the early 2010s (Haimberger et al., 2012). As for satellite data, vertical profiles must be derived algorithmically and calibrated against *in situ* radiosonde measurements. Over time, numerous adjustments to these algorithms have been made to account for such factors as orbital precession and decay. As a result, new versions of these datasets have been released every few years since 1978 (Edwards, 2010). However, despite repeated adjustments, differences remain in the temperature trends from surface, radiosonde, and satellite observations. These are the subject of ongoing research (Santer et al., 2017; Thorne et al., 2011).

Ocean data sources have expanded dramatically since 1990. ICOADS extended its coverage to 1662-2014 using newly recovered marine records and metadata (Freeman et al., 2017; Woodruff et al., 1998). In the 2000s, a major improvement in SST data came from adjustment for biases resulting from differing methods of measuring sea surface temperature (from buckets to engine intake thermometers), especially in the period around World War II (Kent et al., 2007). The World Ocean Circulation Experiment (1990-1997) collected data on subsurface currents at 1000 m, as well as temperature and salinity, using autonomous submersible floats (Gould, 2003). Since 2000, Argo floats have measured temperature, salinity, and current velocity from the surface to 2000m, covering most of the globe with almost 4000 floats by 2018 (Cheng et al., 2017). These new sources provide much more information on ocean heat content at depth. The first IPCC discussion of global ocean heat content appeared in the Third Assessement Report (TAR), which reported a 1948-1998 time series for the upper 300m. By the time of AR5, more accurate global data were available for 1971-2010 to 700 m and for 1957-2009 from 700 to 2000 m.

Beginning in 1992, sparse data from coastal tide gauges were augmented by global sea level measurements from TOPEX/POSEIDON satellite altimetry (Fu et al., 1994). These data were first incorporated in the TAR. Since the early 2000s, those satellites have been replaced by data from subsequent missions.

Knowledge of the state and evolution of the cryosphere increased spectacularly after 1990. Prior to the TAR, the sign of the mass budget of the Greenland and Antarctic ice sheets could not be determined. Through a combination of satellite and airborne altimetry and gravity measurements, and a better knowledge of surface mass balance and perimeter fluxes, a consistent signal of ice loss for both ice sheets was established by the time of AR5 (Shepherd et al., 2012). After 2000, satellite radar interferometry revealed rapid changes in surface velocity at ice-sheet margins, often linked to reduction or loss of ice shelves (Rignot and Kanagaratnam, 2006; Scambos et al., 2004). The Greenland Climate Network (GC-Net) was established in 1994 to monitor climatological and glaciological parameters with Automatic Weather Stations (Steffen and Box, 2001). Data sources for assessing the evolution of mountain glaciers and ice caps improved considerably, with internationally coordinated activities compiling worldwide glacier length and mass balance observations (World Glacier Monitoring Service, Zemp et al., 2015), global glacier outlines (Randolph Glacier Inventory, Pfeffer et al., 2014), and ice thickness of about 1100 glaciers (GlaThiDa, Gärtner-Roer et al., 2014). Whereas sea ice extent and concentration had been continuously monitored since 1979 from multichannel passive microwave imagery, datasets for ice thickness emerged later from upward sonar profiling by submarines (Rothrock et al., 1999) and radar altimetry of sea-ice freeboards (Laxon et al., 2003).

The increased amount and quality of global data permitted AR5 to provide estimates of changes in the global energy inventory, i.e., the amount of incoming solar energy retained by the atmosphere, oceans, land surface, and cryosphere (see Box 3.1 of AR5).

Palaeoclimate perspectives. Since 1990, paleoclimate records have increased in both temporal span and spatio-temporal resolution, including seasonally–annually resolved reconstructions of temperature, hydroclimate, and large-scale circulation modes (Masson-Delmotte et al., 2013). Marine sediment and ice core records provide quantitative estimates of past temperature, ice volume, sea level, and atmospheric chemistry associated with glacial–interglacial cycles over the past 800,000 years (Section 1.2.1.2, Figure 1.2) (EPICA Community Members, 2004; Jouzel, 2013; Lisiecki and Raymo, 2005; Past Interglacials Working Group of PAGES, 2016; Siddall et al., 2003). As dating techniques continue to improve, there has been major progress in the development of seasonally–annually resolved palaeoclimate records covering the last 2,000 years (Abram et al., 2016; Emile-Geay et al., 2017; PAGES 2k Consortium, 2013; PAGES Hydro2k Consortium, 2017; Tierney et al., 2015).

Of particular relevance to AR6 are recent efforts to reconstruct seasonal extremes in continental-scale temperature (Luterbacher, 2004) and ocean temperatures (Abram et al., 2007; Cobb et al., 2003; Cole and Fairbanks, 1990) over the last centuries to millennia. This interval contains well documented periods of human history that can be used to verify climate variability reconstructed using palaeoclimate sources (White et al., 2018). In particular, notable advances from regions of the Southern Hemisphere have improved our description of global and hemispheric climate variability and change (Dätwyler et al., 2018; Nash et al., 2016; Neukom et al., 2014; Neukom and Gergis, 2012; Palmer et al., 2015).

Paleoclimate modeling advanced significantly during this period, with Paleoclimate Modeling Intercomparison Projects (PMIP) assessed by the TAR (PMIP), AR4 (PMIP2), and AR5 (PMIP3). Recent improvements in paleoclimate modeling include data assimilation approaches that combine high-resolution paleoclimate data with AOGCMs to generate gridded reconstruction of climate over the last millennium (e.g. Hakim et al., 2016). Global climate models that incorporate water isotope tracers now provide a rich resource for advanced paleoclimate data-model intercomparisons (Jouzel et al., 1998; Stevenson et al., 2018; Xi, 2014).

Indigenous perspectives. During this period, indigenous and traditional knowledge (ITK) has played an increasing role in historical climatology on decadal and centennial timescales, especially in areas such as the Arctic where instrumental observations are sparse. Inuit communities have contributed to climatic history and community based monitoring (Gearheard et al., 2010; Riedlinger and Berkes, 2001). Indigenous Australian knowledge of climatic patterns has been offered as a complement to sparse observational records (Green et al., 2010; Head et al., 2014), while researchers have documented sophisticated awareness of interannual variability in the timing and seasonality of rainfall in Uganda (Orlove et al., 2010). In order to harmonize scientific and local knowledge, ongoing research seeks to conduct further dialogue, systematize indigenous knowledge, and analyze its utility for multiple purposes, especially adaptation (Alexander et al., 2011; Laidler, 2006).

Human and natural drivers of climate change. Changes in solar irradiance, a natural climate forcing, have been small and slightly negative since about 1980 (Matthes et al., 2017a). The negative radiative forcing (RF) of major volcanic eruptions was considered in the FAR; in subsequent assessments, the negative RF of smaller eruptions has also been included. The FAR (1990) focused attention on human emissions of carbon dioxide, methane, halocarbons, and nitrous oxide; of these, only the sources of CO_2 and halocarbons were well measured, with methane sources known only "semi-quantitatively" (IPCC, 1990, p. 29). Since then, new natural sources of methane have been identified (O'Connor et al., 2010; Ruppel and Kessler, 2017), as well as anthropogenic ones (Conley et al., 2016; Duren and Miller, 2012; Howarth, 2014). [*PLACEHOLDER: add role of ocean circulation as a driver when SROCC is ready*].

Unlike previous assessments, AR5 (2013) characterized anthropogenic radiative forcing relative to greenhouse gas emissions rather than to concentrations, thus accounting directly for how emissions of some substances cause changes in others. For example, emissions of halocarbons cause stratospheric ozone depletion; emission-based RF of halocarbons includes both the positive radiative forcing (RF) of halocarbons and the negative RF of reduced ozone concentrations. Overall, concentration-based and emissions-based forcings are identical, but the latter does a better job of accounting for anthropogenic effects. The RFs of short-lived greenhouse gases such as carbon monoxide and nitrogen oxides other than N_2O were quantified and included in overall calculations. Among the greatest advances has been increased understanding of the nature and complex role of aerosols, with both positive and negative RF. In addition to its positive RF in aerosols (Gustafsson and Ramanathan, 2016), black carbon (soot) from fuel combustion was identified as a significant contributor to accelerating ice melt (AMAP, 2015; Gertler et al., 2016). The extent and role of land use change has been better quantified, and a more complex understanding of its effects on the carbon cycle has emerged (Houghton and Nassikas, 2017).

Understanding and attributing climate change. The FAR (1990) concluded that while both theory and models suggested that anthropogenic warming was underway, its signal could not yet be detected in observational data against the "noise" of natural variability (also see Barnett and Schlesinger, 1987). Since then, increased warming and progressively stronger attribution studies using multiple lines of evidence have identified human activities as the "dominant cause of the observed warming since the mid-20th century" (AR5 SPM). Starting in the early 1990s, "fingerprint" studies examined specific model-predicted changes in certain variables (such as nights warming faster than days, a rising tropopause, a cooling stratosphere, and multi-year record-breaking temperatures) that could not be caused by natural climate drivers such as changes in solar irradiance or volcanic forcing (Davy et al., 2017; Karoly et al., 1994; Mann et al., 2017; Santer, 2003; Santer et al., 2013; Schneider, 1994; Stott et al., 2010).

Although climate models remain imperfect, their spatial resolution has increased dramatically while including ever more physical processes. In the 1990s, coupled AOGCMs were state of the art; by the 2010s, Earth system models (ESMs) and coupled carbon-cycle climate models incorporated land surface, sea ice, snow, vegetation, and other elements of the climate system. By 2000, some major modeling centers had deployed "unified" models for both weather prediction and climate modeling, with the goal of a "seamless" modeling approach that uses the same dynamics, physics, and parameterizations at multiple scales of time and space (WMO, 2015). Cloud processes and feedbacks, including indirect aerosol feedbacks, are better understood empirically, but they remain the single largest source of spread in GCM calculations of climate sensitivity, with numerous parameterization schemes in use (Gettelman and Sherwood, 2016; Stephens, 2005). ENSO forecasting, an exceptionally difficult test for prediction models, has improved slightly since the 1980s (Barnston et al., 2017).

Since climate models and model runs vary along many dimensions, comparing their results requires special techniques. Since the late 1980s, the climate modeling community has developed increasingly sophisticated model intercomparison projects (MIPs) (Covey et al., 2003; Gates et al., 1999). MIPs prescribe standardized experimental design, time periods, output variables, and observational reference data, thus permitting direct comparison of model results and helping to diagnose the reasons for biases and other differences among models and further process understanding. In both CMIP3 and CMIP5 experiments, climate model ensembles successfully reproduced 20th century global trends when they incorporated realistic anthropogenic forcings (Meehl et al., 2007a; Taylor et al., 2012). Yet when only natural forcings were included (creating the equivalent of a "control Earth" without human influences), the same experiment could not reproduce the observed post-1970 warming (Jones et al., 2013). This result held true at both global and continental scales.

Projections of future changes in climate. Because greenhouse gas and aerosol emissions, land use, and other human activities may change in numerous ways, future climate change cannot be precisely predicted. Therefore, each IPCC report has considered a range of possible scenarios, typically a "business as usual" scenario in which societies continue on their present course as well as several others reflecting socioeconomic and policy responses that may limit emissions and/or increase the rate of carbon dioxide removal from the atmosphere. IPCC Working Group III assesses scenarios and their implications for emissions, land use, and other key variables. (For further details on scenarios, see Section 1.6 of this chapter.)

Climate models are then run to simulate the outcomes of each scenario for the climate system. Since 1990, the quality and precision of model projections has improved due to better process understanding as well as higher model resolution. MIPs have increased confidence in the quality of these projections, as have comparisons of projections with observations (see Figure 4.X in chapter 4). Due to the high computational cost of GCM runs, starting with the SAR "Earth system models of intermediate complexity" (EMICs) were also employed, especially for such purposes as long-term projections and estimates of climate change commitment, irreversibility, and thresholds for ice-sheet decay (see Section 1.4.3.2).

[START BOX 1.1 HERE]

Box 1.1: Treatment of uncertainty and calibrated uncertainty language used in IPCC reports

Throughout the IPCC's history, the consistent treatment and communication of scientific uncertainty across all three Working Groups (WGs) has been important (Cubasch et al., 2013; Le Treut et al., 2007). Already in its 1990 first report, the IPCC specified terms and methods for communicating authors' expert judgments (Mastrandrea and Mach, 2011). Over time, the IPCC has developed and revised a framework to treat uncertainties consistently between assessment cycles, reports and across WGs through the use of calibrated language (IPCC, 2005; Moss and Schneider, 2000). The framework was updated in preparation of the AR5 (Mastrandrea et al., 2010, 2011).

Considerable critical attention has focused on whether applying the IPCC framework effectively achieves consistent treatment of uncertainties and clear communication of findings to users (Adler and Hirsch Hadorn, 2014; Shapiro et al., 2010). Specific concerns include, e.g., the transparency and traceability of expert judgements underlying the assessment conclusions (Oppenheimer et al., 2016) or the context-dependent representations and interpretations of probability terms (Budescu et al., 2014).

Mach et al. (2017) investigated the advances and challenges in approaches to expert judgment in the IPCC AR5. Their analysis showed that the shared framework increased the overall comparability of assessment conclusions across all WGs and topics related to climate change, from the physical science basis to resulting impacts, risks, and options for response. While the WGs in the AR5 still favored different expert-judgment scales, the differences more directly reflected the different evidence bases across the WGs. Nevertheless, many challenges in developing and communicating assessment conclusions persist (Mach et al., 2017), especially for findings drawn from multiple disciplines and Working Groups, for findings with substantial (or "deep"; SROCC Chapter 1) uncertainties, and for subjective aspects of judgments.

Approach for the AR6

AR6 follows the approach developed for AR5 (Box 1.1, Figure 1), as described in the "Guidance Notes for

Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties" (Mastrandrea et al., 2010). The three WGs use two metrics to communicate the degree of certainty in key findings, which is based on author teams' evaluations of underlying scientific understanding:

(1) *Confidence* is a qualitative measure of the validity of a finding, based on the type, amount, quality and consistency of evidence (e.g., data, mechanistic understanding, theory, models, expert judgment) and the degree of agreement; and
(2) *Likelihood* provides a quantified measure of uncertainty in a finding expressed probabilistically (e.g., based on statistical analysis of observations or model results, or both, and expert judgement).

Where appropriate, findings can also be formulated as statements of fact without uncertainty qualifiers. Throughout IPCC reports, the calibrated language is clearly identified by being typeset in italics.

The uncertainty guidance note clarifies the relationship between the qualitative description of confidence and the quantitative representation of uncertainty expressed by the likelihood scale. Responding in part to criticisms (Shapiro et al., 2010), it emphasizes traceability of the assessment throughout the process. Key chapter findings elevated to the Executive Summary are supported in the chapter text by detailed descriptions of the underlying evaluations of evidence and agreement, confidence, and likelihood. The guidance note also leaves flexibility to convey the most information when multiple options or combinations of confidence and likelihood are possible to characterize key findings.

Direct comparisons of uncertainties assessed in this Report with those from earlier WGI reports are, however, sometimes difficult due to a number of factors. These include the application of the revised guidance note on uncertainties (in the case of, e.g., WGI AR4, SREX and earlier reports), as well as the availability of new information, improved scientific understanding, continued analyses of data and models, and specific methodological differences in studies assessed by previous reports. For some climate variables, different aspects have been assessed from report to report and therefore a direct comparison between assessments would be difficult and limited.

[START BOX 1.1, FIGURE 1 HERE]

Box 1.1, Figure 1: The IPCC AR6 approach for characterizing understanding and uncertainty in assessment findings. This diagram illustrates the step-by-step process authors use to evaluate and communicate the state of knowledge in their assessment (Mastrandrea et al., 2010). Authors present evidence/agreement, confidence, or likelihood terms with assessment conclusions, communicating their expert judgments accordingly. Example conclusions are drawn from the IPCC WGI AR5. [adapted from Mach et al. (2017)]

[END BOX 1.1, FIGURE 1 HERE]

Box.1.1, Figure 1 illustrates the idealized step-by-step process of the IPCC assessment of scientific understanding and uncertainties (adapted from Mach et al. (2017)). The process starts with evaluation of the available evidence and agreement (Box.1.1, Figure 1, Steps 1–3). The following summary terms are used to describe the available evidence: limited, medium, or robust; and the degree of agreement: low, medium, or high. Generally, evidence is most robust when there are multiple, consistent, independent lines of high-quality evidence.

Next, the level of confidence is evaluated, combining the assessments of evidence and agreement into a single metric (Box.1.1, Figure 1, Steps 3–5). The assessed level of confidence is expressed using five qualifiers: very low, low, medium, high, and very high. It is typeset in italics to highlight that this is based on a formal confidence assessment, e.g., medium confidence. Box.1.1, Figure 1, Step 4, depicts summary statements for evidence and agreement and their relationship to confidence. There is flexibility in this relationship; for a given evidence and agreement statement, different confidence levels can be assigned, but increasing levels of evidence and degrees of agreement correlate with increasing confidence.

Where uncertainties can be quantified probabilistically, assessment conclusions can be expressed with likelihood statements (Box.1.1, Figure 1, Steps 5–6). However, unless indicated otherwise, likelihood statements are limited to findings for which the authors' assessment of confidence is "high" or "very high". Terms used to indicate the assessed likelihood of an outcome or a result include: *virtually certain*: 99–100% probability, *very likely*: 90–100%, *likely*: 66–100%, *about as likely as not*: 33–66%, *unlikely*: 0–33%, *very unlikely*: 0–10%, *exceptionally unlikely*: 0–1%. Additional terms (*extremely likely*: 95–100%, *more likely than not* >50–100%, and *extremely unlikely* 0–5%) may also be used when appropriate. Likelihood can indicate probabilities for single events or broader outcomes. The associated probabilistic judgments may build from statistical or modeling analyses, elicitation of expert views, or other quantitative analyses. The framework encourages authors, where appropriate, to present probability more precisely than can be done with the likelihood scale, for example with complete probability distributions or percentile ranges, including quantification of tails of distributions important for risk management (Mach et al., 2017; see also sections 1.2.4.1 and 1.2.4.2).

Throughout this WGI report and unless stated otherwise, uncertainty is quantified using 90% uncertainty intervals. The 90% uncertainty interval, reported in square brackets, is expected to have a 90% likelihood of covering the value that is being estimated. (i.e., the range encompasses the median value and there is an estimated 5% likelihood of the value being below the lower end of the range or above its upper end). Uncertainty intervals are not necessarily symmetric about the corresponding best estimate. A best estimate of that value is also given where available.

[END BOX 1.1 HERE]

1.3.4 Key findings of previous IPCC assessments

Working Group I (WGI) of the IPCC considers new evidence of climate change based on independent scientific analyses from observations of the climate system, palaeoclimate archives, theoretical studies of climate processes, and simulations using climate models. Each consecutive report builds on previous assessments of the physical science of climate change by incorporating new research and updating previous findings (see previous sections, in particular 1.3.3). The robustness of the IPCC assessment stems from the systematic consideration and combination of multiple lines of independent evidence.

1.3.4.1 Key findings of AR5

The WGI contribution to AR5 is the most comprehensive assessment since the IPCC's first report in 1990. It is also the most extensively reviewed, with over 54,000 comments received and responded to by the authors. AR5 highlighted many important advances in climate science understanding. Compared to WGI AR4 (IPCC, 2007), more palaeoclimate reconstructions, more detailed and longer observations and improved climate models were available, resulting in better understanding of the physical basis of climate change.

The WGI contribution to AR5 comprehensively assessed observations of climate change ("what has changed"), understanding of these changes and their causes ("why has it changed"), and future projections of climate change ("how will it change in the future").

1) Warming of the climate system is unequivocal

The WGI AR5 assessed that warming of the climate system is unequivocal and that many of the observed changes since 1950 are unprecedented over decades to millennia. Changes are evident in all components of the climate system: the atmosphere and ocean have warmed, the amounts of snow and ice have diminished, sea level has risen, and the atmospheric concentrations of greenhouse gases have increased. The WGI AR5 also, for the first time in IPCC, highlighted at the level of the SPM the "other side of the CO_2 problem" (Doney et al., 2009), i.e., ocean acidification caused by the absorption of about 30% of anthropogenic carbon dioxide from the atmosphere.

Many key WGI AR5 findings on recent changes could be placed in a longer-term context, linking the present state of the climate with observational evidence from the historical period and with evidence from paleoclimate archives. For surface air temperature, for example, the WGI AR5 assessed that each of the last three decades has been successively warmer at the Earth's surface than any preceding decade since 1850. In the Northern Hemisphere, 1983–2012 was *likely* the warmest 30-year period of the last 1400 years (*medium confidence*). For sea level, the WGI AR5 assessed with *high confidence* that the rate of sea level rise since the mid-19th century has been larger than the mean rate during the previous two millennia.

The WGI AR5 also assessed the ocean's role in trapping extra energy and highlighted its importance: ocean warming massively dominates the increase in energy stored in the climate system, accounting for more than 90% of the energy accumulated between 1971 and 2010 (*high confidence*). In comparison, warming of the atmosphere only corresponds to roughly 1% of the energy accumulated over the same period.

2) Human influence on the climate system is clear.

The WGI AR5 assessed the vast evidence supporting the human influence on the climate system. The multiple lines of independent evidence include, among others, increasing greenhouse gas concentrations, positive radiative forcing estimates, unequivocal observed warming across climate system components, and the theoretical understanding of the climate system.

As for drivers of climate change, the WGI AR5 assessment confirmed the dominant role of carbon dioxide (CO_2) and the net cooling effect from aerosols. The 40% increase in atmospheric CO_2 since pre-industrial times, primarily from fossil fuel emissions and secondarily from net land use change emissions, contributed most to changes in total radiative forcing since 1750. Concentrations of CO_2, methane (CH_4), and nitrous oxide (N_2O), have all increased to levels unprecedented in at least the last 800,000 years. Aerosols and their interactions with clouds, on the other hand, have offset a substantial portion of the positive global mean radiative forcing resulting from the increase in well-mixed greenhouse gases (*high confidence*).

The evidence for human influence has grown since the time of the WGI AR4 (IPCC, 2007) and attribution of a human contribution to detected changes was possible in WGI AR5 in more climate system components than in previous reports. In the WGI AR5, human influence has been detected in warming of the atmosphere and the ocean; changes in the global water cycle; reductions in snow and ice; global mean sea level rise; and changes in some climate extremes. One of the key assessment findings of the WGI AR5 is that it is *extremely likely* that human influence has been the dominant cause of the observed warming since the mid-20th century.

3) Limiting climate change will require substantial and sustained reductions of greenhouse gas emissions.

A critical policy-relevant finding of WGI AR5 is the close, approximately linear relationship of cumulative total emissions of CO_2 and global mean surface temperature response. This finding has important implications for understanding current changes and projecting possible futures and thus provided crucial information for negotiation of the Paris agreement (UNFCCC, 2015). For example, it implies that continued emissions of greenhouse gases will cause further warming and changes in all components of the climate system, independent of any specific scenario or pathway. Further emissions and increase in atmospheric CO_2 will also lead to further uptake of carbon by the ocean and increase ocean acidification. From the close link between cumulative emissions and warming it follows that any given level of warming (such as the 1.5°C and 2°C warming targets in the Paris agreement) is associated with a total budget of CO_2 emissions. To stay within the budget, higher emissions in earlier decades imply lower emissions later on. In the absence of a large net removal of CO_2 from the atmosphere, stabilizing warming thus requires that CO_2 emissions descend to zero.

Climate projections based on the Representative Concentration Pathways (RCPs) assessed in WGI AR5 result in continued warming over the 21st century in all scenarios, and beyond 2100 under all RCP scenarios except the strong mitigation scenario RCP2.6. Similarly, global mean sea level will continue to rise during the 21st century. Under all RCP scenarios, the rate of sea level rise will *very likely* exceed that observed during 1971-2010 due to increased ocean warming and increased loss of mass from glaciers and ice sheets. By the mid-21st century the magnitudes of the projected changes are substantially affected by the choice of emissions scenario. The WGI AR5 assessed that a 1.5°C target relative to 1850 to 1900 will *likely* be missed under all RCP scenarios except the strong mitigation scenario RCP2.6.

Considering the long term, multi-century perspective, the WGI AR5 assessed that cumulative emissions of CO_2 will largely determine global mean surface warming by the late 21st century and beyond. Past, present and future emissions of CO_2 thus commit the world to substantial multi-century climate change, and most aspects of climate change will thus persist for many centuries even if emissions of CO_2 were stopped immediately. According to the WGI AR5 assessment, a large fraction of this change is essentially irreversible on a multi-century to millennial time scale, except in the case of a large net removal of CO_2 from the atmosphere over a sustained period through as yet unavailable technological means.

1.3.4.2 Key findings of post-AR5 Special Reports

Following the AR5 reports in 2013 and 2014, IPCC assessed new literature relevant to specific topics in three Special Reports. The Special Report on Global Warming of 1.5°C (SR1.5) was produced in response to an invitation of the United Nations Framework Convention on Climate Change (UNFCCC). The subjects of the two others, the Special Report on the Ocean and Cryosphere in a Changing Climate (SROCC) and the Special Report on Climate Change and Land (SRCCL), were the result of consultation with governments. All Special Reports assess material relevant to all three IPCC Working Groups. Here we focus on key findings related to the physical science basis.

The Special Report on Global Warming of 1.5°C (Masson-Delmotte et al., 2018) assessed current knowledge on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening global efforts to respond to climate change, pursue sustainable development, and eradicate poverty. The key findings of SR1.5 most relevant to WGI revolve around three overarching themes. These themes respectively address progress in understanding climate change ("where we are"), potential impacts and associated risks for a global warming of 1.5°C compared to 2°C ("what can be avoided"), and emission pathways and system transitions consistent with 1.5°C global warming ("how do we get there").

1) Global warming continues unabated

The SR1.5 estimates with *very high confidence* that human activities have caused a global warming of approximately 1°C above pre-industrial levels in 2017 and that observed global mean surface temperature for 2006-2015 was 0.87°C higher than the average over the 1850-1900 period. It concluded that the estimated anthropogenic global warming *likely* matches the level of observed warming to within ±20%. Warming greater than the global annual average is being experienced in many regions and seasons, and changes in weather extremes are already detectable today.

The report also concludes that "global warming is *likely* to reach 1.5°C between 2030 and 2052 if it continues to increase at the current rate (*high confidence*)". However, even though warming from anthropogenic emissions will persist for centuries to millennia and will continue to cause further long-term changes such as sea-level rise and associated impacts, past emissions alone are *unlikely* to raise GMST to 1.5°C above pre-industrial levels.

Furthermore, climate models project robust differences in regional climate characteristics between the present day (average of 30-year period centred around 2017) and a global warming of 1.5°C, and between 1.5°C and 2°C, including mean temperature in most land and ocean regions and hot extremes in most inhabited regions (*high confidence*). There is *medium confidence* in robust differences in heavy precipitation events in several regions and the probability of droughts in some regions.

2) Limiting warming to 1.5°C reduces impacts and risks compared to 2°C

The report concludes that "climate-related risks for natural and human systems for global warming of 1.5°C are lower than at 2°C, depending on the magnitude and rate of warming, geographic location, levels of development and vulnerability, and on the choices of adaptation and mitigation options (*high confidence*)". Also, risks are higher if global warming exceeds 1.5°C before returning to that level by the end of the century ("overshoot") than if global warming stabilizes at 1.5°C, especially if the peak temperature is high (*high confidence*).

Comparing 2°C versus 1.5°C warming, the report outlines numerous avoided impacts to land and marine biodiversity and ecosystems. As a prominent example, warm-water coral reefs are projected to decline by a further 70-90% at 1.5°C and even by more than 99% at 2°C (*very high confidence*).

Importantly, by 2100, sea level rise would be around 0.1 m lower with 1.5°C global warming compared to 2°C (*medium confidence*). Even though sea level will continue to rise well beyond 2100, it will do so at a slower rate and a lower magnitude for a lower warming, enabling greater opportunities for adaptation in vulnerable environments such as small islands, low-lying coastal areas, and deltas. Instabilities and/or irreversible loss of the Greenland and Antarctic ice sheets are less likely to be triggered for 1.5°C than for 2°C.

3) Rapid emission cuts are required to limit global warming to 1.5°C

Building upon the understanding from AR5 of the quasi-linear relationship between cumulative net anthropogenic CO_2 emissions since the pre-industrial period and maximum global mean atmospheric temperature, the report assesses the remaining carbon budgets compatible with the 1.5°C or 2°C warming limits. The remaining carbon budget for a one-in-two chance of limiting global warming to 1.5°C is about 770 $GtCO_2$, and about 570 $GtCO_2$ for a two-in-three chance (*medium confidence*). At constant 2017 emissions, these budgets would be depleted by about the years 2035 and 2030, respectively. These remaining budgets are larger than those estimated in AR5 because SR1.5 used GMST as a measure of surface temperature instead of global mean surface air temperature as in AR5 (see section 1.5.3).

It is concluded that all emission pathways with no or limited overshoot of 1.5°C imply global net anthropogenic CO_2 emissions to decline by about 45% from 2010 levels by 2030, reaching net zero around 2050, together with deep reductions in other anthropogenic emissions such as methane and black carbon. For limiting global warming to below 2°C, CO_2 emissions are projected to decline by about 25% by 2030 and reach net zero around 2070.

The report also highlights the use of carbon dioxide removal (CDR) techniques to compensate for residual emissions and achieve net negative emissions to return global warming to 1.5°C following a peak.

The SR1.5 concludes that there is no single answer to the question of whether it is feasible to limit warming to 1.5°C and adapt to the consequences because feasibility has multiple dimensions that need to be considered simultaneously and systematically.

[*PLACEHOLDER for SROCC SPM statements*]

[*PLACEHOLDER for SRCCL SPM statements*]

1.3.5 How do previous climate projections compare with subsequent observations?

Many different sets of climate projections have been produced over the past several decades and it is valuable to assess how well those projections have compared against subsequent observations. Successful outcomes add confidence in the process of making projections for the future. For example, Stouffer and Manabe (2017) compared projections made in the early 1990s with subsequent observations with a focus on the spatial pattern of warming. They found that the projected surface pattern of warming, and the vertical structure of temperature change in both the atmosphere and ocean, were realistic.

AR5 examined earlier IPCC Assessment Reports to evaluate their projections of how GMST and global sea level would change (Cubasch et al., 2013). Although there was good agreement between the past projections and subsequent observations, this type of analysis is complicated because the emissions scenarios used in earlier projections did not precisely match what actually occurred. Any mismatch between the projections and subsequent observations could be due to incorrect specified radiative forcings (e.g. aerosol emissions, greenhouse gas concentrations or volcanic eruptions that were not included) or an incorrect modelled response to those forcings, or both. Alternatively, an agreement between projections and observations may be fortuitous due to a compensating balance of errors, e.g. too low climate sensitivity but too strong radiative forcings.

A set of prior climate model projections were compared to observations and assessed in Hausfather et al. (2019, in prep.), both based on the change in temperature over time and based on the change in temperature with respect to the change in radiative forcing (expressed as the implied TCR, following Otto et al. (2013)). This latter approach partly corrects for any mismatches between the forcings used in the projections and the forcings that actually occurred, though it does have some limitations when the modelled forcings differ greatly from observations.

Model projections of global mean surface temperature and estimated radiative forcings were taken from seven historical studies: (Broecker, 1975; Hansen et al., 1981, 1988; Manabe, 1970; Manabe and Stouffer, 1993; Nordhaus, 1977; Rasool and Schneider, 1971), along with the baseline no-policy scenarios from the first three IPCC assessment reports. They are shown compared to observations over the model forecast period in Figure 1.5 for both change in temperature over time (as a linear trend, top row) and change in temperature with respect to change in radiative forcing (as an implied TCR, bottom row).

[START FIGURE 1.5 HERE]

Figure 1.5: Top row: Trend in temperature change over time (°C per decade) for observations (blue) and climate models projections (red) for a selection of prominent past climate model forecasts. Bottom: Implied Transient Climate Response (°C per doubled CO_2) for observations and models based on the ratio of change in temperature to change in anthropogenic radiative forcing. Radiative forcing values are taken from each separate model; observed radiative forcing estimates use a 1000-member ensemble extended from Dessler and Forster (2018). Observed temperatures are based data from five groups: NASA GISTEMP, Hadley/UEA HadCRUT4, NOAA GlobalTemp, Berkeley Earth, and Cowtan and Way. Both modeled and observed trends are shown over the forecast period of each model between date of publication and the end of 2017 (or the last available model forecast year).

[END FIGURE 1.5 HERE]

In general, past climate projections were quite successful in simulating future warming, particularly when mismatches in forecast and observed radiative forcings were addressed. For example, the Scenario B presented in Hansen et al. (1988) projected around 50 percent more warming than has been observed during the 1988-2017 period, largely due to a misspecification of future radiative forcings. However, the observed change in temperature compared to the observed change in forcings is consistent with the model simulation (Hausfather et al 2019, in prep).

Similarly, while the IPCC FAR projected a higher rate of global mean surface temperature warming than has been observed, this is largely due to an overestimate of future greenhouse gas concentrations – with an increase in anthropogenic forcing between 1990 and 2017 of 1.6Wm^{-2} in the FAR compared to a best observational estimate of 1.1Wm^{-2} (Dessler and Forster, 2018). When this is taken into account, the change in temperature with respect to the change in forcings in the FAR aligns with observations. Note that past climate model projections have tended to overestimate the growth in atmospheric CO_2 concentrations and other components of radiative forcing compared to observations, with a number of models published in the 1970s and 1980s forecasting atmospheric CO_2 concentrations of up to 450 ppm by 2017 (Hausfather et al 2019, in prep).

In addition to global mean surface temperature, the regional projections of past climate models can be evaluated. For example, the First Assessment Report of the IPCC (1990) presented a series of temperature projections for 1990 to 2030 for several regional boxes around the world. Projections were given primarily for a best estimate of global warming of 1.8°C since preindustrial by 2030, but it was noted that the change should be reduced by 30% for the low global warming estimate and 50% higher for the higher estimate. There was *low confidence* in the regional estimates.

These regional projections are compared to the observed temperature change in the period since 1990 (Figure 1.6, following Grose et al. (2017)). Subsequent observed regional temperature change has tracked within the projected range for the best estimate of regional warming in the Sahel, South Asia and Southern Europe boxes, but temperature change has tracked at or below this range for Central North America and Australia boxes (but within the range scaled 30% lower for a lower global warming estimate).

[START FIGURE 1.6 HERE]

Figure 1.6: Range of projected temperature change for 1990-2030 for regions defined in IPCC FAR (1990). Darker red bands show the range of projected change given for the best estimate of 1.8°C global warming since pre-industrial, faint bands show the range scaled for lower and higher estimates of global warming. Blue lines show the observations from several global temperature gridded datasets, red lines show the linear trends in those datasets for 1990-2018 extrapolated to 2030. Observed datasets are: HadCRUT4.6, Cowtan and Way, GISTEMP, Berkeley Earth and University of Delaware.

[END FIGURE 1.6 HERE]

1.4 Developments in observing systems, reanalyses, climate modelling and other techniques

1.4.1 Observational data and observing systems

The quality and quantity of observations of Earth's climate system largely determine the pace of advances in our understanding of changes in Earth's climate. While early efforts used large-scale temperature reconstructions over the 19th to 20th century to identify a causal link between rising greenhouse gases and global-scale temperature (see Section 1.3), recent efforts leverage a growing set of observations gathered from diverse platforms to probe the regional to global-scale changes in the climate system and its causes across a wide variety of climate indicators. In addition to a large set of physical variables related to temperature and hydrological trends and variability, sea level rise, and the circulation of the atmosphere and ocean, key variables include the chemical composition of the atmosphere, as well as a rapidly expanding set of ecological indicators (GCOS, 2015).

Progress in climate science relies on the quality and quantity of observations from a range of platforms: surface-based instrumental measurements, aircraft observations, satellite-based retrievals, in-situ measurements and palaeoclimatic records. Overall, the observational coverage of the climate system is as good for the AR6 as it was for the AR5, with notable improvements in some areas, but also with some emerging risks of loss of coverage or continuity.

Figure 1.7 summarizes some key avenues for weather and climate related information, and how they have become available over time. While some, like satellite imaging and retrievals, have been ever improving and increasing in detail over the last decades, others are in decline. This includes surface temperature observations, where spatial coverage is decreasing in recent years, and some palaeoclimate records such as corals, and ice cores, where climate change itself is a factor in their reduced availability.

In the following, we briefly review the progress and changes in observational capacity since the AR5.

[START FIGURE 1.7 here]

Figure 1.7: Schematic of climate data coverage through time, indicating time span covered by different sources, as well as density of coverage from a given source (i.e. satellite coverage increasing through time, whereas ground-based instrumental coverage is decreasing in recent years, and corals and tropical ice cores are a "vanishing" archive).

[END FIGURE 1.7 here]

Land and atmosphere

For land surface and atmospheric observations, coverage has improved for a number of long-established in situ networks, including the main meteorological networks. The quality of measurements has also shown improvement (GCOS, 2015). Further, there is a general increase in the availability of time series of consistent measurements of sufficient length to provide trend analysis, from both surface networks and orbital platforms. An example is the monitoring of short-lived climate forcers, from networks such as the Aerosols, Clouds, and Trace Gases Research infrastructure (ACTRIS), or the Ozone Monitoring Instrument (OMI) aboard NASAs Auri satellite. (REFS UPCOMING).

Instrumental observations of the atmosphere have also recently expanded to include satellite retrievals of atmospheric CO_2 via the NASA Orbiting Carbon Observatory satellites, which allow for improved quantification of CO_2 fluxes between the atmosphere and the Earth's surface. With the addition of sensors to measure wind speed and direction on the ESA Aeolus satellite, scientists can better constrain the fluxes of heat and momentum associated with atmospheric circulation patterns.

Recently, several programs aimed at reconstructing and digitizing older sources of data, such as hand written weather journals and ships logs, have become active. Examples, many of which have a strong element of citizen science, include Atmospheric Reconstructions over the Earth (ACRE) (http://met-acre.net), oldWeather.org, and weatherrescue.org. Such observations are becoming a valuable source of weather and climate information above and beyond the presently active observational platforms noted above. Ongoing, coordinated efforts to rescue historical climate data archives build on previous efforts, and include IDARE (WMO) - https://www.idare-portal.org as well as the US Climate Data Modernization Program - https://www.ncdc.noaa.gov/climate-information/research-programs/climate-database-modernization-program.

New satellite missions such as ESA's SMOS and NASA's SMAP provide estimates of soil moisture.

Biosphere

Satellite retrievals of land properties have recently expanded to include fluorescence data of land plants as a measure of photosynthetic activity via satellites GOME (Yang et al., 2015) and OCO-2 (Sun et al., 2017).

In the ocean, efforts are underway to coordinate observations of marine biological variables around the globe (Muller-Karger et al., 2018). A large number of coordinated field campaigns during the 2015/2016 El Niño event enabled the collection of short-lived biological phenomonen such as coral bleaching and mortality caused by a months-long ocean heat extreme (Hughes et al., 2018).

International progress towards the identification of Essential Biodiversity Variables is underway, under the umbrella of the GEO-BON group (Navarro et al., 2017).

Cryosphere

For the cryosphere, there has recently been much progress in synthesizing global datasets covering larger areas and longer time periods from multi-platform observations. For glaciers, this concerns an expanded Global Terrestrial Network for Glaciers (GTN-G), which combines inventory data on glacier fluctuations, mass balance and elevation change with glacier outlines and ice thickness, providing input for assessing the global glacier evolution. New data sources include archived and declassified aerial photographs and satellite missions and high-resolution digital elevation models like Arctic DEM and Tandem-X (Braun et al., 2019; Porter et al., 2018). Improvements have also been made in the monitoring of permafrost parameters. The Global Terrestrial Network for Permafrost (GTN-P) provides long-term records of permafrost temperature and active layer thickness at key sites to assess their changes over time.

New data were obtained from ESA’s Cryosat-2 radar altimetry satellite mission, providing changes in the thickness of sea ice and the elevation of the Greenland and Antarctic ice sheets. Other missions include NASA’s Operation IceBridge, collecting airborne remote sensing measurements to bridge the gap between ICESat (Ice, Cloud and land Elevation Satellite) and the upcoming ICESat-2 laser altimetry missions. Longer time series from multiple missions have led to considerable advances in understanding the origin of inconsistencies and reducing uncertainties to quantify changes of the Greenland and Antarctic ice sheets (Bamber et al., 2018).

Other systematic efforts towards synthesizing remotely sensed cryospheric data include ESA’s Climate Change Initiative (CCI) for snow, sea-ice, glaciers, ice sheets, and permafrost. These delivered global datasets on selected Essential Climate Variables (ECVs) to support climate monitoring and modelling, using data from ESA Earth Observation missions, including the recent Copernicus Sentinel series of satellites (http://cci.esa.int/).

Oceans

Regarding ocean observations, a large number of Oceanobs19 community white papers provide an up to date perspective on all aspects of ocean observation relevant to climate [*at the time of FOD only 26 community white papers are published; an analysis will be done after the Oceanobs19 conference*]. These papers emphasize the need to develop synergies between in situ and satellite observations and to enhance interoperability in order to achieve fully integrated observing systems that address users needs. Observing systems are proposed for new variables such as Nitrous Oxyde (Bange et al, white paper in progress) or for complete ecosystems (Lombard et al, white paper in progress).

Recently developed “Deep Argo” floats capable of sampling down to 6,000m, and "Biogeochemical Argo" instruments designed to quantify carbon fluxes, will enable improved estimates of ocean-atmosphere heat and carbon fluxes relevant to climate change.

Basin-scale arrays of moored ocean buoys have expanded since AR5, providing continuous records of ocean and atmosphere properties on regional to basin scales that are especially important in the detection of climate change signals in decades-long records of ocean properties. Key basin-scale arrays include the TAO/TRITON in the Pacific Ocean, the RAMA array in the Indian Ocean, and the PIRATA and OSNAP arrays in the Atlantic Ocean.

Ships logs and other records that extend into the mid-18th century, and in rare cases, into the early part of the second millennium provide rare data about ocean temperatures and currents. Likewise, early records from ports and other coastal observing stations provide datasets that complement instrumental and paleoclimate data from prior to 1900CE.

Palaeoclimate

Palaeoenvironmental archives provide climate data ranging in resolution from sub-monthly (in the case of corals) to thousands of years (in the case of the slowest-accumulating deep-sea sediments); see Figure 1.7 Typically, the higher the resolution, the more limited the temporal coverage of the archive in question. Quantitative reconstructions of past climate and carbon cycle states require calibration of modern-day versions of these archives against instrumental records of climate. In many cases, such reconstructions leverage climate model output to provide a richer and more dynamic interpretation of the archive's sensitivity to different climate variables. In turn, climate models increasingly incorporate palaeo-climate and palaeo-carbon constraints to improve the accuracy of decadal-centennial to glacial-interglacial variability, developing new data assimilation frameworks along the way.

Major efforts completed since AR5 include an ever-expanding set of large-scale, multi-proxy temperature syntheses spanning the last 2000 years under the auspices of the PAGES2K initiative. As of 2018, a number of regional temperature reconstructions exist, including one for every continent and major ocean basins (Tierney et al., 2015). The Last Millennium Reanalysis Project (https://www.atmos.uw.edu/~hakim/LMR/) took advantage of the PAGES2K data collection and homogenization efforts to deliver a gridded reconstruction of global climate over the last millennium by combining the PAGES2K data with the Community Earth System Model in a novel offline data assimilation scheme (Hakim et al., 2016).

Ongoing efforts to expand the number of large-scale, tree-ring-based drought reconstructions have resulted in the Old World Drought Atlas (OWDA; Cook et al. (2015)). The PAGES Iso2K group uses stable water isotopic records from across the world to constrain global hydroclimate variability over the last 2,000 years (http://pastglobalchanges.org/ini/wg/2k-network/projects/iso2k).

New reconstructions of past climate extremes are particularly important to the detection and attribution of anthropogenic impacts on present and future climate extremes. Aside from the advances in drought reconstruction, recent advances include expanded datasets of past El Nino-Southern Oscillation extremes (e.g. Barrett et al., 2018, Grothe et al., submitted) and hurricane activity (e.g. Donnelly et al., 2015).

Recent advances in sea level reconstructions over the last thousands of years (Cook et al., 2015); others) and the last interglacial period (DeConto and Pollard, 2016a; Dutton and Lambeck, 2012; Rovere et al., 2016) provide key constraints on the relationship between global to regional temperature variability and sea level rise from different sources on centennial to millennial timescales.

A large number of paleo-climate archives are under threat from human activities, including long-lived trees disappearing owing to deforestation (especially critical in tropical areas), long-lived corals succumbing to heat-related mortality, tropical ice cores melting under accelerated warming, and loss and/or destruction of historical data archives. While internationally coordinated salvage efforts are focused on recovering these latter sources of pre-instrumental records of past climate, no such coordinated efforts exist for other vulnerable paleoclimate archives.

Improved constraints on the rates and magnitude of regional to global-scale impacts of ongoing climate change require continued, strategic investments in the collection of sustained observations of the climate system, the carbon cycle, and metrics of ecosystem health. While many new data streams, such as high-resolution satellites (e.g. Himawari), are coming online in support of this mission, many existing observational platforms and archives are at grave risk. These include long-term ocean observing sites dating to the mid- to late 20th century, such as the TAO/TRITON ocean buoy array, whose international funding structure remains precarious. With the advent of satellite-based retrievals of many climate parameters of interest, a decrease in the number of surface-based meteorological stations statistics on this may seem less of a concern than without the satellite data. However, we still require robust ground-based observations to calibrate satellite retrievals.

1.4.2 Reanalyses

Reanalyses complement observed datasets in describing the changes through the historical record. Reanalysis datasets are useful because they provide gridded output, physical consistency across variables (within the limitations of the model used), and information about variables (such as potential vorticity) and locations that are not observed. The methods used in the development of reanalyses have progressed since the AR5, and in some cases this has important implications for the information they provide on how the climate is changing. In this section, these new developments will be addressed. For a list of reanalysis datasets used in the present report, see Annex AI.1.

Recent major developments in reanalyses include the assimilation of a wider range of fields, higher spatial resolution, and greater efforts to minimise the influence of a temporally varying observational network. Coupled reanalyses are also being developed, allowing for a consistent picture of the ocean, atmosphere and cryosphere.

The term reanalysis has traditionally implied gridded datasets statistically interpolated from station-based data (see Annex of Ch10). However, more commonly now, reanalyses are created by assimilating historical data using a single modern forecast model. Forecast periods are typically short, often 6 hours, to limit the development of model biases (Dee et al., 2011). Details of many of the early reanalyses are outlined in Table 2.3 of AR5 WGI, including their limitations. These limitations include model biases, changes in the observational systems (e.g., spatial coverage, introduction of satellite data), and time-dependent errors in the underlying observations or in the boundary conditions, which may lead to stepwise changes in time.

Atmospheric reanalyses

Atmospheric reanalyses that were assessed in AR5 are still being used in the literature, and results from ERA-Interim (Dee et al., 2011) and JRA-55 (Ebita et al., 2011; Harada et al., 2016) reanalyses will be used in AR6. In the post-satellite era (post 1979), (Simmons and Poli, 2015) found that the ERA-Interim and JRA-55 reanalyses continued to be consistent, over the last 20 years, with those surface data sets which fully represented the polar regions. This provides confidence to the approach of combining reanalyses results with observed datasets in the AR6 assessment.

The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2) (Gelaro et al. 2017) includes many updates to both the range of variables that are assimilated, and the model used compared to MERRA that was assessed in AR5. Of note is the inclusion is the assimilation of aerosol observations, several improvements to the representation of the stratosphere including ozone, and improved representations of cryospheric processes. However, the MERRA-2 reanalysis cooled sharply over the last few years relative to ERA-Interim and JRA-55 (see Chapter 2).

Since the AR5, the growing demand for high resolution data has led to the development of higher-resolution reanalyses, such as ERA5 (Hersbach and Dee, 2016). ERA5 provides atmospheric fields at about 30 km resolution on 137 vertical levels and is available for the years 1979 to the present but will be extended back to 1950. The desire for higher resolution data has also led to the development of a number of regional datasets e.g. BARRA, Australia.

Many studies will compare results from a number of reanalyses for their particular metric of interest (e.g. Pepler et al., 2018 for surface high pressure systems). More formal intercomparisons are also underway, for instance the S-RIP intercomparison for the upper troposphere and stratosphere (Fujiwara et al., 2017).

Ocean reanalyses

Ocean reanalyses are now more diverse and many have higher resolution than at the time of AR5 (see Annex I). The first Ocean Reanalyses Intercomparison project has been carried out (Balmaseda et al., 2015), and areas of uncertainties have been identified, such as the deep ocean, the Southern Ocean and western boundary currents. Intercomparisons have also been dedicated to specific variables such as ocean heat content (Palmer et al., 2017), eddy kinetic energy (Masina et al., 2017) or the polar regions (Uotila et al., 2019). Due to limited observations and imperfect assimilation methods, ocean reanalyses do not provide a consistent time series of the Atlantic Meridional Overturning Circulation (Karspeck et al., 2017).

Coupled reanalyses

Reanalyses of the atmosphere or ocean alone may not account for important atmosphere-ocean coupling, and thus coupled reanalyses are also being developed, including CERA-SAT (Schepers et al., 2018). CERA-SAT combines an eddy-permitting quarter-degree ocean model with an atmosphere modelled at approximately 65 km horizontal resolution.
https://www.ecmwf.int/en/newsletter/150/meteorology/cera-20c-earth-system-approach-climate-reanalysis

How these reanalyses compare with individual atmosphere or ocean reanalyses is an area of current research.

Limited assimilation 20th century reanalyses

In order to examine longer-term low frequency changes and overcome some of the step-changes due to varying observational networks, some reanalyses limit the ingested observations to a select number of 'white-listed' reliable long observed records. These have resulted in a number of reanalyses of the atmosphere: 20CR (Compo et al., 2011) and ERA-20C (Poli et al., 2016) (1900-2010), and ocean: ORA-20C, (1900-2010). In addition, CERA-20C is a centennial-scale reanalysis that assimilates both atmospheric and oceanic observations back to 1900 (Laloyaux et al., 2018). Another advantage of 20CR is that it includes an ensemble of results, allowing for an estimate of the uncertainty arising from the method choice. The interest in longer timescales has motivated additional centennial reanalyses back to 1900 (ERA-20C) and 1834 (20CRv3, Compo et al., in prep).

Longer reanalyses

[*Discuss Last Millennium reanalyses*] (Tardif et al., 2018)

Recent applications of reanalyses

As their spatial resolution increases, new analysis becomes possible, such as the exploration of fine-scale extremes (e.g. precipitation, wind). The longer reanalyses allow greater confidence in detecting the change in the climate over the last 100 years. The growing interest in longer-term climate forecasts (from seasonal to multi-year and decadal) means that reanalyses are now more routinely being used to develop the initial state for these forecasts. These have been applied under the Decadal Climate Prediction Project (DCPP; (Boer et al., 2016).

[*How reanalyses are used to initialize some CMIP6 models used in this assessment will be discussed here.*]

1.4.3 Climate Models

Numerical models are widely used in climate science across time and spatial scales. They are used to understand the climate of the past and present, and to project future climate. In fact, numerical models are the only tool available to look ahead into possible climate futures under a range of socio-economic scenarios (see Section 1.6). Models are also used to perform idealized experiments, such as instantaneous changes to climate parameters (e.g. a doubling of CO_2 concentrations or an increase in the solar constant) (Eyring et al., 2016a; Myhre et al., 2017), or simulations of the climate conditions of aquaplanets (Webb et al., 2017), in order to understand key processes and feedback mechanisms.

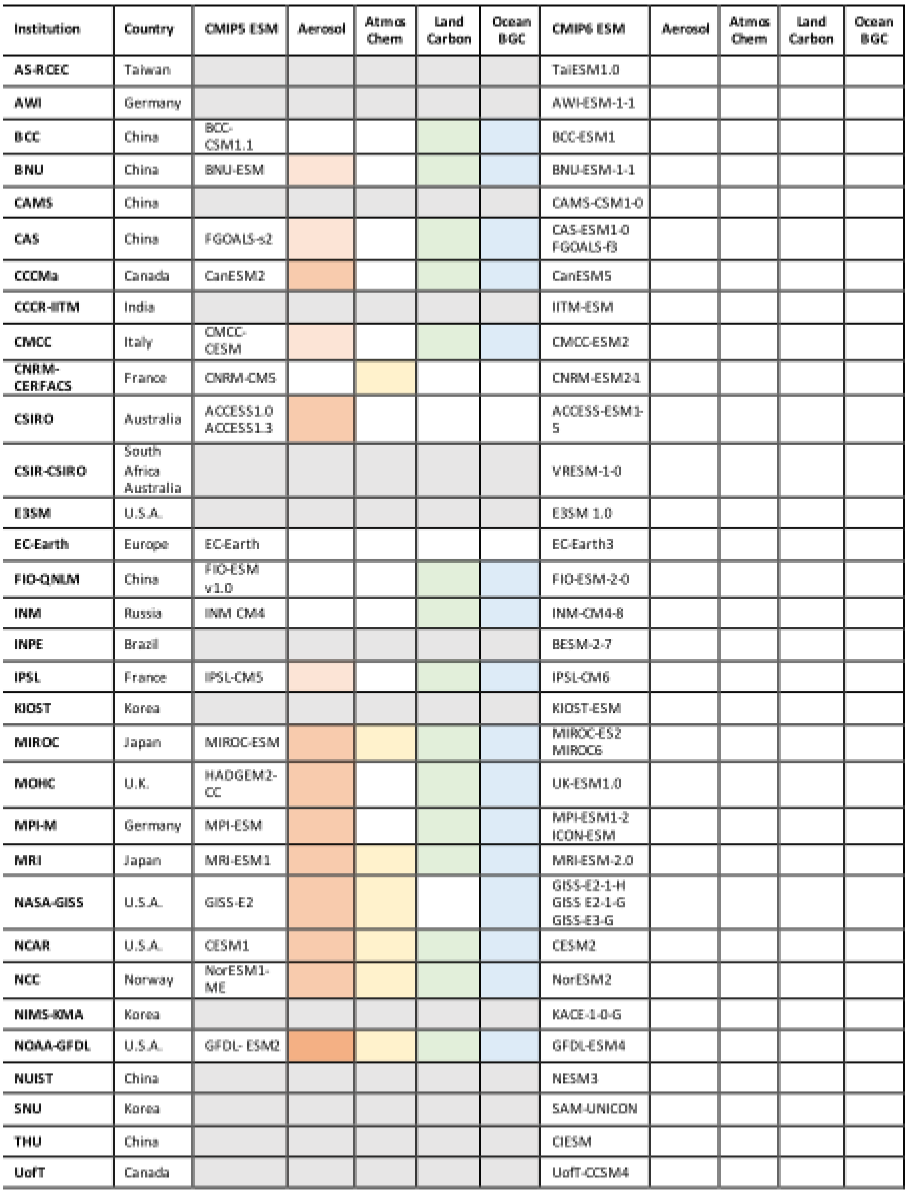
Global Earth System Models (ESMs) are the most complex, most advanced models which form the basis for assessments of future climate assessed by the IPCC. At the core of each ESM is a model of the physical climate system called a Globlal Circulation Model (GCM), to which are added models of the terrestrial and oceanic carbon cycles. The evolution of models up to AR5 was outlined in Section 1.3. We discuss in this section the main evolutions of ESMs since the AR5. Key characteristics of models participating in CMIP5 and CMIP6 are listed in Annex III, and a synthesis is provided in Table 1.2. Other types of models used in this report are then presented briefly.

1.4.3.1 Earth System Models

Earth system models are mathematical formulations of the laws that govern the evolution of climate-relevant systems: atmosphere, ocean, cryosphere, geosphere, biosphere. The laws may be fundamental laws of physics (e.g., Navier stokes equations and thermodynamics for the atmosphere) or empirical relations established based on observations, and when possible, constrained by the fundamental conservation laws (e.g. mass, energy). The evolution of climate-relevant variables is computed numerically using high performance computers, on discrete grids: the spatial resolution of these grids is an important measure of the relevance and accuracy of the model solutions.

[START TABLE 1.2 HERE]

Table 1.2: Table of CMIP5 and CMIP6 ESM complexity (building from table 9.1 of AR5). This table will show in a synthetic way how ESM complexity has grown from CMIP5 to CMIP6. For each item (aerosol, land carbon, etc) two or three categories of complexity will be defined and the table cells colored accordingly, the most intense color being the most complex category (more processes included).



Institution	Country	CMIP5 ESM	Aerosol	Atmos Chem	Land Carbon	Ocean BGC	CMIP6 ESM	Aerosol	Atmos Chem	Land Carbon	Ocean BGC
AS-RCEC	Taiwan						TaiESM1.0				
AWI	Germany						AWI-ESM-1-1				
BCC	China	BCC-CSM1.1					BCC-ESM1				
BNU	China	BNU-ESM					BNU-ESM-1-1				
CAMS	China						CAMS-CSM1-0				
CAS	China	FGOALS-s2					CAS-ESM1-0 FGOALS-f3				
CCCMa	Canada	CanESM2					CanESM5				
CCCR-IITM	India						IITM-ESM				
CMCC	Italy	CMCC-CESM					CMCC-ESM2				
CNRM-CERFACS	France	CNRM-CM5					CNRM-ESM2-1				
CSIRO	Australia	ACCESS1.0 ACCESS1.3					ACCESS-ESM1-5				
CSIR-CSIRO	South Africa Australia						VRESM-1-0				
E3SM	U.S.A.						E3SM 1.0				
EC-Earth	Europe	EC-Earth					EC-Earth3				
FIO-QNLM	China	FIO-ESM v1.0					FIO-ESM-2-0				
INM	Russia	INM CM4					INM-CM4-8				
INPE	Brazil						BESM-2-7				
IPSL	France	IPSL-CM5					IPSL-CM6				
KIOST	Korea						KIOST-ESM				
MIROC	Japan	MIROC-ESM					MIROC-ES2 MIROC6				
MOHC	U.K.	HADGEM2-CC					UK-ESM1.0				
MPI-M	Germany	MPI-ESM					MPI-ESM1-2 ICON-ESM				
MRI	Japan	MRI-ESM1					MRI-ESM-2.0				
NASA-GISS	U.S.A.	GISS-E2					GISS-E2-1-H GISS E2-1-G GISS-E3-G				
NCAR	U.S.A.	CESM1					CESM2				
NCC	Norway	NorESM1-ME					NorESM2				
NIMS-KMA	Korea						KACE-1-0-G				
NOAA-GFDL	U.S.A.	GFDL- ESM2					GFDL-ESM4				
NUIST	China						NESM3				
SNU	Korea						SAM-UNICON				
THU	China						CIESM				
UofT	Canada						UofT-CCSM4				

[END TABLE 1.2 HERE]

Model grid type and resolution have evolved since CMIP5. Cubed-sphere atmospheric grids were introduced in CMIP5 (Donner et al., 2011) to avoid the North Pole singularity and are used by more modelling groups in CMIP6. For the same reason, curvilinear orthogonal grids placing the grid poles over the continents have been used for a long time for the ocean-ice component (Griffies et al., 2000). Finite elements or finite volume formulations using unstructured grids are more flexible, providing higher resolution in focus areas. These methods were not previously used in CMIP due to their high computing cost, but parallel models using unstructured grids are now being developed, such as ICON in Germany (Giorgetta et al., 2018). Two new ocean-ice models with unstructured grids participate in CMIP6: FESOM (Wang et al., 2014) and MPAS (Petersen et al, 2018, submitted to JAMES).

The spatial resolution of ESMs is modestly higher in CMIP6 than it was in CMIP5. Oceanic horizontal resolution has increased both for models used for future projection scenario experiments and for assessing biogeochemical feedbacks, while the change in atmospheric resolution is not systematic (Figure 1.8). Global models with finer horizontal grids represent much better the large-scale circulation of the atmosphere and ocean, bringing key improvements in the simulation of the global hydrological cycle (Roberts et al., 2018). CMIP6 includes a dedicated effort (HighResMip) to explore the impact of higher resolution, such as ~50km, ~25km and even ~10km (see 1.4.4.1). Important improvements, such as reduced SST biases in the Southern Ocean, are documented in the highest-resolution coupled models used for HighResMip (Hewitt et al., 2017b).

[START FIGURE 1.8 HERE]

Figure 1.8: The population distributions of global climate models in terms of nominal horizontal atmospheric and oceanic resolutions. (a) (b) Models used for future projection scenario experiments in CMIP6 and CMIP5 model intercomparison projects respectively. (c) (d) Models used for assessing biogeochemical feedbacks in CMIP6 and CMIP5.The CMIP6 models are those registered as of December, 2018 (https://rawgit.com/WCRP-CMIP/CMIP6_CVs/master/src/CMIP6_source_id.html), while the CMIP5 models are those available at the IPCC Data Distribution Centre AR5 Reference Snapshot (http://www.ipcc-data.org/sim/gcm_monthly/AR5/Reference-Archive.html). [To be updated].

[END FIGURE 1.8 HERE]

The number of atmospheric vertical levels has increased in order to raise the top level of models and better represent stratospheric processes (Charlton-Perez et al., 2013; Kawatani et al., 2019). Half the modelling groups use "high top" models with a top level above the stratopause (a pressure of about 1 hPa); four groups have switched to "high top" models since CMIP5. The number of vertical levels in the ocean models has also increased, in order to achieve finer meshes over the water column and especially in the upper mixed layer. Six modelling groups used ocean models with less than 40 layers in CMIP5, but only one group (NASA-GISS) does so in CMIP6 (See Annex III).

Atmospheric models include parameterizations of physical processes such as radiation, clouds, turbulence, convection, and gravity waves that are not represented by grid-scale dynamics. The CMIP6 models have undergone updates in some of their parameterizations in terms of schemes and parameters over their CMIP5 counterparts. Most notably, CLUBB (Cloud Layers Unified by Binormals), an advanced scheme to treat cloud and turbulence in an integrated theory, has been developed and tested (Bogenschutz et al., 2013; Golaz et al., 2002; Guo et al., 2015), and it is now adopted in some CMIP6 models. Although the CLUBB scheme has theoretical and scientific advantages over traditional separated approaches, it is computationally more expensive; some modeling groups did not adopt it for CMIP6 for this reason (Zhao et al., 2018).

The representation of **atmospheric aerosols** is advancing, both in Earth System Models and in the more detailed Chemistry-Climate Models (CCMs). Most models now include explicit treatment of tropospheric aerosol and aerosol precursor emission and transport, although the norm is a bulk treatment where only the total mass of each aerosol type is predicted. In CCMs, recent advances include improved treatment of stratospheric aerosols and chemistry, updates to the treatment of volcanic aerosols, explicit tropospheric ozone chemistry, and increased complexity in cloud representation and aerosol-cloud interactions (Morgenstern et al., 2017). Broadly, aerosol-cloud microphysics has been a key topic for the aerosol and chemistry modelling communities since AR5, leading to improved understanding of the climate influence of aerosols and short-lived climate forcers, but also still representing a major source of scientific uncertainty and inter-model diversity.

Models of **ocean and cryosphere dynamics** have evolved significantly since CMIP5. The SROCC documents the key role of ocean mesoscale eddies in CO_2 uptake, in oceanic heat uptake, and in generating freshwater anomalies, as well as the equator-to-pole transports of these properties. Eddy parameterizations are used in coarse resolution ESMs, but they fail to mimic some aspects of the coupled high resolution ocean-ice-atmosphere system, especially in the Southern Ocean (Poulsen et al., 2018). Ocean-atmosphere feedbacks at the eddy scale arise from SST anomalies as well as surface current anomalies which modify the wind stress. Eddy feedbacks are shown to have effects on the larger scales, for example on the dynamics of ocean western boundary currents in the Pacific (Ma et al., 2016) and in the Atlantic (Renault et al., 2016). The explicit representation of ocean eddies, due to increased grid resolution (typically, from 1° to ¼°), is thus a major advance in a number of CMIP6 models (Hewitt et al., 2017b).

Progress has been made since AR5 regarding the simulation of ocean-cryosphere interactions. More models consider the drift of icebergs, as it ensures that the freshwater input due to iceberg melting is not artificially concentrated at the coast, although such refinements are still not incorporated into CMIP6 (Griffies et al., 2016; Nowicki et al., 2016). The ocean interaction with ice shelves is better accounted for by new parameterizations that more realistically represent heat and freshwater fluxes occurring at depth, rather than at the ocean surface. All CMIP6 ESMs include a sea ice component (Annex III, Table AIII.3, and Table 9.A.1 of AR5; Notz et al., 2016).). While the core modelling is technically similar to CMIP5 versions, advances have been made through focusing on the diagnosis and correction of some shortcomings of the simulations adopted in AR5, in particular the persistent underestimation of the rapid decline in summer Arctic sea-ice extent and the inability to reproduce the slightly increasing trend in Antarctic sea-ice extent observed in the past decades. Investigations have confirmed that these discrepancies can be partly attributed to the large internal variability of the Arctic and Antarctic climate systems (Ding et al., 2017; Jones et al., 2016a; Swart et al., 2015; Turner et al., 2015), although systematic biases still play a significant role in the (Notz and Stroeve, 2018; Rosenblum and Eisenman, 2016, 2017; Turner and Comiso, 2017). As a consequence, simulations of sea ice in ESMs have been used to estimate the ranges of possible internal variability (Serreze and Stroeve, 2015) and the sea-ice sensitivity to external forcings (Notz and Stroeve, 2016; Rosenblum and Eisenman, 2016). On the other hand, recent improvements in stand-alone sea-ice models have significantly contributed to the understanding of the physical processes underlying the systematic biases of sea-ice simulations in ESMs. Such improvements include more realistic mechanisms of ice–ocean–atmosphere interaction (Dupont et al., 2015; Spreen et al., 2017), ice–ice interactions (Sammonds et al., 2017), and more complex thermodynamics (Li et al., 2017; Massonnet et al., 2018), e.g. through the use of multiple ice categories or better parametrization of albedo changes, caused e.g. by surface melt ponds.

Glacier and ice-sheet models have greatly improved since the AR5. In particular, the resolution of ice-sheet models has continuously increased, not only because of increasing computing power and parallelization, but also due to spatial grid refinements, including nested grids, subgrid interpolation schemes, and adaptive mesh approaches (Cornford et al., 2013; Cuzzone et al., 2018). Thanks in part to the recent boost in satellite data availability, data-assimilation methods have been increasingly used to infer non-measurable variables needed as inputs to the modelling of glaciers and ice sheets in transient state (Goldberg et al., 2015; Pattyn, 2018). Improved understanding of key physical processes — including grounding line dynamics, stratigraphy and microstructure evolution, sub-shelf melting, and glacier and ice-shelf calving, among others (DeConto and Pollard, 2016b; Depoorter et al., 2013; Faria et al., 2014, 2018; Haseloff and Sergienko, 2018) — has served to motivate and guide the development of glacier and ice-sheet models. Even though most of these processes are still not fully implemented in models, the knowledge is still used to improve validation procedures and reducing model uncertainties. Despite the sophistication of current glacier and ice-sheet models, their coupling to global climate models is still complicated and is a matter of current research.

ESMs include the terrestrial and oceanic **carbon cycle** so that natural sources and sinks of CO_2 or other greenhouse gases can be simulated in the same numerical framework as the anthropogenic forcings. **Land models** have developed through the implementation of relatively sophisticated land use and land cover change representations to explore the impacts of land management on surface fluxes of carbon, water and energy (Lawrence et al., 2016). In terms of biogeochemical cycles, the importance of nitrogen availability to limit the terrestrial carbon sequestration has been recognized (Zaehle et al., 2014) and, thus, an increasing number of models now include a prognostic representation of the terrestrial nitrogen cycle and its coupling to the land carbon cycle (Jones et al., 2016a). Although the responses of permafrost to climate change is another area of focus (Gasser et al., 2018), CO_2 and CH_4 releases from permafrost are not implemented in an interactive manner in CMIP6 generation models.

Ocean biogeochemical models range in complexity from geochemical only (no representation of biological compartments), to NPZD class (nutrients, plankton, zooplankton and detritus), to increasingly complex versions with several plankton functional types (Annex III, Table AIII.3). Since AR5, models have evolved to enhance the consistency of the exchanges between ocean, atmosphere and land, through riverine input and dust deposition (Aumont et al., 2015; Stock et al., 2014). Other developments include flexible plankton stoichiometric ratios (Galbraith and Martiny, 2015), improvements in the representation of nitrogen fixation (Paulsen et al., 2017), and the limitation of plankton growth by iron (Aumont et al., 2015). Several modelling centers carried out large ensembles of simulations of the historical and/or future periods using their CMIP5 ESMs with interactive ocean biogeochemistry, including CESM1-BEC (Brady et al., 2019; Freeman et al., 2018; Krumhardt et al., 2017; Long et al., 2016; Lovenduski et al., 2016; McKinley et al., 2016, 2017), MPI-ESM-LR (Li and Ilyina, 2018), and GFDL-ESM2M (Frölicher et al., 2016; Rodgers et al., 2015). These simulations allow an unprecedented look at internal variability versus forced change in ocean biogeochemical fields of interest, such as air-sea CO_2 flux, nutrient and oxygen concentrations, sea surface temperature, and phytoplankton productivity.

Increasing resolution and increasing complexity place huge demands on model development teams and on computing resources. As a result, the number of climate centres that carry out IPCC-relevant global simulations has grown slowly from one intercomparison project to the next: from 10 in CMIP1 to 17 in CMIP5 and 26 in CMIP6 (Figure 1.9). At the same time, the need for accurate climate information at the regional scale is increasing, and many modelling centers use the global scenarios to develop regional climate models. High-resolution global climate models, such as those taking part in HighResMip, provide more detailed information at the regional scale (Roberts et al., 2018). However, due to the high cost of these models, only a limited number of scenarios are available. Regional information can be derived from standard CMIP6 models using regional climate models and downscaling techniques, presented in Chapter 10 and in the Atlas. Regional climate models are more diverse than the global ESMs and engage a wider international community (Figure 1.9).

[START FIGURE 1.9 HERE]

Figure 1.9: A world map showing the increased diversity of modelling centres contributing to CMIP (idea, use different symbols or colors or sizes for climate centres that participated in CMIP3, CMIP5, CMIP6), and also modelling contributions to CORDEX. [TO BE UPDATED, CORDEX information is incomplete]

[END FIGURE 1.9 HERE]

1.4.3.2 Models of lower complexity

Earth System Models of Intermediate Complexity (EMICs) complement the model hierarchy and fill the gap between conceptual, simple climate models and full-blown atmosphere–ocean general circulation models (AOGCMs) and Earth system models (ESMs) (Claussen et al., 2002). EMICs are simplified; they include processes in a more parameterized form and have generally lower resolution compared to the complex ESMs. As a result, EMICs require much less in terms of computer resources and can be integrated for many thousands of years without supercomputers (Hajima et al., 2014). The EMICs used in climate change research, however, are highly heterogeneous, ranging from zonally averaged or mixed-layer ocean models coupled to statistical–dynamical models of the atmosphere to low-resolution 3-dimensional ocean general circulation models coupled to simplified dynamical models of the atmosphere. An increasing number of EMICs include interactive representations of the global carbon cycle, with varying levels of complexity and numbers of processes considered (Zickfeld et al., 2013). Given the heterogeneity of the EMICs community, modelers tend to focus on specific research questions and develop individual models accordingly.

EMICs have been used extensively in past IPCC reports, providing long-term integrations on paleo-climate and future timescales, including stabilization pathways and a range of commitment scenarios, with perturbed physics ensembles and sensitivity studies, or with simulations targeting the uncertainty in global climate-carbon cycle systems (e.g., Collins et al., 2013; Meehl et al., 2007b). In this report, EMICs are again used in a number of chapters. Chapters 4 and 5, for example, draw on EMIC results for the assessment of long-term climate change beyond 2100 (Sections 4.7.1, 5.4.9), zero-emission commitments, overshoot and recovery (Section 4.7.2), impacts of carbon dioxide removal (CDR) on the climate system and the carbon cycle (Section 4.7.2, 5.6.2) and long-term carbon cycle – climate feedbacks (Section 5.4.9). While some EMICs contribute to parts of the CMIP6 suite of MIPs, a coordinated EMICs modeling effort similar to the ones for AR4 (Plattner et al., 2008) and AR5 (Eby et al., 2013; Zickfeld et al., 2013) is not in place for IPCC AR6. More recently, a number of studies have pointed to the possibility of systematically different climate responses to external forcings in EMICs and complex ESMs (Frölicher and Paynter, 2015; Pfister and Stocker, 2017, 2018) that need to be considered when applying EMICs for long-term projections and sensitivity studies complementing complex ESMs in the context of this report.

Physical emulators make up a class of heavily parametrized simplified climate models designed to reproduce the responses of the more complex models, and provide rapid translations of emissions, via concentrations and radiative forcing, into probabilistic estimates of climate impacts. For example, in the AR5, the Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC) energy balance model was used to estimate the greenhouse gas concentration time series resulting from the Representative Concentration Pathways (RCPs). They are also heavily used in the Integrated Assessment Model community, as translators of the complex information from Earth System Modelling into global temperature responses.

Since the AR5, development has progressed for several such simplified climate models, and their use is increasing. Two models in particular (MAGICC and Smith et al. (2018)) were heavily used in the SR1.5 to categorize mitigation pathways into classes of scenarios that peak near 1.5°C, overshoot 1.5°C, or stay below 2°C and similar. The report concluded that there was *high agreement* in the relative temperature response of pathways, but *medium agreement* on the precise absolute magnitude of warming, introducing a level of imprecision in the attribution of a single pathway into a given category. Other recently updated models include OSCAR and BernSCM. Recent progress generally includes added complexity of atmospheric chemistry and treatment of the carbon cycle, inclusion of recent estimates of the radiative forcing of greenhouse gases, and tuning of parameterizations to represent more recent Earth System Model results (generally CMIP5 and recently CMIP6).

For a more thorough overview of the use of simple models in the present report, see Cross-Chapter Box 1.5 “Temperature-based scenario classification using physical emulators”.

1.4.3.3 Model tuning and adjustment

When developing climate models, choices have to be made in a number of areas. For Earth System Models, these include (i) model formulation: although equations for fluids such as the atmosphere and ocean are well known and have been applied in models for a long time, different mathematical formulations exist. There are no unique equations for complex processes such as vegetation in ocean ecosystems; (ii) model resolution, grid type, coupling and numerical methods. These choices are often related to the available computer power (higher resolution is more computationally costly) and computer architecture (some numerical methods are better suited for highly parallel computing); (iii) parameterization of processes unresolved by the model equations or by the model spatio-temporal resolution. For example, the evolution of an individual cloud is not resolved by a standard atmospheric GCM grid (100km resolution). Instead, clouds are parameterized using integrated variables (e.g., cloud fraction) and empirical formulae.

Choices must also be made within each formulation, numerical method and parameterization, as, for each of these, several parameters can be set. The acceptable range for these parameters is set by mathematical consistency (e.g., convergence of a numerical scheme), physical considerations (e.g., energy conservations), observations or a combination thereof. The art of modelling is to choose a set of parameters that both falls within this range and mimics observations or their statistics.

An initial set of such choices is usually made by (often extensive) groups of modellers working on one single component of the earth system (ocean, atmosphere, sea ice…). As components are assembled to build an ESM, the choices are refined to best represent a number of pre-defined “tuning targets”. When these are met the model is deemed “fit for purpose” and a release is made for using in intercomparisons such as CMIP or other science projects. Tuning targets come in three levels: mean climate, regional phenomena and features, and historical trend (Hourdin et al., 2017). One example of such a goal is that “the climate system should reach a mean equilibrium temperature close to observations when energy received from the sun is close to its real value (340 w.m-2)”. Whether tuning should be performed to approach realistic climate-related features, such as accurately simulating the global mean temperature evolution over the historical era, or rather be performed for each individual process independently such that all collective behaviour is emergent, is a matter of debate in the climate community (Burrows et al., 2018)

Each modelling group has its own strategy and, after the AR5, a survey was conducted to understand the tuning approach used in 23 CMIP5 modelling centers. The results are discussed in (Hourdin et al., 2017) which stress that the behaviour of ESMs depends on the tuning strategy, which should therefore be documented. In CMIP6 each modelling group now describes the three levels of tuning both for the complete ESM and for components ([gradually] available at https://explore.es-doc.org/). Global tuning targets for CMIP6 model include: top-of-the-atmosphere (TOA) heat flux and its radiative components, the decomposition of each of these fluxes in terms of clear sky and radiative effect of clouds, global-mean ocean temperature, sea-ice extent, sea-ice volume, glacial mass balance, global root mean square error (RMSE) of precipitation [to be completed when model documentation is complete]. The TOA heat flux balance is achieved using a diversity of approaches, usually unique to each modelling group: for example, adjustments of the aerosol indirect effects, adjustments to ocean albedo, marine DMS parameterization, cloud properties by reducing the autoconversion threshold for liquid precipitation over the ocean. [to be completed when CMIP6 model documentation is complete].

Regional tuning targets include: ocean meridional overturning circulation (AMOC, AABW cell), regional sea surface temperatures, temperature profiles in the ocean, seasonal sea-ice extent (e.g. Labrador Sea, Greenland Sea), regional land properties, latitudinal distribution of radiation, spatial contrasts in top-of-atmosphere radiative fluxes or surface fluxes, stationary waves in the Northern Hemisphere [to be completed when CMIP6 model documentation is complete].

Trend tuning is not systematic and can include: adjustments of aerosol indirect effect (guided by available observations) to obtain near-observed 20th century surface temperature evolution [to be completed when CMIP6 model documentation is complete].

1.4.4 Modelling techniques, comparisons and performance assessments

A key approach in climate science is the comparison of results from multiple model simulations with each other and against observations. These simulations have typically been performed by separate models set up with consistent boundary conditions and forcings, as in the series of Phases of the Coupled Model Intercomparison Project (CMIP,Eyring et al., 2016; Meehl et al., 2000, 2007a; Taylor et al., 2012) run under the auspices of the World Climate Research Program WCRP (see section 1.4.4.1). Such multi-model ensembles (MMEs) have proven highly useful, as they help quantify, and reduce the influence of, the particular sets of parametrizations and physical components simulated by individual models. The primary usage of MMEs is to provide a well quantified model range, but when used carefully they can also increase confidence in projections (Knutti et al., 2010).

Since the AR5, increases in computing power have made it increasingly possible to investigate simulated internal variability using large initial conditions ensembles (ICEs). Such ensembles employ a single climate model in a fixed configuration, but starting from a variety of different initial states. In some experiments these initial states only differ slightly. As the climate system is chaotic, such tiny changes in temperatures, winds, and humidity may lead to different evolutions for the system as a whole, as is well known in weather forecasting. Other experiments start from a set of well-separated ocean initial conditions to sample the uncertainty in the circulation state of the ocean and its role in longer-timescale variations.

Although mostly applied in numerical weather prediction, ICEs can also be used to evaluate climate model parameterizations, if models are initialized appropriately (Phillips et al., 2004; Williams et al., 2013), mostly within the framework of seamless weather and climate predictions (e.g. Brown et al., 2012; Hurrell et al., 2009; Palmer et al., 2008). Initializing an atmospheric model in hindcast mode and observing the biases as they develop permits testing of the parameterized processes, by starting from a known state rather than one dominated by quasi-random short term variability (Ma et al., 2014; Vannière et al., 2014; Williams et al., 2013).

Due to the large computational requirements of any ensemble large enough to fully span the range of modelled variability, only a limited number of large ICEs is yet available. Examples in the literature supporting the present report include the CESM Large Ensemble (Kay et al., 2015), the MPI Grand Ensemble (Maher 2019; submitted), and the CanESM2 large ensembles (Kirchmeier-Young et al., 2017).

Recently, the ICE technique has been extended to observation-based large ensembles (McKinnon and Deser, 2018)and to regional modelling (Mote et al., 2015; Schaller et al., 2018), the latter often produced using crowdsourcing and volunteer computing power.

A third common technique is the perturbed physics ensemble (PPE). These are used to assess uncertainty based on a single model, with individual parameters perturbed to reflect the full range of their uncertainty (Hawkins and Sutton, 2009a; Knutti et al., 2010; Tebaldi and Knutti, 2007). Statistical methods can then be used to detect which parameters are the main drivers of uncertainty across the ensemble. PPEs have been used frequently in simpler models, such as EMICs, and are now being applied to more complex models. The disadvantage of PPEs is that they do not explore structural uncertainty, i.e. differences or shortcomings in the parametrizations themselves, and thus the estimated uncertainty will depend on the underlying model and may be an underestimation of the “true” uncertainty.

[*PLACEHOLDER: PPEs TO BE ADDED.*]

Together, the three ensemble methods (MMEs, ICEs, PPEs) allow investigation of climate models’ uncertainty arising from internal variability, boundary conditions, model formulations and parameterizations. Figure 1.10 illustrates the ensemble types.

[START FIGURE 1.10 HERE]

Figure 1.10: Illustration of common types of model ensemble, simulating the time evolution of a quantity V (such as surface temperature or precipitation). (a) Multi-model ensemble, where each model has its own realization of the processes affecting V, and its own internal variability around the baseline value (dashed line). (b) Initial condition ensemble, where several realizations from a single model are compared. These differ only by minute perturbations to the initial conditions of the simulation, such that over time, internal variability will progress differently in each ensemble member. (c) Perturbed physics ensemble, which also compares realizations from a single model, but where one or more quantities that may affect V are

systematically changed to allow for a quantification of the impact of those quantities on the model results.

[END FIGURE 1.10 HERE]

1.4.4.1 The sixth phase of the Coupled Model Intercomparison Project (CMIP6)

The present report assesses a range of results from CMIP5 that were not published until after the AR5. In addition, the first results of the 6th phase of CMIP (CMIP6) will be assessed. The CMIP6 experiment design is somewhat different to previous phases. It now consists of a limited set of DECK (Diagnostic, Evaluation and Characterization of Klima) simulations and the historical simulation that must be performed by all participating models, and a wide range of CMIP6-Endorsed Model Intercomparison Projects (MIPs) covering specialized topics (Eyring et al., 2016a). Participation in CMIP6-Endorsed MIPs is voluntary and at the discretion of each modelling centre.

The CMIP DECK simulations form the basis for a range of assessments and projections in the following chapters. As in CMIP5, they consist of a preindustrial control simulation (piControl, where “pre-industrial” is taken as 1850 conditions), an idealized abrupt quadrupling of CO_2 concentrations relative to piControl, a 1% per year increase in CO_2 concentrations relative to piControl, and a transient simulation with prescribed sea-surface temperatures for the period 1979-2014 (AMIP). In addition, all participating models perform a historical simulation for the period 1850-2014. For the latter, common CMIP6 forcings are prescribed. These include emissions (concentrations) of short-lived species (Hoesly et al., 2018) and long-lived greenhouse gases (Meinshausen et al., 2017), biomass burning emissions (van Marle et al., 2017), global gridded land-use forcing data (Lawrence et al., 2016), solar forcing (Matthes et al., 2017a), and stratospheric aerosol data from volcanoes (Zanchettin et al., 2016). For AMIP simulations, common sea surface temperatures (SSTs) and sea ice concentrations (SICs) are prescribed. For simulations with prescribed aerosol abundances (i.e. not calculated from emissions), optical properties and fractional changes in cloud droplet effective radius are prescribed in order to provide a more consistent representation of aerosol forcing relative to earlier phases. For models without ozone chemistry, time-varying gridded ozone concentrations and nitrogen deposition are also provided.

Beyond the DECK and the historical simulations, the CMIP6-Endorsed MIPs aim to investigate the responses of models to forcings, their potential systematic biases, their variability and usability for projections and predictions, and their responses to detailed future scenarios such as the Shared Socioeconomic Pathways (SSPs) (Section 1.6). Table 1.3 lists the 23 CMIP6-Endorsed MIPs, the main science questions they pose, the number of models participating in each. Results from a range of these MIPs will be assessed in the following chapters (also shown in Table 1.3).

[START FIGURE 1.11 HERE]

Figure 1.11: Structure of the CMIP6 multi-model intercomparison project (Eyring et al., 2016a). The centre shows the common DECK and historical experiments that all participating models must perform, the outer circle shows the topics covered by the endorsed MIPs.

[END FIGURE 1.11 HERE]

[START TABLE 1.3 HERE]

Table 1.3: CMIP6-Endorsed MIPS and participating models used in this assessment. [To be completed for the SOD]

CMIP6-Endorsed MIP name	Topics	Participating models	Key references	Used in sections...
AerChemMIP	Aerosols and Chemistry Model Intercomparison Project		(Collins et al., 2017)	
C4MIP	Coupled Climate Carbon Cycle Model Intercomparison Project		(Jones et al., 2016a)	
CDRMIP	The Carbon Dioxide Removal Model Intercomparison Project			
CFMIP	Cloud Feedback Model Intercomparison Project		(Webb et al., 2017)	
DAMIP	Detection and Attribution Model Intercomparison Project		(Gillett et al., 2016)	
DCPP	Decadal Climate Prediction Project		(Boer et al., 2016)	
FAFMIP	Flux-Anomaly-Forced Model Intercomparison Project		(Gregory et al., 2016b)	
GeoMIP	Geoengineering Model Intercomparison Project		(Kravitz et al., 2015)	

GMMIP	Global Monsoons Model Intercomparison Project		(Zhou et al., 2016)	
HighResMIP	High Resolution Model Intercomparison Project		(Haarsma et al., 2016)	
ISMIP6	Ice Sheet Model Intercomparison Project for CMIP6		(Nowicki et al., 2016)	
LS3MIP	Land Surface, Snow and Soil Moisture		(van den Hurk et al., 2016)	
LUMIP	Land-Use Model Intercomparison Project		(Lawrence et al., 2016)	
OMIP	Ocean Model Intercomparison Project		(Orr et al., 2017)	
PAMIP	Polar Amplification Model Intercomparison Project		(Smith et al., 2019)	
PMIP	Palaeoclimate Modelling Intercomparison Project		(Kageyama et al., 2018)	
RFMIP	Radiative Forcing Model Intercomparison Project		(Pincus et al., 2016)	
ScenarioMIP	Scenario Model Intercomparison Project		(O&apos;Neill et al., 2016)	

VolMIP	Volcanic Forcings Model Intercomparison Project		(Zanchettin et al., 2016)	
CORDEX	Coordinated Regional Climate Downscaling Experiment		(Gutowski Jr. et al., 2016)	
DynVarMIP	Dynamics and Variability Model Intercomparison Project		(Gerber and Manzini, 2016)	
SIMIP	Sea Ice Model Intercomparison Project		(Notz et al., 2016)	
VIACS AB	Vulnerability, Impacts, Adaptation and Climate Services Advisory Board		(Ruane et al., 2016)	

[END TABLE 1.3 HERE]

1.4.4.2 CMIP Evaluation Tools

For the first time in CMIP, comprehensive evaluation tools are available that run alongside the Earth System Grid Federation (ESGF) to produce comprehensive results as soon as the model output is published to the CMIP archive.

The Earth System Model Evaluation Tool (ESMValTool, Eyring et al. (2016c)) is an open source community development tool that includes a large variety of diagnostics and performance metrics relevant for coupled Earth System processes not only for the mean, variability and trends, but also for emergent constraints. It reproduces the majority of figures of the AR5 climate model evaluation chapter (Flato et al., 2013). ESMValTool includes other standalone model evaluation packages such as the NCAR Climate Variability Diagnostic Package (CVDP, Phillips et al. (2014)) and routines provided by the WMO Expert Team on Climate Change Detection and Indices for the evaluation of extreme events (Min et al., 2011). It also includes detailed diagnostics for key processes and variability such as monsoons, ENSO and MJO.

The Coordinated set of Model Evaluation Capabilities (CMEC) includes the PCMDI Metrics Package (PMP, Gleckler et al EOS, 2016), the International Land Modeling Benchmarking Project package (ILAMB, Luo et al. (2012)), and the parallel toolkit for extreme climate analysis (TECA, Prabhat et al. (2012)). CMEC is an open source tool that uses a suite of statistical error measures to compare results from simulations with the observations across space and time scales. It provides a database of summary statistics for knowledge discovery with developments that are complementary to the ESMValTool effort.

These tools are used in several chapters of this report for the creation of the figures that show CMIP results (e.g., Chapters 3, 4, and 5). This allows us not only to ensure traceability of the results, but also provides an additional level of quality control whether published figures can be reproduced. It also allows updating published figures with, as much as possible, the same set of models in all figures, and to assess model improvements across different phases of CMIP (Section 3.8.2).

These new developments are facilitated by the definition of common formats for CMIP model output (Balaji et al., 2018) and the availability of observations (obs4MIPs, Ferraro et al., 2015) and reanalyses in the same format as CMIP output. The evaluation tools for the first time ensure traceability and reproducibility of the results at all stages, using a well-established analysis. The tools are also used to support routine evaluation at individual model centres and enable a fast track to assess improvements of individual models or generations of model ensembles (Eyring et al., 2016b).

1.4.4.3 Evaluation against observations

Techniques used for evaluating climate models against observations were assessed in AR5 (Flato et al., 2013), and have progressed rapidly since (Eyring et al., 2019) The most direct approach that is continued to be widely used is to compare climatologies or time series of simulated model output with observations while considering observational uncertainty. In addition to a comparison of climatological means, trends and variability, AR5 already made use of a large set of performance metrics for a quantitative evaluation of the models.

Since the AR5, objective summaries of model agreement with observations have become more prominent, and now extend well beyond the large scale mean climate (e.g. Bellenger et al., 2014; Covey et al., 2016; Goelzer et al., 2018; Meehl et al., 2007a; Pendergrass and Deser, 2017). They provide an overall summary of model performance across multiple variables and components of the Earth system (e.g. Anav et al., 2013; Gleckler et al., 2008; Guan and Waliser, 2017) and are used in this report additionally to assess model improvements across different CMIP ensembles and differences in model performance between different classes of models, such as high- versus low-resolution models (see e.g. Section 3.3).

In addition, process- or regime-oriented evaluation of models has been expanded since the AR5. By focusing on processes, causes of systematic errors in the models can be identified and insights can be gained whether a mean state or trend is correctly simulated for the right reasons. This approach is commonly used for the evaluation of clouds (e.g. Bony et al., 2015; Dal Gesso et al., 2015; Jin et al., 2017; Konsta et al., 2012; Williams and Webb, 2009), dust emissions (e.g. Parajuli et al., 2016; Wu et al., 2016) as well as aerosol-cloud (e.g. Gryspeerdt and Stier, 2012) and chemistry-climate (SPARC-CCMVal, 2010) interactions. Recently, process-oriented diagnostics have also been used to evaluate specific phenomena such as the El Niño Southern Oscillation (ENSO, Guilyardi et al. (2016)), the Madden–Julian Oscillation (MJO) (Ahn et al., 2017; Jiang et al., 2018), monsoons (Boo et al., 2011), and tropical cyclones (Kim et al., 2018).

Instrument simulators that improve the direct comparison of modelled variables such as clouds, precipitation and upper tropospheric humidity with observations from satellites have also been further developed (e.g. Cesana and Waliser, 2016; Chepfer et al., 2018; Jin et al., 2017; Kay et al., 2011; Klein et al., 2013; Konsta et al., 2016; Swales et al., 2018; Zhang et al., 2018). These approaches consist of converting model variables to what a satellite would be providing by using methods such as radiative transfer calculations or by sampling the model output in the same way than the observations. Within the framework of the Cloud Feedback Model Intercomparison Project (CFMIP) contribution to CMIP6 (Webb et al., 2017), a new version of the Cloud Feedback Model Intercomparison Project Observational Simulator (COSP, Swales et al., 2018) has been released which makes use of a collection of observation proxies or satellite simulators.

1.4.4.4 Climate informatics

The growing data volume from Earth system observations and models urge the need for new theories and tools that complement classical approaches to extract relevant information. A significant development since the AR5 is an emerging field of climate informatics, a promising and growing path of research (Reichstein et al., 2019). Data science methods such as data mining (Friedman et al., 2001), causal graphical model discovery (Runge et al., 2015), and other machine learning techniques (Reichstein et al., 2019) that have successfully been applied in other scientific disciplines (e.g., bioinformatics) provide new ways of analysing Earth system data.

The most common approach, climate networks, uses complex network analysis to investigate interdependency within a climate dataset (Tsonis and Roebber, 2004). In a climate network, each node typically represents the value of a climate variable in a particular grid cell, or a climate index (Bracco et al., 2018; Donges et al., 2009; Fountalis et al., 2014; Kirtman et al., 2013; Tsonis et al., 2007; Wang et al., 2009). Links between nodes represent a strong statistical relationship, commonly defined based on methods such as pairwise correlation, mutual information, or phase synchronization (Barreiro et al., 2011; Boers et al., 2013; Tsonis and Roebber, 2004; Yamasaki et al., 2009). Climate networks were first used to study the behaviour of global geopotential height (Tsonis and Roebber, 2004). Since then, the method has been further developed for multivariate networks (Steinhaeuser et al., 2012) and lagged interaction (Tirabassi and Masoller, 2016; Wang et al., 2013). Such climate networks may produce novel insights not revealed by classical methods regarding the topology, dynamics and teleconnection of the climate system. Numerous studies have applied climate networks in model evaluation and intercomparison at both local and global scales (Bracco et al., 2018; Feldhoff et al., 2015; Fountalis et al., 2014, 2015; Lange et al., 2015; Steinhaeuser and Tsonis, 2014; Tantet and Dijkstra, 2014). The method has also been used to investigate large-scale circulations, modes of variability, and their teleconnections (Arizmendi and Barreiro, 2017; Berezin et al., 2012; Bracco et al., 2018; Deza et al., 2015; Donges et al., 2009, 2011; Ebert-Uphoff and Deng, 2012; Fountalis et al., 2015; Gozolchiani et al., 2011; Guez et al., 2012; Ludescher et al., 2014; Martín-Gómez and Barreiro, 2016, 2017; Tsonis and Swanson, 2008; Wang et al., 2013; Yamasaki et al., 2008). Further studies have applied networks to the dynamics of the Indian monsoon, statistical prediction of climate indices, and identification of sudden changes and extreme events (Boers et al., 2015; Malik et al., 2012; Marwan and Kurths, 2015; Rehfeld et al., 2013; Steinhaeuser et al., 2011; Stolbova et al., 2014, 2016).

Climate network analyses in which linkages are based solely on correlation cannot, however, be used to directly assess cause-effect relationships between modes of variability or ocean-atmosphere interaction processes. To do so, a different type of climate network based on causal discovery was introduced where techniques such as transfer entropy, recurrence-based methods, and Granger causality define the linkages (Deza et al., 2015; Ebert-Uphoff and Deng, 2012, 2014, 2017, Hlinka et al., 2013, 2017). These approaches illustrate pathways of information flow, both direct and indirect, from one node to another, thereby providing information that helps to identify the cause-effect relationships between climate interactions at different locations (Ebert-Uphoff and Deng, 2012, 2014, 2017, Hlinka et al., 2013, 2017). This was extended to allow the identification of major gateways for spreading and mediating perturbations in the atmosphere, such as regions of strong ascent in the tropics (Runge et al., 2014, 2015). Advancing the understanding of climate variability requires that results from climate network studies be interpreted in physical terms, and thus these approaches can complement studies of atmospheric dynamics and process-based climate model analysis. To improve the detection of multivariate extreme events (Zscheischler et al., 2018), machine learning anomaly detection techniques are being explored (Barz et al., 2019).

1.4.5 Techniques for constraining uncertainties and informing projections

Since the AR5, new or further developed techniques allow constraining the uncertainty in multi-model climate projections with observations, narrowing the uncertainty in climate responses and feedbacks.

1.4.5.1 Scaling based on detection and attribution

Results from detection and attribution have been considered as a possible way to constrain estimates of changes in the climate system and some key properties in the future (Bindoff et al., 2013; Kirtman et al., 2013). In particular, scaling factors derived from detection and attribution analyses, applied to observed global temperature changes, can adjust model responses to different external forcings to best match the observations. If the scaling relationship over the historical time period is found to be robust, it may provide a useful way to adjust future projections, assuming the empirical relationship will continue to hold (Gillett et al., 2012; Kirtman et al., 2013; Stott et al., 2013; Stott and Jones, 2012). Future projections and associated uncertainties can then be estimated by applying the scaling factors to projected changes in response to individual forcing agents and summing. Biases in the resulting projections could arise from errors in historical forcings, errors in the simulated patterns response to those forcings, or departures from linearity or linear additivity in the response to forcings (Kirtman et al., 2013), and derived uncertainties may be large if scaling factors are weakly constrained because of degeneracies in the responses to different (Collins et al., 2012), or if the responses to some forcings included are weak. While linear additivity has been found to hold for temperature responses at global and continental scales in general, it may not hold for precipitation in certain cases of future projections (Marvel et al., 2015; Shiogama et al., 2013). The robustness of the scaling factors is a key to the usability of this approach, but scaling factors are not always robust (Bindoff et al., 2013; Gillett et al., 2013a; Jones et al., 2013; Ribes et al., 2013). Since the signal to noise ratio shrinks at smaller spatial scales and shorter periods of time, scaling factors derived from regional analyses and for short periods tend to be less robust (Jones et al., 2016b).

1.4.5.2 Emergent constraints on climate feedbacks, sensitivities and projections

An emergent constraint is a relationship between an uncertain aspect of future climate change and an observable feature of the Earth System, evident across an ensemble of models (Allen and Ingram, 2002). Complex Earth system models (ESMs) simulate variations on timescales from hours to centuries, so in principle ESMs tell us how aspects of the current climate relate to its sensitivity to anthropogenic forcing. Where an ensemble of different ESMs agrees on a relationship between a short-term observable variation and a longer-term sensitivity, an observation of the short-term variation in the real world can be converted, via the model-based relationship, into an ‘emergent constraint’ on the sensitivity. This is shown schematically in Figure 1.12.

Emergent constraints are attractive because they use the spread in model projections to estimate the sensitivities of the real climate system to anthropogenic forcing, providing one way to make an ensemble of ESMs more than the sum of the parts. As emergent constraints depend on identifying those observable aspects of the climate system which are most related to climate projections, they also help to focus model evaluation on the most relevant observations (Hall et al., in press). However, there are risks that indiscriminate data-mining of the multidimensional outputs from ESMs could lead to spurious correlations (Caldwell et al., 2014) and less than robust emergent constraints on future changes (Bracegirdle and Stephenson, 2013). To mitigate against this risk, emergent constraints need to be tested “out of sample” (Caldwell et al., 2018), and should ideally be based on sound physical understanding and mathematical theory (Hall et al., in press). In this report, we evaluate emergent constraints developed using the previous CMIP5 ensemble against the newer CMIP6 models.

For general applications and discussions of recent usage of emergent constraints, see Section 3.8.2.3. Assessment of individual emergent constraints appear throughout later chapters.

[START FIGURE 1.12 HERE]

Figure 1.12: The principle of Emergent Constraints. An ensemble of models (blue dots) define a relationship between an observable trend or variation in the climate (x-axis) and an uncertain climate sensitivity or feedback (y-axis). An observation of the x-axis variable can then be combined with the model-derived relationship to provide a tighter estimate of the climate sensitivity or feedback on the y-axis (adapted from Eyring et al. (2019)).

[END FIGURE 1.12 HERE]

1.4.5.3 Weighting techniques for model comparisons

Many results in the present report, and in the assessed literature, are based on ensembles of climate model simulations or projections. Such ensemble-based results have commonly assumed that each individual model is of equal value (“model democracy”). In other words, when combining simulations to estimate the mean and variance of quantities of interest, they are typically unweighted (Haughton et al., 2015). However, exceptions to this approach exist, and more studies on this topic have appeared since the AR5 (Eyring et al., 2019). Ensembles are typically pared down by removing either poorly performing model simulations or model simulations that are perceived to add little additional information - typically where multiple simulations have come from the same model. They may also be weighted based on model performance differences relative to some set of observations - typically time series of global mean properties such as surface temperature).

Several recent studies have attempted to quantify the impact of various strategies for selection or weighting of ensemble members based on some set of criteria (Haughton et al., 2015; Sanderson et al., 2017). Boé (2018) investigated the dependence of ensemble members sharing climate components. Regarding the detection of anthropogenic forced signals versus internal climate variability, Frankcombe et al. (2015) found that the ensemble mean of runs from a single climate model provides a good estimate of a forced signal even when only a few ensemble members are available. In cases where only a single member is available for each model, however, the scaled ensemble mean from all available climate model simulations of the same forcing generally performs better. However, such a scaled mean leads to increasing errors the further the simulation is taken from the time period used in the weighting.

Model weighting strategies have been further employed since the AR5 to reduce the spread in climate projections for a given scenario by using weights based on one or more model performance metrics (Knutti et al., 2017; Lorenz et al., 2018; Sanderson et al., 2017; Wenzel et al., 2016). However, models may share representations of processes, parameterization schemes, or even parts of code, leading to common biases. The models may therefore not be fully independent, calling into question inferences derived from multi-model ensembles (MMEs) (Abramowitz et al., 2018). Selecting models based on performance criteria alone was shown by Herger et al. (2018a) to result in a poorer ensemble mean than a random selection of ensemble members.

Concern has been raised about the large extent of code-sharing within the CMIP5 multi-model ensemble (Sanderson et al., 2015b). Boé (2018) showed that a clear relationship exists between the number of components shared by climate models and how similar the simulations are. The resulting similarities in behaviour need to be accounted for in the generation of best-estimate multi-model climate projections. This has led to calls to move beyond equally-weighted multi-model means towards weighted means that take into account both model performance and model dependence (Knutti et al., 2017; Sanderson et al., 2015b, 2017). Model independence has been defined in terms of performance differences within an ensemble (Knutti et al., 2013, 2017; Lorenz et al., 2018; Masson and Knutti, 2011; Sanderson et al., 2015b, 2015a, 2017). However, this is very sensitive to the choice of variable, observational data set, metric, time period, and region (Herger et al., 2018a). The adequacy of the constraint provided by the data and experimental methods can be tested using a calibration-validation style partitioning of observations into two sets (Bishop and Abramowitz, 2013), or a "perfect model approach" where one of the ensemble members is treated as the reference dataset and all model weights are calibrated against it (Bishop and Abramowitz, 2013), or a "perfect model approach" where one of the ensemble members is treated as the reference dataset and all model weights are calibrated against it (Bishop and Abramowitz, 2013; Herger et al., 2018a, 2018b; Knutti et al., 2017; Sanderson et al., 2017; Wenzel et al., 2016). Sunyer et al. (2014) use a Bayesian framework to account for model dependencies and changes in model biases.

1.5 Cross-cutting topics for this assessment: variability, regional definitions, uncertainty, reference periods and attribution

This section highlights some of the cross-cutting methods applied in the climate change literature and topics discussed repeatedly throughout this report. First, climate change trends are discussed, with a particular focus on regional climate variability (Section 1.5.1). This section also presents the regional definitions used in this report (Section 1.5.2). A consistent set of reference periods to describe past, historical, current and future climate change assists the knowledge integration across IPCC Working Groups (WGs) and the policy-relevance of the findings, if those periods coincide with those used in the policy discussions (Section 1.5.3). Future projections assessed in the various chapters are subject to a number of uncertainties, with their general typology being introduced here (Section 1.5.4). The attribution of observed trends and weather events, including those considered 'extreme events', to human-induced climate change is now applied on ever more local scales (Section 1.5.5).

1.5.1 Natural variability and the emergence of the climate change signal

1.5.1.1 How does variability influence trends over short periods?

Natural variations in both weather and longer timescale phenomena can temporarily mask or enhance any long-term (multi-decadal) anthropogenic trends. These effects are larger on small spatial and temporal scales, but can occur on the global scale as well. For example, Cross-Chapter Box 3.1 discusses how observed and simulated changes in global surface air temperature compare over the recent past. More broadly, Figure 1.13 shows a set of examples using a large ensemble of model simulations with a single GCM (Maher et al. 2019, in review). The long-term trends in various climate metrics are clearly visible when considering the ensemble as a whole (grey shading). However, when considering single realisations (colours), the trends over short periods can vary considerably (thin coloured lines). All the simulations have very similar trends for ocean heat content (OHC) which is an integrated measure of climate change, but can have significantly different trends for global surface air temperature (GSAT), UK summer temperatures and Arctic sea-ice variations for the same period. For 11-year periods, both positive and negative trends can be found in all these metrics, even though the long-term trend is for increasing temperatures and decreasing sea-ice. Climate change trends are traditionally defined over 20-or 30-year periods to isolate the long-term trends, but - depending on the observed variable, its variability and applied detection method - an appropriate period can be shorter or longer (WMO, 2017).

It should not be a surprise if observations, which are akin to a single realisation, show short-term trends which are apparently different from the long-term trend or the expectation from climate models – in fact, it should be expected (*high confidence*).

[START FIGURE 1.13 HERE]

Figure 1.13: Simulated changes in various climate metrics using historical and RCP4.5 scenarios using the MPI Grand Ensemble (Maher et al. 2019, in review). The top row shows temperature-related metrics (Ocean Heat Content to 2000m, annual global surface air temperature and UK summer temperatures) and the bottom row shows Arctic sea-ice related metrics (annual ice volume and September sea-ice area). The grey shading shows the 5-95% range from the 100-member ensemble, and the coloured lines represent three individual ensemble members. All three members shown have very similar OHC trends (top left) but vary considerably for other climate metrics (only two are shown for each). Trends are shown with thin solid lines for the 2011-2021 period.

[END FIGURE 1.13 HERE]

1.5.1.2 The emergence of the climate change signal

The signal of climate change is most obvious at the global scale, but is increasingly emerging from the background 'noise' of internal variability on smaller spatial scales and in a range of climate variables. An example for air temperature is shown in Figure 1.14, which contrasts the changes in observed temperature in two countries: the UK and Ghana. Both countries are at the same longitude and cover the same spatial area (around 240,000 km^2, or 0.05% of the planet), but Ghana is located in the tropics, in the West African Monsoon region, where variability in temperature from year-to-year is smaller than in the extra-tropics where the UK sits at the end of one of the major global storm track regions. Both countries show a similar temporal fingerprint of the global temperature change signal but, for Ghana, the signal of temperature change has already emerged more clearly from the background variations than for the UK.

Numerous studies have focussed on this topic of climate change ‘emergence’ (also see FAQ1.2). It has been studied in observations of historical temperature change (e.g. Mahlstein et al., 2011), and of temperature changes in the future (e.g. Hawkins and Sutton, 2012). The concept has also been extensively studied for other climate variables such as precipitation (e.g. Giorgi and Bi, 2009), regional sea level change (Lyu et al., 2014) and extremes (e.g. King et al., 2015), and applied to issues such as the effects on crop growing regions (Rojas et al., 2019).

Although there is considerable attention given to the magnitude of any change, regions which have a larger signal of change relative to the background variations will potentially face greater risks as they will see unusual or unprecedented climates more quickly (e.g. Frame et al., 2017). As in Figure 1.14, the signal of temperature change is often smaller in tropical countries, but their lower amplitude of variability means they may see the effects of climate change earlier than the mid-latitudes. In addition, the tropical countries with lowest variability in temperature are often amongst the most vulnerable nations (e.g. Harrington et al., 2016), increasing the risk. Providing more information about changes and variations on regional scales, and the associated attribution to particular causes, is therefore important for adaptation planning.

[START FIGURE 1.14 HERE]

Figure 1.14: Observed temperatures in the UK and Ghana from 1900-2018 in the Berkeley Earth temperature dataset, and GMST from HadCRUT4. The shaded band indicates the amplitude of internal variability [over X year periods] for each region. After Sutton et al. (2015).

[END FIGURE 1.14 HERE]

1.5.2 Regional climate change

1.5.2.1 Foundations of the definition of climate regions

Climate change is a multiscale phenomenon with diverse cross-scale feedbacks. The evolution of trends in the global climate system emerges from the aggregate of regional climate changes, but it drives also a great variety of regional impacts. One useful element in climate change research has been the use of characteristic climate zones, clusters or regions, across which the emergent climate change signal can be analysed and projected. Several traditional methods exists to define these climate regions (Geiger, 1954; Köppen, 1936; Sanderson, 1999; Thornthwaite, 1948; Trewartha, 1954), but also new approaches: as the climate signal emerges from small spatial scales and evolves out of short-term variations, characteristic patterns are formed, which manifest themselves as multiscale structures in space and time that can be detected with new data-driven ‘complex network’ approaches (Steinhaeuser et al., 2011). Such structures, clusters or patterns, may be studied separately for each climate variable, like sea surface temperatures or pressures, for instance through spectral studies of climate-proxy time series (Boers, 2018), or aggregated in multiple variables to reveal spatio-temporal patterns that express the full complexity of the coupled climate system (Grigholm et al., 2009; Rubel et al., 2017; Vidal et al., 2010).

Many of these spatio-temporal patterns are related to geophysical features, like orography, buoyancy or Earth’s motion. This led scientists to define typical space and time scales for various meteorological and climatic phenomena (Figure 1.15), including the classical statistical definition of climate by the World Meteorological Organization (WMO) as the average weather over a period of 30 years (WMO, 2017).

[START FIGURE 1.15 HERE]

Figure 1.15: Spatial and temporal scales of atmospheric processes and their relations to the region sets used in this report, namely reference land and ocean regions (Reference), WGII-type regions (WGII-Type), and typological land and ocean regions (Typological). The domain "Local" stands for local domains not formally defined but occasionally mentioned in specific situations (see Figure 10.1 in Chapter 10 for a comparison with various modelled processes at regional and global scales. [To be updated]

[END FIGURE 1.15 HERE]

Understanding and predicting climate change at the regional scale remains, however, one of the greatest challenges of climate science. The complexity of this problem from a modelling point of view is discussed in Chapter 10. From the viewpoint of observations; one way of approaching this issue is by averaging the signals of the aggregated variables over several decades, in such a way that more stable and definite climate regions emerge. This process is called climate classification and gives rise to climate regions loosely defined as spatial domains where the aggregated variables form similar patterns.

There are several approaches to the climate classification of climate regions. When climate observation data was sparse and limited, the aggregation of climate variables was implicitly achieved through the consideration of biomes, giving rise to the traditional vegetation-based classification (Köppen, 1936). In the last decades, the substantial increases in climate observations, climate modelling, and data processing capabilities have allowed new approaches to climate classification, e.g. through interpolation of aggregated global data from thousands of stations (Beck et al., 2018; Belda et al., 2014; Peel et al., 2007). Experience shows that each method has strengths and weaknesses through trade-offs between detail and convenience. For instance, a very detailed classification, with numerous complex-shaped regions derived from a large set of variables, may be most useful for the validation of climate models (Beck et al., 2018; Rubel and Kottek, 2010), whereas geometrically simple, convex regions are often best suited domains for regional climate modelling and downscaling (e.g. the Coordinated Reginal Climate Downscaling Experiment, CORDEX domains, see Giorgi and Gutowski (2015)).

1.5.2.2 Types of regions used in AR6

IPCC's recognition of the importance of regional climates can be traced back to its First Assessment Report (IPCC, 1990), where climate projections for 2030 were presented for five subcontinental regions. In subsequent reports, there has been a growing emphasis on the analysis of regional climate, including two special reports: one on regional impacts (IPCC, 1997) and another on extreme events, SREX (IPCC, 2012). A general feature of previous IPCC reports is that the number and coverage of climate regions vary according to the subject and across IPCC Working Groups (WGs). Such varied definitions have the advantage of optimizing the results for a particular application (e.g. national boundaries are crucial for decision making, but they rarely delimit distinctive climate regions), whereas variable region definitions may have the disadvantage of hindering multidisciplinary assessments and comparisons between studies or WGs.

In this report, regional climate change is addressed through the introduction of four classes of regions. The first two are the unified reference sets of (1) land and (2) ocean regions, respectively, which are used throughout the report. These are supplemented by additional sets of (3) typological regions and (4) continental-scale "Working Group II (WGII) -type" regions, which are invoked in some chapters to describe specific issues (Figure 1.16). Reference land and ocean regions are sub-continental domains defined in terms of characteristic climate and environmental features, as recognized from the literature assessed in this report. Merging the diverse functions and purposes of the regions assessed in the literature into a common reference set implies that the resulting regions are detailed enough for a basic climate classification and regional impact assessment, but simple enough to be used as domains for regional simulations and downscaling (Giorgi and Gutowski, 2015). The Atlas shows averages over those regions from CMIP6 model results.

In conformity with the approach previously adopted by the AR5, the starting point for defining the AR6 reference sets of land regions was the collection of 26 regions introduced in SREX (IPCC, 2012). The SREX collection was then revised, reshaped, complemented and optimized to reflect the recent scientific literature and lately observed climate-change trends, giving rise to the novel AR6 reference set of 37 land regions. Additionally, AR6 introduces, for the first time, a whole new reference set of 12 ocean regions which complete the coverage of the whole Earth. Particular aspects of climate change are also through higher-resolution, specialized domains called typological regions, like monsoon regions, mountains, megacities, etc. Finally, consistency with WGII regions is also pursued in Chapter 12 with the use of a Continental Set of WGII-Type Regions (Figure 1.16). All four type of regions will be presented systematically in the Atlas.

[START FIGURE 1.16 HERE]

Figure 1.16: Main types of regions used in this report. (a): AR6 WGI reference set of land and ocean regions, used throughout this report. There are 37 land regions and 12 ocean regions in total. Notice that SPO, NPO and EPO continue on the left side of the map, indicated with an asterisk. For the meaning of the acronyms and details of each region, see the Atlas. [The reference set of ocean regions are still tentative and will be confirmed in the SOD]. (b): Example of typological land regions. Land monsoon domains adopted in Chapter 8 [to be updated accordingly with chapter 8], as defined in AR5 WGI. The acronyms stand for North America Monsoon System (NAMS), North Africa (NAF), Southern Asia (SAS), East Asian Summer (EAS), South America Monsoon System (SAMS), South Africa (SAF), and Australian-Maritime Continent (AUSMC). All the regions are within 40°S to 40°N. For further details, see Chap. 8. (c): Example of typological ocean regions. Ocean biome zones used in Chapters 5 and 9, which reflect the historical mean of the dynamics. The following regions are displayed: (0) Northern Hemisphere High Latitudes, (1) Northern Hemisphere Subtropics, (2) Equatorial, (3) Southern Hemisphere Subtropics, (4) Southern Hemisphere High Latitudes, (5) Arabian Sea, (6) Eastern Boundaries, (7) Amazon River, (8) Gulf of Mexico and (9) Indonesian Flowthrough. For more information, see Chapter 5. (d): WGII-type regions used in Chapter 12, as defined in AR5 WGII Part B.

[END FIGURE 1.16 HERE]

1.5.3 Anomalies, baselines and warming since pre-industrial

1.5.3.1 Why are anomalies used?

Variations in observed and simulated climate variables are often presented as ‘anomalies’, i.e. the changes relative to a ‘baseline’ or ‘reference period’, rather than using the absolute values. This is done for several reasons. First, when combining data from multiple locations, anomalies are often used because the absolute values can vary over short spatial scales which are not densely observed or simulated, whereas the correlation scale for anomalies can be much larger (e.g. for temperature, Hansen and Lebedeff, 1987). As a specific example, Callendar, (1938) was able to accurately demonstrate that Earth’s land regions were warming using observations of temperature anomalies from just 147 well-spaced locations (Hawkins and Jones, 2013). Second, different datasets can produce different absolute values for the same climate variable, meaning that effective comparisons require removing the absolute differences to compare the variations. This is particularly true when comparing climate simulations with each other, or when comparing simulations with observations, but can also occur when comparing observation-based datasets (Figure 1.17). Understanding the reasons for any absolute differences is important, but often the most relevant aspect for climate change research and decision makers is the change in a specific observed or simulated variable. These reasons motivate the need to define a suitable baseline period to allow effective comparisons. For some variables, such as precipitation, the anomalies are often expressed as percentages because they have higher spatial correlation than the anomalies themselves.

The choice of reference period has important consequences for evaluating both observations and simulations of the climate, for comparing observations with simulations, and for presenting climate projections. There is usually no perfect choice of baseline as many factors have to be considered and compromises may need to be made. It is important therefore to evaluate the sensitivity of an analysis or assessment to the choice of baseline (Figure 1.17, Hawkins and Sutton, 2016).

[START FIGURE 1.17 HERE]

Figure 1.17: Global mean surface air temperature from the range of CMIP5 historical simulations (1861-2005) using absolute values (top) and anomalies relative to two different baselines (bottom). In order to compare the models with each other and with reanalyses and observations (colours), a baseline or reference period has to be chosen, and that choice can affect the comparison. (Taken from Hawkins and Sutton, 2016, and to be updated with CMIP6 data.)

[END FIGURE 1.17 HERE]

1.5.3.2 What is meant by a ‘pre-industrial’ baseline?

The definition of ‘pre-industrial’ is required as this report assesses literature on carbon budgets and emissions scenarios which are compatible with the Paris Agreement aspirations to limit global temperatures to specific thresholds ‘*above pre-industrial levels*’. Different choices can result in different conclusions. For example, Millar et al. (2017) and Schurer et al. (2017) demonstrated that the remaining carbon budget and the chance of crossing global temperature thresholds is sensitive to the choice of pre-industrial baseline. Pfleiderer et al., (2018) also highlighted that projections of risks from hot extremes and sea level rise at target warming levels are dependent on the assumptions made about a pre-industrial baseline.

Historically, the widespread use of fossil-fuel driven machinery started the Industrial Revolution in Britain in the late 18th century (Ashton, 1997), but the global effects were relatively small for several decades. The text of the Paris Agreement does not precisely define what is meant by ‘pre-industrial’. In line with the 18th century onset of the industrial revolution, previous IPCC assessment reports considered pre-industrial to be 1750 (e.g. for its radiative forcing definition) (Knutti et al., 2016); Stocker et al., IPCC AR5, 2013), while making the pragmatic choice in AR5 to approximate pre-industrial global temperatures as the average of the 1850-1900 period. As anthropogenic radiative forcing had already increased slightly by 1850, some warming may not have been included, but there was no instrumental global temperature dataset available for the period before 1850 to estimate or attribute any temperature change. Although Lüning and Vahrenholt (2017) suggest a much longer context for defining pre-industrial, estimates of natural radiative forcings and global temperature are too uncertain to allow a reliable estimate for longer periods.

Several studies since AR5 have attempted to estimate and attribute the change in global temperatures before 1850. Hawkins et al. (2017) used observations and simulations to determine a range for the warming from the 1720-1800 period up to 1986-2005 of 0.55-0.80°C, which is slightly larger than the equivalent values starting from 1850-1900. The 1720-1800 period was chosen as it has approximately the same levels of natural radiative forcings as present-day. From proxy evidence, PAGES2K (2019, in review) found that the global average temperature for the period around 1750 was indistinguishable from 1850-1900, though the uncertainties are around 0.2°C. Schurer et al. (2017) used climate model simulations of the last millennium to estimate that there was an additional 0.0-0.2°C anthropogenic warming that occurred before 1850. Haustein et al. (2017a) also implies an additional attributable warming from 1750 to 1850-1900 of around 0.05K.

In this report, the term ‘*pre-industrial*’ is retained for the period around 1750, normalizing anthropogenic forcing to zero at that time. It is *likely (medium confidence)* that some additional anthropogenic warming occurred before 1850 which needs to be accounted for when considering remaining carbon budgets consistent with avoiding particular policy-relevant temperature limits. The magnitude of this warming is plausibly between 0.0-0.1°C. The term ‘*early-industrial’* is introduced for the 1850-1900 period to more clearly distinguish it from the pre-industrial period and resolve differences in terminology used in different circumstances. As any anthropogenic warming which occurred before 1850 is at least partially offset by the volcanic activity during 1850-1900, the average global temperature during the early-industrial period is considered as an approximate proxy for "true" pre-industrial global temperatures. This is consistent with IPCC SR1.5 which also considered average global temperature during 1850-1900 to be equivalent to pre-industrial. The validity of the early-industrial period as a proxy for other aspects of pre-industrial climate, such as regional temperatures or sea level, is not assessed.

An additional factor, which has become better understood since the AR5, is the role of the type of observation used to construct the global mean surface temperature (GMST). In all existing observation based global temperature reconstructions, sea surface temperatures are used for ocean regions, air temperatures are used over land regions, and these are 'blended' together to form the global dataset (also see FAQ 1.4). Cowtan et al. (2015) highlighted that, in model simulations, this choice underestimates the warming that occurs during the historical period compared to sampling air temperatures everywhere. Chapter 2 discusses this issue in more detail and assesses that the observed warming since the early-industrial period should be increased by 6% to account for this effect (see Section 2.3.1.1). Further research on pre-1850 temperatures, and the change in observed air temperatures over the ocean would be beneficial to increasing confidence in these assessments.

[START CROSS-CHAPTER BOX 1.3 HERE]

Cross-Chapter Box 1.3: Baselines used in AR6

Pre-industrial and early-industrial baselines

Radiative forcings in previous IPCC assessment reports have always been referenced to 1750, during which the natural radiative forcings (e.g. orbital, solar, volcanic) are similar to today, but before the effects of fossil fuel combustion associated with the industrial revolution arose. In AR6 we retain the definition of '*pre-industrial*' as the period around 1750 to examine changes in radiative forcing and to consider remaining carbon budgets. The term '*early-industrial*' is introduced for the 1850-1900 period to distinguish it from the pre-industrial period (see 1.5.3.2).

Modern baseline

IPCC AR5 used 1986-2005 as a modern baseline when estimating past observed warming and to present the relative changes in future climate using model projections. The reasons for this choice were that 2005 was the final year of the historical simulations, and 20 years was deemed long enough to average over natural variations in a multi-model ensemble of simulations and be representative of the current state. The equivalent '*modern*' period for AR6 is defined to be 1995-2014, to end in the final year of the CMIP6 historical simulations. Projections with alternative modern baselines (such as 1986-2005 or the WMO current standard climate normal period of 1981-2010) will be presented in the Atlas.

Future periods

In AR5 there were three future periods – near-term, mid-term and long-term. These are three important timescales to provide assessments for, so this structure is retained in AR6 with the near-term referring to 2021-2040, mid-term referring to 2041-2060 and the long-term referring to 2081-2100. Note that the Atlas will produce projections for a wider range of future periods and warming levels.

Paleo-climate periods

In AR6, various terms are used to refer to periods further in the past, defined in the Table below.

[START CROSS-CHAPTER BOX 1.3, TABLE 1 HERE]

Cross-Chapter Box 1.3, Table 1:

Period	**Age/year***	**Significance of climate state**
Little Ice Age (LIA)	1450–1850 CE (defined by AR5)	Series of globally heterogeneous cold periods lasting decades to centuries and including some of the lowest temperatures of the post-glacial period.
Medieval Climate anomaly (MCA)	950–1250 CE (defined by AR5)	Loosely defined interval of relative warmth, especially prevalent in the circum North Atlantic region that preceded the LIA.
Last Millennium	850–1850 CE (PMIP) or 1000-1999 CE	PMIP interval for transient climate model experiments. Encompasses the MCA and LIA, with demonstrable effects of volcanic and solar forcing.
Mid-Holocene	multiple centuries centered around 6 ka	Approximate time during the current inter-glaciation (Holocene) when GMST was highest. PMIP interval for climate model experiments.
Holocene Thermal Maximum (HTM)	Time-transgressive 10–5 ka	Loosely defined millennial-scale interval of maximum Holocene temperature occurring at different times regionally. Most pronounced in the NH where summer insolation was higher than now due to orbital configuration.
Post-glacial	8.2 ka–present	The fundamental features of the modern climate system were essentially in place as the influence of remnant Pleistocene ice sheets waned and the last substantial ice-sheet-impounded meltwater flooded the northern high-latitude ocean around 8.2 ka.
8.2 ka event		
Last deglacial transition (aka, glacial termination)	18–11 ka	Global warming occurred in two main steps, with increases in atmospheric CO_2 and global sea level essentially synchronous with global temperature rise.
Younger Dryas	12.85-11.65 ka	
Bolling-Allerod	14.64-12.85 ka	
meltwater pulse 1A (MWP-1A)	14.65-14.31 ka	Period of fastest sea level rise during the deglacial, very likely (medium confidence) between 8 and 15 m.
Heinrich stadial 1 (HS1)	~ 19-14.31 ka	
Last Glacial Maximum (LGM)	21–19 ka	The most recent glaciation when climate was distinctly different than now. Atmospheric CO_2 was lower (about 200 ppm). Large ice sheets covered most of North America and NW Europe.

*** Ma = millions of years (ago); ka = thousands of years (ago); CE = Common Era**

[END CROSS-CHAPTER BOX 1.3, TABLE 1 HERE]

[END CROSS-CHAPTER BOX 1.3 HERE]

1.5.4 Sources of uncertainty in climate projections

When considering the range of future projections of the physical climate system there are several different contributing sources of uncertainty, often separated into scenario uncertainty, model response uncertainty and uncertainty due to internal variability.

Scenario uncertainty

Divergent future projections often result from different scenarios being assumed for anthropogenic drivers of climate change (see Section 1.6 for a detailed description of scenarios). The RCP and SSP scenarios, which form the basis for climate projections assessed in this report, are designed to span a plausible range of future pathways but the real world will differ from these example storylines. Although termed an ‘uncertainty’, this component is distinct from other uncertainties, given that - at least from the viewpoint of decision makers - future anthropogenic emissions can be considered as the outcome of a set of collective choices (see Section 1.6.2). Scenario uncertainty is often the largest source of uncertainty when looking to the long-term, but is relatively small in the next few decades, especially globally (Hawkins and Sutton, 2009b).

Model response uncertainty

Assuming a particular scenario, there is uncertainty in how the climate will respond to the specified emissions or radiative forcing combinations. A range of climate models are used to sample uncertainty in our understanding of the key physical processes and to define the ‘model response’ uncertainty. There are several subcategories of this ‘model response’ uncertainty related to, for example, carbon cycle feedbacks, radiative forcing efficiencies, cloud parameterisations and other climate feedbacks, but these are hard to quantify individually.

Internal variability

In the absence of any changes in radiative forcing there would still be intrinsic uncertainty in the projections due to internal climate variability - the random fluctuations of the climate like those associated with modes of variability (e.g. ENSO, IPO, AMV).

Uncertainty quantification and missing uncertainties

From long-term model projections it is possible to approximately quantify the relative amplitude of these uncertainty sources. A sample of different scenarios defines the scenario uncertainty, and ensemble means from different models can estimate the model response uncertainty. The unforced component of internal variability can be approximated from individual ensemble members of the same climate model (see Figure 1.18). In principle, the intrinsic uncertainty due to internal variability can be estimated probabilistically – it is ‘aleatoric’ – whereas the other two sources of uncertainty are ‘epistemic’ and should not be considered as reliable probabilities due to their ad-hoc sampling approaches. The real world will also experience future changes in natural forcing, i.e. variations in volcanic and solar activity, which are not included in the projections but could be significant for short periods (e.g. Bethke et al., 2017). Interactions between these different sources of uncertainty are also plausible as, for example, changes in radiative forcings could alter the phasing or amplitude of internal variability.

[START FIGURE 1.18 HERE]

Figure 1.18: The ‘cascade of uncertainties’ in climate projections of global mean surface temperature change for 2080-2099 from CMIP5. The multi-model mean for each scenario is indicated at the top of the cascade. This branches downwards to show the multi-realisation mean for each model (middle row), and further branches into the individual realisations (bottom row), though often only a single realisation is available. For this time period, the scenario uncertainty and model response uncertainty are larger than the internal

variability. (To be updated to CMIP6 and include a near-term regional example to highlight the role of internal variability on smaller spatial and temporal scales.)

[END FIGURE 1.18 HERE]

1.5.5 Attribution of climatic changes

Attribution of climate change intends to connect an observed change to one or several drivers, and to quantify their respective contribution. This field of research started out with detecting statistically significant trends in global temperature patterns and attributing them to human influences (Hasselmann, 1997; Hegerl et al., 1997). Moving to individual events, studies that investigated the European heatwave in 2003 were some of the first that attributed a part of the likelihood of such an extreme occurring to the human influence (Stott et al., 2004). Now, a wide array of the changes in the climate system can be attributed to human influence, including changes in regional temperature, precipitation, and also features that integrate many drivers of change such as regional sea-level. The attribution of impacts is now also an emerging field. The wide range of attribution methods and applications are outlined in Box 1.4.

[START CROSS-CHAPTER BOX 1.4 HERE]

Cross-Chapter Box 1.4: Attribution in the IPCC Sixth Assessment Report

Attribution exercises provide valuable information to a wide range of stakeholders to allow them to understand the drivers of the change or extreme event they are experiencing (James et al., 2019; Parker et al., 2017; Sippel et al., 2015; Stott and Walton, 2013)

Definitions and practice of detection and attribution have evolved over the years, starting with a guidance paper (Hegerl et al., 2010). Other relevant reviews and IPCC assessments providing orientation include: (National Academies of Sciences Engineering and Medicine, 2016); AR5 WGI Chapter 10 and AR5 WGII Chapter 18. There have also been many developments in the attribution of events (Jézéquel et al., 2018). Here we briefly describe new developments in the different approaches of attribution, providing examples from the literature relevant to Working Grous I and II (WGII and WGII).

Factors to consider in attribution studies

Climate changes or events of relevance in the context of this report are those where human-induced climate change might have played a role. For most variables in the physical climate system, for example global mean temperature, baseline conditions on human time-scales will consist of some variability on both sides of quasi-static conditions (See 1.5.3). For impacted systems, baseline conditions may or may not be static. Agricultural productivity, for example, has been increasing over recent decades as a consequence of technological progress in crop management (e.g. Hochman et al., 2017). For such systems, deviation from this increase could be a consequence of climate change.

Attribution studies firstly require a reliable description of the observed change or of extreme event in question. This requires observations that are deemed of high enough temporal and spatial coverage, quality and homogeneity to capture the change or event. In some cases, such observations are not available, for instance, there are too few sea-level records prior to the satellite era to accurately capture change across the Pacific Ocean (Palanisamy et al., 2015).

Common to all attribution studies is that they draw on a modelling approach (physical, conceptual or empirical) to establish the counterfactual system behaviour. One example of such a counterfactual system is a dynamical climate model simulation of the historical period with greenhouse gas forcing omitted from the suite of forcing agents (e.g. Ribes and Terray, 2013). If not all important drivers are taken into account in an attribution study, it is important to highlight which potentially confounding factors are not considered

(Hegerl et al., 2010), e.g. for climate attribution land-surface feedbacks or land-use changes or absorbing aerosols (Hauser et al., 2016; Lejeune et al., 2018; Mueller et al., 2018; Whan et al., 2015).

All studies make the assumption that models used are fit for purpose. The veracity of the model assessment will be included in the examination of each study and the robustness of the result crucially depends on this assessment. The range of variables analysed can lead to highly uncertain outcomes in some cases (Uhe et al., 2017) and very robust estimates of the influence of anthropogenic climate change in other cases (Haustein et al., 2017; Otto et al., 2018).

Detection and attribution of observed large-scale changes in climate variables – e.g. global near-surface air temperature

Detection and attribution of large-scale trends in climate variables such as near-surface air temperature will provide the basis for the assessment of the causes of those trends, and are found in WGI Chapter 3. The methods used will generally follow the approaches detailed in Hegerl et al. (2010) and Stone et al. (2009). Detection of observed changes will include efforts to characterize the internal variability contribution as compared to the externally forced climate response using a range of statistical detection and attribution time series and fingerprint techniques (e.g. Frankcombe et al., 2015; Hannart, 2016). Time series methods aim to determine if the change is outside the range of internal variability while fingerprint techniques rely on regressing observations onto model-simulated climate response patterns (i.e. fingerprints), assuming that the climate system generates unique responses to various external forcings. There can also be the attribution of detected changes to a number of individual forcings, including the proportion attributable to greenhouse gas influence, aerosol influence, or other forcing (e.g. Gillett et al., 2013b; Slangen et al., 2016). The ‘fit’ between observations and these fingerprints is termed a ‘scaling factor’ (See Figure 10.4 of AR5 WGI Chapter 10). The scaling factors obtained in attribution studies may be used to constrain projections, under the assumption that the scaling factors which provide a best fit between simulated and observed historical changes and associated uncertainties may be applied to future climate change (Allen et al., 2000; Stott and Kettleborough, 2002). There can however be various feedbacks and localized factors that also influence temperature trends, particularly in the diurnal range. These include variations in soil moisture, water vapour (Dai et al., 1999; Zhou et al., 2009), and the depth of the boundary layer which relates to the effective heat capacity of the atmosphere (Davy and Esau, 2016). Multi-variable (e.g. temperature and precipitation) analyses have thus been found to provide increased confidence in the recognition of the signal (Paeth et al., 2017; Yan et al., 2016).

Attribution of changes at regional scales

The WGI report has a renewed focus of attribution of changes on regional scales, due to their relevance to WGII, policymakers and other stakeholders. Changes in regional climate at the scale of a continent, country or region are more complex to attribute to external drivers (See 1.5.1.2), mainly due to increased internal variability on smaller spatial scales which decreases the signal-to-noise ratio (See 1.5.1.1). In addition, some non-greenhouse gas human forcings, such as land use change and aerosol forcings, tend to have strong regional footprints (Lejeune et al., 2018; Nabat et al., 2014; Persad et al., 2017) further complicating efforts at attribution. Fingerprinting methodologies (Dileepkumar et al., 2018; Ribes et al., 2009) can still be used for regional attribution studies.

The attribution of change in components of the climate system such as monsoons or regional sea-level can be more complex than single variables, as they integrate the response to temperature changes, amongst other factors.

Change in features such as the South Asian summer monsoon can be due to many factors including rapid and substantial changes in land use, land management and industrial activities over the subcontinent, variability in the Indian Ocean, along with the response to rising global greenhouse gas emissions (Singh et al., 2019). Attributing changes in such systems can be done qualitatively, but new efforts to model the monsoon system allow more quantitative statements on the influences from climate change. This forms a case study in AR6 WGI Chapter 10.

In AR6 WGI, Chapter 9, the attribution of changes in regional sea-level is presented for the first time. While there is some confidence in the change in components of sea-level change, such as that due to thermal expansion (Marcos and Amores, 2014), for attribution of change at a regional scale (e.g. the Pacific Ocean), there are confounding factors such as the Pacific Decadal Oscillation. Accounting for these variations allows the signal of change due to human-induced forcing to be revealed (Hamlington et al., 2014; Palanisamy et al., 2015). An alternative approach is to consider regional sea-level as the sum of attributed global mean sea-level change, unattributed global mean sea-level change, and unattributed local relative sea-level change (Strauss et al. 2016) and use the combined information to estimate which part would not have happened in the absence of attributed global mean sea-level change.

While decadal variability was seen as a confounding factor to the signal of sea-level changes in the Pacific in the examples above, in some cases, it is seen as a component of the causal factors. This is important when explaining short-term trends to policy makers, e.g. the rainfall trends from the 1980s to 2010s in south-west US (Lehner et al., 2018) or recent Eurasian cooling (Mori et al., 2019). In the literature this is referred to as process-based attribution as it seeks to highlight the physical processes and uncertainties involved in the driver's influence, including those drivers that are internal variability. This style of attribution study is very useful in communicating the influence of climate change on recent changes and links closely with the study of event attribution.

Event Attribution

Event attribution is the attribution of the drivers of a particular event (e.g. Hope et al., 2016) or class of events e.g. (Christidis et al., 2015; Lewis et al., 2014). The events assessed are usually recent records that have been broken or major events with widespread impacts. An example of an extreme event might be a record hot week or month over the scale of a country. The basic principle of event attribution is that the characteristics (often occurrence probability and intensity) of a type of weather or climate event (or an individual event) are analysed under present day climate conditions and counterfactual conditions in a "world that might have been" without anthropogenic climate change. The attribution of changes in extremes were assessed in AR5 WGI Section 10.6 for the first time based upon a very small body of literature. In AR6 WGI these changes in extremes are assessed in Chapter 11.

A wide range of approaches and events are described in special issues published in the Bulletin of the American Meteorological Society (BAMS) each year (Herring et al., 2014, 2015, 2016, 2019, Peterson et al., 2012, 2013). The studies in these special issues cover a wide range of events from around the globe (Jézéquel et al., 2018). Jézéquel et al. (2018) reviewed the methods in these studies and describes two main approaches. One is a probabilistic approach that focuses on quantifying the role of anthropogenic climate change on the probability of a particular class of events occurring or crossing a threshold. This is sometimes also called the risk-based approach and the 'fraction of attributable risk' or statements on the likelihood of a particular event occurring with or without climate change can be made. The other is a storyline approach that aims at unveiling the qualitative ways in which anthropogenic climate change affects the processes leading to the event (see section1.2.4.3). These approaches can be complementary, however, the clear definition of the event and the framing of the attribution question and method is imperative in the comparison of studies (Otto et al., 2016).

The largest differences in framing result from the level of conditioning of the specific event on a range of factors. Conditional attribution links anthropogenic climate change combined with a precursor to either an extreme observable, or its impacts. This precursor is an internal element of the climate system which played a role in the occurrence of the event. This approach is not specific to event attribution, as seen in the examples of regional attribution above that were conditioned on decadal variability. Conditioning factors can also include the exact circulation state (Meredith et al., 2015), the observed sea surface temperatures (Otto et al., 2015a), forecasts of the event (Hope et al., 2016, 2018), or the large scale warming only (Lewis and Karoly, 2013). There are also studies that combine different levels of conditioning (e.g. Cheng et al., 2018; Philip et al., 2018a). As the results crucially depend on the event definition and framing, in some cases alternative framing means that direct comparison of results from different studies is not possible. In order to be able to assess the confidence in assessments of changes in particular types of weather events it is important to either assess multi-method and multi-model approaches that combine different framings in a single study (e.g. Grose et al., 2018; Martins et al., 2017; Philip et al., 2018; Uhe et al., 2017; Van Oldenborgh et al., 2018) or assess multiple studies on the same event or type of event.

Attribution of impacts

In the context of IPCC (refer to the Glossary), impacts refer to effects of climate extremes or climate change on natural and human systems. Whereas attribution of physical impacts of climate change on variables such as sea level rise or droughts are assessed in WGI (Funk et al., 2013; Uhe et al., 2017; (Philip et al., 2018a)), attribution of climate change on other natural and human systems will be assessed by WGII (e.g., Hansen et al., 2016; Hansen and Cramer, 2015; Stone et al., 2013).

Climate impacts on an ecological or social system are the result of interactions of a climate hazard with vulnerability and exposure of the system. Therefore, detecting and attributing an anthropogenic climate signal in observed impacts starts from identifying the climate variables that create the hazard, how they have changed and why (Otto, 2017; Sippel and Otto, 2014). Trends in vulnerability and exposure should also be considered ((Otto et al., 2015b); Sheridan and Allen, 2018). However, final detection and attribution of the impacts can still be complicated by the convergence of multiple factors, variables and feedbacks, sometimes non-linear ones.

There are now a number of studies where attribution assessments of changes in climatic variables (e.g. local temperatures or precipitation) are combined with what that change means for systems of interest, for example fire or river flow and inundation (Hope et al., 2019; Kirchmeier-Young et al., 2019; Schaller et al., 2016).

Attribution of (observed/past) changes, such as changes in probabilities of extreme weather, to human influence on the climate is useful as it lends confidence to predictions/projections of future change, and may also be policy-relevant in relation to climate-related loss and damage. However, it is important to recognise caveats regarding the challenges of untangling trends in hazards, sensitivity, vulnerability and exposure in determining actual impacts.

Attribution of adaptation actions has been attempted, for example in the context of water management in cities (Grant et al., 2013; Low et al., 2015) but in general it can be confounded by the presence of contemporaneous drivers unrelated to climate change, including population changes.

Attribution in the WGI and WGII assessments

In WGI, attribution of changes in large-scale indicators of change in the atmosphere, ocean and cryosphere will be assessed in Chapter 3, attribution of changes in extremes and extreme events will be assessed in Chapter 11, while attribution of regional changes in water cycle in Chapter 8, the ocean and cryosphere will be assessed in Chapter 9, and other aspects of regional climate change in Chapter 10. Attribution of changes in human and natural systems will be assessed by WGII.

[END CROSS-CHAPTER BOX 1.4 HERE]

1.6 Dimensions of Integration: Scenarios, temperature levels and cumulative carbon emissions

This section describes and discusses the emission and concentration scenarios that are considered in this Report, building a common reference point with the Working Groups II and III (WGII and WGIII) to synthesize knowledge across the physical sciences, impact and adaptation and mitigation research. Two additional ‘dimensions of integration’ to synthesize the literature are presented: global-mean temperature levels as well as a categorization of emission scenarios or geophysical impacts in relation to their cumulative carbon emissions (see Figure 1.19).

[START FIGURE 1.19 HERE]

Figure 1.19: The Dimensions of Integration (DI) across Chapters and Working Groups in the IPCC AR6 assessment report. Building on the Synthesis Reports of the Fifth IPCC Assessment report (background image detail) this report adopts three explicit dimensions of integration to integrate knowledge across chapters and Working Groups. The first dimension (DI 1) are scenarios, the second dimension (DI 2) are global-mean temperature levels relative to pre-industrial levels and the third dimension (DI 3) are cumulative CO_2 emissions.

[END FIGURE 1.19 HERE]

1.6.1 Dimensions of knowledge integration within and across Working Groups

While scenarios are a key tool for integration across working groups, scenarios allow the integration of knowledge *within* each scientific community. For example, agricultural yield, infrastructure and human health impacts of increased drought occurrences, extreme rainfall events and hurricanes are often examined in isolation. New insights can however be gained on climate impacts in WGII, if compound effects of multiple cross-sectoral impacts are considered across multiple research communities under consistent scenario frameworks (Leonard et al., 2014; Warszawski et al., 2014). Similarly, a synthesis of WGI knowledge on sea level rise contributions is enabled by a consistent application of future scenarios across all specialised research communities, such as ice-sheet surface mass balances, mountain glacier loss projections and thermosteric expansion from ocean heat uptake (e.g. Kopp et al., 2014) (Chapter 9).

Scenarios used for a synthesis of findings across Working Groups. Building on earlier results in AR4, AR5 and the Special Reports, this Report continues to provide consistent analysis of specific scenarios, but also on the knowledge integration across the two policy-relevant dimensions: emissions and global-mean temperatures. Simplified, those two policy-relevant dimensions frame the cause-effect chain investigated by WGI: emissions and the resulting projected temperatures. The handover with WGIII are the emissions, as WGIII considers drivers of emissions and mitigation options. The handover with WGII are the geophysical climate projections from the Earth System Models (Figure 1.20). This offers a strong synthesis across the Working Groups, as mitigation, impact or adaptation results can be tied towards these three dimensions: scenarios, cumulative emissions and temperatures.

Not only does a consistent application of scenarios serve the integration of knowledge across the three Working Groups. Also, the scenario generation process itself is a cross-Working Group activity. The scenario generation starts in the scientific community related to WGIII, new storylines (O'Neill et al., (2014); see also Section 1.2.4.3) are quantified in terms of their the drivers GDP, population, technology, energy and land use demand and their resulting emissions (Riahi et al., 2017a). Then, numerous complementation and harmonisation activities within the WGIII and WGI communities are performed, gridding anthropogenic short-lived forcers, providing open biomass burning emission estimates, land use patterns, observed and projected greenhouse gas concentration time series, stratospheric aerosol fields, stratospheric and tropospheric ozone, nitrogen deposition datasets, solar irradiance and aerosol optical property estimates. These activities are compiled under the WCRP CMIP6 input4mips umbrella (Durack et al., 2018) (see Section 1.6.2.1). With those completed datasets, the Earth System Models are then run, providing the sets of experiments under multiple model intercomparison protocols that are now part of CMIP6 (Eyring et al., 2016a) (see Section 1.4.3). Using emulators calibrated with the Earth System Models' temperature responses under those given scenarios, the WGI community is then feeding back tools to WGIII that allow to compute several high-level climate indicators (concentrations, temperatures, sea level rise) for a much wider set of hundreds of scenarios that are assessed by WGIII. The main use of the climate projections is however the further assessments of its implied future geophysical climate impacts - feeding into specialised impact models to assess the ecological, food security, infrastructure and human impacts under the main set of scenarios (Figure 1.20).

[START FIGURE 1.20 HERE]

Figure 1.20: The scenario generation process that weaves through the three Working Groups and its scientific communities. The top level indicates the main set of models used in that scenario generation process, with the lower level indicating the datasets. Also, the three dimensions of integration (scenarios, cumulative carbon emissions and global-mean temperature levels) are indicated as open circles, with cumulative emissions sitting at the handover between WGIII (orange) and WGI (blue), and global-mean temperatures sitting - simplified speaking - at the connection point between WGI and WGII (green).

[END FIGURE 1.20 HERE]

[START FIGURE 1.21 HERE]

Figure 1.21: Analysis of the marker SSP scenarios, RCP and the wider AR6 scenario database regarding cumulative carbon emissions over time (panel a). The implied CO_2-induced warming given those cumulative emissions and the TCRE is shown for SSP scenarios and SR1.5 emission scenario database (panel b). The variation of non-CO_2 emission rates at the time of peak cumulative emissions is here exemplified with total methane emissions that can substantially influence the remaining carbon budget (cf. Collins et al. (2018)) (panel c). Overall, the GWP-weighted sum of all greenhouse gas emissions is a close indicator of cumulative carbon emissions until 2050 in the literature scenarios, lending some support to policy architectures that address GWP-weighted emission baskets as one of many options (see discussion in Chapter 7) (panel d). The timing of net positive and net negative emissions across the 9 SSP marker scenarios over time (panels e on the right side). [Note: this graph is only a sketch to highlight a few aspects of the AR6 emission database. To be updated]

[END FIGURE 1.21 HERE]

The temperature and cumulative-emission based scenario classification.

The Integrated Assessment Model (IAMs) community provides a wealth of hundreds of scenarios, in addition to the ESMs scenario runs carried out under CMIP6 for a set of “marker scenarios”. These IAMs scenarios follow various shared policy assumptions (SPAs) - resulting in a mix of low and high emission scenarios with various timings, multi-gas shares and regional differences. This wealth of scenarios can then be classified according to a scenario’s peak temperature (or the likelihood to exceed a certain temperature level relative to pre-industrial), relating directly to a key policy variable of interest. Examining the emission pathway characteristics of all scenarios in one temperature class allows for a better insight of cost-optimal and second-best emission milestones and characteristics while at the same time providing insights regarding the flexibility to divert from the middle-of-the-road pathways in a specific scenario class. The disadvantage is clearly that uncertainties are folded into the scenario classification that are external to the scenarios themselves. However, with a proper characterisation and synthesis of uncertainties across the AR6 report, ranging from the CO_2-induced warming, non-CO_2 greenhouse gas and aerosol effect, as well as carbon cycle and Earth system feedbacks. This integration of uncertainties is assessed in this WGI Report. Furthermore, a temperature-defined scenario classification enables a closer integration of results across the various research communities – linking to temperature-tagged impact results from WGII, but also paleoclimatic studies assessed elsewhere in this report (see Section 1.6.3). In addition to temperature-based scenario classifications, this report will perform a cumulative carbon emission classification of scenarios, as described in Section 1.6.4.

Cumulative carbon emissions and global-mean temperatures are representative for a broad spectrum of climate effects.

Global mean temperature levels are nearly-linearly related to a number of a number of regional climate impacts, temperatures (Mitchell, 2003; Mitchell et al., 2000; Tebaldi and Arblaster, 2014), aggregated impacts against temperature levels have been widely used and embedded in the iconic ‘Reasons for concern’ (RFC) figure (Smith et al., 2009; IPCC, 2014). The RFC framework has been further expanded in the SR15, the SROCC and SRCCL by explicitly looking at the differential impacts between half-degree warming levels (cf. King et al. (2017), and more specific impacts. Global-mean temperatures are hence the ‘pars-pro-toto’ representation and approximation of a much wider range of regional climate impacts, cognizant of some of the limitations as for example regional precipitation responses also strongly depend on the forcings themselves, the vertical structure of the troposphere (Andrews et al., 2010) and aerosols in particular (Frieler et al., 2012). Similarly, cumulative carbon emissions are a good proxy and a pars-pro-toto, offering the opportunity to synthesise insights by WGI along the dimension of cumulative carbon emissions. With the overwhelming majority of future greenhouse gas induced warming resulting from elevated carbon dioxide concentrations across the scenarios, it is also key to keep the second-order variations in mind. For example, methane emission rates shortly before and at the time of peak warming levels can have a strong effect on the remaining carbon budget (Collins et al., 2018) (see Figure 1.21, panel c). In summary, in addition to scenarios, knowledge integration across the cumulative emission and temperature axes opens additional opportunities to synthesize knowledge across Chapters and Working Groups.

[START FIGURE 1.22 HERE]

Figure 1.22: The marker SSP scenarios used throughout the AR6 report, their cumulative CO_2 emissions and 2050 GHG emission levels in the context of the risks from climate change. Shown is the Synthesis Report Figure SPM.10 from AR5, updated by the 21st century characteristics of the new SSP scenarios in panel b and c. [Note, this is only a hand-drawn sketch].

[END FIGURE 1.22 HERE]

Nuances and limitations of the ‘dimensions of integration’.

Ever since the ‘dimensions of integration’ have emerged in the scientific literature, a body of literature has also investigated the limitations, non-linearities and shortcomings of those. Regarding the dimension of cumulative emissions, the potential disadvantage is – to the extent that CO_2 trajectories and non-CO_2 emissions materially differ (see e.g. Figure 1.21, panel c) – that the categorisation of scenarios according to their cumulative carbon emissions does not imply similarly distinct climate outcomes of the adjacent emission-defined scenario classes. As further explored as part of the WGIII assessment, one potential limitation when presenting emission pathway characteristics in cumulative emission budget categories, the knowledge around path-dependencies and lock-in effects should also be fully considered. For example, continuously high emission early-on might imply strongly net negative emissions later on to reach the same cumulative emission and temperature target envelope by the end of the century. This report will explore options to address some of those potential issues from a WGI perspective. Regarding the dimension of global-mean temperatures, for example, distilling geophysical climate effects for low warming before the emergence of 1.5°C specific scenarios is often performed by using early-century time slices of higher emission scenarios. Similarly, for 2°C, higher scenarios or idealized scenarios had been used before RCP2.6 climate results were available. Distilling robust results from time slices of transient but ultimately higher warming scenarios is for example hampered by relatively higher aerosol emissions compared to scenarios in which 1.5°C or well-below 2°C temperature levels above pre-industrial levels are achieved and maintained. Low aerosol emission levels are projected under low mitigation scenarios for the middle and end of this century, rendering the geographical and precipitation responses different from a transient 1.5°C snapshot of a higher warming scenario. Another aspect is how long-term sea level rise correlates with the global-mean temperatures. For sea level rise, time is important as several sea level rise contributions are approximately proportional to the integral over global-mean temperature. Thus, sea level rise after a 1°C warming for 50 years will be quite a bit lower than the sea level rise that arises from keeping that 1°C warming for 150 years.

1.6.2 Scenarios reflecting choices within an uncertain future

As a tool to methodologically examine the future, scenarios have risen to prominence since the ‘Limits to Growth’ report in 1972 by Meadows et al. (1972) (see Cross Chapter Box 2 on “Scenarios and other methods to characterise the future” in SRCCL). Rather than predicting the future, scenarios examine future developments in a “what-if” explorative sense (cf. Moss et al., 2010). While there are some probabilistic socio-economic and emission scenarios in the literature (e.g. Webster et al., 2003), the scenario literature does not assign probabilities to individual scenarios, as the future is intrinsically unpredictable. The plausibility assigned to various scenarios can change over time. For example, the likelihood of a scenario of ‘regional rivalry’ would have been discussed very differently during the adoption of the Paris Agreement in 2015 compared to just two years later. The public acceptability and assessments of potentials of large-scale biomass plantations with carbon capture and storage (CCS) also changes over time and across countries and leads to differing assessments as towards their likelihood or desirability of scenarios that employ high shares of that particular negative emission technology (e.g. Fuss et al., 2014). In summary, the foundational principle of scenarios is that they are “what-if” projections, discussed in regard to their (changing) plausibility, facilitating factors, side effects and their respective desirability, rather than scenarios being deterministic or probabilistic predictions.

Scenarios are a core element to WGI, even though largely exogenous. Scenarios have been used in IPCC reports since the First Assessment Report (Legget, 1992) with so-called IS92, SRES, and RCPs informing more than three decades of climate change research. For this WGI Report, the emissions of the main set of scenarios are the Shared Socioeconomic Pathways (SSPs, Riahi et al 2017), reflecting future emissions that result from socio-economic scenarios that are assessed in detail in WGIII. However, the scenario generation process with the harmonisation of emissions, completion with natural forcings, biomass burning emissions, land use patterns, greenhouse gas concentrations and ultimately the climate projection is a process that weaves through all three Working Groups of the IPCC and their respective scientific communities (Figure 1.20). In addition to those transient long-term scenarios, multiple idealized pathways and time-slice experiments independent of scenarios are investigated by climate models. Ever after the first transient climate modelling runs in 1988 with a General Circulation Model (Hansen et al., 1988), the transient modelling experiments with scenarios are a core element of physical climate science. Except for seasonal and most decadal predictions, future climate projections are conditional on the respective scenario.

The use of different scenarios for climate change projections introduces a so-called ‘scenario-uncertainty’ in the projections (Collins et al., 2013) (see Section 1.5.4). However, ‘scenario uncertainty’ might be a slight misnomer, as scenarios are technically not an uncertainty, but an outcome of many collective choices (Knutti et al., 2008). Future emissions are, to a large extent, the outcome of a collective choice in relation to population growth, economic activity, or choices regarding an activities’ emission intensity. For example, the future share with which electricity demand is met by coal power plants, or renewables or whether energy efficiency is lowering energy demand, are explicit or implicit collective choices. Scenarios are hence fundamentally different from geo-physical uncertainties. On the other hand, from an adaptation planning perspective, an investment into long-term water infrastructure, for example, faces the uncertainty as to what the collective aggregate choice of humanity that ultimately determine human-induced emission levels.

Long-term scenario uncertainties can be made accessible by means of ‘scenario storylines’. ‘Storylines’ in this context (see Section 1.2.4.3 for a broader discussion on ‘storylines’ that also discusses ‘event storylines’) are descriptions of that state of a future world and the large-scale development towards there (e.g. ‘regional rivalry’ vs. ‘global cooperation’) that are deemed plausible with the current state of knowledge and historical experiences. They do not ‘seek truth’, but attempt to ‘stimulate, provoke, and communicate visions of what the future could hold for us’ (Rounsevell and Metzger, 2010) in settings, where either limited knowledge or inherent unpredictability in social systems prevents a forecast or numerical prediction. Storylines are nothing new in climate research, as they are the explicit or implicit starting point of any scenario exercise, whether for SRES scenarios or SSPs (e.g. O’Neill et al., 2017a).

However, a new paradigm has emerged over the decades of considering socio-economic storylines and emission futures as orthogonal. Until the mid 2000s, socio-economic storylines have often been represented by a single marker or illustrative scenario. That led to the misperception that a certain socio-economic development path dictated greenhouse gas and short-lived climate forcer levels. Within reference scenarios, this paradigm started to be differentiated when the high-economic A1 scenario family in the set of SRES scenarios was represented by three scenarios, A1FI, A1B and A1T, that imply high, medium and comparatively lower future emission levels (SRES, Nakicenovic and Swart, 2000). The set of scenarios that followed, the Representative Concentration Pathways (RCPs, Moss et al., 2010), were intentionally devoid of the socio-economic underlying storylines, and was the starting point for a more systematic exploration of the two-dimensional space of socio-economic storylines (O'Neill et al., 2014) and emission levels. This new matrix approach made explicit that any socio-economic development storyline can be consistent with almost any emission future assuming the appropriate level of mitigation action. This approach was further developed with the current set of scenarios used, the SSPs. Employing various levels of mitigation action, the new SSP-RCP scenarios span five broad future socio-economic developments and emission futures that are consistent with global warming of 1.5°C, or well-below 2°C above pre-industrial levels on the one hand, and, on the other hand, high emission levels that would reach global mean temperature levels beyond 4°C this century. When assuming a more sustainability-oriented future, in contrast to one in which regional rivalry is a dominating element, the emission levels consistent with the lower temperature levels are achievable with comparatively low mitigation efforts. However, in all scenarios, substantial co-benefits of mitigation action materialize, such as reduced air pollution and increasingly cost-savings for electricity consumers due to falling technology costs of renewable energies.

The five shared socio-economic pathways represent the broad developments of 'sustainability' (SSP1), a 'middle of the road' development (SSP2), 'regional rivalry' (SSP3), 'inequality' (SSP4) and 'fossil fuel intensive' development (SSP5) (Figure 1.23) While the lowest emission levels are generally not achieved in a world that is otherwise set on a course of fossil-fuel development, likewise, a sustainability-oriented socio-economic world development is not envisaged to go hand in hand with very high emission levels, even without additional mitigation action. A total of nine scenarios populating a range of forcing levels across all five socio-economic developments have been prepared to drive the Earth System Models for the CMIP6 (see Figure 1.23). Of those, this report mainly focuses on those four scenarios in "Tier 1" (SSP1-2.6, SSP2-34, SSP3-70 and SSP5-85) that all climate modelling groups were asked to run as a priority, in addition to the low emission scenarios SSP1-1.9, which examines the lower temperature targets envisaged in the Paris Agreement (see Section 1.4.4 on CMIP6).

Multi-scenario analysis can enhance robustness of policy-relevant results. Depending on the research or policy question, an integration of uncertainties across a multitude of scenarios enables policy-relevant results. For example, the remaining amount of cumulative carbon emissions to stay well below 2°C or below 1.5°C, the so-called remaining carbon budget, is crucially dependent on the non-CO_2 forcing contribution at the time of peak temperatures. While for example the RCP2.6 scenario had comparatively low non-CO_2 emission levels, an analysis across a large set of low emission scenarios is enhancing the robustness and enables the uncertainty analysis of derived carbon budgets within WGI (see Chapter 5).

Idealized scenarios go beyond the key set of socio-economically anchored scenarios. This report explores a range of idealized scenarios, temperature levels and examinations of the more complete set of scenarios collected by the integrated assessment community in recent years, asssembled in the AR6 scenario database that is set up by WGIII. Idealized scenarios refer to experiments where CO_2 concentrations are, for example, increased by 1% per year, or instantly quadrupled and have extensively been used in previous and current intercomparison projects. The idealized experiments are used to diagnose climate sensitivity and the pattern of feedbacks across the suite of models.

[START FIGURE 1.23 HERE]

Figure 1.23: The five future shared socio-economic scenarios SSP1 to SSP5, their model-specific reference scenarios and mitigation scenario within each future world. Here, the nine marker SSP scenarios from ScenarioMIP are shown with the higher priority scenarios SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 being shown in higher opaqueness. The illustrative temperature evolution is derived from the default MAGICC 7.0 setting used to produce the greenhouse gas concentrations for those SSP scenarios (greenhousegases.science.unimelb.edu.au). Note that those temperature evolutions are illustrative only and subject to large uncertainties. The black stripes on the respective scenario panels indicate SSP scenarios that were not selected to be marker scenarios, but span the scenario range more fully [Note, this graph is a sketch only. To be updated].

[END FIGURE 1.23 HERE]

1.6.2.1 *Scenarios with their shared socio-economic pathways, their reference and mitigation scenarios*

This section provides some background and synthesis regarding the considered Shared Socio-economic Pathways (SSPs). The long-term and multi-faceted nature of climate change requires scenarios to describe how socio-economic evolutions in the 21st century could influence future energy and land use, resulting emissions and possibilities to mitigate them, as well as the evolution of human vulnerability and exposure to climate change impacts. These evolutions are driven by demographic trends, economic processes, technological innovation, governance and lifestyles. Although many scenarios of future socio-economic developments could be plausible, a small set of scenarios are needed to harmonize assumptions and facilitate research coordination and synthesis.

The five Shared Socioeconomic Pathways (SSPs) were developed by the research community to serve this goal (Nakicenovic et al., 2014). Each SSP is an internally consistent, plausible and integrated description of a possible future. Between SSPs, they are contrasted in terms of socio-economic challenges to mitigation and to adaptation. The SSPs form a set of qualitative storylines describing societal futures (O'Neill et al., 2017b) associated with quantitative projections of socio-economic determinants such as population, GDP and urbanization (Dellink et al., 2017; Jiang and O'Neill, 2017; KC and Lutz, 2017), as well as quantifications of the energy system, land use and GHG emissions developments (Riahi et al., 2017a). Socio-economic driving forces consistent with any of the SSPs can be combined with a set of climate policy assumptions (Kriegler et al., 2014) that together would lead to emissions and concentration outcomes consistent with the RCPs, therefore creating the SSP-RCPs scenarios matrix (van Vuuren et al., 2014).

[START TABLE 1.4 HERE]

Table 1.4: The marker SSP scenarios and their specific challenges to mitigation and adaptation. Figure taken from IPCC SR1.5 (O'Neill et al. 2017b).

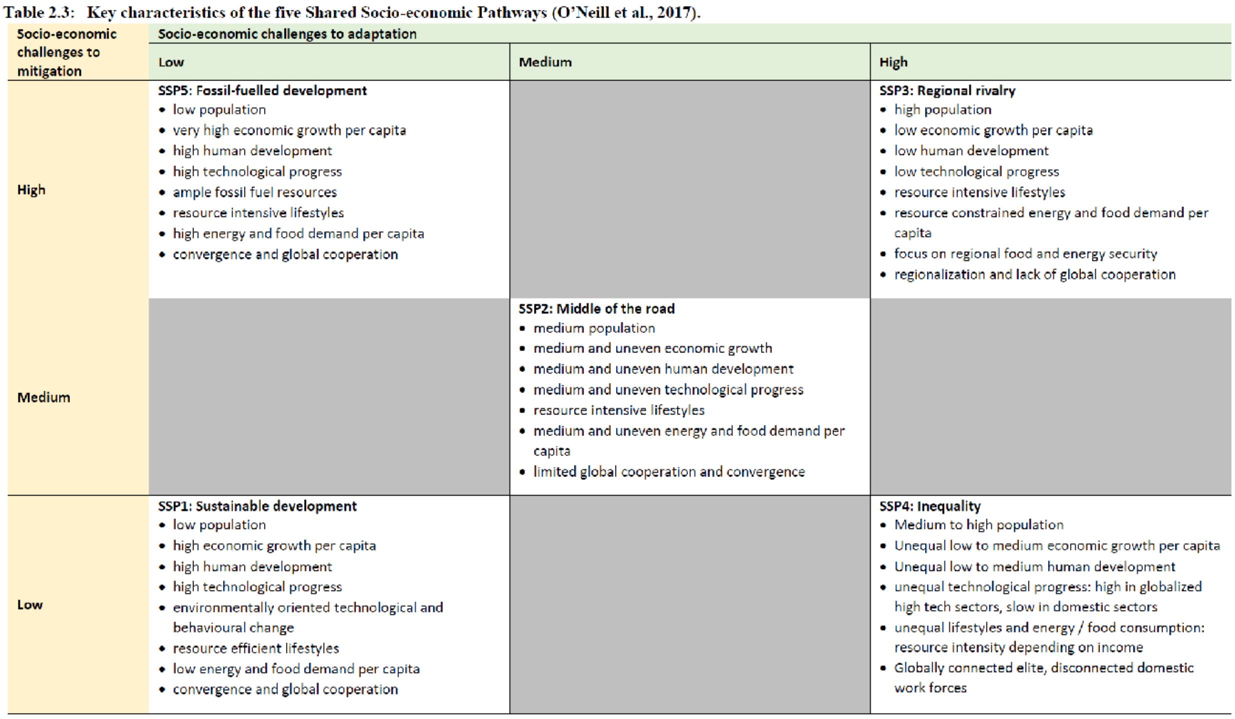


Table 2.3: Key characteristics of the five Shared Socio-economic Pathways (O'Neill et al., 2017).

Socio-economic challenges to mitigation	**Socio-economic challenges to adaptation**		
	Low	**Medium**	**High**
High	**SSP5: Fossil-fuelled development** • low population • very high economic growth per capita • high human development • high technological progress • ample fossil fuel resources • resource intensive lifestyles • high energy and food demand per capita • convergence and global cooperation		**SSP3: Regional rivalry** • high population • low economic growth per capita • low human development • low technological progress • resource intensive lifestyles • resource constrained energy and food demand per capita • focus on regional food and energy security • regionalization and lack of global cooperation
Medium		**SSP2: Middle of the road** • medium population • medium and uneven economic growth • medium and uneven human development • medium and uneven technological progress • resource intensive lifestyles • medium and uneven energy and food demand per capita • limited global cooperation and convergence	
Low	**SSP1: Sustainable development** • low population • high economic growth per capita • high human development • high technological progress • environmentally oriented technological and behavioural change • resource efficient lifestyles • low energy and food demand per capita • convergence and global cooperation		**SSP4: Inequality** • Medium to high population • Unequal low to medium economic growth per capita • Unequal low to medium human development • unequal technological progress: high in globalized high tech sectors, slow in domestic sectors • unequal lifestyles and energy / food consumption: resource intensity depending on income • Globally connected elite, disconnected domestic work forces

[END TABLE 1.4 HERE]

There is less clarity compared with early scenario exercises about what is “business-as-usual”. For more than two decades of scenario research, the standard paradigm has been that a ‘business-as-usual’ world is modelled in which no new policy or regulatory frameworks for climate mitigation are assumed. These scenarios answered the question: What emissions are to be expected in the absence of additional renewable energy and climate policies? For example, air pollution related policy assumptions still lead to strongly reduced aerosol emissions even in the high emission scenarios without climate policies (such as RCP8.5). However, strong reduction in costs of mitigation technologies that were often induced by climate and energy policies at the start, such as for solar PV and wind power, could be seen as undermining to some extent the overall definition of “business-as-usual” that is devoid of climate policies. Thus, to steer away from the ambiguous term ‘business-as-usual’, the scenario communities have generally adopted the name ‘reference scenario’ to describe the high-emission and hypothetical scenarios that might happen if economic and policy trends would break with the past and no new climate, renewable energy or land use policies were being enacted.

The scenarios now offer unprecedented detail for climate model simulations. With future emission trajectories being developed by the integrated assessment communities, the emission scenarios are processed and complemented by a number of other research groups in order to allow comprehensive climate model experiments (Durack et al., 2018). First, historical emission data was combined with future scenarios, drawing on various expertise regarding historical emission inventories (Gidden et al., 2018). Secondly, the emission scenarios from the integrated assessment community focuses on global and regional emissions of major greenhouse gases (CO_2, CH_4, N_2O), some aggregated (HFCs, PFCs) and individual halogenated species (SF_6, sometimes NF_3) and aerosols. In order to complement other anthropogenic drivers, emissions of gases controlled under the Montreal Protocol are included, as well as a number of individual smaller industrial gases (WMO, 2014a). Reactive gas emissions (such as CO, SOx, CH_4, NOx, VOC) are downscaled to provide a 1°x1° degree or finer spatial and annual resolution of historical and future emissions, so that chemistry climate models can be driven (Hoesly et al., 2018). Thirdly, as some General Circulation Models (GCMs) do not have an interactive carbon cycle and none of the Earth System Models explicitly models the smaller trace gases for computational efficiency, greenhouse gas concentrations are provided for the greenhouse gas concentration-driven runs (Meinshausen et al., 2017). For CMIP6, those greenhouse gas concentration fields included for the first time the latitudinal gradient and seasonality. Fourthly, the Earth System Models without interactive chemistry are provided with, for example, tropospheric and stratospheric ozone fields consistent with the respective scenarios (Hegglin, et al., in preparation,). Fifthly, nitrogen deposition fields are generated allowing dynamic vegetation models with a nitrogen cycle to create more realistic carbon cycle simulations (Hegglin et al.). Also, historical landuse and landcover maps have been provided in a high spatial resolution and consistent with the socio-economic drivers within the SSPs. Natural forcings are also provided, specifically waveband resolved solar forcing in a level of detail that was not available for CMIP5 (Matthes et al., 2017b) and spatially resolved volcanic aerosols historical time series (Thomason et al., 2018). This large set of input fields is accessible via the ESGF/PCMDI servers as so-called ‘input4mip’ variables (for scenario, emission and other forcing data, see https://www.wcrp-climate.org/wgcm-cmip/wgcm-cmip6 .

[START FIGURE 1.24 HERE]

Figure 1.24: Examples for the input datasets for the SSP scenarios, showing the range of SO2 emission scenarios over the 21st century [Note, a future version of this graph will show the RCP range in the background], and also a very high and low spatial emission example from the SSP3.-7.0 and SSP3-7.0-lowNTCF scenarios in 2100, respectively (top row). As landuse examples for the SSP scenarios, the spatial change in cropland cover in year 2100 to year 2015 is shown in the scenario SSP3-7.0 (left panel), the global cropland change over time in all SSP scenarios compared with the RCP scenarios (middle panel) and the change in forest cover - with afforestation and reforestation in the SSP1-1.9 and SSP1-2.6 scenarios indicating the strongest increase in global forest cover (right panel). Source: Top graphs produced by CICERO on the basis of SSP database 2.0. Bottom graphs adapted from Fig 4 in O'Neill et al. (2016) with the cropland cover map being based on the land-cover dataset from LUMIP (Hurtt et al, in preparation - available at: http://luh.umd.edu/).

[END FIGURE 1.24 HERE]

The SSP scenarios are emission and concentration scenarios, not forcing scenarios. It is worth noting that although this detailed scenario information is often described as forcing scenarios or elements thereof, the input information on anthropogenic forcers to Earth System Models only comes in the form of emissions and concentrations (i.e. dry mol fractions for greenhouse gases or mass and size distributions for aerosols), and landuse/landcover maps, not to actual forcing data. The radiative forcing labels of the RCP and SSP scenarios, such as "2.6" in RCP2.6, are approximate nameplate labels. The actual global mean effective forcing will be different from Earth System Model to Earth System Model due to different radiative forcing schemes, uncertainties in aerosol-cloud interactions and different fast feedback mechanisms, among other reasons. The advantage of using approximate radiative forcing labels however is that a clear ranking between the scenarios can be established and that multiple climate driving forcers that are at play in those scenarios can be summarized into one number. The classification in this report according to cumulative carbon emissions (see Section 1.6.4) and temperature levels (Section 1.6.3 and Cross-Chapter Box 1.5 on emulators) complements those forcing labels.

[START FIGURE 1.25 HERE]

Figure 1.25: An illustrative comparison of the relative importance of greenhouse gas concentrations for projected climate change. The blue shaded area indicates the approximate forcing exerted by CO_2 in three of the SSP scenarios, SSP1-1.9, SSP1-2.6 and SSP3-7.0. The CO_2 concentrations under the SSP1-1.9 scenarios approximately reach 350 ppm after 2150, those of SSP1-2.6 around 400 ppm and the SSP3-7.0 as one of the higher scenarios will reach levels of nearly 1500 ppm CO_2 in the longer term until 2300. Also shown are the effects of reducing short-lived climate forcers in the SSP3-7.0 scenario at the example of methane (panel c, black arrows in the top right), when comparing the SSP3-7.0 scenarios with the AerChemMIP variant SSP3-7.0-lowNTCF [To be updated]

[END FIGURE 1.25 HERE]

1.6.2.2 Scenarios in the context of the Paris Agreement

The long-term goal of the Paris Agreement is "to is to keep the increase in global average temperature to well below 2 °C above pre-industrial levels; and to limit the increase to 1.5 °C". Furthermore, the 1.5°C target emerged as part of the Paris Agreement, for example due to the expected climate impacts and implied sea level rise of 2°C warming (e.g. Levermann et al., 2013). Therefore a range of SSP marker scenarios as well as the larger AR6 scenario database are examined according to the degree the individual scenarios are in line with the Paris Agreement targets. Specifically, following from the IPCC SR1.5 classification of emission scenarios in various categories by both the likelihood to stay below certain temperature levels, as well as – in the case of 1.5°C – their respective implications for no overshoot or a low or higher initial overshoot.

The current emissions targets under the Paris Agreement reach until 2030. This report is using the existing literature of the aggregate emission levels under the nationally determined contributions (NDCs) of the Paris Agreement to put the scenarios investigated in this WGI into context. A much closer look at aggregate NDCs is performed in WGIII, so that here only the aggregate global emission ranges (UNFCCC, 2016) are compared against the scenarios' 2025 and 2030 emission levels (see also Cross-Chapter Box 1.1 on the global stocktake process)

[Placeholder for a table with explanatory text to be inserted that provides results of the contextualisation of the AR6 emission scenario database in the light of the Paris agreement]

[START FIGURE 1.26 HERE]

Figure 1.26: Historical concentrations for the past 2000 years of CO_2, CH_4 and N_2O (Meinshausen et al., 2017), and [draft sketch of] temperature reconstructions joined with scenario information up to year 2300. The temperature proxies over the last 2000 years were compiled by the Pages 2K project (Emile-Geay et al., 2017) and also shown are northern hemispheric temperature reconstructions by Mann et al. (1999) (dark blue ranges). Future temperature projections are from the CMIP6 ScenarioMIP experiment, examined in Chapter 4 of this report. The grey vertical band indicates the 21st century. [Note: this is a draft sketch figure only].

[END FIGURE 1.26 HERE]

[START FIGURE 1.27 HERE]

Figure 1.27: Illustrative synthesis figure on the "decision power/policy-relevance" of scenarios in the context of the Paris Agreement. The 'decision power' for this analysis is here defined as the range between reference and various mitigation scenarios that include shared policy assumptions (SPAs), separated by gases and scenario characteristics in relation to their effect (attributable warming) on peak 21st century temperatures [and end of century sea level rise] (y-axis). The individual elements on the x-axis can be: Next decade cumulative CO_2 emissions, CH_4 emissions, non-methane SLCF, second half of century net negative CO_2 emissions, and GHG emission levels in 2030 (possibly shown by various metrics, (GWP|GTP, and GWP* in some form)). For example, methane emissions, cumulative CO_2 emissions, cumulative GHG emissions (GWP|GTP\GWP* weighted), SLCF emissions and other GHG emissions. [dependent on AR6 scenario database analysis].

[END FIGURE 1.27 HERE]

1.6.3 Temperature levels as additional tool for cross-Working Group integration

This section provides the methodological underpinning for an additional 'dimension of integration' along global-mean temperature bands.

As the IPCC SR1.5 concluded, every half a degree or even smaller fractions of a degree of warming matter in terms of climate impacts (see IPCC SR1.5; Schleussner et al., 2016 - see also Chapter 11). Following these SR1.5 results, this report adopts the half-degree temperature bands, starting from a pre-industrial reference point (see Section 1.5.3), across which climate projections, impacts, adaptation challenges and mitigation challenges can be integrated within and across the three WGs. Specifically, the categorisation is performed in half-degree steps with 1.5°C, 2.0°C, 3.0°C, 4.0°C as the central points the higher importance 'Tier 1' levels, with additional half-degree categories around 2.5°C, 3.5°C up to a level around 6.0°C (see Table 1.5) [This will depend on CMIP6 results].

The average global temperature during the early-industrial period (1850-1900) is approximately equivalent to pre-industrial temperature, and so can be used as a baseline to assess issues associated with warming levels. However, it is also *likely* (*medium confidence*) that there was some anthropogenic warming which occurred between pre-industrial and early-industrial periods, which was at least partially offset by volcanic activity during the early-industrial period. The magnitude of this warming is plausibly 0.0-0.1C which is pertinent for assessments involving remaining carbon budgets consistent with the Paris Agreement and earlier policy targets that refer to pre-industrial temperature levels (see 1.5.3.2).

[START TABLE 1.5 HERE]

Table 1.5: Description of the Tier 1 and Tier 2 global mean-surface air temperature relative to pre-industrial levels.

Tier 1 temperature reference levels	**Notes**
1.5°C	In line with climate futures and impacts that would result from limiting warming at 1.5°C - in line with the Paris Agreement target to pursue best efforts to limiting warming to 1.5°C
2.0°C	Impacts are those that would be avoided, if Paris Agreement target to limit warming to "well below 2.0°C" were achieved.
3.0°C	In line with a climate future that would result of the Paris Agreement 2.0°C target would be missed by 1°C.
4.0°C	In line with a climate future that would result by the end of the century under most no-climate-policy reference scenarios, although temperatures could rise as high as [Z] degree (see Chapter 4).
Tier 2 temperature reference levels	
1.0°C (~current), 2.5°C, 3.5°C, 4.5°C, 5.5°C, 6.0°C, 6.5°C, 7.0°C	Temperature levels at half-degree steps that complete the full range from 1.0°C to the maximal temperatures shown by CMIP6 models under the SSP5-8.5 scenarios by the end of the 21st century (tbc - see Chapter 4).

[END TABLE 1.5 HERE]

The methods to provide averaged climate at certain temperature levels can be ordered into three sub-categories. As the IPCC Special Report on 1.5°C found (Section 3.2.1 therein), there is the need to distinguish between three cases: firstly, information that is drawn from transient climate responses for those temperature levels, i.e. from climate simulations that 'pass through' the respective warming levels. In that case, the methods to derive the climate information pegged a certain temperature level uses for example an empirical scaling relationship approach (Seneviratne et al., 2016, 2018; Wartenburger et al., 2017) or 'time sampling' approach described in James et al. (2017); secondly, information that is drawn from (relatively) short-term stabilisation scenarios, e.g. from climate projections that are the result of scenarios that reach and stabilise at a particular temperature level by the end of the 21st century; thirdly, there is a multi-millennial response time associate with each warming level. For slow-onset and integral climate impacts, the time dimension will be fundamentally important as for example sea level rise response to 1°C of warming is very different after 20 or 100 or 1000 years.

[START CROSS-CHAPTER BOX 1.5 HERE]

Cross-Chapter Box 1.5: Physical emulators of global mean temperatures for scenario classification and knowledge integration.

This box describes simplified parameterisations and simple climate models, which have been used to emulate the characteristic responses of higher complexity process-based models or Earth System Models, their overall temperature response or the dynamics of their sub-models (like the carbon cycle, or thermosteric sea level rise) since the beginnings of the IPCC (see Harvey and Schneider, 1985; Houghton et al., 1997). The main use of emulators is to extrapolate the insights from Earth System Models (ESM) as well as observational constraints to a large set of emission scenarios. The computational efficiency of various emulating approaches opens new analytical possibilities given that Earth System Models take a lot of resources for each simulation. The applicability and usefulness of emulating approaches is obviously constrained by their skill to reflect certain Earth System Model responses (such as global-mean or hemispheric land/ocean temperatures) and by their ability to extrapolate skilfully outside the calibrated range. While physical emulators have been used for decades in various applications (e.g. the temperature classification of Working Group III (WGIII) scenarios in AR4 and AR5 has been undertaken with a calibrated version of MAGICC), recently renewed interest in emulators emerged as the IPCC Special Report on Global Warming of 1.5ºC, with the timescales involved in the report's production precluding Earth system models running multiple future scenarios in time to for assessment therein.

The term emulators is different from the term simple climate models. Simple climate models can be used as emulators of ESM models, but such emulation can also be performed with very simple parameterisations (‘one-or-few-line-climate-models’), statistical methods like neural networks, genetic algorithms or other Artificial Intelligence approaches. The term simple climate models (SCMs) generally refers to a broad class of lower dimensional models of the energy balance, radiative transfer, carbon cycle, or a combination of such physical components. SCMs are however also suitable for performing emulations of climate-mean variables of ESMs given that their structural flexibility can capture both the parametric and structural uncertainties across Earth System Model responses. The advantage of SCMs compared to simpler or statistical approaches is that their rudimentary physical process parameterisations provide additional reason to trust moderate extrapolations from the response space that is covered by Earth System Models. Simple climate models do not have to be run in ‘emulation’ mode, though, as they can also be used to test consistency across multiple lines of evidence with regard to climate sensitivity ranges, transient climate responses (TCR), transient climate response to cumulative emissions (TCRE) and carbon cycle feedbacks (see Chapters 5, 7).

Current emulators can be classified into many different categories, depending on their comprehensiveness (i.e. whether they emulate glacier responses or the whole Earth System with permafrost, sea level rise and a large set of gas cycles), or their ocean heat uptake parameterisations, which strongly affect the long-term climate responses (i.e. a simple diffusive ocean or an upwelling, diffusive entrainment parameterisation), and/or their overall model complexity (single line impulse response functions or compact Earth System models), but also according to their parameterisation and model structure. We here provide an approximate categorisation of the literature according to model complexity. Impulse response function characterisations of the Earth’s temperature response and climate models with a small set of equations (e.g. DICE, AR5-IR) are in the first category. The more comprehensive simple climate models that do not have a purely diffusive ocean (e.g. MAGICC, BernSCM, Hector) or impulse response representations that come with a sophisticated representation of one or more Earth System elements (e.g. OSCAR) are in the second category. The third category comprises statistical approaches, ranging from neural networks to more recent AI approaches, which are particularly well suited to emulate variability - a capacity that is outside the standard design ambitions for simple climate models. However, the literature overview below is particularly focussed on those models that attempt to emulate global mean temperatures (among other things), acknowledging that the literature on emulators for specific climate system domains is much wider.

[START CROSS-CHAPTER BOX 1.5, TABLE 1 HERE]

Cross-Chapter Box 1.5, Table 1: categorisation of different approaches that can be used to emulated global-mean temperatures of Earth System Models.

Emulator Type[4]	**Examples in the literature**	**Notes on general use in literature / in AR6**
The impulse response and diffusive ocean SCMs	● AR5-IR (Supplementary Material 8.SM.11 of Myhre et al. (2013)) ● "Two-layer EBM" (Geoffroy et al., 2013) ● Bern-SAR (IPCC SAR); Bern-TAR (IPCC TAR) ● "5-equation IR" (Jenkins et al., 2019) ● FaIR (Smith et al., 2018) ● DICE (Knutti et al., 2003);	Often used for emission metric calculations with simplified impulse response (IR) equations for concentrations and temperatures. See for example Supplementary Material 8.SM.11 in the Fifth Assessment Report. The more encompassing of the impulse response models are also used for multi-gas assessments and ESM emulations. *[AR6 usage tbc]*
Comprehensive SCMs "upwelling, diffusion, entrainment" or "compact Earth System Models"	● UDE-EBM (Schlesinger et al., 1990) ● ACC2 (Tanaka et al., 2007) ● BernSCM (Strassmann and Joos, 2018) ● Hector (Hartin et al., 2015), ● HILDA (SIEGENTHALER and JOOS, 1992) ● MAGICC. Version 5.3 (Raper et al., 2001; Wigley et al., 2009), Version 6.0 (Meinshausen et al., 2011c; Wigley et al., 2009) and ● OSCAR 2.2 (Gasser et al., 2017)	Several simple climate models have been used in the past under a wide range of applications ranging from metric calculations, scenario classification in WGIII, probabilistic assessments with historical constraints, uncertainty integration across various domains and sea level rise projections. Also used to project GHG concentrations from emission scenarios. *[AR6 usage tbc]*
Statistical approaches	Neural networks (Knutti et al., 2003) [to be completed.]	Various applications to analyse, emulate and probabilistically investigate the behaviour of more complex models. *[AR6 usage tbc]*

[END CROSS-CHAPTER 1.5, TABLE 1 HERE]

An intercomparison of emulators investigates limitations and skills of emulators, which often depend on their complexity. Simple climate models can provide good approximations of the hemispheric-scale and land/ocean scale of surface air temperatures, sea level rise contributions, and global carbon cycle responses, but come with a number of potential limitations. As one example, at the time of the IPCC AR5, very simple climate models were used in historical constraining studies that suggested rather low climate sensitivities (such as a median of 1.9K) to be in line with the observational records (e.g. Otto et al., 2013). Subsequent publications discussed to what degree simplified model structures could be responsible for those particular results, given that resolving the global-mean responses of heterogeneous radiative forcers such as aerosols might be difficult in global-mean models (Shindell, 2014), and effectively time-variable or state-dependent climate sensitivities as shown from Earth System models (Houghton et al., 1997; Meinshausen et al., 2011a) were not included in some of the studies that suggested lower climate sensitivities on the basis of observational constraints. Some studies suggest, for example, that including the effect of time-changing temperature patterns on effective or inferred climate sensitivity increases the observationally constrained values from a best estimate of 1.9K to 3.2K (Andrews et al., 2018) (see Chapter 7). Also, the divergence of

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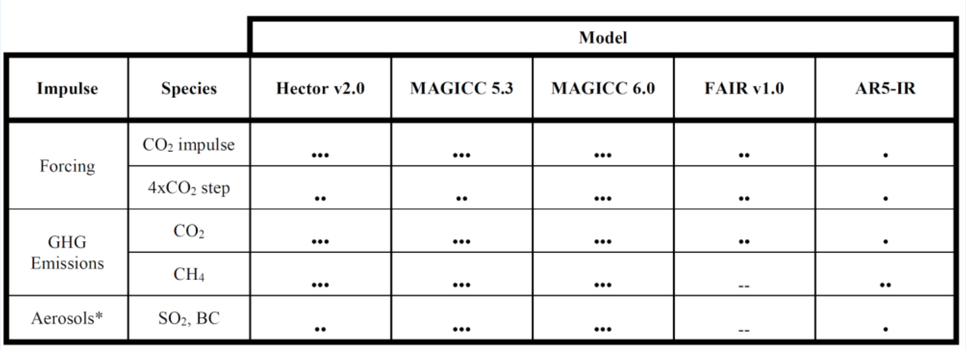
[4] categorisation following Schwarber et al. 2019 [10.5194/esd-2018-63])

two simple climate models as shown in the IPCC Special Report on 1.5°C regarding projected non-CO_2 forcing, also created interest in a renewed effort to transparently test the skill of various emulators (see section 1.4.3.2). *[Note: Efforts are currently underway to calibrate a range of simple models to CMIP6 output to be shown here by the time of the SOD]*.

[START CROSS-CHAPTER BOX 1.5, TABLE 2 HERE]

Cross-Chapter Box 1.5, Table 2: [Placeholder table for assessment]. Evaluation of emulators under various impulse response experiments (Schwarber et al., 2018). For the skill of three comprehensive 4-box simple climate models (ACC2, BernSAR, MAGICC, TOTEM) with Earth System models and Models of intermediate complexity (EMICs), see also Joos et al., 2013). Earlier comparisons among simple climate modules in DICE, MERGE, FUND, PAGE and IMAGE, including MAGICC4 are shown in van Vuuren et al. (2011) [The intention is to show test and skill results of OpenSCM by the time of SOD, see https://github.com/openclimatedata/openscm].



		Model				
Impulse	**Species**	**Hector v2.0**	**MAGICC 5.3**	**MAGICC 6.0**	**FAIR v1.0**	**AR5-IR**
Forcing	CO_2 impulse	•••	•••	•••	••	•
	$4xCO_2$ step	••	••	•••	••	•
GHG Emissions	CO_2	•••	•••	•••	••	•
	CH_4	•••	•••	•••	--	••
Aerosols*	SO_2, BC	••	•••	•••	--	•

[END CROSS-CHAPTER BOX 1.5, TABLE 2 HERE]

As in previous Assessment Reports, physical emulators are used in various Chapters of the Working Group I (WGI) Report. In this report, their applications in WGI are centred around:

1) Chapter 7 investigates temperature response to individual forgings in a bottom up approach and those will be compared to the top-down detection and attribution results and models in Chapter 3.
2) Chapter 7 provides some discussion on physical emulators and models of various complexity in its section 7.6 “Process understanding and model evaluation of climate response”.
3) Chapter 7 will derive emission metrics, which are in the literature based on either IRF or comprehensive SCM studies.
4) Chapter 7 will compile the state of our understanding regarding climate sensitivity and TCR from multiple lines of evidence, with one important pillar of evidence being derived from constraining simple models with historical observational data (e.g. Skeie et al., 2018)
5) Chapter 4 [possibly] uses physical emulators to understand spread of CMIP6 models and compare to independent assessments of key climate system properties like equilibrium climate sensitivity (ECS), transient climate response (TCR) and effective radiative forcings (ERF) and assess contributions to projected temperature uncertainty.
6) Chapter 5 will use physical emulators in its assessment of the remaining carbon budget, in particular the estimated non-CO_2 warming contributions at the time of peak warming.
7) Chapter 9 [possibly] uses studies and integrative assessments with emulators to combine multiple contributions to global-mean and regional sea level rise.

The main functionality of emulators across the Working Groups is however that they play a key role in ‘communicating’ WGI physical climate science knowledge to the research community associated with Working Group II and III. Some individual research studies associated with the WGIII community for example investigate whether current infrastructure until its technical lifetime commits the world to 1.5°C global warming or not (Skeie et al., 2018). The more overarching application of emulators is however related to scenario classifications in Working Group III. Analysing various features of the broad scenario database, like the point of peak emissions, the 2030 emission levels in line with 1.5C or 2.0ºC global mean temperature goals etc, requires a large amount of multi-gas scenarios to be analysed regarding their global mean temperature implications. This service has in the past been provided by calibrated physical emulators like MAGICC, which is also built into the integrated assessment models, like IMAGE, MESSAGE and REMIND in some variations.

There are a number of research frontiers related to emulators. The fundamental quest to find simplified and computationally efficient parameterisations of the Earth System processes has not changed for 20 years. While various models have pursued different avenues of trying to be either as simple as possible for teaching purposes, or as comprehensive as possible to allow for a propagation of uncertainties across multiple Earth System domains (MAGICC and others), other models have focussed on higher complexity representation of specific domains (e.g. OSCAR). The common theme in many models however is to improve parameterisations that reflect the latest findings in complex Earth System Model interactions, such as the nitrogen cycle addition to the carbon cycle, or tropospheric and stratospheric ozone exchange, with the aim of emulating their global mean temperature response. Also, within the simple models that can represent a rudimentary reflection of spatial heterogeneity (the four box simple climate models), the ambition is to represent heterogeneous forcers more adequately, for example black carbon (Stjern et al., 2017), provide an adequate representation of the forcing-feedback framework (see e.g. Sherwood et al., 2015), investigate new parameterisations of ocean heat uptake (Tailleux et al., 2017), and implement better representations of volcanic aerosol induced cooling (Gregory et al., 2016a).

[START CROSS-CHAPTER BOX 1.5, FIGURE 1 HERE]

Cross-Chapter Box 1.5, Figure 1: Left panel: A comparison between an the global-mean temperature response of an upwelling-diffusion energy balance simple climate model in 1997 to early AOGCM results by by Manabe and Stouffer (1994), reproduced from the IPCC Technical Paper on simple climate models (Houghton et al., 1997). The non-linearity or state-dependency of the climate sensitivity in AOGCMs or ESMs is evident by the difference to a constant-climate sensitivity simple climate model as used in IPCC Second Assessment Report. More advances in simple climate models of similar structure account for those state-dependent climate sensitivities and time-variable effective sensitivities, but an appropriate representation of those effects within the forcing-feedback framework is still an active area of research. Right panel: A depiction of the basic elements of simple climate models in 1997 (Houghton et al., 1997). The new generation of simple climate models includes a number of additional processes and interactions, such as carbon cycle feedbacks, permafrost modules (Schneider von Deimling et al., 2012), absorption spectra overlaps between CO_2, CH_4 and N_2O (Etminan et al., 2016). [Note, will be updated to current generation additional high-level modules].

[END CROSS-CHAPTER BOX 1.5, FIGURE 1 HERE]

[END CROSS-CHAPTER BOX 1.5 HERE]

1.6.4 Cumulative CO_2 Emissions as a new dimension of integration

Following the key result of AR5 (Figure SPM.10 in AR5 WGI) regarding the near-linear relationship between cumulative carbon emissions and global-mean surface air temperatures, this Assessment Report will use cumulative carbon emissions to categorise investigated emission scenarios across the three Working Groups. Also, CO_2 is the single most important driver of future anthropogenic climate change, with approximately 68-85% of peak radiative forcing being expected to result from radiative forcing by elevated CO_2 concentrations (*high confidence*) (see Figure 1.25). The advantage of using cumulative carbon emissions is that uncertainties in the cause-effect chain from emission to temperatures are not folded into the categorisation of scenarios, as a raw scenario characteristic is used. For example, an advanced understanding of methane induced radiative forcing and its overlaps with CO_2 and N_2O absorption spectra (Etminan et al., 2016) can lead to a revision of end-of-century total forcings under the community scenarios and their nameplate radiative forcing level (RCP*X*). While those forcing identifiers are still used to combine the full range of forcers, a raw categorisation by cumulative carbon emissions has the advantage of being an inherent emission scenario characteristic rather than a derived, and potentially variable, one. The relationship between cumulative greenhouse gas emissions and cumulative carbon emissions is also a rather close one, as shown for the SR1.5 scenario database (Figure 1.6.3, panel d) in the case of applying Global Warming Potential with a time horizon of 100 years (GWP-100) AR4 metric values in line with the second Kyoto Protocol commitment period. Given the differing lifetimes of the various greenhouse gases, those cumulative GWP-weighted CO_2 equivalent emissions do not yield the same temperature outcomes as cumulative CO_2 emissions of the same amount would. However, the close relationship between cumulative GHG emissions and CO_2 emissions indicates that cost-effective implementations of GWP-weighted emission baskets does not yield a widely different cumulative CO_2 emission amount across the various modelling frameworks that contributed to the SR1.5 emission scenario database [to be updated with AR6 database]. From a Working Group I perspective, that open the opportunity to analyse the broad emission scenario literature also by using cumulative CO_2 emissions as a key indicator.

[Placeholder: Extra analysis will compare the temperature bands to CO_2 equivalent concentration bands that have been used in the past for scenario classification in WGIII with the temperature and cumulative emission dimensions of integration. Probabilities of exceedance will also be analysed, if possible. This is being undertaken here in the WGI report because equivalent concentration numbers and temperature exceedance findings are issues that WGI can contribute to]

1.6.5 How do AR6 scenarios compare with those used in previous IPCC reports?

Climate scenarios evolve over time, providing a 'history of the future'. As many different sets of climate projections have been produced over the past several decades using different sets of scenarios, those former scenarios are here compared against the current ones.

Why are there still many different scenario generations discussed in the literature? There is a consecutive nature of climate science research from initially creating emission scenarios by WGIII related communities, then deriving their climate outcomes by WGI communities and only afterwards in a third step using that climate information to drive impact and adaptation studies (see Figure 1.20). This leads to multiple delays that result in the scientific impact literature often lagging behind in terms of its scenario foundation to the mitigation and climate system literature. It is hence important to provide an approximate comparison across the various scenario generations (see Table 1.6).

[START FIGURE 1.28 HERE]

Figure 1.28: Comparison of range of CO_2 emissions from scenarios used in previous assessment up to AR6, namely the IS92 scenarios from 1992 (top panel), the SRES scenarios from year 2000 (second panel), the RCP scenarios designed around 2010 (third panel) and the SSP scenarios (second bottom panel). In addition, the full set of the AR6 set of scenarios is shown in the lower panel [Note: Placeholder dataset from SR1.5 emission database; Other gases methane and nitrous oxide to be added].

[END FIGURE 1.28 HERE]

[START TABLE 1.6 HERE]

Table 1.6: Overview of SSP scenarios used in this report and approximately corresponding in earlier climate scenarios RCPs and SRES *[to be updated - depending on results from Chapter 4 in comparison with previous ARs]*.

SSPX-Y scenario	Description from an emission / concentration and temperature perspective	Closest RCP scenarios	Closest SRES scenario
SSP1-1.9	Low overshoot scenario to achieve a 1.5°C warming level by 2100. *[check against Chapter 4 and 7 findings]*	Not available. No equivalently low RCP scenario.	Not available. No equivalently low SRES scenario.
SSP1-2.6	Scenario to achieve a below 2.0°C scenario with a likely chance. *[check against Chapter 4 and 7 findings]*	RCP2.6. Although RCP2.6 emissions were second highest in RCP set of scenarios, SSP-RCP scenarios are again higher up to 2020.	Not available.
SSP4-3.4	Scenario that fails to stay below 2.0°C in [most] CMIP6 runs *[check against Chapter 4 results]* and indicates a lower level of mitigation efforts, approximately in line with aggregate NDCs by 2030 [*check*]	Not available. In between RCP 2.6 and RCP 4.5	Not available.
SSP2-4.5	Scenario that indicates a diversion from no-climate-policy reference cases, by implementing low levels of mitigation	RCP4.5 and until 2050 also RCP6.0 as the latter was similar to RCP4.5 in the early decades.	SRES B1 or A1T
SSP4-6.0	The notional level of 6.0 can be considered a low reference scenario or low-ambition mitigation scenario, in line with the SSP1 and SSP4 socio-economic development pathways.	RCP4.5 and until 2050 also RCP6.0 as the latter was similar to RCP4.5 in the early decades.	Also SRES B1 or A1T
SSP3-7.0	A medium reference scenario with no climate policy.	in between RCP6.0 and RCP8.5, although non-CO_2 emissions higher than in RCPs	SRES A2
SSP5-8.5	A high reference scenario with no climate policy. Emission levels as high as SSP5-8.5 seem implausible under any of the SSPs except for the fossil-intensive SSP5 socio-economic development	RCP8.5, although CO_2 emissions under SSP5-8.5 are higher towards the end of the century.	SRES A1FI, the fossil intensive SRES A1 scenario.
SSP3-7.0 Low NTCF	A variation of the medium reference scenario SSP3-7.0 but with mitigation of non-CO_2 species methane, black carbon and other short-lived climate pollutants (SLCP)	n between RCP6.0 and RCP8.5, as RCP scenarios generally showed a narrow and comparatively low level of SLCP emissions across the range of RCPs.	Not available.
SSP5-3.4 Overshoot	A mitigation variation of SSP5-8.5 that initially follows unconstrained emission growth in a fossil-intensive setting until 2040-ish [Check] and then implements the deepest net negative CO2 emissions of all SSP scenarios in second half of 21st century to reach SSP1-2.6 forcing levels in the 22nd century.	Not available. Initially, until 2040, similar to RCP8.5	Not available. Initially, until 2040, similar to SRES A1FI.

[This table will be coordinated with WGIII]

[END TABLE 1.6 HERE]

[START FIGURE 1.29 HERE]

Figure 1.29: Comparison of CO_2, methane and nitrous oxide concentration projections under the SSP scenarios and RCP pathways. The SSP scenarios (coloured solid lines) span a wider range than the RCP scenarios for CO_2, whereas the top emission levels for CH_4 and N_2O are somewhat reduced in comparison to the RCP range. That is despite the fact that gas cycles have been adapted in AR6, suggesting higher future carbon, methane and nitrous oxide concentrations for the same RCP set of emissions (compare higher thin dashed lines with the thicker dashed lines).

[END FIGURE 1.29 HERE]

The first prominent set of IPCC emission scenarios were the so-called IS92 scenarios in 1992. Apart from reference scenarios, those IS92 scenarios also included a set of stabilisation scenarios, the so-called S scenarios. Those 'S' pathways were designed to lead to CO_2 stabilisation levels of 350ppm, 450ppm etc. By 1996, those latter stabilisation levels were complemented in the scientific literature by alternative trajectories that assumed a delayed onset of mitigation action (Figure 1. In IPCC 1995 and see also Wigley et al., 1996). By 2000, the IPCC Special Report produced the so-called SRES scenarios (Nakicenovic and Swart, 2000), albeit without mitigation scenarios. The four broad SRES scenario families A1, A2, B1 and B2 were the first scenarios that emphasized socio-economic scenario storylines (see Section 1.2.4.3 on a discussion on the different uses of the term "storyline"). Represented by three scenarios for the high-growth A1 scenario family, those 6 illustrative marker SRES scenarios (A1FI, A1B, A1T, A2, B1, and B2) can still be sometimes found in today's impact literature. The void of missing mitigation scenarios was filled by a range of community exercises, including the so-called post-SRES scenarios (Swart et al., 2002). The RCP scenarios then broke new ground after the main SRES scenarios did not include any mitigation scenarios by also providing low pathways that implied strong mitigation action, including negative CO_2 emissions on a large scale, namely the RCP2.6. As shown in Figure 1.28, the upper side of the scenario range has not substantially shifted. For the SSP scenarios, the higher end of CO_2 emissions further increased a bit, although the most significant change is again the addition of a very low mitigation scenario in. Also, the SSP scenario family includes an overshoot scenario SSP5-3.4-OS that initially follows the highest emission scenario before featuring a collapsing decline of emissions and strongly net negative CO_2 emissions in the second half of 21st century. An additional aspect of the scenario classes over time is the later peak of global emission for the lower scenarios. To some extent, this is simply a consequence of new scenario families adjusting to the real-world evolution of recent emissions. Those tracked approximately at the two-third quantile or upper half in the case of fossil and industrial CO_2 emissions (see Figure 1.28) in the recent decade, making scenarios that assume an early peak of global emissions before 2010 redundant. For another set of emissions, namely aerosol emissions, the SSP scenarios have an advantage over the RCP scenarios, as the latter had a rather uniformly strong reduction across all RCP levels in short-lived pollution species.

Is a scenario's consistency with recent emission developments a good indicator in terms of the scenarios' long-term validity? Over the last decades, a persistent feature how scenarios have been discussed was related to the question whether recent emission trends make certain future scenarios more or less likely. At the onset of SRES scenarios, the public debate was often whether the emission scenarios over-dramatize actual world emission developments (e.g. Castles and Henderson, 2003). With the strong emission boom throughout the 2000s, that debate then shifted towards the question of whether the lower future mitigation scenarios are now rendered unfeasible (Pielke et al., 2008; van Vuuren and Riahi, 2008). That debate continued into the 2010s. The RCP set of scenarios happened to not show the same ranking of scenarios according to their 2020 and longer-term emission levels. Specifically, in the period until 2020, the lowest mitigation scenario RCP2.6 was in fact the second highest emission scenario before embarking on a strong global emission decline after 2020. Implicitly, this feature was cautioning against the assumption that a short-term trend predicates a long-term trajectory. With the onset of the consideration of cumulative carbon emissions as a key indicator for future climate change, a nuance has been brought to the debate. That is that delay in the onset of mitigation does not exclude low concentration levels, but it comes at the cost of having to bring about even lower emissions in the future to keep overall cumulative emissions the same.

Recent emission trends are within the scenario envelope, but seldomly in its middle. Fossil & industrial CO_2 emissions have historically tracked the lower edge of the IS92 scenarios until the year 2000. In relation to SRES and RCP scenarios, that changed. Historical emissions now approximately tracked the upper half of SRES and RCP projections (Figure 1.28), with only the most recent emission developments indicating slow-down of global emission growth *[to be updated – cf Chapter 2, 5 and others]*.

There are known limitations of the SSP scenarios and historical datasets. There are some limitations associated with the current set of scenarios. For example, recent decreases in SO_2 aerosol emissions since 2013 in the East-Asia region (Zheng et al., 2018) are not fully captured in the last years of the historical aerosol emissions that reach until end of 2014. Future SSP scenarios from 2015 onwards however capture that lower evolution of aerosol emissions in that region. Another limitation is that substances controlled under the Montreal Protocol are uniformly reduced following the Kigali Agreement, rather than representing a full range of possible high and lower emission futures, possibly even lower than the Kigali phase-out pathways (UNEP, 2016). While this might have advantages to dissect the potential effect of the Paris Agreement and climate-focussed mitigation action, it might suggest a too narrow band of future temperatures if the research question is to examine the full range of possible geophysical futures in the absence of international agreements.

[START CROSS-CHAPTER BOX 1.6 HERE]

Cross-Chapter Box 1.6: Scenarios, Projections, Pathways and temperature-levels

This Box provides an overview of definitions of key terms regarding the investigation of the broad set of possible future evolutions of human-induced emissions, climate change, and its impacts. It builds on the Synthesis Report of IPCC AR5 and the set of three AR6 Special Reports. A feature in this Assessment Report is the added emphasis on temperature-levels to support consistency and comparability across the three Working Groups and across Assessment Reports. See the respective glossaries in WGI, WGII and WGIII for additional terms and definitions. [*Placeholder: to be updated for SOD*]

Climate prediction. A climate prediction or climate forecast is the result of an attempt to produce (starting from a particular state of the climate system) an estimate of the actual evolution of the climate in the future, for example, at seasonal, interannual or decadal time scales. Because the future evolution of the climate system may be highly sensitive to initial conditions, have chaotic elements and are subject to natural variability, such predictions are usually probabilistic in nature. [*adapted from WGI AR5*]

Climate projection. A climate projection is the simulated response of the climate system to a scenario of future emission or concentration of greenhouse gases and aerosols, generally derived using climate models. Climate projections are distinguished from climate predictions by their dependence on the emission/concentration/radiative forcing scenario used, which is in turn based on assumptions concerning, for example, future socioeconomic and technological developments that may or may not be realized. [*adapted from SR1.5, WGI AR5, SYR AR5*]

Regional Climate Scenarios. A narrative used to describe how the future might unfold for a region (IPCC-TGICA et al., 2007). These are often used to guide impact understanding and adaptation efforts. They can include quantitative information based on scaled historical data or derived from GCM-based internally consistent future climates.

Scenario. A plausible description of how the future may develop based on a coherent and internally consistent set of assumptions about key driving forces (e.g., rate of technological change, prices) and relationships. Note that scenarios are neither predictions nor forecasts, but are used to provide a view of the implications of developments and actions in a ‘what-if’ kind of investigation. In a broader sense, the term ‘scenarios’ is often used to encompass ‘pathways’. In the Sixth Assessment Report a minimum set of five scenarios is chosen to assist cross-working group comparisons: the so-called SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 scenarios that span a wide range of plausible futures from potentially below 1.5°C best-estimate warming to very high warming in excess of 4°C over the course of this century. [*adapted from SR1.5, WGI AR5*]

Emissions scenario. A plausible representation of the future development of emissions of substances that are potentially radiatively active (e.g., greenhouse gases, aerosols), plus human-induced land cover changes that can be radiatively active via albedo changes, based on a coherent and internally consistent set of assumptions about driving forces (such as demographic and socioeconomic development, technological change) and their key relationships. *[adapted from AR5 WG1 Glossary]*

Concentrations scenario. A plausible representation of the future development of atmospheric concentrations of substances that are potentially radiatively active (e.g., greenhouse gases, aerosols, tropospheric ozone), plus human-induced land cover changes that can be radiatively active via albedo changes, and used as input to a climate model to compute climate projections. [*NEW*]

Socioeconomic scenario. A scenario that describes a plausible future in terms of population, gross domestic product, and other socioeconomic factors relevant to understanding the implications of climate change. [*WGIII AR5*]

Scenario storyline. A narrative description of a longer-term scenario (or family of scenarios), highlighting the main (socio-economic) scenario characteristics, relationships between key driving forces and the dynamics of their evolution.

Pathway. A plausible or idealized trajectory of emissions and or concentrations. The difference to scenarios is that pathways are disconnected or independent from a coherent set of assumptions about key driving forces, which might or might not have been used to generate those pathways. The idealized pathways with 1% annual increases in CO_2 concentrations or, strictly speaking, the 'representative concentration *pathways* (RCPs)' are two prominent examples in this category. While the RCPs have been derived from a consistent set of socio-economic and technological drivers, they are - unlike the new SSP-RCP scenarios - purposefully separated from those socio-economic drivers. In the IPCC Special report, the term 'pathway' has also been used to describe 'target-oriented scenarios', such as pathways compatible with 1.5°C global warming. [*NEW, different from SR1.5*]

Trajectories. The general term to emphasise the time-evolution of emissions, concentrations, climate impacts or other quantities as opposed to an emphasis on the outcome. Specifically, while many scenarios and pathways can lead to the same, e.g., 2100 radiative forcing, temperature level or cumulative emissions (or any other target quantities), their trajectories might differ. [*NEW*]

Temperature-levels. A categorisation for future global and regional climate change, associated impacts, emission and concentration scenarios by global-mean surface air temperature relative to pre-industrial levels around approximately 1750 in half-degree steps. The categorisation is performed around half-degree levels, with the higher-priority 'Tier 1' levels being 1.5°C, 2.0°C, 3.0°C and 4.0°C. The 'Tier 2' temperature levels complement those at all half-degree steps between 1.0°C and 6.0°C - or at the highest temperature level that can be assessed from CMIP6 SSP5-8.5 projections (see Table 1.6 in Chapter 1). Given that some impact analysis is based on previous scenarios, i.e. RCPs or SRES, and mitigation analysis is based on new emission scenarios in addition to the main SSP scenarios, these temperature-levels assist in the comparison of climate states across scenarios and in the synthesis across the broader literature. There are several advantages and limitations of cross-chapter and cross-working group comparisons by temperature levels as opposed to scenarios. For specific applications, temperature-levels will need to be complemented by information in regard to their associated CO_2 concentrations (e.g. fertilization or ocean acidification), or socio-economic conditions (e.g. to estimate societal impacts). For the classification of emission scenarios by their best-estimate temperature outcome, also the information of whether 'peaking' or, for example, 2100 temperature levels are used for the classification, is important. There are various methods to determine the climate states or climate impacts at certain temperature levels. Each method comes with its challenges and limitations. The transferability of results is sometimes challenging, as e.g. time changing forcing or response patterns create differences in regional climates for the same global-mean temperature level, depending on whether near-term transient climate, end of century or equilibrium climate is considered. (see Section 1.6.3 and Table 1.5)

Representative Concentration Pathways (RCPs). Scenarios that include time series of emissions and concentrations of the full suite of greenhouse gases and aerosols and chemically active gases, as well as land use/land cover (Moss et al., 2010). The word representative signifies that each RCP provides only one of many possible scenarios that would lead to the specific radiative forcing characteristics. The term pathway emphasizes that not only the long-term concentration levels are of interest, but also the trajectory taken over time to reach that outcome. (Moss et al., 2010). RCPs usually refer to the portion of the concentration pathway extending up to 2100, for which Integrated Assessment Models produced corresponding emission scenarios. Extended Concentration Pathways (ECPs) describe extensions of the RCPs from 2100 to 2300 that were calculated using simple rules generated by stakeholder consultations, and do not represent fully consistent scenarios. Four RCPs produced from Integrated Assessment Models were selected from the published literature and are used in the Fifth IPCC Assessment and also used in this Assessment for comparison, spanning the range from approximately below 2°C warming to high (>4°C) warming best-estimates by the end of the 21st century: RCP2.6, RCP4.5 and RCP6.0 and RCP8.5. [*adapted from SR1.5, WGI AR5, SYR AR5, WGIII AR5*]

Shared socio-economic pathways (SSPs). Shared socio-economic pathways (SSPs) have been developed to complement the RCPs. By design, the RCP emission and concentration pathways were stripped of their association with a certain socio-economic development. Different levels of emissions and climate change along the dimension of the RCPs can hence be explored against the backdrop if different socio-economic development pathways (SSPs) on the other dimension in a matrix. This integrative SSP-RCP framework is now widely used in the climate impact and policy analysis literature (see e.g. http://iconics-ssp.org), where climate projections obtained under the RCP scenarios are analysed against the backdrop of various SSPs. As several emission updates were due, a new set of emission scenarios was developed in conjunction with the SSPs. Hence, the abbreviation SSP is now used for two things: On the one hand SSP1, SSP2, …, SSP5 is used to denote the five socio-economic scenario families. On the other hand, the abbreviations SSP1-1.9, SSP1-2.6, … SSP5-8.5 are used to denote the newly developed emission scenarios that are the result of an SSP implementation within an integrated assessment model. Those SSP scenarios are bare of climate policy assumption, but in combination with so-called share policy assumptions (SPAs), various nameplate radiative forcing levels of 1.9, 2.6, …, or 8.5 W/m^2 are reached by the end of the century, respectively.

[START CROSS-CHAPTER BOX 1.6, TABLE 1 HERE]

Cross-Chapter Box 1.6, Table 1: Overview of different RCP and SSP acronyms as used in this report. SSPX is the abbreviation of the socio-economic family. SSPX-Y is the abbreviation for a new emission or concentration scenario, where X is the numbering of the SSP socio-economic family (1 to 5) and the Y indicates the approximate radiative forcing ranking by the end of the century. Several impact studies refer to an SSPX-RCPY setting. Mostly, this refers to a model setup, when an original RCP emission or climate scenario from the IPCC AR5 generation has been combined with a SSP socio-economic development assumption. In other words, an SSPX is one of a collection of alternative futures of socio-economic development in the absence of climate policy intervention. The implementation of various policies within those SSPs (for example via the so-called shared policy assumptions SPAs, (Kriegler et al., 2014) then lead to emission scenarios that can be categorised by their 2100 radiative forcing levels Y, called SSPX-Y. Abbreviation

	Levels	Description	Key references
SSP pathway “SSP *X*”	X stands for the shared socio-economic pathway family (1, 2, ...5)	The shared socio-economic pathways, i.e. the socio-economic developments with storylines regarding - inter alia- GDP, population, urbanisation, economic collaboration, human and technological development projections that describe different future worlds in the absence of additional climate policy. The quantification of those storylines regarding their energy, landuse and emission implications is then undertaken in a second step and model dependent.	(O’Neill et al., 2014, 2017b; Riahi et al., 2017b) for the quantification.
RCP pathway “RCP *Y*”	Y stands for approximate nameplate radiative forcing level in 2100, at	Representative Concentration Pathways. Those are greenhouse gas concentration and aerosol emission time series from several integrated assessment models that have been stripped off their socio-economic	(Meinshausen et al., 2011b; Moss et al., 2010; van Vuuren et al., 2011a)

	levels 2.6, 4.5, 6.0 or 8.5.	backgrounds. The CMIP5 intercomparison has developed the climate futures in line with the RCPs.	
The SSP pathway and RCP pathway combination "SSP*X*-RCP*Y*"	X and Y as above.	Combination of the SSPs socio-economic background family X with climate futures stemming from AOGCM or Earth system model runs that used the RCP Y.	See special issue on (van Vuuren et al., 2014). See also wide range of literature gathered in the ICONICS database (http://iconics-ssp.org).
The SSP scenario "SSP X-Y"	X and Y as above.	The integrated update of the SSPs and RCPs, in which the whole matrix of five SSP families (X=1,2,...,5) and seven RCP levels (Y=1.9,2.6,3.4,4.5,6.0,7.0 and 8.5) is explored. The main scenarios, called 'Marker SSP scenarios' in this report are SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP4-7.0 and SSP5-8.5. Those are the four 'Tier 1' scenarios of ScenarioMIP in addition to SSP1-1.9 which is the scenario that most closely reflects the lower Paris Agreement 1.5°C goal. In addition, there are four 'Tier 2' scenarios, two within the 'middle of the road' socio-economic family, i.e. SSP3-3.4 and SSP3-6.0, one variant of the SSP4-7.0 scenario which considers low short-lived climate forcer emissions, SSP4-7.0-lowNTCF, and one strong peak & decline scenario that first follows SSP5-8.5 and then descends to strong net negative emissions: SSP5-3.4-OS.	

[END CROSS-CHAPTER BOX 1.6, TABLE 1 HERE]

Baseline / Reference scenarios, business-as-usual, pathways or levels. The state against which change is measured. In the context of transformation pathways, the term 'baseline scenarios' refers to scenarios that are based on the assumption that no mitigation policies or measures will be implemented beyond those that are already in force and / or are legislated or planned to be adopted. Baseline scenarios are not intended to be predictions of the future, but rather counterfactual constructions that can serve to highlight the level of emissions that would occur without further policy effort. Typically, baseline scenarios are then compared to mitigation scenarios that are constructed to meet different goals for greenhouse gas (GHG) emissions, atmospheric concentrations, or temperature change. The term 'baseline scenario' is used interchangeably with 'reference scenario' and 'no policy scenario'. In much of the literature the term is also synonymous with the term 'business-as-usual (BAU) scenario,' although the term 'BAU' has fallen out of favour because the idea of 'business-as-usual' in century-long socioeconomic projections is hard to fathom. *[adapted from SR1.5, taken from WGIII AR5]*

[END CROSS-CHAPTER BOX 1.6 HERE]

1.7 Gaps and opportunities for integration of climate knowledge

Throughout the present report, the authors of each chapter identify knowledge gaps that represents significant opportunities for improving our understanding of the climate system, including its natural variability and its response to anthropogenic forcing. In the text below, we take a holistic view of the WGI contribution to the AR6 cycle, and highlight three cross-cutting opportunities that reflect the diversity of the challenges in climate science as they relate to the quantification of climate change risks and vulnerabilities.

Opportunity area #1: Creating an integrated framework for the assessment of the social-ecological impacts of climate change, and opportunities for adaptation and mitigation

Humans have become the primary driver of global environmental change (SR1.5). IPCC Special Reports and Assessment Reports outline a variety of strategies to minimize the ongoing risks of present climate change (adaptation) while reducing the magnitude of future climate change (mitigation). As the role for the IPCC shifts from a focus on the detection of climate change signals in the Earth System to a focus on the relative benefits of a variety of climate solutions, the separations between WGI, WGII, and WGIII represent barriers to the integration of knowledge. As the gap between our current emissions trajectories and those required to remain under established international targets (1.5 – 2°C) climate solutions grows wider, the scale of any climate risk mitigation efforts requires urgent, global-scale action. Indeed, any meaningful action to reduce the impacts of climate change - whether by adaptation or mitigation exercises - involves large-scale shifts in the global economy (i.e. decarbonization of electricity), land use (i.e. afforestation), and/or planetary energy balance (i.e. solar radiation management), that a fully integrated assessment of the social-ecological system is required in order to provide adequate policy guidance. End-to-end assessments of policy pathways that include key feedbacks between social and physical systems are not possible under the current structure of the IPCC assessment reporting processes.

Opportunity area #2: Improving knowledge of past, present, and future sea level rise

Sea level rise sits at the nexus of acute societal risk and large uncertainties, with a wide range of projections having been made for the coming decades. While analysis of present-day data is focused on quantifying the rates of ice sheet melting as a transient response to anthropogenic climate change (Hay et al., 2015) studies that focus on quantifying the equilibrium response of global sea level to a variety of climatic forcings hold unique promise as key constraints on the rates of and magnitude of ice sheet melting during the geologic past (DeConto and Pollard, 2016b). Recent studies consider sea level rise estimates over the last millennium (Kopp et al., 2016), the most recent interglacials (Dutton et al., 2015), and the Eocene - the most recent time period during which atmospheric CO_2 concentrations were similar to those of the 21st century (Burke et al., 2018). Such studies provide an opportunity to quantify not only the magnitude of equilibrium sea level rise to a given level of global temperature variability, but can, through the combination of higher-resolution sea level reconstructions with climate models that contain representative ice sheet physics, constrain the rates of transient sea level rise to changes in global temperature. Such an effort will result in critical gains in our ability to provide policy-relevant estimates of near- and long-term sea level rise, in particular data-driven estimates of potential worst-case scenarios that may drive decisions around sea level rise adaptation in vulnerable locations.

Opportunity area #3: Accelerating improvements in the observational record of climate variability and change with integration of paleoclimate datasets

With each passing year, the climate record lengthens while becoming more diverse through the addition of newly observed climate variables and observational platforms. Even so, in the near-term, the biggest gains in our observational capacity of the Earth’s climate system will likely come from a more complete integration of paleoclimate observations and newly available early instrumental data into extended reanalyses datasets that can inform the accuracy of numerical climate models. Such integration leverages ongoing development of climate models that can simulate paleoclimate records in their units of analysis (i.e. oxygen isotopes, tree ring width, etc), in many cases using physical climate variables as input for so-called “proxy system models” (Dee et al., 2015; Evans et al., 2013). Early efforts towards proxy-model integration aim to generate gridded climate data spanning the last centuries using data assimilation techniques (Hakim et al., 2016). As these efforts mature, they will open new avenues for improvements in the state of climate knowledge, with particularly high potential in the following key areas:

i. detection and attribution of changes in the frequency and severity of climate extremes
ii. links between climate variability and change, ecosystem structure and function, and biogeochemical cycles
iii. improvements in the initialization of climate models with applications to near-term (decadal-scale) prediction of climate variability and change

1.8 Structure / key elements of AR6

[*This is a preliminary version, which will be updated for the SOD with the outlines of all chapters*]

The WGI contribution to the IPCC 6th Assessment Report has twelve chapters plus the Atlas and can be grouped into three main categories:

Global Information (Chapters 2, 3 and 4). These chapters assess climate information from global to hemispheric scales. The three chapters start with an assessment of the changing state of the climate system (Chapter 2), including the atmosphere, biosphere, ocean and cryosphere. It then assesses the human influence on the changing climate (Chapter 3), covering the attribution of observed changes, and the evaluation of climate models used to conduct the attribution studies. Chapter 4 assesses climate change projections, from the near to the long term, including climate change beyond 2100, as well as the assessment for potential abrupt changes and low-probability-high-impact changes.

Process Understanding (Chapters 5, 6, 7, 8 and 9). These five chapters provide end-to-end assessments of fundamental Earth system processes: the carbon budget and biogeochemical cycles (Chapter 5), short-lived climate forcers (Chapter 6), the Earth's energy budget (Chapter 7), the water cycle (Chapter 8) and the ocean, cryosphere and sea-level changes (Chapter 9). All these chapters provide assessments of observed changes, including relevant paleoclimatic information, understanding of processes and mechanisms, as well as projections, including model evaluation.

Regional Information (Chapters 10, 11, 12 and Atlas). Since AR5, a large volume of climate information, understanding, observed impacts and projections at regional scales has been published. This new knowledge is reflected in this report with three chapters covering regional information. Chapter 10 provides the basis for regional climate information, including methods, physical processes and an assessment of observed changes at regional scales. Chapter 11 builds on the regional framework and addresses extreme weather and climate events, including their definition. It assesses observations for extremes, and the understanding of mechanisms, drivers and feedbacks leading to extremes. The chapter also covers new methods to perform event attribution, and an assessment of projected changes of extremes. The main objective of Chapter 12 is to provide a comprehensive, region-specific assessment of observed impacts of anthropogenic climate change and regional projections under key future scenarios. The chapter therefore contributes to the overall risk framework of the AR6 by assessing the hazard component of the risk (cf. Figure 1 of Cross-Chapter Box 1.2). Lastly this report builds upon the Atlas presented in AR5, with the development of a novel, interactive Atlas, which synthesizes information by expanding and integrating results from the rest of the report. The interactive Atlas tool extends the regional assessment with flexible spatial and temporal analyses.

Integration across the WGI report and with Working Groups II and III occurs in various forms. As already mentioned in Section 1.6, one important venue of integration within WGI and among working groups is the presentation of results at various temperature levels. Chapters 8 to 12 and the Atlas contribute to common topics with WGII in two specific areas: regional climate information and a common risk framework. This should produce a more integrated assessment of impacts of climate change across working groups. In particular, Chapter 12 provides a "handshake" instead of just a "handover" of information useful for the evaluation of climate change impacts. The science assessed in Chapters 4 to 7, such as the carbon budget or short-lived climate forcers, are topics in common with WGIII and relevant for the mitigation of climate change. In addition, Chapter 1 provides the introduction to the scenarios as an overarching topic for easier integration across all three Working Groups.

There are a number of cross cutting themes in this report. A summary of some key themes and their integration across chapters is described in Table 1.7.

[START TABLE 1.7 HERE]

Table 1.7: Cross cutting themes in AR6 WGI, and the main chapters that deal with them. **Bold** numbers in the table indicate the chapters which have extensive coverage. [Indicative only, will be updated with new information from chapters].

Thematic focus	**Main chapters**
Cryosphere	**9, 3**, 1, 2, 4, 8, 12, Atlas.5
Oceans	**9, 3, 5**, 1, 2, 4, Atlas.4, Atlas.5
Biosphere	**3, 2**, 1, 4, 5, 8, 12
Water cycle	**8, 11**, 2, 3, 10
Modes of variability	**1, 2, 3, 4**, 5, 8, 10
Atmospheric circulation	**3, 4**, 2, 3, 5, 8, 10, 11
Polar regions	**9, Atlas.5**, 8, 12
Megacities	**6, 12**, 10
Climate services	**12**, 1, 10, Atlas.6
Radiative Forcing	**6, 7**, 2
Paleoclimate	**1, 2**, 5, 7, 8, Box 11.1
Monsoons	**8, 11**, 2, 10, Atlas.5 A
CDR and SRM	**5, 4**, 8
Values and ethics	**1**, 10, Atlas.6
Case studies	**Atlas.5–Atlas.7**, 6, 10, Box 11.2, Box 11.3, Box 12.1, Cross-Chapter Box 11.2, Box 12.2
Risk	**1, Cross-Chapter Box 1.2, 12**

[END TABLE 1.7 HERE]

Frequently Asked Questions

FAQ 1.1: Do we understand climate change better now, compared to when the IPCC started?

Yes — much better. The first IPCC report, in 1990, predicted that human-caused climate change would soon occur, but could not yet confirm that it was already happening. Today, evidence is abundant that the climate has already changed since the mid-20th century, and we know that human emissions of carbon dioxide, methane, and other gases are the principal cause of that change. With much more and much better data, we understand more about how the oceans and atmosphere interact, as well as about the ice and snow that cover large parts of the Earth. Compared with the computer climate simulations of 1990, today's Earth system models include many more physical processes, and they can make more specific projections of future changes in different places. Many early climate model predictions have been confirmed.

Since 1990, large numbers of new instruments have been deployed to collect data in the air, on land, at sea, and in outer space. These instruments measure temperature, clouds, winds, ice, snow, ocean currents, sea level, soot and dust in the air, and many other aspects of the climate system. New satellite instruments, as well as decades of additional data from older observing systems, have provided a wealth of new, increasingly accurate data. Ice cores, sediments, fossils, and other evidence from the distant past have taught us much about how Earth's climate has changed throughout its history. We also now know that most of the heat in the overall climate system is being retained in the oceans, and that even the deep ocean is warming up. In 1990, relatively little was known about exactly how the gigantic glaciers of Greenland and Antarctica would respond to warming. With much more data and better models of their behavior, evidence has emerged of unexpectedly high melt rates that may lead to major changes within this century, including substantial sea level rise.

The major natural factors contributing to climate change on timescales of decades to centuries are volcanic eruptions and the sun's heat. Today, data show us that the sun's heat has not changed much in the last century, and that major volcanic eruptions have occasionally cooled the planet for short periods of time (typically 1-3 years). The main human causes of climate change are heat-trapping gases emitted by burning fossil fuels, which warm the planet, and tiny particles in the air such as soot from burning coal, which have both warming and cooling effects depending on their size, color, and location. Since 1990 measurements of all these factors have become more accurate and precise, while older data have been recovered and integrated into the long-term record.

While most climate models in 1990 focused on the atmosphere, using only highly simplified oceans, today's Earth system models include detailed models of oceans, ice, snow, vegetation, and often many other variables as well. An important test of models is their ability to simulate past climates. Several rounds of such testing have taken place since 1990, and the testing itself has become more rigorous and extensive. As a group, in these tests models have predicted the actual changes reasonably well. Since there is no way to do a controlled laboratory experiment on the actual Earth, climate simulations can also provide a kind of "control Earth" to see what would have happened without human influences. These experiments show that without our influence, the observed post-1960s warming would not have occurred.

Finally, climate models make specific predictions of exactly how the climate should change if human influences and not natural causes are the reason, and many of those predictions have been confirmed by observations. For example, nights are warming faster than days; satellite measurements show that less heat is escaping to space; and the lower atmosphere (troposphere) is warming but the upper atmosphere (stratosphere) is cooling.

[*Figure proposal: 2-panel schematic of climate models then in 1990 (FAR) vs. climate models now in AR6. The figure below (from AR4) is an initial idea. FAR would have only solar radiation, GHGs, rain, clouds, land surface, prescribed ice, and swamp ocean. CMIP6 would add volcanoes, sulphates, aerosols, carbon cycle, rivers, overturning ocean circulation, interactive vegetation, air chemistry, ocean biogeochemistry, ocean eddies, "high-top" atmosphere (top level above stratopause), terrestrial nitrogen cycle, and dynamic sea ice at a minimum.]*

[START FAQ 1.1, FIGURE 1 HERE]

FAQ 1.1, Figure 1: [PLACEHOLDER]

[END FAQ 1.1, FIGURE 1 HERE]

FAQ 1.2: At what point do we know it's climate change?

[PLACE HOLDER: This FAQ will be reshaped later to better coordinate with related FAQs in Chapters 2 and 3 (on detection and attribution)]

The signs of climate change are most obvious at the global scale, but they are increasingly clear on smaller spatial scales and in a range of climate variables. Regions which have a larger signal of change relative to the size of background climate variations will potentially face greater risks as they will see unusual or unprecedented climates earlier.

Observed and projected temperature change is often smaller in the tropics than at higher latitudes, but smaller variations means that tropical countries have potentially seen the effects of climate change earlier (see FAQ Figure 1.2). Often it is not necessarily the size of the change which is most important for climate-related risks, instead, it is the size of the change relative to the background fluctuations of the climate to which ecosystems or society is already adapted to.

[*Paragraph on projections and the implication of mitigation choices. A future where a strong mitigation strategy is in place will have different climate signal emerging compared to a projection where less mitigation occurs. Figure to be updated to include :*

- *Example of differences between climate signals*
- *Air temperature changes vs precip or sea level changes in the future*
- *How emergence depends on the GHG mitigation pathway / scenario chosen*]

[START FAQ 1.2, FIGURE 1 HERE]

FAQ 1.2, Figure 1: Observed variations in regional temperatures since 1920 from CRUTEM4. Europe has warmed by a larger amount than tropical Africa, but the background variations are also larger (shading represents 1 and 3 standard deviations of background interannual variations). The signal of observed temperature change emerged earlier in tropical Africa than in Europe.

[END FAQ 1.2, FIGURE 1 HERE]

FAQ 1.3: What can past climate teach us about the future?

Rising greenhouse gas concentrations are driving a suite of profound changes to the earth system, including warming, sea level rise, increases in climate and weather extremes, ocean acidification, and ecological shifts. Past climate variability over the last centuries to millennia serves as the most relevant baseline against which to measure anthropogenic changes in climate. Farther back in time, larger reorganizations of the earth system provide critical information about the rates and magnitudes of physical, chemical, and ecological changes under a suite of different greenhouse gas concentrations. Careful observation of these past changes challenges our understanding of how our planet operates, and also allows us to test our latest models that are used for predicting future climate change. Of particular relevance, the "hothouse Earth" of ~50 million years ago represents the most recent time that atmospheric carbon dioxide concentrations were as high as those projected for the late 21st century if emission rates continue at present rates.

Although we have been taking measurements of the Earth's climate for centuries, the vast majority of instrumental observations began during the late 20th century, during a period already experiencing rapid human-made (anthropogenic) warming. Unlocking information spanning millions of years of the Earth's history, so-called 'paleoclimate records' are indirect climate measurements (from tree rings, ice cores, corals, and ocean and lake sediments, for example) that climate scientists use to understand current and future climate change.

The earth climate is a complex system in which the different components (atmosphere, ocean, cryosphere, etc) respond with very different paces to forcing. As a consequence of this, it will take several millennia for the earth system to come into equilibrium with present-day atmospheric greenhouse gas concentrations, past climate states help scientists understand the true sensitivity of the earth system to both small and large changes in climate forcing.

At their most basic level, records of past climate change serve as a critical backdrop for current anthropogenic climate trends, in many cases allowing for the separation of natural causes of climate change (natural variability) and greenhouse-induced trends in earth's climate. In recent millennia, atmospheric CO_2 concentrations were relatively stable, such that changes in solar irradiance and volcanic eruptions represented the primary external drivers of global climate variability. During this time, global temperature variations amounted to less than 0.5°C and sea level varied by no more than 10cm. Exceptionally high-resolution records spanning the last several centuries allow for the quantification of past climate extremes such as drought, El Niño/La Niña events, wildfires, and even tropical storms. Indeed, the last millennia provides a wealth of data that climate scientists use to probe the relationship between global climate state and the character of climate extremes. As such, it offers a "baseline" to which human-induced changes can be compared, and also a rich testbed for climate models that are used to project 21st century climate changes, which must account for natural as well as solar-, volcanic-, and greenhouse-forced climate variability.

Rising greenhouse gas concentrations reflect large-scale changes in the Earth's carbon cycle, such that studies of past changes in carbon fluxes and associated climate changes are highly relevant to projections of future anthropogenic climate change. Over the last million years, Earth has transitioned from glacial climate states characterized by markedly lower atmospheric CO_2 concentrations (200 parts per million) to interglacial climate states (with CO_2 concentrations of 280-300 parts per million) every ~100,000 years. Profound shifts in polar ice sheet mass, sea ice extent, sea level, ocean circulation, global temperature, precipitation patterns, vegetation and climate extremes accompanied these glacial-interglacial shifts. Intriguingly, glacial states are marked by examples of abrupt climate changes that illustrate the potential for rapid climate responses to much slower changes in climate forcing – a high-risk but highly uncertain scenario for 21st century climate changes.

Much further back in geologic time, deep-sea sediments record a climate state when changes in volcanic activity/crustal formation rates and weathering caused atmospheric CO_2 concentrations to climb to ~800ppm or higher – similar to levels expected in coming decades if emissions continue at present rates. During the Eocene period, roughly 50 million years ago, global temperatures were as much as 8°C warmer, sea level was 20-40m higher, and ocean pH varied appreciably. While the rates of present-day atmospheric CO_2

change, temperature change, ocean pH change, and sea level rise are many times higher than they were during past geologic intervals, these “hothouse” worlds hold key lessons for our climate future. In particular, they provide a window into how our planet may eventually end up like, if emissions of greenhouse gases continue unabated, and allow us to test how well our climate models perform under these extreme conditions. This is especially true as models that were constructed and tested against instrumental climate data are charged with projecting climate changes that occur under vastly different boundary conditions than today. As such, past climate data allows us to test the general applicability of our models, and therefore the reliability of our future climate predictions

[*Figure concept:*
4 vertical panels, illustrating (from left to right):
- *i) the PETM,*
- *ii) the last millennium/pre-industrial,*
- *iii) present-day, and*
- *iv) 2100 projections (RCP8.5 or similar)*

with an infographic denoting changes in the following variables:
- *atmospheric* CO_2 *concentrations*
- *global temperature*
- *global sea level*
- *(other variables?)*]

[START FAQ 1.3, FIGURE 1 HERE]

FAQ 1.3, Figure 1: [PLACEHOLDER]

[END FAQ 1.3, FIGURE 1 HERE]

FAQ 1.4: How do we calculate global temperature change?

We calculate global surface temperature change by analyzing the readings of thermometers all over the globe using statistical techniques to take into account areas like the poles where there are fewer measurements. Multiple independent groups of scientists work with an ever increasing number of readings and all have very similar results.

The surface temperature of the world has, on average, increased by around 1 °C since the pre-industrial period – hence the term 'global warming'. Making such a statement implies that we are confident in the ability of science to determine how surface temperatures change over time.

Multiple scientific organizations monitor global surface temperature and all datasets rely on long-term series of temperature measurements made of the air near the surface over land and of the ocean surface, collected by ships, buoys and satellites. Much like having multiple watches that may be set differently but still consistently count seconds and minutes, the numerous temperature measurements may all be calibrated slightly differently but can still give comparable changes. For that reason it is easier to measure temperature change, and not the absolute average temperature of the Earth's surface.

Three main issues arise when estimating changes in global temperature from a large set of measurements spread unevenly across the globe. The first is how to deal with areas where measurements are sparse or mostly unavailable, such as close to the poles. While the different groups producing temperature records all perform rigorous analyses in order to handle the fact that the measurements are not spread evenly, they differ somewhat in how they treat areas with no information.

The second issue, which has recently seen a lot of discussion, is what type of measurement to use over the ocean regions. Traditionally, ship or buoy measurements of the temperature of surface water, have been combined with air temperature measurements (typically at 2 metres) over land. However, analyses with global climate models have tended to use simulated air temperatures everywhere. As air temperatures over the ocean can be expected to warm slightly faster than surface water, it is important to use the same methodology when comparing measurements to models.

The third issue is which time period to report the changes over. As global temperatures have a natural year-to-year variability, scientists normally average at least 20 years to obtain a representative value - but which years? For current temperatures, they naturally use the latest two decades. The period before significant human influence is more difficult to define, partly because measurements were much more sparse in the 18th and 19th centuries. Currently scientists use an 'early industrial' period from 1850 to 1900 as the starting point, though sometimes the 'pre-industrial' period around 1750 is also used.

While global temperatures have risen by about one degree over the last hundred years or so, the formal assessment, based on several independently produced data series, is that surface air temperatures changed by +0.87 °C between the average of 1850-1900 and 2006-2015.

[START FAQ 1.4, FIGURE 1 HERE]

FAQ 1.4, Figure 1: Suggestion: Global map of measurement site/point densities. With a side list of all the different techniques (eg, buoys, satellites, ships etc – could have icons for each?) Present placeholder is from Rennie et al. (2014).

[END FAQ 1.4, FIGURE 1 HERE]

References

A. KATTENBERG, R. G., GRASSL, H., MEEHL, G. A., MITCHELL, J. F. B., STOUFFER, R. J., TOKIOKA, T., et al. (1995). “Climate Models - Projections of Future Climate,” in *Climate Change 1995: The Science of Climate Change. Contribution of Working Group I to the Second Assessment Report of the Intergovernmental Panel on Climate Change,* 285–357.

Abram, N. J., Gagan, M. K., Liu, Z., Hantoro, W. S., McCulloch, M. T., and Suwargadi, B. W. (2007). Seasonal characteristics of the Indian Ocean Dipole during the Holocene epoch. *Nature* 445, 299–302. doi:10.1038/nature05477.

Abram, N. J., McGregor, H. V., Tierney, J. E., Evans, M. N., McKay, N. P., and Kaufman, D. S. (2016). Early onset of industrial-era warming across the oceans and continents. *Nature* 536, 411–418. doi:10.1038/nature19082.

Abramowitz, G., Herger, N., Gutmann, E., Hammerling, D., Knutti, R., Leduc, M., et al. (2018). Model dependence in multi-model climate ensembles: weighting, sub-selection and out-of-sample testing. *Earth Syst. Dyn. Discuss.*, 1–20. doi:10.5194/esd-2018-51.

Adler, C. E., and Hirsch Hadorn, G. (2014). The IPCC and treatment of uncertainties: topics and sources of dissensus. *Wiley Interdiscip. Rev. Clim. Chang.* 5, 663–676. doi:10.1002/wcc.297.

Agarwal, A., and Narain, S. (2012). “Global warming in an unequal world: A case of environmental colonialism (selected excerpts),” in *Handbook of Climate Change and India*, ed. N. Dubash (Routledge). doi:10.4324/9780203153284.

Ahn, M.-S., Kim, D., Sperber, K. R., Kang, I.-S., Maloney, E., Waliser, D., et al. (2017). MJO simulation in CMIP5 climate models: MJO skill metrics and process-oriented diagnosis. *Clim. Dyn.* 49, 4023–4045. doi:10.1007/s00382-017-3558-4.

Alexander, C., Bynum, N., Johnson, E., King, U., Mustonen, T., Neofotis, P., et al. (2011). Linking Indigenous and Scientific Knowledge of Climate Change. *Bioscience* 61, 477–484. doi:10.1525/bio.2011.61.6.10.

Allen, M. R., and Ingram, W. J. (2002). Constraints on future changes in climate and the hydrologic cycle. *Nature* 419, 228–232. doi:10.1038/nature01092.

Allen, M. R., Stott, P. A., Mitchell, J. F. B., Schnur, R., and Delworth, T. L. (2000). Quantifying the uncertainty in forecasts of anthropogenic climate change. *Nature* 407, 617–620. doi:10.1038/35036559.

AMAP (2015). *AMAP assessment 2015 : black carbon and ozone as Arctic climate forcers*. Oslo : Arctic Monitoring and Assessment Programme (AMAP).

Anav, A., Friedlingstein, P., Kidston, M., Bopp, L., Ciais, P., Cox, P., et al. (2013). Evaluating the Land and Ocean Components of the Global Carbon Cycle in the CMIP5 Earth System Models. *J. Clim.* 26, 6801–6843. doi:10.1175/JCLI-D-12-00417.1.

Anderson, A. A., and Huntington, H. E. (2017). Social Media, Science, and Attack Discourse: How Twitter Discussions of Climate Change Use Sarcasm and Incivility. *Sci. Commun.* 39, 598–620. doi:10.1177/1075547017735113.

Andrews, T., Forster, P. M., Boucher, O., Bellouin, N., and Jones, A. (2010). Precipitation, radiative forcing and global temperature change. *Geophys. Res. Lett.* 37, n/a-n/a. doi:10.1029/2010GL043991.

Andrews, T., Gregory, J. M., Paynter, D., Silvers, L. G., Zhou, C., Mauritsen, T., et al. (2018). Accounting for Changing Temperature Patterns Increases Historical Estimates of Climate Sensitivity. *Geophys. Res. Lett.* 45, 8490–8499. doi:10.1029/2018GL078887.

Angström, K. (1900). Über die Bedeutung des Wasserdampfes und der Kohlensäure bei der Absorption der Erdatmosphäre. *Ann. Phys.* 3, 720–732.

Anonymous (1901). Knut Angstrom on Atmospheric Absorption. *Mon. Weather Rev.* 29, 268.

Arizmendi, F., and Barreiro, M. (2017). ENSO teleconnections in the southern hemisphere: A climate network view. *Chaos An Interdiscip. J. Nonlinear Sci.* 27, 093109. doi:10.1063/1.5004535.

Arnold, J. R., and Libby, W. F. (1949). Age determinations by radiocarbon content: Checks with samples of known age. *Science (80-.).* 110, 678–680. doi:10.1126/science.110.2869.678.

Arrhenius, S. (1896). XXXI. On the influence of carbonic acid in the air upon the temperature of the ground. *London, Edinburgh, Dublin Philos. Mag. J. Sci.* 41, 237–276. doi:10.1080/14786449608620846.

Arrhenius, S., and Borns, H. (1908). *Worlds in the Making: The Evolution of the Universe*. New York: Harper and Brothers.

Ashton, T. . (1997). *The industrial revolution, 1760-1830*. Oxford: Oxford University Press Available at: https://trove.nla.gov.au/work/8794617?q&sort=holdings+desc&_=1553489019694&versionId=210078368 [Accessed March 25, 2019].

Ashwin, P., Wieczorek, S., Vitolo, R., and Cox, P. (2012). Tipping points in open systems: bifurcation, noise-induced and rate-dependent examples in the climate system. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* 370, 1166–1184. doi:10.1098/rsta.2011.0306.

Aumont, O., Ethé, C., Tagliabue, A., Bopp, L., and Gehlen, M. (2015). PISCES-v2: an ocean biogeochemical model for carbon and ecosystem studies. *Geosci. Model Dev.* 8, 2465–2513. doi:10.5194/gmd-8-2465-2015.

Balaji, V., Taylor, K. E., Juckes, M., Lautenschlager, M., Blanton, C., Cinquini, L., et al. (2018). Requirements for a global data infrastructure in support of CMIP6. *Geosci. Model Dev. Discuss.*, 1–28. doi:10.5194/gmd-2018-52.

Balmaseda, M. A., Hernandez, F., Storto, A., Palmer, M. D., Alves, O., Shi, L., et al. (2015). The Ocean Reanalyses Intercomparison Project (ORA-IP). *J. Oper. Oceanogr.* 8, s80–s97. doi:10.1080/1755876X.2015.1022329.

Bamber, J. L., Westaway, R. M., Marzeion, B., and Wouters, B. (2018). The land ice contribution to sea level during the satellite era. *Environ. Res. Lett.* 13, 063008. doi:10.1088/1748-9326/aac2f0.

Barnett, T. P., and Schlesinger, M. E. (1987). Detecting changes in global climate induced by greenhouse gases. *J. Geophys. Res.* 92, 14772. doi:10.1029/JD092iD12p14772.

Barnston, A. G., Tippett, M. K., Ranganathan, M., and L'Heureux, M. L. (2017). Deterministic skill of ENSO predictions from the North American Multimodel Ensemble. *Clim. Dyn.* 0, 1–20. doi:10.1007/s00382-017-3603-3.

Barreiro, M., Marti, A. C., and Masoller, C. (2011). Inferring long memory processes in the climate network via ordinal pattern analysis. *Chaos An Interdiscip. J. Nonlinear Sci.* 21, 013101. doi:10.1063/1.3545273.

Barrett, H. G., Jones, J. M., and Bigg, G. R. (2018). Reconstructing El Niño Southern Oscillation using data from ships' logbooks, 1815–1854. Part II: Comparisons with existing ENSO reconstructions and implications for reconstructing ENSO diversity. *Clim. Dyn.* 50, 3131–3152. doi:10.1007/s00382-017-3797-4.

Barz, B., Rodner, E., Garcia, Y. G., and Denzler, J. (2019). Detecting Regions of Maximal Divergence for Spatio-Temporal Anomaly Detection. *IEEE Trans. Pattern Anal. Mach. Intell.* 41, 1088–1101. doi:10.1109/TPAMI.2018.2823766.

Beck, H. E., Zimmermann, N. E., McVicar, T. R., Vergopolan, N., Berg, A., and Wood, E. F. (2018). Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Sci. Data* 5, 180214. Available at: https://doi.org/10.1038/sdata.2018.214.

Belda, M., Holtanová, E., Halenka, T., and Kalvová, J. (2014). Climate classification revisited: from Köppen to Trewartha. *Clim. Res.* 59, 1–13. doi:10.3354/cr01204.

Bellenger, H., Guilyardi, E., Leloup, J., Lengaigne, M., and Vialard, J. (2014). ENSO representation in climate models: from CMIP3 to CMIP5. *Clim. Dyn.* 42, 1999–2018. doi:10.1007/s00382-013-1783-z.

Bentz, B. J., Régnière, J., Fettig, C. J., Hansen, E. M., Hayes, J. L., Hicke, J. A., et al. (2010). Climate Change and Bark Beetles of the Western United States and Canada: Direct and Indirect Effects. *Bioscience* 60, 602–613. doi:10.1525/bio.2010.60.8.6.

Bereiter, B., Eggleston, S., Schmitt, J., Nehrbass-Ahles, C., Stocker, T. F., Fischer, H., et al. (2015). Revision of the EPICA Dome C CO 2 record from 800 to 600 kyr before present. *Geophys. Res. Lett.* 42, 542–549. doi:10.1002/2014GL061957.

Berezin, Y., Gozolchiani, A., Guez, O., and Havlin, S. (2012). Stability of Climate Networks with Time. *Sci. Rep.* 2, 666. doi:10.1038/srep00666.

Berner, R. A. (1995). A. G. Högbom and the development of the concept of the geochemical carbon cycle. *Am. J. Sci.* 295, 491–495.

Bethke, I., Outten, S., Otterå, O. H., Hawkins, E., Wagner, S., Sigl, M., et al. (2017). Potential volcanic impacts on future climate variability. *Nat. Clim. Chang.* 7, 799–805. doi:10.1038/nclimate3394.

Bindoff, N. L., Stott, P. A., AchutaRao, K. M., Allen, M. R., Gillett, N., Gutzler, D., et al. (2013). "Detection and Attribution of Climate Change: from Global to Regional," in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, et al. (Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press), 867–952. doi:10.1017/CBO9781107415324.022.

Bintanja, R., and van de Wal, R. S. W. (2008). North American ice-sheet dynamics and the onset of 100,000-year glacial cycles. *Nature* 454, 869–872. doi:10.1038/nature07158.

Bishop, C. H., and Abramowitz, G. (2013). Climate model dependence and the replicate Earth paradigm. *Clim. Dyn.* 41, 885–900. doi:10.1007/s00382-012-1610-y.

Bjerknes, V. (1906). *Fields of Force: Supplementary Lectures, Applications to Meteorology*. New York: Columbia University Press.

Bjerknes, V., Sandström, J. W., Hesselberg, T., and Devik, O. M. (1910). *Dynamic Meteorology and Hydrography*. Washington: Carnegie Institution of Washington.

Boé, J. (2018). Interdependency in Multimodel Climate Projections: Component Replication and Result Similarity. *Geophys. Res. Lett.* 45, 2771–2779. doi:10.1002/2017GL076829.

Boer, G. J., Smith, D. M., Cassou, C., Doblas-Reyes, F., Danabasoglu, G., Kirtman, B., et al. (2016). The Decadal Climate Prediction Project (DCPP) contribution to CMIP6. *Geosci. Model Dev.* 9, 3751–3777. doi:10.5194/gmd-9-3751-2016.

Boers, N. (2018). Early-warning signals for Dansgaard-Oeschger events in a high-resolution ice core record. *Nat. Commun.* 9, 2556. doi:10.1038/s41467-018-04881-7.

Boers, N., Bookhagen, B., Marengo, J., Marwan, N., von Storch, J.-S., and Kurths, J. (2015). Extreme Rainfall of the South American Monsoon System: A Dataset Comparison Using Complex Networks. *J. Clim.* 28, 1031–1056. doi:10.1175/JCLI-D-14-00340.1.

Boers, N., Bookhagen, B., Marwan, N., Kurths, J., and Marengo, J. (2013). Complex networks identify spatial patterns of extreme rainfall events of the South American Monsoon System. *Geophys. Res. Lett.* 40, 4386–4392. doi:10.1002/grl.50681.

Bogenschutz, P. A., Gettelman, A., Morrison, H., Larson, V. E., Craig, C., and Schanen, D. P. (2013). Higher-Order Turbulence Closure and Its Impact on Climate Simulations in the Community Atmosphere Model. *J. Clim.* 26, 9655–9676. doi:10.1175/JCLI-D-13-00075.1.

Bohr, J. (2017). Is it hot in here or is it just me? Temperature anomalies and political polarization over global warming in the American public. *Clim. Change* 142, 271–285. doi:10.1007/s10584-017-1934-z.

Bolin, B. (2007). *A History of the Science and Politics of Climate Change: The Role of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Bolin, B., Döös, B. R., Jäger, J., and Warrick, R. A. (1986). *The Greenhouse Effect, Climatic Change, and Ecosystems*. Wiley.

Bony, S., Stevens, B., Frierson, D. M. W., Jakob, C., Kageyama, M., Pincus, R., et al. (2015). Clouds, circulation and climate sensitivity. *Nat. Geosci.* 8, 261–268. doi:10.1038/ngeo2398.

Boo, K.-O., Martin, G., Sellar, A., Senior, C., and Byun, Y.-H. (2011). Evaluating the East Asian monsoon simulation in climate models. *J. Geophys. Res.* 116, D01109. doi:10.1029/2010JD014737.

Bowen, G. J., Maibauer, B. J., Kraus, M. J., Röhl, U., Westerhold, T., Steimke, A., et al. (2015). Two massive, rapid releases of carbon during the onset of the Palaeocene–Eocene thermal maximum. *Nat. Geosci.* 8, 44–47. doi:10.1038/ngeo2316.

Bracco, A., Falasca, F., Nenes, A., Fountalis, I., and Dovrolis, C. (2018). Advancing climate science with knowledge-discovery through data mining. *npj Clim. Atmos. Sci.* 1, 20174. doi:10.1038/s41612-017-0006-4.

Bracegirdle, T. J., and Stephenson, D. B. (2013). On the Robustness of Emergent Constraints Used in Multimodel Climate Change Projections of Arctic Warming. *J. Clim.* 26, 669–678. doi:10.1175/JCLI-D-12-00537.1.

Bradley, R. S. (2015). *Paleoclimatology*. Elsevier doi:10.1016/C2009-0-18310-1.

Brady, R. X., Lovenduski, N. S., Alexander, M. A., Jacox, M., and Gruber, N. (2019). On the role of climate modes in modulating the air--sea \chem{CO_2} fluxes in eastern boundary upwelling systems. *Biogeosciences* 16, 329–346. doi:10.5194/bg-16-329-2019.

Brasseur, G. P., and Gallardo, L. (2016). Climate services: Lessons learned and future prospects. *Earth's Futur.* 4, 79–89. doi:10.1002/2015EF000338.

Braun, M. H., Malz, P., Sommer, C., Farías-Barahona, D., Sauter, T., Casassa, G., et al. (2019). Constraining glacier elevation and mass changes in South America. *Nat. Clim. Chang.* 9, 130–136. doi:10.1038/s41558-018-0375-7.

Broecker, W. S. (1975). Climatic Change: Are We on the Brink of a Pronounced Global Warming? *Science (80-.).* 189, 460–463. doi:10.1126/science.189.4201.460.

Broecker, W. S., Gerard, R., Ewing, M., and Heezen, B. C. (1960). Natural radiocarbon in the Atlantic Ocean. *J. Geophys. Res.* 65, 2903–2931. doi:10.1029/JZ065i009p02903.

Broecker, W. S., and Olson, E. A. (1960). Radiocarbon from Nuclear Tests, II. *Science (80-.).* 132, 712–721. doi:10.1126/science.132.3429.712.

Broecker, W. S., Peng, T. H., and Takahashi, T. (1980). A strategy for the use of bomb-produced radiocarbon as a tracer for the transport of fossil fuel CO2 into the deep-sea source regions. *Earth Planet. Sci. Lett.* 49, 463–468. doi:10.1016/0012-821X(80)90087-4.

Broecker, W. S., Thurber, D. L., Goddard, J., Ku, T. -l., Matthews, R. K., and Mesolella, K. J. (1968). Milankovitch Hypothesis Supported by Precise Dating of Coral Reefs and Deep-Sea Sediments. *Science (80-.).* 159, 297–300. doi:10.1126/science.159.3812.297.

Brown, A., Milton, S., Cullen, M., Golding, B., Mitchell, J., and Shelly, A. (2012). Unified Modeling and Prediction of Weather and Climate: A 25-Year Journey. *Bull. Am. Meteorol. Soc.* 93, 1865–1877. doi:10.1175/BAMS-D-12-00018.1.

Brulle, R. J., Carmichael, J., and Jenkins, J. C. (2012). Shifting public opinion on climate change: an empirical assessment of factors influencing concern over climate change in the U.S., 2002–2010. *Clim. Change* 114, 169–188. doi:10.1007/s10584-012-0403-y.

Brunet, G., Jones, S., and Ruti, P. M. (2015). *Seamless prediction of the Earth System: from minutes to months*. , eds. G. Brunet, S. Jones, and P. M. Ruti World Meteorological Organization.

Bryan, K., Manabe, S., and Pacanowski, R. C. (1975). A Global Ocean-Atmosphere Climate Model. Part II. The Oceanic Circulation. *J. Phys. Oceanogr.* 5, 30–46. doi:10.1175/1520-0485(1975)005<0030:AGOACM>2.0.CO;2.

Budescu, D. V., Por, H.-H., Broomell, S. B., and Smithson, M. (2014). The interpretation of IPCC probabilistic statements around the world. *Nat. Clim. Chang.* 4, 508–512. doi:10.1038/nclimate2194.

Burke, K. D., Williams, J. W., Chandler, M. A., Haywood, A. M., Lunt, D. J., and Otto-Bliesner, B. L. (2018). Pliocene and Eocene provide best analogs for near-future climates. *Proc. Natl. Acad. Sci.* 115, 13288–13293. doi:10.1073/pnas.1809600115.

Burrows, S. M., Dasgupta, A., Reehl, S., Bramer, L., Ma, P.-L., Rasch, P. J., et al. (2018). Characterizing the Relative Importance Assigned to Physical Variables by Climate Scientists when Assessing Atmospheric Climate Model

Fidelity. *Adv. Atmos. Sci.* 35, 1101–1113. doi:10.1007/s00376-018-7300-x.

Caldwell, P. M., Bretherton, C. S., Zelinka, M. D., Klein, S. A., Santer, B. D., and Sanderson, B. M. (2014). Statistical significance of climate sensitivity predictors obtained by data mining. *Geophys. Res. Lett.* 41, 1803–1808. doi:10.1002/2014GL059205.

Caldwell, P. M., Zelinka, M. D., and Klein, S. A. (2018). Evaluating Emergent Constraints on Equilibrium Climate Sensitivity. *J. Clim.* 31, 3921–3942. doi:10.1175/JCLI-D-17-0631.1.

Callendar, G. S. (1938). The artificial production of carbon dioxide and its influence on temperature. *Q. J. R. Meteorol. Soc.* 64, 223–240. doi:10.1002/qj.49706427503.

Cassidy, D. C. (1985). Meteorology in Mannheim: The Palatine Meteorological Society, 1780-1795. *Sudhoffs Arch.* 69, 8–25. Available at: •Cassidy- Palatine Meteo Soc.

Castles, I., and Henderson, D. (2003). Economics, Emissions Scenarios and the Work of the IPCC. *Energy Environ.* 14, 415–435. doi:10.1260/095830503322364430.

CBD (2018). KEY MESSAGES FROM THE WORKSHOP ON "BIODIVERSITY AND CLIMATE CHANGE: INTEGRATED SCIENCE FOR COHERENT POLICY." Sharm El-Sheikh, Egypt Available at: https://www.cbd.int/doc/c/c429/2df7/dc8cc589bbf1f5b58f8a1d63/cop-14-inf-22-en.pdf.

Cesana, G., and Waliser, D. E. (2016). Characterizing and understanding systematic biases in the vertical structure of clouds in CMIP5/CFMIP2 models. *Geophys. Res. Lett.* 43, 10,538-10,546. doi:10.1002/2016GL070515.

Chamberlin, T. C. (1897). A Group of Hypotheses Bearing on Climatic Changes. *J. Geol.* 5, 653–683. doi:10.1086/607921.

Chamberlin, T. C. (1898). The Influence of Great Epochs of Limestone Formation upon the Constitution of the Atmosphere. *J. Geol.* 6, 609–621. doi:10.1086/608185.

Charlton-Perez, A. J., Baldwin, M. P., Birner, T., Black, R. X., Butler, A. H., Calvo, N., et al. (2013). On the lack of stratospheric dynamical variability in low-top versions of the CMIP5 models. *J. Geophys. Res. Atmos.* 118, 2494–2505. doi:10.1002/jgrd.50125.

Chen, D., and Chen, H. W. (2013). Using the Köppen classification to quantify climate variation and change: An example for 1901–2010. *Environ. Dev.* 6, 69–79. doi:10.1016/j.envdev.2013.03.007.

Cheng, L., Hoerling, M., Smith, L., and Eischeid, J. (2018). Diagnosing Human-Induced Dynamic and Thermodynamic Drivers of Extreme Rainfall. *J. Clim.* 31, 1029–1051. doi:10.1175/JCLI-D-16-0919.1.

Cheng, L., Trenberth, K. E., Fasullo, J., Boyer, T., Abraham, J., and Zhu, J. (2017). Improved estimates of ocean heat content from 1960 to 2015. *Sci. Adv.* 3, e1601545. doi:10.1126/sciadv.1601545.

Chepfer, H., Noel, V., Chiriaco, M., Wielicki, B., Winker, D., Loeb, N., et al. (2018). The Potential of a Multidecade Spaceborne Lidar Record to Constrain Cloud Feedback. *J. Geophys. Res. Atmos.* 123, 5433–5454. doi:10.1002/2017JD027742.

Christidis, N., Jones, G. S., and Stott, P. A. (2015). Dramatically increasing chance of extremely hot summers since the 2003 European heatwave. *Nat. Clim. Chang.* 5, 46–50. doi:10.1038/nclimate2468.

Clark, P. U., Shakun, J. D., Marcott, S. A., Mix, A. C., Eby, M., Kulp, S., et al. (2016). Consequences of twenty-first-century policy for multi-millennial climate and sea-level change. *Nat. Clim. Chang.* 6, 360–369. doi:10.1038/nclimate2923.

Claussen, M., Mysak, L., Weaver, A., Crucifix, M., Fichefet, T., Loutre, M., et al. (2002). Earth system models of intermediate complexity: closing the gap in the spectrum of climate system models. *Clim. Dyn.* 18, 579–586. doi:10.1007/s00382-001-0200-1.

Clayton, H. H. (1927). *World Weather Records*. Washington: Smithsonian Institution.

Cobb, K. M., Charles, C. D., Cheng, H., and Edwards, R. L. (2003). El Niño/Southern Oscillation and tropical Pacific climate during the last millennium. *Nature* 424, 271–276. doi:10.1038/nature01779.

Cole, J. E., and Fairbanks, R. G. (1990). The Southern Oscillation recorded in the δ 18 O of corals from Tarawa Atoll. *Paleoceanography* 5, 669–683. doi:10.1029/PA005i005p00669.

Collins, M., Chandler, R. E., Cox, P. M., Huthnance, J. M., Rougier, J., and Stephenson, D. B. (2012). Quantifying future climate change. *Nat. Clim. Chang.* 2, 403–409. doi:10.1038/nclimate1414.

Collins, M., Knutti, R., Arblaster, J., Dufresne, J.-L., Fichefet, T., Friedlingstein, P., et al. (2013). "Long-term Climate Change: Projections, Commitments and Irreversibility," in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, et al. (Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press), 1029–1136. doi:10.1017/CBO9781107415324.024.

Collins, W. J., Lamarque, J.-F., Schulz, M., Boucher, O., Eyring, V., Hegglin, M. I., et al. (2017). AerChemMIP: quantifying the effects of chemistry and aerosols in CMIP6. *Geosci. Model Dev.* 10, 585–607. doi:10.5194/gmd-10-585-2017.

Collins, W. J., Webber, C. P., Cox, P. M., Huntingford, C., Lowe, J., Sitch, S., et al. (2018). Increased importance of methane reduction for a 1.5 degree target. *Environ. Res. Lett.* 13, 054003. doi:10.1088/1748-9326/aab89c.

Compo, G. P., Whitaker, J. S., Sardeshmukh, P. D., Matsui, N., Allan, R. J., Yin, X., et al. (2011). The Twentieth Century Reanalysis Project. *Q. J. R. Meteorol. Soc.* 137, 1–28. doi:10.1002/qj.776.

Conley, S., Franco, G., Faloona, I., Blake, D. R., Peischl, J., and Ryerson, T. B. (2016). Methane emissions from the 2015 Aliso Canyon blowout in Los Angeles, CA. *Science (80-.).* 351, 1317–1320. doi:10.1126/science.aaf2348.

Connelly, A., Carter, J., Handley, J., and Hincks, S. (2018). Enhancing the practical utility of risk assessments in climate change adaptation. *Sustain.* 10, 1–12. doi:10.3390/su10051399.

Conservation Foundation (1963). *Implications of Rising Carbon Dioxide Content of the Atmosphere*. New York: The Conservation Foundation Available at: •Conser. Found. 1963 Implic. at.

Cook, E. R., Seager, R., Kushnir, Y., Briffa, K. R., Büntgen, U., Frank, D., et al. (2015). Old World megadroughts and pluvials during the Common Era. *Sci. Adv.* 1. Available at: http://advances.sciencemag.org/content/1/10/e1500561.abstract.

Cornford, S. L., Martin, D. F., Graves, D. T., Ranken, D. F., Le Brocq, A. M., Gladstone, R. M., et al. (2013). Adaptive mesh, finite volume modeling of marine ice sheets. *J. Comput. Phys.* 232, 529–549. doi:10.1016/j.jcp.2012.08.037.

Covey, C., AchutaRao, K. M., Cubasch, U., Jones, P., Lambert, S. J., Mann, M. E., et al. (2003). An overview of results from the Coupled Model Intercomparison Project. *Glob. Planet. Change* 37, 103–133. doi:10.1016/S0921-8181(02)00193-5.

Covey, C., Gleckler, P. J., Doutriaux, C., Williams, D. N., Dai, A., Fasullo, J., et al. (2016). Metrics for the Diurnal Cycle of Precipitation: Toward Routine Benchmarks for Climate Models. *J. Clim.* 29, 4461–4471. doi:10.1175/JCLI-D-15-0664.1.

Cowtan, K., Hausfather, Z., Hawkins, E., Jacobs, P., Mann, M. E., Miller, S. K., et al. (2015). Robust comparison of climate models with observations using blended land air and ocean sea surface temperatures. *Geophys. Res. Lett.* 42, 6526–6534. doi:10.1002/2015GL064888.

Crawford, E. (1997). Arrhenius' 1896 Model of the Greenhouse Effect in Context. *Ambio* 26, 6–11.

Croll, J. (1864). XIII. On the physical cause of the change of climate during geological epochs. *London, Edinburgh, Dublin Philos. Mag. J. Sci.* 28, 121–137. doi:10.1080/14786446408643733.

Croll, J. (1885). *Climate and time in their geological relations*. Edinburgh: Adam and Charles Black.

Crutzen, P. J., and Stoermer, E. F. (2000). The "Anthropocene." *IGBP Newsl.*, 17–18. Available at: http://www.igbp.net/download/18.316f18321323470177580001401/1376383088452/NL41.pdf.

Cubasch, U., Wuebbles, D., Chen, D., Facchini, M. C., Frame, D., Mahowald, N., et al. (2013). "Introduction," in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, et al. (Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press), 119–158. doi:10.1017/CBO9781107415324.007.

Cushman, G. T. (2004). Enclave Vision: Foreign Networks in Peru and the Internationalization of El Niño Research during the 1920s. in *Proceedings of the International Commission on History of Meteorology* (International Commission on the History of Meteorology), 65–74.

Cuzzone, J. K., Morlighem, M., Larour, E., Schlegel, N., and Seroussi, H. (2018). Implementation of higher-order vertical finite elements in ISSM v4.13 for improved ice sheet flow modeling over paleoclimate timescales. *Geosci. Model Dev.* 11, 1683–1694. doi:10.5194/gmd-11-1683-2018.

Dai, A., Trenberth, K. E., and Karl, T. R. (1999). Effects of clouds, soil moisture, precipitation, and water vapor on diurnal temperature range. *J. Clim.* 12, 2451–2473. doi:10.1175/1520-0442(1999)012<2451:EOCSMP>2.0.CO;2.

Dakos, V., Scheffer, M., van Nes, E. H., Brovkin, V., Petoukhov, V., and Held, H. (2008). Slowing down as an early warning signal for abrupt climate change. *Proc. Natl. Acad. Sci.* 105, 14308–14312. doi:10.1073/pnas.0802430105.

Dal Gesso, S., Siebesma, A. P., and de Roode, S. R. (2015). Evaluation of low-cloud climate feedback through single-column model equilibrium states. *Q. J. R. Meteorol. Soc.* 141, 819–832. doi:10.1002/qj.2398.

Dansgaard, W. (1954). The O18-abundance in fresh water. *Geochim. Cosmochim. Acta* 6, 241–260.

Dansgaard, W., Johnsen, S. J., Möller, J., and Langway, C. C. (1969). One thousand centuries of climatic record from Camp Century on the Greenland ice sheet. *Science (80-.).* 166, 377–380. doi:10.1126/science.166.3903.377.

Dätwyler, C., Neukom, R., Abram, N. J., Gallant, A. J. E., Grosjean, M., Jacques-Coper, M., et al. (2018). Teleconnection stationarity, variability and trends of the Southern Annular Mode (SAM) during the last millennium. *Clim. Dyn.* 51, 2321–2339. doi:10.1007/s00382-017-4015-0.

Davy, R., and Esau, I. (2016). Differences in the efficacy of climate forcings explained by variations in atmospheric boundary layer depth. *Nat. Commun.* 7. doi:10.1038/ncomms11690.

Davy, R., Esau, I., Chernokulsky, A., Outten, S., and Zilitinkevich, S. (2017). Diurnal asymmetry to the observed global warming. *Int. J. Climatol.* 37, 79–93. doi:10.1002/joc.4688.

Dayrell, C. (2019). Discourses around climate change in Brazilian newspapers: 2003–2013. *Discourse Commun.* 13, 149–171. doi:10.1177/1750481318817620.

DeConto, R. M., and Pollard, D. (2016a). Contribution of Antarctica to past and future sea-level rise. *Nature* 531, 591–597. doi:10.1038/nature17145.

DeConto, R. M., and Pollard, D. (2016b). Contribution of Antarctica to past and future sea-level rise. *Nature* 531, 591. Available at: http://dx.doi.org/10.1038/nature17145.

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., et al. (2011). The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Q. J. R. Meteorol. Soc.* 137, 553–597. doi:10.1002/qj.828.

Dee, S., Emile-Geay, J., Evans, M. N., Allam, A., Steig, E. J., and Thompson, D. M. (2015). PRYSM: An open-source framework for PRoxY System Modeling, with applications to oxygen-isotope systems. *J. Adv. Model. Earth Syst.* 7, 1220–1247. doi:10.1002/2015MS000447.

Dellink, R., Chateau, J., Lanzi, E., and Magné, B. (2017). Long-term economic growth projections in the Shared Socioeconomic Pathways. *Glob. Environ. Chang.* 42, 200–214. doi:10.1016/j.gloenvcha.2015.06.004.

Depoorter, M. A., Bamber, J. L., Griggs, J. A., Lenaerts, J. T. M., Ligtenberg, S. R. M., van den Broeke, M. R., et al. (2013). Calving fluxes and basal melt rates of Antarctic ice shelves. *Nature* 502, 89. Available at: http://dx.doi.org/10.1038/nature12567.

Dessai, S., Bhave, A., Birch, C., Conway, D., Garcia-Carreras, L., Gosling, J. P., et al. (2018). Building narratives to characterise uncertainty in regional climate change through expert elicitation. *Environ. Res. Lett.* 13, 074005. doi:10.1088/1748-9326/aabcdd.

Dessler, A. E., and Forster, P. M. (2018). An Estimate of Equilibrium Climate Sensitivity From Interannual Variability. *J. Geophys. Res. Atmos.* 123, 8634–8645. doi:10.1029/2018JD028481.

Detenber, B., Rosenthal, S., Liao, Y., and Ho, S. (2016). Audience Segmentation for Campaign Design: Addressing Climate Change in Singapore. *Int. J. Commun.* 10, 4736–4758.

Dewulf, A. (2013). Contrasting frames in policy debates on climate change adaptation. *Wiley Interdiscip. Rev. Clim. Chang.* 4, 321–330. doi:10.1002/wcc.227.

Deza, J. I., Barreiro, M., and Masoller, C. (2015). Assessing the direction of climate interactions by means of complex networks and information theoretic tools. *Chaos An Interdiscip. J. Nonlinear Sci.* 25, 033105. doi:10.1063/1.4914101.

Dileepkumar, R., Achutarao, K., and Arulalan, T. (2018). Human influence on sub-regional surface air temperature change over India. *Sci. Rep.* 8. doi:10.1038/s41598-018-27185-8.

Ding, Q., Schweiger, A., L'Heureux, M., Battisti, D. S., Po-Chedley, S., Johnson, N. C., et al. (2017). Influence of high-latitude atmospheric circulation changes on summertime Arctic sea ice. *Nat. Clim. Chang.* 7, 289–295. doi:10.1038/nclimate3241.

Dlugokenky, E., and Tans, P. (2019). *Trends in atmospheric carbon dioxide*. National Oceanic & Atmospheric Administration, www.esrl.noaa.gov/gmd/ccgg/trends/global.html.

Doney, S. C., Fabry, V. J., Feely, R. A., and Kleypas, J. A. (2009). Ocean Acidification: The Other CO 2 Problem. *Ann. Rev. Mar. Sci.* 1, 169–192. doi:10.1146/annurev.marine.010908.163834.

Donges, J. F., Schultz, H. C. H., Marwan, N., Zou, Y., and Kurths, J. (2011). Investigating the topology of interacting networks. *Eur. Phys. J. B* 84, 635–651. doi:10.1140/epjb/e2011-10795-8.

Donges, J. F., Zou, Y., Marwan, N., and Kurths, J. (2009). The backbone of the climate network. *EPL (Europhysics Lett.* 87, 48007. doi:10.1209/0295-5075/87/48007.

Donnelly, J. P., Hawkes, A. D., Lane, P., MacDonald, D., Shuman, B. N., Toomey, M. R., et al. (2015). Climate forcing of unprecedented intense-hurricane activity in the last 2000 years. *Earth's Futur.* 3, 49–65. doi:10.1002/2014EF000274.

Donner, L. J., Wyman, B. L., Hemler, R. S., Horowitz, L. W., Ming, Y., Zhao, M., et al. (2011). The Dynamical Core, Physical Parameterizations, and Basic Simulation Characteristics of the Atmospheric Component AM3 of the GFDL Global Coupled Model CM3. *J. Clim.* 24, 3484–3519. doi:10.1175/2011JCLI3955.1.

Dörries, M. (2006). In the public eye: Volcanology and climate change studies in the 20th century. *Hist. Stud. Phys. Biol. Sci.* 37, 87–125. doi:10.1525/hsps.2006.37.1.87.

Douglas, H. (2009). *Science, Policy, and the Value-Free Ideal*. University of Pittsburgh Press Available at: https://www.amazon.com/Science-Policy-Value-Free-Heather-Douglas/dp/0822960265.

Douglass, A. E. (1914). A method of estimating rainfall by the growth of trees. *Bull. Am. Geogr. Soc.* 46, 321–335. Available at: https://pdfs.semanticscholar.org/59c4/24adad2c19856490e312ecef202e4bb4ccaa.pdf.

Douglass, A. E. (1919). *Climatic cycles and tree-growth: a study of the annual rings of trees in relation to climate and solar activity*. Washington, D.C.: Carnegie Institution of Washington Available at: https://books.google.com/books?hl=en&lr=&id=sfjNAAAAMAAJ&oi=fnd&pg=PA9&dq=Climatic+Cycles+and+Tree+Growth:+A+Study+of+the+Annual+Rings+of+Trees+in+Relation+to+Climate+and+Solar+Activity&ots=s6yhMdS1U5&sig=2KmUV-gPwFPGwsjgKPibDojEj1k.

Douglass, A. E. (1922). Some aspects of the use of the annual rings of trees in climatic study. *Sci. Mon.* 15, 5–21.

Dove, H. W., and Sabine, M. E. (1853). *The Distribution of Heat over the Surface of the Globe: Illustrated by Isothermal, Thermic Isabnormal, and Other Curves of Temperature*. London: Taylor and Francis.

Drijfhout, S., Bathiany, S., Beaulieu, C., Brovkin, V., Claussen, M., Huntingford, C., et al. (2015). Catalogue of abrupt shifts in Intergovernmental Panel on Climate Change climate models. *Proc. Natl. Acad. Sci.* 112, E5777–E5786. doi:10.1073/pnas.1511451112.

Dupont, F., Higginson, S., Bourdallé-Badie, R., Lu, Y., Roy, F., Smith, G. C., et al. (2015). A high-resolution ocean and sea-ice modelling system for the Arctic and North Atlantic oceans. *Geosci. Model Dev.* 8, 1577–1594.

doi:10.5194/gmd-8-1577-2015.

Durack, P., Taylor, K., Eyring, V., Ames, S., Hoang, T., Nadeau, D., et al. (2018). Toward Standardized Data Sets for Climate Model Experimentation. *Eos (Washington. DC).* 99. doi:10.1029/2018EO101751.

Duren, R. M., and Miller, C. E. (2012). Measuring the carbon emissions of megacities. *Nat. Clim. Chang.* 2, 560–562. doi:10.1038/nclimate1629.

Dutton, A., Carlson, A. E., Long, A. J., Milne, G. A., Clark, P. U., DeConto, R., et al. (2015). Sea-level rise due to polar ice-sheet mass loss during past warm periods. *Science (80-.).* 349, aaa4019-aaa4019. doi:10.1126/science.aaa4019.

Dutton, A., and Lambeck, K. (2012). Ice Volume and Sea Level During the Last Interglacial. *Science (80-.).* 337, 216–219. doi:10.1126/science.1205749.

Ebert-Uphoff, I., and Deng, Y. (2012). Causal Discovery for Climate Research Using Graphical Models. *J. Clim.* 25, 5648–5665. doi:10.1175/JCLI-D-11-00387.1.

Ebert-Uphoff, I., and Deng, Y. (2014). Causal Discovery from Spatio-Temporal Data with Applications to Climate Science. in *2014 13th International Conference on Machine Learning and Applications* (IEEE), 606–613. doi:10.1109/ICMLA.2014.96.

Ebert-Uphoff, I., and Deng, Y. (2017). Causal discovery in the geosciences—Using synthetic data to learn how to interpret results. *Comput. Geosci.* 99, 50–60. doi:10.1016/j.cageo.2016.10.008.

Eby, M., Weaver, A. J., Alexander, K., Zickfeld, K., Abe-Ouchi, A., Cimatoribus, A. A., et al. (2013). Historical and idealized climate model experiments: an intercomparison of Earth system models of intermediate complexity. *Clim. Past* 9, 1111–1140. doi:10.5194/cp-9-1111-2013.

Eddy, J. A. (1976). The Maunder Minimum. *Science (80-.).* 192, 1189–1202. doi:10.1126/science.192.4245.1189.

Edwards, P. N. (2010). *A Vast Machine: Computer Models, Climate Data, and the Politics of Global Warming*. Cambridge: MIT Press.

Ekholm, N. (1901). On the variations of the climate of the geological and historical past and their causes. *Q. J. R. Meteorol. Soc.* 27, 1–62. Available at: http://onlinelibrary.wiley.com/doi/10.1002/qj.49702711702/abstract.

Elliott, K. C. (2017). *A Tapestry of Values: An Introduction to Values in Science*. Oxford University Press Available at: https://www.amazon.com/Tapestry-Values-Introduction-Science/dp/0190260807.

Emile-Geay, J., McKay, N. P., Kaufman, D. S., von Gunten, L., Wang, J., Anchukaitis, K. J., et al. (2017). A global multiproxy database for temperature reconstructions of the Common Era. *Sci. Data* 4, 170088. doi:10.1038/sdata.2017.88.

Emiliani, C. (1955). Pleistocene Temperatures. *J. Geol.* 63, 538–578. doi:10.1086/626295.

Emiliani, C. (1978). The cause of the ice ages. *Earth Planet. Sci. Lett.* 37, 349–354. doi:10.1016/0012-821X(78)90050-X.

EPICA Community Members (2004). Eight glacial cycles from an Antarctic ice core. *Nature* 429, 623–628. doi:10.1038/nature02599.

Etminan, M., Myhre, G., Highwood, E. J., and Shine, K. P. Radiative forcing of carbon dioxide, methane, and nitrous oxide: A significant revision of the methane radiative forcing. doi:10.1002/2016GL071930.

Evans, M. N., Tolwinski-Ward, S. E., Thompson, D. M., and Anchukaitis, K. J. (2013). Applications of proxy system modeling in high resolution paleoclimatology. *Quat. Sci. Rev.* 76, 16–28. doi:10.1016/j.quascirev.2013.05.024.

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., et al. (2016a). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geosci. Model Dev.* 9, 1937–1958. doi:10.5194/gmd-9-1937-2016.

Eyring, V., Cox, P. M., Flato, G. M., Gleckler, P. J., Abramowitz, G., Caldwell, P., et al. (2019). Taking climate model evaluation to the next level. *Nat. Clim. Chang.* 9, 102–110. doi:10.1038/s41558-018-0355-y.

Eyring, V., Gleckler, P. J., Heinze, C., Stouffer, R. J., Taylor, K. E., Balaji, V., et al. (2016b). Towards improved and more routine Earth system model evaluation in CMIP. *Earth Syst. Dyn.* 7, 813–830. doi:10.5194/esd-7-813-2016.

Eyring, V., Righi, M., Lauer, A., Evaldsson, M., Wenzel, S., Jones, C., et al. (2016c). ESMValTool (v1.0) – a community diagnostic and performance metrics tool for routine evaluation of Earth system models in CMIP. *Geosci. Model Dev.* 9, 1747–1802. doi:10.5194/gmd-9-1747-2016.

Faria, S. H., Kipfstuhl, S., and Lambrecht, A. (2018). *The EPICA-DML Deep Ice Core: A Visual Record*. Berlin: Springer doi:10.1007/978-3-662-55308-4_3.

Faria, S. H., Weikusat, I., and Azuma, N. (2014). The microstructure of polar ice. Part II: State of the art. *J. Struct. Geol.* 61, 21–49. doi:10.1016/j.jsg.2013.11.003.

Feldhoff, J. H., Lange, S., Volkholz, J., Donges, J. F., Kurths, J., and Gerstengarbe, F.-W. (2015). Complex networks for climate model evaluation with application to statistical versus dynamical modeling of South American climate. *Clim. Dyn.* 44, 1567–1581. doi:10.1007/s00382-014-2182-9.

Ferraro, R., Waliser, D. E., Gleckler, P., Taylor, K. E., and Eyring, V. (2015). Evolving Obs4MIPs to Support Phase 6 of the Coupled Model Intercomparison Project (CMIP6). *Bull. Am. Meteorol. Soc.* 96, ES131-ES133. doi:10.1175/BAMS-D-14-00216.1.

Ferrel, W. (1856). An Essay on the Winds and Currents of the Ocean. *Nashv. J. Med. Surg.* 11, 287-301,375-389. Available at: •Ferrel 1856 WindsCurrents pt 1%0A•Ferrel 1856 WindsCurrents pt 2.

Field, C. B., Barros, V. R., Dokken, D. J., Mach, K. J., Mastrandrea, M. D., Bilir, T. E., et al. (2014). IPCC, 2014: Summary for policymakers. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

Fischer, H., Meissner, K. J., Mix, A. C., Abram, N. J., Austermann, J., Brovkin, V., et al. (2018). Palaeoclimate constraints on the impact of 2 °C anthropogenic warming and beyond. *Nat. Geosci.* 11, 474–485. doi:10.1038/s41561-018-0146-0.

Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S. C., Collins, W., et al. (2013). "Evaluation of Climate Models," in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, et al. (Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press), 741–866. doi:10.1017/CBO9781107415324.020.

Fleming, J. R. (1998). *Historical Perspectives on Climate Change*. New York: Oxford University Press.

Fløttum, K., and Gjerstad, Ø. (2017). Narratives in climate change discourse. *Wiley Interdiscip. Rev. Clim. Chang.* 8, e429. doi:10.1002/wcc.429.

Foote, E. (1856). Circumstances affecting the Heat of the Sun's Rays. *Am. J. Sci. Arts* 22, 382–383.

Forino, G., von Meding, J., and Brewer, G. J. (2015). A conceptual governance framework for climate change adaptation and disaster risk reduction integration. *Int. J. Disaster Risk Sci.* doi:10.1007/s13753-015-0076-z.

Fountalis, I., Bracco, A., and Dovrolis, C. (2014). Spatio-temporal network analysis for studying climate patterns. *Clim. Dyn.* 42, 879–899. doi:10.1007/s00382-013-1729-5.

Fountalis, I., Bracco, A., and Dovrolis, C. (2015). ENSO in CMIP5 simulations: network connectivity from the recent past to the twenty-third century. *Clim. Dyn.* 45, 511–538. doi:10.1007/s00382-014-2412-1.

Fourier, J. B. J. (1822). *Théorie analytique de la chaleur*. Paris: F. Didot.

Frame, D., Joshi, M., Hawkins, E., Harrington, L. J., and de Roiste, M. (2017). Population-based emergence of unfamiliar climates. *Nat. Clim. Chang.* 7, 407. Available at: http://dx.doi.org/10.1038/nclimate3297.

Frankcombe, L. M., England, M. H., Mann, M. E., and Steinman, B. A. (2015). Separating internal variability from the externally forced climate response. *J. Clim.* 28, 8184–8202. doi:10.1175/JCLI-D-15-0069.1.

Freeman, E., Woodruff, S. D., Worley, S. J., Lubker, S. J., Kent, E. C., Angel, W. E., et al. (2017). ICOADS Release 3.0: a major update to the historical marine climate record. *Int. J. Climatol.* 37, 2211–2232. doi:10.1002/joc.4775.

Freeman, N. M., Lovenduski, N. S., Munro, D. R., Krumhardt, K. M., Lindsay, K., Long, M. C., et al. (2018). The Variable and Changing Southern Ocean Silicate Front: Insights From the CESM Large Ensemble. *Global Biogeochem. Cycles* 32, 752–768. doi:10.1029/2017GB005816.

Frieler, K., Meinshausen, M., Mengel, M., Braun, N., Hare, W., Frieler, K., et al. (2012). A Scaling Approach to Probabilistic Assessment of Regional Climate Change. *J. Clim.* 25, 3117–3144. doi:10.1175/JCLI-D-11-00199.1.

Frölicher, T. L., and Paynter, D. J. (2015). Extending the relationship between global warming and cumulative carbon emissions to multi-millennial timescales. *Environ. Res. Lett.* 10, 075002. doi:10.1088/1748-9326/10/7/075002.

Frölicher, T. L., Rodgers, K. B., Stock, C. A., and Cheung, W. W. L. (2016). Sources of uncertainties in 21st century projections of potential ocean ecosystem stressors. *Global Biogeochem. Cycles* 30, 1224–1243. doi:10.1002/2015GB005338.

Fu, L.-L., Christensen, E. J., Yamarone, C. A., Lefebvre, M., Ménard, Y., Dorrer, M., et al. (1994). TOPEX/POSEIDON mission overview. *J. Geophys. Res.* 99, 24369. doi:10.1029/94JC01761.

Fujiwara, M., Wright, J. S., Manney, G. L., Gray, L. J., Anstey, J., Birner, T., et al. (2017). Introduction to the SPARC Reanalysis Intercomparison Project (S-RIP) and overview of the reanalysis systems. *Atmos. Chem. Phys.* 17, 1417–1452. doi:10.5194/acp-17-1417-2017.

Funk, C., Husak, G., Michaelsen, J., Shukla, S., Hoell, A., Fieldbrad, L., et al. (2013). 15 . ATTRIBUTION OF 2012 AND 2003 – 12 RAINFALL DEFICITS IN EASTERN KENYA AND SOUTHERN SOMALIA. *Bull. Amer. Meteor. Soc.* 94, S45–S48.

Fuss, S., Canadell, J. G., Peters, G. P., Tavoni, M., Andrew, R. M., Ciais, P., et al. (2014). Betting on negative emissions. *Nat. Clim. Chang.* 4, 850–853. doi:10.1038/nclimate2392.

Galbraith, E. D., and Martiny, A. C. (2015). A simple nutrient-dependence mechanism for predicting the stoichiometry of marine ecosystems. *Proc. Natl. Acad. Sci.* 112, 8199–8204. doi:10.1073/pnas.1423917112.

Gärtner-Roer, I., Naegeli, K., Huss, M., Knecht, T., Machguth, H., and Zemp, M. (2014). A database of worldwide glacier thickness observations. *Glob. Planet. Change* 122, 330–344. doi:10.1016/j.gloplacha.2014.09.003.

Gasser, T., Ciais, P., Boucher, O., Quilcaille, Y., Tortora, M., Bopp, L., et al. (2017). The compact Earth system model OSCAR v2.2: description and first results. *Geosci. Model Dev* 10, 271–319. doi:10.5194/gmd-10-271-2017.

Gasser, T., Kechiar, M., Ciais, P., Burke, E. J., Kleinen, T., Zhu, D., et al. (2018). Path-dependent reductions in CO2 emission budgets caused by permafrost carbon release. *Nat. Geosci.* 11, 830–835. doi:10.1038/s41561-018-0227-0.

Gates, W. L., Boyle, J. S., Covey, C., Dease, C. G., Doutriaux, C. M., Drach, R. S., et al. (1999). An Overview of the Results of the Atmospheric Model Intercomparison Project (AMIP I). *Bull. Am. Meteorol. Soc.* 80, 29–55. doi:10.1175/1520-0477(1999)080<0029:AOOTRO>2.0.CO;2.

GCOS (2015). Status of the global observing system for climate (GEOS No. 195). Geneva, Switzerland.

Ge, Q., Zheng, J., Tian, Y., Wu, W., Fang, X., and Wang, W.-C. (2008). Coherence of climatic reconstruction from historical documents in China by different studies. *Int. J. Climatol.* 28, 1007–1024. doi:10.1002/joc.1552.

Gearheard, S., Pocernich, M., Stewart, R., Sanguya, J., and Huntington, H. P. (2010). Linking Inuit knowledge and meteorological station observations to understand changing wind patterns at Clyde River, Nunavut. *Clim. Change* 100, 267–294. doi:10.1007/s10584-009-9587-1.

Geiger, R. (1954). "Klassifikationen der Klimate nach W. Köppen," in *Landolt-Börnstein: Zahlenwerte und Funktionen aus Physik, Chemie, Astronomie, Geophysik und Technik, (alte Serie), Vol. 3.* (Berlin: Springer), 603−607.

Geng, Y., Fujita, T., Chiu, A., Dai, H., and Hao, H. (2018). Responding to the Paris Climate Agreement: global climate change mitigation efforts. *Front. Energy* 12, 333–337. doi:10.1007/s11708-018-0587-6.

Genz, J., Aucan, J., Merrifield, M., Finney, B., Joel, K., and Kelen, A. (2009). Wave Navigation in the Marshall Islands: Comparing Indigenous and Western Scientific Knowledge of the Ocean. *Oceanography* 22, 234–245. doi:10.5670/oceanog.2009.52.

Geoffroy, O., Saint-Martin, D., Olivié, D. J. L., Voldoire, A., Bellon, G., Tytéca, S., et al. (2013). Transient Climate Response in a Two-Layer Energy-Balance Model. Part I: Analytical Solution and Parameter Calibration Using CMIP5 AOGCM Experiments. *J. Clim.* 26, 1841–1857. doi:10.1175/JCLI-D-12-00195.1.

Gerber, E. P., and Manzini, E. (2016). The Dynamics and Variability Model Intercomparison Project (DynVarMIP) for CMIP6: assessing the stratosphere–troposphere system. *Geosci. Model Dev.* 9, 3413–3425. doi:10.5194/gmd-9-3413-2016.

Gertler, C. G., Puppala, S. P., Panday, A., Stumm, D., and Shea, J. (2016). Black carbon and the Himalayan cryosphere: A review. *Atmos. Environ.* 125, 404–417. doi:10.1016/j.atmosenv.2015.08.078.

Gettelman, A., and Sherwood, S. C. (2016). Processes Responsible for Cloud Feedback. *Curr. Clim. Chang. Reports* 2, 179–189. doi:10.1007/s40641-016-0052-8.

Gidden, M. J., Riahi, K., Smith, S. J., Fujimori, S., Luderer, G., Kriegler, E., et al. (2018). Global emissions pathways under different socioeconomic scenarios for use in CMIP6: a dataset of harmonized emissions trajectories through the end of the century. *Geosci. Model Dev. Discuss.*, 1–42. doi:10.5194/gmd-2018-266.

Gillett, N. P., Arora, V. K., Flato, G. M., Scinocca, J. F., and von Salzen, K. (2012). Improved constraints on 21st-century warming derived using 160 years of temperature observations. *Geophys. Res. Lett.* 39, n/a-n/a. doi:10.1029/2011GL050226.

Gillett, N. P., Arora, V. K., Matthews, D., and Allen, M. R. (2013a). Constraining the Ratio of Global Warming to Cumulative CO 2 Emissions Using CMIP5 Simulations*. *J. Clim.* 26, 6844–6858. doi:10.1175/JCLI-D-12-00476.1.

Gillett, N. P., Fyfe, J. C., and Parker, D. E. (2013b). Attribution of observed sea level pressure trends to greenhouse gas, aerosol, and ozone changes. *Geophys. Res. Lett.* 40, 2302–2306. doi:10.1002/grl.50500.

Gillett, N. P., Shiogama, H., Funke, B., Hegerl, G., Knutti, R., Matthes, K., et al. (2016). The Detection and Attribution Model Intercomparison Project (DAMIP v1.0) contribution to CMIP6. *Geosci. Model Dev.* 9, 3685–3697. doi:10.5194/gmd-9-3685-2016.

Giorgetta, M. A., Brokopf, R., Crueger, T., Esch, M., Fiedler, S., Helmert, J., et al. (2018). ICON-A, the Atmosphere Component of the ICON Earth System Model: I. Model Description. *J. Adv. Model. Earth Syst.* 10, 1613–1637. doi:10.1029/2017MS001242.

Giorgi, F., and Bi, X. (2009). Time of emergence (TOE) of GHG-forced precipitation change hot-spots. *Geophys. Res. Lett.* 36, 653–656. Available at: http://doi.wiley.com/10.1029/2009GL037593.

Giorgi, F., and Gutowski, W. J. (2015). Regional Dynamical Downscaling and the CORDEX Initiative. *Annu. Rev. Environ. Resour.* 40, 467–490. doi:10.1146/annurev-environ-102014-021217.

Gleckler, P. J., Taylor, K. E., and Doutriaux, C. (2008). Performance metrics for climate models. *J. Geophys. Res.* 113, D06104. doi:10.1029/2007JD008972.

Global Atmospheric Research Programme, and World Climate Research Programme (1980). *Report of the first session of the Joint Scientific Committee for the World Climate Research Programme and the Global Atmospheric Research Program*. Geneva: World Meteorological Organization.

Goelzer, H., Nowicki, S., Edwards, T., Beckley, M., Abe-Ouchi, A., Aschwanden, A., et al. (2018). Design and results of the ice sheet model initialisation experiments initMIP-Greenland: an ISMIP6 intercomparison. *Cryosph.* 12, 1433–1460. doi:10.5194/tc-12-1433-2018.

Golaz, J.-C., Larson, V. E., and Cotton, W. R. (2002). A PDF-Based Model for Boundary Layer Clouds. Part I: Method and Model Description. *J. Atmos. Sci.* 59, 3540–3551. doi:10.1175/1520-0469(2002)059<3540:APBMFB>2.0.CO;2.

Goldberg, D. N., Heimbach, P., Joughin, I., and Smith, B. (2015). Committed retreat of Smith, Pope, and Kohler Glaciers over the next 30 years inferred by transient model calibration. *Cryosph.* 9, 2429–2446. doi:10.5194/tc-9-2429-2015.

Good, P., Jones, C., Lowe, J., Betts, R., and Gedney, N. (2013). Comparing Tropical Forest Projections from Two Generations of Hadley Centre Earth System Models, HadGEM2-ES and HadCM3LC. *J. Clim.* 26, 495–511. doi:10.1175/JCLI-D-11-00366.1.

Gould, J. (2003). WOCE and TOGA—The Foundations of the Global Ocean Observing System. *Oceanography* 16, 24–30. doi:10.5670/oceanog.2003.05.

Gozolchiani, A., Havlin, S., and Yamasaki, K. (2011). Emergence of El Niño as an Autonomous Component in the Climate Network. *Phys. Rev. Lett.* 107, 148501. doi:10.1103/PhysRevLett.107.148501.

Grant, S. B., Fletcher, T. D., Feldman, D., Saphores, J. D., Cook, P. L. M., Stewardson, M., et al. (2013). Adapting urban water systems to a changing climate: Lessons from the millennium drought in southeast Australia. *Environ. Sci. Technol.* 47, 10727–10734. doi:10.1021/es400618z.

Great Britain Meteorological Office, and Shaw, N. (1920). *Réseau Mondial, 1910: Monthly and annual summaries of pressure, temperature, and precipitation at land stations*. London: H. M. Stationery Office.

Green, D., Billy, J., and Tapim, A. (2010). Indigenous Australians' knowledge of weather and climate. *Clim. Change* 100, 337–354. doi:10.1007/s10584-010-9803-z.

Gregory, J. M., Andrews, T., Good, P., Mauritsen, T., and Forster, P. M. (2016a). Small global-mean cooling due to volcanic radiative forcing. *Clim. Dyn.* 47, 3979–3991. doi:10.1007/s00382-016-3055-1.

Gregory, J. M., Bouttes, N., Griffies, S. M., Haak, H., Hurlin, W. J., Jungclaus, J., et al. (2016b). The Flux-Anomaly-Forced Model Intercomparison Project (FAFMIP) contribution to CMIP6: investigation of sea-level and ocean climate change in response to CO&lt;sub&gt;2&lt;/sub&gt; forcing. *Geosci. Model Dev.* 9, 3993–4017. doi:10.5194/gmd-9-3993-2016.

Griffies, S. M., Böning, C., Bryan, F. O., Chassignet, E. P., Gerdes, R., Hasumi, H., et al. (2000). Developments in ocean climate modelling. *Ocean Model.* 2, 123–192. doi:10.1016/S1463-5003(00)00014-7.

Griffies, S. M., Danabasoglu, G., Durack, P. J., Adcroft, A. J., Balaji, V., Böning, C. W., et al. (2016). OMIP contribution to CMIP6: experimental and diagnostic protocol for the physical component of the Ocean Model Intercomparison Project. *Geosci. Model Dev.* 9, 3231–3296. doi:10.5194/gmd-9-3231-2016.

Grigholm, B., Mayewski, P. A., Kang, S., Zhang, Y., Kaspari, S., Sneed, S. B., et al. (2009). Atmospheric soluble dust records from a Tibetan ice core: Possible climate proxies and teleconnection with the Pacific Decadal Oscillation. *J. Geophys. Res. Atmos.* 114. doi:10.1029/2008JD011242.

Grose, M. R., Black, M., Risbey, J. S., Uhe, P., Hope, P. K., Haustein, K., et al. (2018). Severe Frosts in Western Australia in September 2016. *Bull. Am. Meteorol. Soc.* 99, S150–S154. doi:10.1175/BAMS-D-17-0088.1.

Grose, M. R., Risbey, J. S., and Whetton, P. H. (2017). Tracking regional temperature projections from the early 1990s in light of variations in regional warming, including 'warming holes.' *Clim. Change* 140, 307–322. doi:10.1007/s10584-016-1840-9.

Gryspeerdt, E., and Stier, P. (2012). Regime-based analysis of aerosol-cloud interactions. *Geophys. Res. Lett.* 39, n/a-n/a. doi:10.1029/2012GL053221.

Guan, B., and Waliser, D. E. (2017). Atmospheric rivers in 20 year weather and climate simulations: A multimodel, global evaluation. *J. Geophys. Res. Atmos.* 122, 5556–5581. doi:10.1002/2016JD026174.

Guez, O., Gozolchiani, A., Berezin, Y., Brenner, S., and Havlin, S. (2012). Climate network structure evolves with North Atlantic Oscillation phases. *EPL (Europhysics Lett.* 98, 38006. doi:10.1209/0295-5075/98/38006.

Guilyardi, E., Wittenberg, A., Balmaseda, M., Cai, W., Collins, M., McPhaden, M. J., et al. (2016). Fourth CLIVAR Workshop on the Evaluation of ENSO Processes in Climate Models: ENSO in a Changing Climate. *Bull. Am. Meteorol. Soc.* 97, 817–820. doi:10.1175/BAMS-D-15-00287.1.

Guo, H., Golaz, J.-C., Donner, L. J., Wyman, B., Zhao, M., and Ginoux, P. (2015). CLUBB as a unified cloud parameterization: Opportunities and challenges. *Geophys. Res. Lett.* 42, 4540–4547. doi:10.1002/2015GL063672.

Gustafsson, Ö., and Ramanathan, V. (2016). Convergence on climate warming by black carbon aerosols. *Proc. Natl. Acad. Sci.* 113, 4243–4245. doi:10.1073/pnas.1603570113.

Gutowski Jr., W. J., Giorgi, F., Timbal, B., Frigon, A., Jacob, D., Kang, H.-S., et al. (2016). WCRP COordinated Regional Downscaling EXperiment (CORDEX): a diagnostic MIP for CMIP6. *Geosci. Model Dev.* 9, 4087–4095. doi:10.5194/gmd-9-4087-2016.

Haarsma, R. J., Roberts, M. J., Vidale, P. L., Senior, C. A., Bellucci, A., Bao, Q., et al. (2016). High Resolution Model Intercomparison Project (HighResMIP v1.0) for CMIP6. *Geosci. Model Dev.* 9, 4185–4208. doi:10.5194/gmd-9-4185-2016.

Hadley, G. (1735). Concerning the Cause of the General Trade-Winds. *Philos. Trans. R. Soc. London* 39, 58–62. doi:10.1098/rstl.1735.0014.

Haimberger, L., Tavolato, C., and Sperka, S. (2012). Homogenization of the global radiosonde temperature dataset through combined comparison with reanalysis background series and neighboring stations. *J. Clim.* 25, 8108–8131. doi:10.1175/JCLI-D-11-00668.1.

Hajima, T., Kawamiya, M., Watanabe, M., Kato, E., Tachiiri, K., Sugiyama, M., et al. (2014). Modeling in Earth system science up to and beyond IPCC AR5. *Prog. Earth Planet. Sci.* 1, 29. doi:10.1186/s40645-014-0029-y.

Hakim, G. J., Emile-Geay, J., Steig, E. J., Noone, D., Anderson, D. M., Tardif, R., et al. (2016). The last millennium climate reanalysis project: Framework and first results. *J. Geophys. Res. Atmos.* 121, 6745–6764. doi:10.1002/2016JD024751.

Halley, E. (1686). An Historical Account of the Trade Winds, and Monsoons, Observable in the Seas between and Near the Tropicks, with an Attempt to Assign the Phisical Cause of the Said Winds. *Philos. Trans. R. Soc. London* 1, 153–168. doi:10.1098/rstl.1686.0026.

Hamilton, L. C., and Stampone, M. D. (2013). Blowin' in the Wind: Short-Term Weather and Belief in Anthropogenic Climate Change. *Weather. Clim. Soc.* 5, 112–119. doi:10.1175/WCAS-D-12-00048.1.

Hamlington, B. D., Strassburg, M. W., Leben, R. R., Han, W., Nerem, R. S., and Kim, K. Y. (2014). Uncovering an anthropogenic sea-level rise signal in the Pacific Ocean. *Nat. Clim. Chang.* 4, 782–785. doi:10.1038/nclimate2307.

Hann, J. von (1883). *Handbuch der Klimatologie*. Stuttgart: J. Engelhorn.

Hann, J. von, and Ward, R. D. (1903). *Handbook of Climatology*. New York: Macmillan.

Hannart, A. (2016). Integrated optimal fingerprinting: Method description and illustration. *J. Clim.* 29, 1977–1998. doi:10.1175/JCLI-D-14-00124.1.

Hansen, G., and Cramer, W. (2015). Global distribution of observed climate change impacts. *Nat. Clim. Chang.* 5, 182–185. Available at: https://doi.org/10.1038/nclimate2529.

Hansen, G., Stone, D., Auffhammer, M., Huggel, C., and Cramer, W. (2016). Linking local impacts to changes in climate: a guide to attribution. *Reg Env. Chang.* 16, 527–541. doi:10.1007/s10113-015-0760-y.

Hansen, J., Fung, I., Lacis, A., Rind, D., Lebedeff, S., Ruedy, R., et al. (1988). Global climate changes as forecast by Goddard Institute for Space Studies three-dimensional model. *J. Geophys. Res.* 93, 9341. doi:10.1029/JD093iD08p09341.

Hansen, J., Johnson, D., Lacis, A., Lebedeff, S., Lee, P., Rind, D., et al. (1981). Climate Impact of Increasing Atmospheric Carbon Dioxide. *Science (80-.).* 213, 957–966. doi:10.1126/science.213.4511.957.

Hansen, J., and Lebedeff, S. (1987). Global Trends of Measured Surface Air Temperature. *J. Geophys. Res.* doi:10.1029/JD092iD11p13345.

Hansen, J., Ruedy, R., Sato, M., and Lo, K. (2010). GLOBAL SURFACE TEMPERATURE CHANGE. *Rev. Geophys.* 48, RG4004. doi:10.1029/2010RG000345.

HARADA, Y., KAMAHORI, H., KOBAYASHI, C., ENDO, H., KOBAYASHI, S., OTA, Y., et al. (2016). The JRA-55 Reanalysis: Representation of Atmospheric Circulation and Climate Variability. *J. Meteorol. Soc. Japan. Ser. II* 94, 269–302. doi:10.2151/jmsj.2016-015.

Harrington, L. J., Frame, D. J., Fischer, E. M., Hawkins, E., Joshi, M., and Jones, C. D. (2016). Poorest countries experience earlier anthropogenic emergence of daily temperature extremes. *Environ. Res. Lett.* 11, 055007. doi:10.1088/1748-9326/11/5/055007.

Hartin, C. A., Patel, P., Schwarber, A., Link, R. P., and Bond-Lamberty, B. P. (2015). A simple object-oriented and open-source model for scientific and policy analyses of the global climate system – Hector v1.0. *Geosci. Model Dev.* 8, 939–955. doi:10.5194/gmd-8-939-2015.

Harvey, L. D. D., and Schneider, S. H. (1985). Transient climate response to external forcing on 10 ^{0} –10 ^{4} year time scales part 1: Experiments with globally averaged, coupled, atmosphere and ocean energy balance models. *J. Geophys. Res.* 90, 2191. doi:10.1029/JD090iD01p02191.

Haseloff, M., and Sergienko, O. V. (2018). The effect of buttressing on grounding line dynamics. *J. Glaciol.* 64, 417–431. doi:10.1017/jog.2018.30.

Hasselmann, K. (1997). Multi-pattern fingerprint method for detection and attribution of climate change. *Clim. Dyn.* 13, 601–611. doi:10.1007/s003820050185.

Hassol, S. J., Torok, S., and Lewis Patrick, S. L. (2016). (Un)Natural Disasters: Communicating Linkages Between Extreme Events and Climate Change. *WMO Bull.* 65. Available at: https://public.wmo.int/en/resources/bulletin/unnatural-disasters-communicating-linkages-between-extreme-events-and-climate.

Haughton, N., Abramowitz, G., Pitman, A., and Phipps, S. J. (2015). Weighting climate model ensembles for mean and variance estimates. *Clim. Dyn.* 45, 3169–3181. doi:10.1007/s00382-015-2531-3.

Hauser, M., Orth, R., and Seneviratne, S. I. (2016). Role of soil moisture versus recent climate change for the 2010 heat wave in western Russia. *Geophys. Res. Lett.* 43, 2819–2826. doi:10.1002/2016GL068036.

Haustein, K., Allen, M. R., Forster, P. M., Otto, F. E. L., Mitchell, D. M., Matthews, H. D., et al. (2017a). A real-time Global Warming Index. *Sci. Rep.* doi:10.1038/s41598-017-14828-5.

Haustein, K., Allen, M. R., Forster, P. M., Otto, F. E. L., Mitchell, D. M., Matthews, H. D., et al. (2017b). A real-time Global Warming Index. *Sci. Rep.* 7, 15417. doi:10.1038/s41598-017-14828-5.

Hawkins, E., and Jones, P. D. (2013). On increasing global temperatures: 75 years after Callendar. *Q. J. R. Meteorol. Soc.* 139. doi:10.1002/qj.2178.

Hawkins, E., and Sutton, R. (2009a). The Potential to Narrow Uncertainty in Regional Climate Predictions. *Bull. Am. Meteorol. Soc.* 90, 1095–1108. doi:10.1175/2009BAMS2607.1.

Hawkins, E., and Sutton, R. (2009b). The Potential to Narrow Uncertainty in Regional Climate Predictions. *Bull. Am. Meteorol. Soc.* 90, 1095–1108. doi:10.1175/2009BAMS2607.1.

Hawkins, E., and Sutton, R. (2012). Time of emergence of climate signals. *Geophys. Res. Lett.* 39. doi:10.1029/2011GL050087.

Hawkins, E., and Sutton, R. (2016). Connecting climate model projections of global temperature change with the real world. *Bull. Am. Meteorol. Soc.* 97. doi:10.1175/BAMS-D-14-00154.1.

Hay, C. C., Morrow, E., Kopp, R. E., and Mitrovica, J. X. (2015). Probabilistic reanalysis of twentieth-century sea-level rise. *Nature* 517, 481–484. doi:10.1038/nature14093.

Hays, J. D., Imbrie, J., and Shackleton, N. J. (1976). Variations in the Earth's Orbit: Pacemaker of the Ice Ages. *Science (80-.).* 194, 1121–1132. doi:10.1126/science.194.4270.1121.

Hazeleger, W., van den Hurk, B. J. J. M., Min, E., van Oldenborgh, G. J., Petersen, A. C., Stainforth, D. A., et al. (2015). Tales of future weather. *Nat. Clim. Chang.* 5, 107–113. doi:10.1038/nclimate2450.

Head, L., Adams, M., Mcgregor, H. V, and Toole, S. (2014). Climate change and Australia. *WIREs Clim Chang.* 5, 175–197. doi:10.1002/wcc.255.

Hegerl, G. C., Hasselmann, K., Cubasch, U., Mitchell, J. F. B., Roeckner, E., Voss, R., et al. (1997). Multi-fingerprint detection and attribution analysis of greenhouse gas, greenhouse gas-plus-aerosol and solar forced climate change. *Clim. Dyn.* 13, 613–634. doi:10.1007/s003820050186.

Hegerl, G. C., Hoegh-Guldberg, O., Casassa, G., Hoerling, M. P., Kovats, R. S., Parmesan, C., et al. (2010). "Good practice guidance paper on detection and attribution related to anthropogenic climate change," in *Meeting Report of the Intergovernmental Panel on Climate Change Expert Meeting on Detection and Attribution of Anthropogenic Climate Change*.

Hegglin, M. I., Kinnison, D., Lamarque, J.-F. J.-F., and Al., E. CCMI nitrogen deposition database (1850-2100) in support of CMIP6. *Geosci. Model Dev.*

Herger, N., Abramowitz, G., Knutti, R., Angélil, O., Lehmann, K., and Sanderson, B. M. (2018a). Selecting a climate model subset to optimise key ensemble properties. *Earth Syst. Dyn.* 9, 135–151. doi:10.5194/esd-9-135-2018.

Herger, N., Angélil, O., Abramowitz, G., Donat, M., Stone, D., and Lehmann, K. (2018b). Calibrating Climate Model Ensembles for Assessing Extremes in a Changing Climate. *J. Geophys. Res. Atmos.* 123, 5988–6004. doi:10.1029/2018JD028549.

Herring, S. C., Christidis, N., Hoell, A., Hoerling, M. P., and Stott, P. A. (2019). Explaining Extreme Events of 2017 from a Climate Perspective. *Bull. Amer. Meteor. Soc.* 100, S1–S117. doi:10.1175/BAMS-ExplainingExtremeEvents2017.1.

Herring, S. C., Hoell, A., Hoerling, M. P., Kossin, J. P., Schreck, C. J., and Stott, P. A. (2016). Introduction to explaining extreme events of 2015 from a climate perspective. *Bull. Am. Meteorol. Soc.* 97, S1–S3. doi:10.1175/BAMS-D-16-0313.1.

Herring, S. C., Hoerling, M. P., Kossin, J. P., Peterson, T. C., and Stott, P. A. (2015). Explaining Extreme Events of 2014 from a Climate Perspective. *Bull. Am. Meteorol. Soc.* 96, S1–S172. doi:10.1175/BAMS-ExplainingExtremeEvents2014.1.

Herring, S. C., Hoerling, M. P., Peterson, T. C., and Stott, P. A. (2014). Explaining extreme events of 2013 from a climate perspective. *Bull. Am. Meteorol. Soc.* 95, S1–S96. doi:10.1175/1520-0477-95.9.S1.1.

Hersbach, H., and Dee, D. (2016). ERA5 reanalysis is in production. *ECMWF Newsl.* 147. Available at: https://www.ecmwf.int/en/newsletter/147/news/era5-.

Hewitt, C. D., Stone, R. C., and Tait, A. B. (2017a). Improving the use of climate information in decision-making. *Nat. Clim. Chang.* 7. doi:10.1038/nclimate3378.

Hewitt, H. T., Bell, M. J., Chassignet, E. P., Czaja, A., Ferreira, D., Griffies, S. M., et al. (2017b). Will high-resolution global ocean models benefit coupled predictions on short-range to climate timescales? *Ocean Model.* 120, 120–136. doi:10.1016/j.ocemod.2017.11.002.

Hine, D. W., Phillips, W. J., Cooksey, R., Reser, J. P., Nunn, P., Marks, A. D., et al. (2015). Preaching to different choirs: How to motivate dismissive, uncommitted, and alarmed audiences to adapt to climate change? *Glob. Environ. Chang.* 36, 1–11.

Hlinka, J., Hartman, D., Vejmelka, M., Runge, J., Marwan, N., Kurths, J., et al. (2013). Reliability of Inference of Directed Climate Networks Using Conditional Mutual Information. *Entropy* 15, 2023–2045. doi:10.3390/e15062023.

Hlinka, J., Jajcay, N., Hartman, D., and Paluš, M. (2017). Smooth information flow in temperature climate network reflects mass transport. *Chaos An Interdiscip. J. Nonlinear Sci.* 27, 035811. doi:10.1063/1.4978028.

Hochman, Z., Gobbett, D. L., and Horan, H. (2017). Climate trends account for stalled wheat yields in Australia since 1990. *Glob. Chang. Biol.* 23, 2071–2081. doi:10.1111/gcb.13604.

Hoegh-Guldberg, O., Jacob, D., Taylor, M., Bindi, M., Brown, S., Camilloni, I., et al. (2018). "Impacts of 1.5ºC Global Warming on Natural and Human Systems," in *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,* eds. V. Asson-Delmotte, P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P. R. Shukla, et al.

Hoesly, R. M., Smith, S. J., Feng, L., Klimont, Z., Janssens-Maenhout, G., Pitkanen, T., et al. (2018). Historical (1750–2014) anthropogenic emissions of reactive gases and aerosols from the Community Emissions Data System (CEDS). *Geosci. Model Dev.* 11, 369–408. doi:10.5194/gmd-11-369-2018.

Hope, P., Black, M. T., Lim, E.-P., Dowdy, A., Wang, G., Fawcett, R. J. B., et al. (2019). On Determining the Impact of Increasing Atmospheric CO 2 on the Record Fire Weather in Eastern Australia in February 2017. *Bull. Am. Meteorol. Soc.* 100, S111–S117. doi:10.1175/BAMS-D-18-0135.1.

Hope, P., Lim, E.-P., Hendon, H., and Wang, G. (2018). The Effect of Increasing CO 2 on the Extreme September 2016 Rainfall Across Southeastern Australia . *Bull. Am. Meteorol. Soc.* 99, S133–S138. doi:10.1175/bams-d-17-0094.1.

Hope, P., Wang, G., Lim, E.-P., Hendon, H. H., and Arblaster, J. M. (2016). What caused the record-breaking heat across Australia in October 2015? *Bull. Am. Meteorol. Soc.* 97, S122–S126. doi:10.1175/BAMS-D-16-0141.1.

Houghton, J. T., Ding, Y., Griggs, D. J., Noguer, M., Linden, P. J. van der, Dai, X., et al. (2001). *Climate change 2001: the scientific basis : contribution of Working Group I to the third assessment report of the Intergovernmental Panel on Climate Change*.

Houghton, J. T., Gylvan, L., Filho, M., Griggs, D. J., and Maskell, K. (1997). An Introduction to Simple Climate Models used in the IPCC Second Assessment Report. Available at: http://large.stanford.edu/courses/2015/ph240/girard1/docs/houghton.pdf [Accessed March 18, 2019].

Houghton, R. A., and Nassikas, A. A. (2017). Global and regional fluxes of carbon from land use and land cover change 1850-2015. *Global Biogeochem. Cycles* 31, 456–472. doi:10.1002/2016GB005546.

Hourdin, F., Mauritsen, T., Gettelman, A., Golaz, J.-C., Balaji, V., Duan, Q., et al. (2017). The Art and Science of Climate Model Tuning. *Bull. Am. Meteorol. Soc.* 98, 589–602. doi:10.1175/BAMS-D-15-00135.1.

House, F. B., Gruber, A., Hunt, G. E., and Mecherikunnel, A. T. (1986). History of satellite missions and measurements of the Earth Radiation Budget (1957–1984). *Rev. Geophys.* 24, 357–377. doi:10.1029/RG024i002p00357.

Howarth, C., and Painter, J. (2016). Exploring the science–policy interface on climate change: The role of the IPCC in informing local decision-making in the UK. *Palgrave Commun.* 2, 16058. doi:10.1057/palcomms.2016.58.

Howarth, R. W. (2014). A bridge to nowhere: methane emissions and the greenhouse gas footprint of natural gas. *Energy Sci. Eng.* 2, 47–60. doi:10.1002/ese3.35.

Howell, R. A. (2013). It's not (just) 'the environment, stupid!' Values, motivations, and routes to engagement of people adopting lower-carbon lifestyles. *Glob. Environ. Chang.* 23, 281–290.

Hughes, T. P., Anderson, K. D., Connolly, S. R., Heron, S. F., Kerry, J. T., Lough, J. M., et al. (2018). Spatial and temporal patterns of mass bleaching of corals in the Anthropocene. *Science (80-.).* 359, 80–83. doi:10.1126/science.aan8048.

Hulme, M. (2009). *Why we disagree about climate change: understanding controversy, inaction and opportunity*. Cambridge, UK: Cambridge University Press.

Hulme, M. (2018). "Gaps" in Climate Change Knowledge. *Environ. Humanit.* 10, 330–337. doi:10.1215/22011919-4385599.

Humboldt, A. von (1817). Sur les lignes isothermes. *Ann. Chim. Phys.* 5, 102–112.

Humphreys, W. J. (1913). Volcanic dust and other factors in the production of climatic changes, and their possible relation to ice ages. *J. Franklin Inst.* 176, 131–160. doi:10.1016/S0016-0032(13)91294-1.

Hurrell, J., Meehl, G. A., Bader, D., Delworth, T. L., Kirtman, B., and Wielicki, B. (2009). A Unified Modeling Approach to Climate System Prediction. *Bull. Am. Meteorol. Soc.* 90, 1819–1832. doi:10.1175/2009BAMS2752.1.

Intemann, K. (2015). Distinguishing Between Legitimate and Illegitimate Values in Climate Modeling. *Eur. J. Philos. Sci.* 5. doi:10.1007/s13194-014-0105-6.

IPCC-TGICA, Group, T., Support, S., Assessment, C., Panel, I., and Change, C. (2007). General Guidelines on the Use of Scenario Data for climate impact and adaptation assessment. *Finnish Environ. Inst.* 312, 66. doi:10.1144/SP312.4.

IPCC (1990). *Climate Change: The IPCC Scientific Assessment*. , eds. J. T. Houghton, G. J. Jenkins, and J. J. Ephraums Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

IPCC (1997). The Regional Impacts of Climate Change: An Assessment of Vulnerability.

IPCC (2005). Guidance notes for lead authors of the IPCC Fourth Assessment Report on addressing uncertainties. 4.

IPCC (2007). *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC)*. , eds. S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, et al. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

IPCC (2012). Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation.

IPCC (2013a). "Annex V: Contributors to the IPCC WGI Fifth Assessment Report," in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, et al. (Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press), 1477–1496. doi:10.1017/CBO9781107415324.

IPCC (2013b). "Summary for Policymakers," in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, et al. (Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press), 1–30. doi:10.1017/CBO9781107415324.004.

IPCC (2019). The Ocean and Cryosphere in a Changing Climate. A Special Report of Working Groups I and II of the

Intergovernmental Panel on Climate Change.

James, R. A., Jones, R. G., Boyd, E., Young, H. R., Otto, F. E. L., Huggel, C., et al. (2019). “Attribution: How Is It Relevant for Loss and Damage Policy and Practice? BT - Loss and Damage from Climate Change: Concepts, Methods and Policy Options,” in, eds. R. Mechler, L. M. Bouwer, T. Schinko, S. Surminski, and J. Linnerooth-Bayer (Cham: Springer International Publishing), 113–154. doi:10.1007/978-3-319-72026-5_5.

James, R., Washington, R., Schleussner, C.-F., Rogelj, J., and Conway, D. (2017). Characterizing half-a-degree difference: a review of methods for identifying regional climate responses to global warming targets. *Wiley Interdiscip. Rev. Clim. Chang.* 8, e457. doi:10.1002/wcc.457.

Jasanoff, S. (2010). A New Climate for Society. *Theory, Cult. Soc.* 27, 233–253. doi:10.1177/0263276409361497.

Jasanoff, S. (2011). “Cosmopolitan Knowledge: Climate Science and Global Civic Epistemology,” in *The Oxford Handbook of Climate Change and Society*, eds. J. S. Dryzek, R. B. Norgaard, and D. Schlosberg (Oxford University Press). doi:10.1093/oxfordhb/9780199566600.003.0009.

Jaspal, R., and Nerlich, B. (2014). When climate science became climate politics: British media representations of climate change in 1988. *Public Underst. Sci.* 23, 122–141. doi:10.1177/0963662512440219.

Jenkins, S., Leach, N., Wu, B., Nicholls, Z., and Allen, M. (2019). A minimal state-dependent impulse-response model of the atmospheric composition and surface temperature response to multi-gas emissions scenarios. Available at: https://meetingorganizer.copernicus.org/EGU2019/EGU2019-8206.pdf [Accessed March 21, 2019].

Jevrejeva, S., Moore, J. C., Grinsted, A., Matthews, A. P., and Spada, G. (2014). Trends and acceleration in global and regional sea levels since 1807. *Glob. Planet. Change* 113, 11–22. doi:10.1016/j.gloplacha.2013.12.004.

Jézéquel, A., Dépoues, V., Guillemot, H., Trolliet, M., Vanderlinden, J. P., and Yiou, P. (2018). Behind the veil of extreme event attribution. *Clim. Change* 149, 367–383. doi:10.1007/s10584-018-2252-9.

Jiang, L., and O’Neill, B. C. (2017). Global urbanization projections for the Shared Socioeconomic Pathways. *Glob. Environ. Chang.* 42, 193–199. doi:10.1016/j.gloenvcha.2015.03.008.

Jiang, X., Adames, Á. F., Zhao, M., Waliser, D., and Maloney, E. (2018). A Unified Moisture Mode Framework for Seasonality of the Madden–Julian Oscillation. *J. Clim.* 31, 4215–4224. doi:10.1175/JCLI-D-17-0671.1.

Jin, D., Oreopoulos, L., and Lee, D. (2017). Regime-based evaluation of cloudiness in CMIP5 models. *Clim. Dyn.* 48, 89–112. doi:10.1007/s00382-016-3064-0.

Jones, C. D., Arora, V., Friedlingstein, P., Bopp, L., Brovkin, V., Dunne, J., et al. (2016a). C4MIP &amp;ndash; The Coupled Climate–Carbon Cycle Model Intercomparison Project: experimental protocol for CMIP6. *Geosci. Model Dev.* 9, 2853–2880. doi:10.5194/gmd-9-2853-2016.

Jones, G. S., Stott, P. A., and Christidis, N. (2013). Attribution of observed historical near-surface temperature variations to anthropogenic and natural causes using CMIP5 simulations. *J. Geophys. Res. Atmos.* 118, 4001–4024. doi:10.1002/jgrd.50239.

Jones, G. S., Stott, P. A., and Mitchell, J. F. B. (2016b). Uncertainties in the attribution of greenhouse gas warming and implications for climate prediction. *J. Geophys. Res. Atmos.* 121, 6969–6992. doi:10.1002/2015JD024337.

Jones, P. D., Briffa, K. R., Osborn, T. J., Lough, J. M., van Ommen, T. D., Vinther, B. M., et al. (2009). High-resolution palaeoclimatology of the last millennium: a review of current status and future prospects. *The Holocene* 19, 3–49. doi:10.1177/0959683608098952.

Jones, R. N. (2014). 2. Foundations for Decision Making. *Contrib. Work. Gr. II to Fifth Assess. Rep. Intergov. Panel Clim. Chang.*, 195–228. doi:10.1017/CBO9781107415379.007.

Joos, F., Roth, R., Fuglestvedt, J. S., Peters, G. P., Enting, I. G., Von Bloh, W., et al. (2013). Carbon dioxide and climate impulse response functions for the computation of greenhouse gas metrics: a multi-model analysis. *Atmos. Chem. Phys* 13, 2793–2825. doi:10.5194/acp-13-2793-2013.

Jouzel, J. (2013). A brief history of ice core science over the last 50 yr. *Clim. Past* 9, 2525–2547. doi:10.5194/cp-9-2525-2013.

Jouzel, J., Hoffman, G., Koster, R. D., and Armegaud, A. (1998). “Model evaluations of the water isotope-climate relationships used in reconstructuring palaeotemperatures,” in *Isotope techniques in the study of environmental change: Proceedings of an International Symposium on Isotope Techniques in the Study of Past and ... and the Atmosphere*, ed. International Atomic Energy Agency (Vienna: IAEA), 485–502.

Kageyama, M., Braconnot, P., Harrison, S. P., Haywood, A. M., Jungclaus, J. H., Otto-Bliesner, B. L., et al. (2018). The PMIP4 contribution to CMIP6 – Part 1: Overview and over-arching analysis plan. *Geosci. Model Dev.* 11, 1033–1057. doi:10.5194/gmd-11-1033-2018.

Kandlikar, M., Risbey, J., and Dessai, S. (2005). Representing and communicating deep uncertainty in climate-change assessments. *Comptes Rendus Geosci.* 337, 443–455. doi:10.1016/j.crte.2004.10.010.

Karoly, D., Cohen, J., Meehl, G., Mitchell, J., Oort, A., Stouffer, R., et al. (1994). An example of fingerprint detection of greenhouse climate change. *Clim. Dyn.* 10, 97–105. doi:10.1007/BF00210339.

Karoly, D. J., Hope, P., and Jones, P. D. (1996). Decadal variations of the southern hemisphere circulation. *Int. J. Climatol.* 16. doi:10.1002/(SICI)1097-0088(199607)16:7<723::AID-JOC54>3.0.CO;2-6.

Karspeck, A. R., Stammer, D., Köhl, A., Danabasoglu, G., Balmaseda, M., Smith, D. M., et al. (2017). Comparison of the Atlantic meridional overturning circulation between 1960 and 2007 in six ocean reanalysis products. *Clim. Dyn.* 49, 957–982. doi:10.1007/s00382-015-2787-7.

Kato, T., and Ellis, J. (2016). Communicating Progress in National and Global Adaptation to Climate Change. *Clim. Chang. Expert Gr.* Paper No., 47. doi:10.1787/5jlww009v1hj-en.

Katsaros, K. B., and Brown, R. A. (1991). Legacy of the Seasat Mission for Studies of the Atmosphere and Air-Sea-Ice Interactions. *Bull. Am. Meteorol. Soc.* 72, 967–981. doi:10.1175/1520-0477(1991)072<0967:LOTSMF>2.0.CO;2.

Kawatani, Y., Hamilton, K., Gray, L. J., Osprey, S. M., Watanabe, S., and Yamashita, Y. (2019). The effects of a well-resolved stratosphere on the simulated boreal winter circulation in a climate model. *J. Atmos. Sci.* 0, JAS-D-18-0206.1. doi:10.1175/JAS-D-18-0206.1.

Kay, J. E., Deser, C., Phillips, A., Mai, A., Hannay, C., Strand, G., et al. (2015). The Community Earth System Model (CESM) Large Ensemble Project: A Community Resource for Studying Climate Change in the Presence of Internal Climate Variability. *Bull. Am. Meteorol. Soc.* 96, 1333–1349. doi:10.1175/BAMS-D-13-00255.1.

Kay, J. E., Holland, M. M., and Jahn, A. (2011). Inter-annual to multi-decadal Arctic sea ice extent trends in a warming world. *Geophys. Res. Lett.* 38. doi:10.1029/2011GL048008.

KC, S., and Lutz, W. (2017). The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. *Glob. Environ. Chang.* 42, 181–192. doi:10.1016/J.GLOENVCHA.2014.06.004.

Keeling, C. D., Bacastow, R. B., Bainbridge, A. E., Ekdahl, C. A., Guenther, P. R., Waterman, L. S., et al. (1976). Atmospheric carbon dioxide variations at Mauna Loa Observatory, Hawaii. *Tellus* 28, 538–551. doi:10.1111/j.2153-3490.1976.tb00701.x.

Kelman, I. (2015). Climate Change and the Sendai Framework for Disaster Risk Reduction. *Int. J. Disaster Risk Sci.* 6, 117–127. doi:10.1007/s13753-015-0046-5.

Kelman, I. (2017). Linking disaster risk reduction, climate change, and the sustainable development goals. *Disaster Prev. Manag.* 26, 254–258. doi:10.1108/DPM-02-2017-0043.

Kent, E. C., Woodruff, S. D., and Berry, D. I. (2007). Metadata from WMO Publication No. 47 and an Assessment of Voluntary Observing Ship Observation Heights in ICOADS. *J. Atmos. Ocean. Technol.* 24, 214–234. doi:10.1175/JTECH1949.1.

Khrgian, A. K., and Hardin, R. (1970). *Meteorology: A Historical Survey*. Jerusalem: Israel Program for Scientific Translations.

Kidson, J. W. (1999). Principal Modes of Southern Hemisphere Low-Frequency Variability Obtained from NCEP–NCAR Reanalyses. *J. Clim.* 12, 2808–2830. doi:10.1175/1520-0442(1999)012<2808:PMOSHL>2.0.CO;2.

Kim, W. M., Yeager, S., Chang, P., and Danabasoglu, G. (2018). Low-Frequency North Atlantic Climate Variability in the Community Earth System Model Large Ensemble. *J. Clim.* 31, 787–813. doi:10.1175/JCLI-D-17-0193.1.

King, A. D., Donat, M. G., Fischer, E. M., Hawkins, E., Alexander, L. V., Karoly, D. J., et al. (2015). The timing of anthropogenic emergence in simulated climate extremes. *Environ. Res. Lett.* 10, 094015. doi:10.1088/1748-9326/10/9/094015.

King, A. D., Karoly, D. J., and Henley, B. J. (2017). Australian climate extremes at 1.5 °C and 2 °C of global warming. *Nat. Clim. Chang.* 7, 412–416. doi:10.1038/nclimate3296.

Kirchmeier-Young, M. C., Gillett, N. P., Zwiers, F. W., Cannon, A. J., and Anslow, F. S. (2019). Attribution of the Influence of Human-Induced Climate Change on an Extreme Fire Season. *Earth's Futur.* 7, 2–10. doi:10.1029/2018EF001050.

Kirchmeier-Young, M. C., Zwiers, F. W., and Gillett, N. P. (2017). Attribution of Extreme Events in Arctic Sea Ice Extent. *J. Clim.* 30, 553–571. doi:10.1175/JCLI-D-16-0412.1.

Kirtman, B., Power, S. B., Adedoyin, J. A., Boer, G. J., Bojariu, R., Camilloni, I., et al. (2013). "Chapter 11: Near-term Climate Change: Projections and Predictability," in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* doi:10.1017/CBO9781107415324.023.

Klein, S. A., Zhang, Y., Zelinka, M. D., Pincus, R., Boyle, J., and Gleckler, P. J. (2013). Are climate model simulations of clouds improving? An evaluation using the ISCCP simulator. *J. Geophys. Res. Atmos.* 118, 1329–1342. doi:10.1002/jgrd.50141.

Knutti, R., Allen, M. R., Friedlingstein, P., Gregory, J. M., Hegerl, G. C., Meehl, G. A., et al. (2008). A Review of Uncertainties in Global Temperature Projections over the Twenty-First Century. *J. Clim.* 21, 2651–2663. doi:10.1175/2007JCLI2119.1.

Knutti, R., Furrer, R., Tebaldi, C., Cermak, J., and Meehl, G. A. (2010). Challenges in Combining Projections from Multiple Climate Models. *J. Clim.* 23, 2739–2758. doi:10.1175/2009JCLI3361.1.

Knutti, R., Masson, D., and Gettelman, A. (2013). Climate model genealogy: Generation CMIP5 and how we got there. *Geophys. Res. Lett.* 40, 1194–1199. doi:10.1002/grl.50256.

Knutti, R., Rogelj, J., Sedlácek, J., and Fischer, E. M. (2016). A scientific critique of the two-degree climate change target. *Nat. Geosci.* 9, 13–18. doi:10.1038/ngeo2595.

Knutti, R., Sedláček, J., Sanderson, B. M., Lorenz, R., Fischer, E. M., and Eyring, V. (2017). A climate model projection weighting scheme accounting for performance and interdependence. *Geophys. Res. Lett.* doi:10.1002/2016GL072012.

Knutti, R., Stocker, T. F., Joos, F., and Plattner, G.-K. (2003). Probabilistic climate change projections using neural networks. *Clim. Dyn.* 21, 257–272. doi:10.1007/s00382-003-0345-1.

Konsta, D., Chepfer, H., and Dufresne, J.-L. (2012). A process oriented characterization of tropical oceanic clouds for climate model evaluation, based on a statistical analysis of daytime A-train observations. *Clim. Dyn.* 39, 2091–2108. doi:10.1007/s00382-012-1533-7.

Konsta, D., Dufresne, J.-L., Chepfer, H., Idelkadi, A., and Cesana, G. (2016). Use of A-train satellite observations (CALIPSO–PARASOL) to evaluate tropical cloud properties in the LMDZ5 GCM. *Clim. Dyn.* 47, 1263–1284. doi:10.1007/s00382-015-2900-y.

Kopp, R. E., Horton, R. M., Little, C. M., Mitrovica, J. X., Oppenheimer, M., Rasmussen, D. J., et al. (2014). Probabilistic 21st and 22nd century sea-level projections at a global network of tide-gauge sites. *Earth's Futur.* 2, 383–406. doi:10.1002/2014EF000239.

Kopp, R. E., Kemp, A. C., Bittermann, K., Horton, B. P., Donnelly, J. P., Gehrels, W. R., et al. (2016). Temperature-driven global sea-level variability in the Common Era. *Proc. Natl. Acad. Sci.* 113, E1434–E1441. doi:10.1073/pnas.1517056113.

Köppen, W. (1936). "Das geographische System der Klimate," in *Handbuch der Klimatologie* (Berlin: Gebrueder Borntraeger).

Kravitz, B., Robock, A., Tilmes, S., Boucher, O., English, J. M., Irvine, P. J., et al. (2015). The Geoengineering Model Intercomparison Project Phase 6 (GeoMIP6): simulation design and preliminary results. *Geosci. Model Dev.* 8, 3379–3392. doi:10.5194/gmd-8-3379-2015.

Kriegler, E., Edmonds, J., Hallegatte, S., Ebi, K. L., Kram, T., Riahi, K., et al. (2014). A new scenario framework for climate change research: the concept of shared climate policy assumptions. *Clim. Change* 122, 401–414. doi:10.1007/s10584-013-0971-5.

Krumhardt, K. M., Lovenduski, N. S., Long, M. C., and Lindsay, K. (2017). Avoidable impacts of ocean warming on marine primary production: Insights from the CESM ensembles. *Global Biogeochem. Cycles* 31, 114–133. doi:10.1002/2016GB005528.

Kuhn, T. S. (1977). *The Essential Tension: Selected Studies in Scientific Tradition and Change*. Chicago: University of Chicago Press Available at: https://www.amazon.com/Essential-Tension-Selected-Scientific-Tradition/dp/0226458067.

Laidler, G. J. (2006). Inuit and Scientific Perspectives on the Relationship Between Sea Ice and Climate Change: The Ideal Complement? *Clim. Change* 78, 407–444. doi:10.1007/s10584-006-9064-z.

Laloyaux, P., de Boisseson, E., Balmaseda, M., Bidlot, J. R., Broennimann, S., Buizza, R., et al. (2018). CERA-20C: A Coupled Reanalysis of the Twentieth Century. *J. Adv. Model. Earth Syst.* 10, 1172–1195. doi:10.1029/2018MS001273.

Lamb, H. H. (1965). The early medieval warm epoch and its sequel. *Palaeogeogr. Palaeoclimatol. Palaeoecol.* 1, 13–37. doi:10.1016/0031-0182(65)90004-0.

Lamb, H. H. (1995). *Climate, History, and the Modern World*. London: Routledge.

Landsberg, H. E. (1961). Solar radiation at the earth's surface. *Sol. Energy* 5, 95–98. doi:10.1016/0038-092X(61)90051-2.

Lange, S., Donges, J. F., Volkholz, J., and Kurths, J. (2015). Local Difference Measures between Complex Networks for Dynamical System Model Evaluation. *PLoS One* 10, e0118088. doi:10.1371/journal.pone.0118088.

Langway Jr, C. C. (2008). *The history of early polar ice cores*. Hanover, NH: U.S. Army Engineer Research and Development Center, Cold Regions Research and Engineering Laboratory.

Lawrence, D. M., Hurtt, G. C., Arneth, A., Brovkin, V., Calvin, K. V, Jones, A. D., et al. (2016). The Land Use Model Intercomparison Project (LUMIP) contribution to CMIP6: rationale and experimental design. *Geosci. Model Dev.* 9, 2973–2998. doi:10.5194/gmd-9-2973-2016.

Laxon, S., Peacock, N., and Smith, D. (2003). High interannual variability of sea ice thickness in the Arctic region. *Nature* 425, 947–950. doi:10.1038/nature02050.

Le Roy Ladurie, E. (1967). *Histoire du climat depuis l'an mil*. Paris: Flammarion.

Le Treut, H., Sommervile, R., Cubasch, U., Ding, Y., Mauritzen, C., Mokssit, A., et al. (2007). "Historical Overview of Climate Change.," in *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Changelimate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth*, eds. S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, et al. (Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press), 93–127.

Lee, T. M., Markowitz, E. M., Howe, P. D., Ko, C.-Y., and Leiserowitz, A. A. (2015). Predictors of public climate change awareness and risk perception around the world. *Nat. Clim. Chang.* 5, 1014–1020. doi:10.1038/nclimate2728.

Legget, J. et al (1992). Emissions scenarios for the IPCC: an update. In: Climate change 1992: The Supplementary Report to the IPCC Scientific Assessment [Houghton, J.T., B.A. Callander, and S.K. Varney (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York,.

Lehner, F., Deser, C., Simpson, I. R., and Terray, L. (2018). Attributing the U.S. Southwest's Recent Shift Into Drier Conditions. *Geophys. Res. Lett.* 45, 6251–6261. doi:10.1029/2018GL078312.

Lejeune, Q., Davin, E. L., Gudmundsson, L., Winckler, J., and Seneviratne, S. I. (2018). Historical deforestation locally increased the intensity of hot days in northern mid-latitudes. *Nat. Clim. Chang.* 8, 386–390. doi:10.1038/s41558-018-0131-z.

Lenton, T. M., Held, H., Kriegler, E., Hall, J. W., Lucht, W., Rahmstorf, S., et al. (2008). Tipping elements in the Earth's climate system. *Proc. Natl. Acad. Sci.* 105, 1786–1793. doi:10.1073/pnas.0705414105.

Leonard, M., Westra, S., Phatak, A., Lambert, M., van den Hurk, B., McInnes, K., et al. (2014). A compound event framework for understanding extreme impacts. *Wiley Interdiscip. Rev. Clim. Chang.* 5, 113–128. doi:10.1002/wcc.252.

Levermann, A., Clark, P. U., Marzeion, B., Milne, G. A., Pollard, D., Radic, V., et al. (2013). The multimillennial sea-level commitment of global warming. *Proc. Natl. Acad. Sci.* 110, 13745–13750. doi:10.1073/pnas.1219414110.

Lewis, J. M. (2003). OOISHI'S OBSERVATION. *Bull. Am. Meteorol. Soc.* 84, 357–370. doi:10.1175/BAMS-84-3-357.

Lewis, S. C., and Karoly, D. J. (2013). Anthropogenic contributions to Australia's record summer temperatures of 2013. *Geophys. Res. Lett.* 40, 3705–3709. doi:10.1002/grl.50673.

Lewis, S., Karoly, D., and Yu, M. (2014). Quantitative estimates of anthropogenic contributions to extreme national and State monthly, seasonal and annual average temperatures for Australia. *Aust. Meteorol. Oceanogr. J.* 64, 215–230. Available at: http://www.bom.gov.au/amm/docs/2014/lewis2_hres.pdf [Accessed August 18, 2016].

Li, H., and Ilyina, T. (2018). Current and Future Decadal Trends in the Oceanic Carbon Uptake Are Dominated by Internal Variability. *Geophys. Res. Lett.* 45, 916–925. doi:10.1002/2017GL075370.

Li, J.-L. F., Richardson, M., Hong, Y., Lee, W.-L., Wang, Y.-H., Yu, J.-Y., et al. (2017). Improved simulation of Antarctic sea ice due to the radiative effects of falling snow. *Environ. Res. Lett.* 12, 084010. doi:10.1088/1748-9326/aa7a17.

Lisiecki, L. E., and Raymo, M. E. (2005). A Pliocene-Pleistocene stack of 57 globally distributed benthic δ 18 O records. *Paleoceanography* 20, n/a-n/a. doi:10.1029/2004PA001071.

Lohmann, U., Sausen, R., Bengtsson, L., Cubasch, U., Perlwitz, J., and Roeckner, E. (1993). The Köppen climate classification as a diagnostic tool for general circulation models. *Clim. Res.* 3, 177–193. doi:10.3354/cr003177.

Long, M. C., Deutsch, C., and Ito, T. (2016). Finding forced trends in oceanic oxygen. *Global Biogeochem. Cycles* 30, 381–397. doi:10.1002/2015GB005310.

Longino, H. E. (1990). *Science as Social Knowledge: Values and Objectivity in Scientific Inquiry*. Princeton University Press Available at: https://www.amazon.com/Science-Social-Knowledge-Objectivity-Scientific/dp/0691020515.

Lorenz, R., Herger, N., Sedláček, J., Eyring, V., Fischer, E. M., and Knutti, R. (2018). Prospects and Caveats of Weighting Climate Models for Summer Maximum Temperature Projections Over North America. *J. Geophys. Res. Atmos.* 123, 4509–4526. doi:10.1029/2017JD027992.

Louie, K., and Liu, K. (2003). Earliest historical records of typhoons in China. *J. Hist. Geogr.* 29, 299–316. doi:10.1006/jhge.2001.0453.

Lovenduski, N. S., McKinley, G. A., Fay, A. R., Lindsay, K., and Long, M. C. (2016). Partitioning uncertainty in ocean carbon uptake projections: Internal variability, emission scenario, and model structure. *Global Biogeochem. Cycles* 30, 1276–1287. doi:10.1002/2016GB005426.

Low, K. G., Grant, S. B., Hamilton, A. J., Gan, K., Saphores, J.-D., Arora, M., et al. (2015). Fighting drought with innovation: Melbourne's response to the Millennium Drought in Southeast Australia. *Wiley Interdiscip. Rev. Water* 2, 315–328. doi:10.1002/wat2.1087.

Lúcio, F. D. F., and Grasso, V. (2016). The Global Framework for Climate Services (GFCS). *Clim. Serv.* doi:10.1016/j.cliser.2016.09.001.

Ludescher, J., Gozolchiani, A., Bogachev, M. I., Bunde, A., Havlin, S., and Schellnhuber, H. J. (2014). Very early warning of next El Niño. *Proc. Natl. Acad. Sci.*, 201323058. doi:10.1073/pnas.1323058111.

Lüning, S., and Vahrenholt, F. (2017). Paleoclimatological Context and Reference Level of the 2°C and 1.5°C Paris Agreement Long-Term Temperature Limits. *Front. Earth Sci.* doi:10.3389/feart.2017.00104.

Luo, Y. Q., Randerson, J. T., Abramowitz, G., Bacour, C., Blyth, E., Carvalhais, N., et al. (2012). A framework for benchmarking land models. *Biogeosciences* 9, 3857–3874. doi:10.5194/bg-9-3857-2012.

Luterbacher, J. (2004). European Seasonal and Annual Temperature Variability, Trends, and Extremes Since 1500. *Science (80-.).* 303, 1499–1503. doi:10.1126/science.1093877.

Lüthi, D., Le Floch, M., Bereiter, B., Blunier, T., Barnola, J.-M., Siegenthaler, U., et al. (2008). High-resolution carbon dioxide concentration record 650,000–800,000 years before present. *Nature* 453, 379–382. doi:10.1038/nature06949.

Lyu, K., Zhang, X., Church, J. A., Slangen, A. B. A., and Hu, J. (2014). Time of emergence for regional sea-level change. *Nat. Clim. Chang.* 4, 1006–1010. doi:10.1038/NCLIMATE2397.

Ma, H.-Y., Xie, S., Klein, S. A., Williams, K. D., Boyle, J. S., Bony, S., et al. (2014). On the Correspondence between Mean Forecast Errors and Climate Errors in CMIP5 Models. *J. Clim.* 27, 1781–1798. doi:10.1175/JCLI-D-13-00474.1.

Ma, X., Jing, Z., Chang, P., Liu, X., Montuoro, R., Small, R. J., et al. (2016). Western boundary currents regulated by interaction between ocean eddies and the atmosphere. *Nature* 535, 533. Available at:

https://doi.org/10.1038/nature18640.

MacFarling Meure, C., Etheridge, D., Trudinger, C., Steele, P., Langenfelds, R., van Ommen, T., et al. (2006). Law Dome CO 2 , CH 4 and N 2 O ice core records extended to 2000 years BP. *Geophys. Res. Lett.* 33, L14810. doi:10.1029/2006GL026152.

Mach, K. J., Freeman, P. T., Mastrandrea, M. D., and Field, C. B. (2016). A multistage crucible of revision and approval shapes IPCC policymaker summaries. *Sci. Adv.* 2, e1600421. doi:10.1126/sciadv.1600421.

Mach, K. J., Mastrandrea, M. D., Freeman, P. T., and Field, C. B. (2017). Unleashing expert judgment in assessment. *Glob. Environ. Chang.* 44, 1–14. doi:10.1016/j.gloenvcha.2017.02.005.

Machta, L. (2002). METEOROLOGICAL BENEFITS FROM ATMOSPHERIC NUCLEAR TESTS. *Health Phys.* 82, 635–643. doi:10.1097/00004032-200205000-00010.

Mahlstein, I., Knutti, R., Solomon, S., and Portmann, R. W. (2011). Early onset of significant local warming in low latitude countries. *Environ. Res. Lett.* 6. doi:10.1088/1748-9326/6/3/034009.

Mahony, M. (2014). The predictive state: Science, territory and the future of the Indian climate. *Soc. Stud. Sci.* 44, 109–133. doi:10.1177/0306312713501407.

Mahony, M. (2015). Climate change and the geographies of objectivity: the case of the IPCC's burning embers diagram. *Trans. Inst. Br. Geogr.* 40, 153–167. doi:10.1111/tran.12064.

Malik, N., Bookhagen, B., Marwan, N., and Kurths, J. (2012). Analysis of spatial and temporal extreme monsoonal rainfall over South Asia using complex networks. *Clim. Dyn.* 39, 971–987. doi:10.1007/s00382-011-1156-4.

Manabe, S. (1970). "The Dependence of Atmospheric Temperature on the Concentration of Carbon Dioxide," in *Global Effects of Environmental Pollution*, ed. S. F. Singer (Dordrecht: Springer Netherlands), 25–29. doi:10.1007/978-94-010-3290-2_4.

Manabe, S., Bryan, K., and Spelman, M. J. (1975). A Global Ocean-Atmosphere Climate Model. Part I. The Atmospheric Circulation. *J. Phys. Oceanogr.* 5, 3–29. doi:10.1175/1520-0485(1975)005<0003:AGOACM>2.0.CO;2.

Manabe, S., and Möller, F. (1961). On the Radiative Equilibrium and Heat Balance of the AtmosphereE. *Mon. Weather Rev.* 89, 503–532. doi:10.1175/1520-0493(1961)089<0503:OTREAH>2.0.CO;2.

Manabe, S., and Stouffer, R. J. (1993). Century-scale effects of increased atmospheric C02 on the ocean–atmosphere system. *Nature* 364, 215–218. doi:10.1038/364215a0.

Manabe, S., and Stouffer, R. J. (1994). Multiple-Century Response of a Coupled Ocean–Atmosphere Model to an Increase of Atmospheric Carbon Dioxide. *J. Clim.* 7, 5–23. doi:10.2307/26197823.

Mann, M. E., Bradley, R. S., and Hughes, M. K. (1999). Northern hemisphere temperatures during the past millennium: Inferences, uncertainties, and limitations. *Geophys. Res. Lett.* 26, 759–762. doi:10.1029/1999GL900070@10.1002/(ISSN)1944-8007.GRL40.

Mann, M. E., Miller, S. K., Rahmstorf, S., Steinman, B. A., and Tingley, M. (2017). Record temperature streak bears anthropogenic fingerprint. *Geophys. Res. Lett.* 44, 7936–7944. doi:10.1002/2017GL074056.

Marcos, M., and Amores, A. (2014). Quantifying anthropogenic and natural contributions to thermosteric sea level rise. *Geophys. Res. Lett.* 41, 2502–2507. doi:10.1002/2014GL059766.

Martín-Gómez, V., and Barreiro, M. (2016). Analysis of oceans' influence on spring time rainfall variability over Southeastern South America during the 20th century. *Int. J. Climatol.* 36, 1344–1358. doi:10.1002/joc.4428.

Martín-Gómez, V., and Barreiro, M. (2017). Effect of future climate change on the coupling between the tropical oceans and precipitation over Southeastern South America. *Clim. Change* 141, 315–329. doi:10.1007/s10584-016-1888-6.

Martins, E.S.P.R., Coelho, C.A.S., Haarsma, R., Otto, F.E.L., King, A.D., van Oldenborgh, G.J., Kew, S., Philip, S., Vasconcelos Junior, F.C. and Cullen, H. (2017). A multimethod attribution analysis of the prolonged Northeast Brazil hydrometeorological drought (2012-16). *Bull. Am. Meteorol. Soc.* 98, 65–68.

Marvel, K., Schmidt, G. A., Shindell, D., Bonfils, C., LeGrande, A. N., Nazarenko, L., et al. (2015). Do responses to different anthropogenic forcings add linearly in climate models? *Environ. Res. Lett.* 10, 104010. doi:10.1088/1748-9326/10/10/104010.

Marwan, N., and Kurths, J. (2015). Complex network based techniques to identify extreme events and (sudden) transitions in spatio-temporal systems. *Chaos An Interdiscip. J. Nonlinear Sci.* 25, 097609. doi:10.1063/1.4916924.

Masina, S., Storto, A., Ferry, N., Valdivieso, M., Haines, K., Balmaseda, M., et al. (2017). An ensemble of eddy-permitting global ocean reanalyses from the MyOcean project. *Clim. Dyn.* 49, 813–841. doi:10.1007/s00382-015-2728-5.

Masson-Delmotte, V., Schulz, M., Abe-Ouchi, A., Beer, J., Ganopolski, A., González Rouco, J. F., et al. (2013). "Information from Paleoclimate Archives," in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, et al. (Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press), 383–464. doi:10.1017/CBO9781107415324.013.

Masson, D., and Knutti, R. (2011). Climate model genealogy. *Geophys. Res. Lett.* 38, n/a-n/a. doi:10.1029/2011GL046864.

Massonnet, F., Vancoppenolle, M., Goosse, H., Docquier, D., Fichefet, T., and Blanchard-Wrigglesworth, E. (2018). Arctic sea-ice change tied to its mean state through thermodynamic processes. *Nat. Clim. Chang.* 8, 599–603. doi:10.1038/s41558-018-0204-z.

Mastrandrea, M. D., Field, C. B., Stocker, T. F., Edenhofer, O., Ebi, K. L., Frame, D. J., et al. (2010). Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties. Intergovernmental Panel on Climate Change (IPCC). IPCC guidance note. 7 pp.

Mastrandrea, M. D., and Mach, K. J. (2011). Treatment of uncertainties in IPCC Assessment Reports: past approaches and considerations for the Fifth Assessment Report. *Clim. Change* 108, 659–673. doi:10.1007/s10584-011-0177-7.

Mastrandrea, M. D., Mach, K. J., Plattner, G.-K., Edenhofer, O., Stocker, T. F., Field, C. B., et al. (2011). The IPCC AR5 guidance note on consistent treatment of uncertainties: a common approach across the working groups. *Clim. Change* 108, 675–691. doi:10.1007/s10584-011-0178-6.

Matthes, K., Funke, B., Andersson, M. E., Barnard, L., Beer, J., Charbonneau, P., et al. (2017a). Solar forcing for CMIP6 (v3.2). *Geosci. Model Dev.* 10, 2247–2302. doi:10.5194/gmd-10-2247-2017.

Matthes, K., Funke, B., Andersson, M. E., Barnard, L., Beer, J., Charbonneau, P., et al. (2017b). Solar forcing for CMIP6 (v3.2). *Geosci. Model Dev.* 10, 2247–2302. doi:10.5194/gmd-10-2247-2017.

Maury, M. F. (1855). *The Physical Geography of the Sea*. New York: Harper & Brothers.

Maury, M. F. (1860). *The Physical Geography of the Sea, and its Meteorology*. New York: Harper & Brothers.

Maury, M. F., and United States Naval Observatory (1849). *Wind and Current Charts of the North and South Atlantic*. Washington: National Observatory.

McBean, G. A. (2012). Integrating disaster risk reduction towards sustainable development. *Curr. Opin. Environ. Sustain.* 4, 122–127. doi:10.1016/j.cosust.2012.01.002.

McCright, A. M., and Dunlap, R. E. (2011). Cool dudes: The denial of climate change among conservative white males in the United States. *Glob. Environ. Chang.* 21, 1163–1172. doi:10.1016/j.gloenvcha.2011.06.003.

McIntyre, A., Moore, T. C., Andersen, B., Balsam, W., Bé, A., Brunner, C., et al. (1976). The Surface of the Ice-Age Earth. *Science (80-.).* 191, 1131–1137. doi:10.1126/science.191.4232.1131.

McKinley, G. A., Fay, A. R., Lovenduski, N. S., and Pilcher, D. J. (2017). Natural Variability and Anthropogenic Trends in the Ocean Carbon Sink. *Ann. Rev. Mar. Sci.* 9, 125–150. doi:10.1146/annurev-marine-010816-060529.

McKinley, G. A., Pilcher, D. J., Fay, A. R., Lindsay, K., Long, M. C., and Lovenduski, N. S. (2016). Timescales for detection of trends in the ocean carbon sink. *Nature* 530, 469. Available at: https://doi.org/10.1038/nature16958.

McKinnon, K. A., and Deser, C. (2018). Internal Variability and Regional Climate Trends in an Observational Large Ensemble. *J. Clim.* 31, 6783–6802. doi:10.1175/JCLI-D-17-0901.1.

Meadows, D. H., Meadows, D. L., Randers, J., and Behrens III, W. W. (1972). *The Limits to Growth: A Report for the Club of Rome's Project on the Predicament of Mankind*. New York: Universe Books.

Medicine, I. of, Engineering, N. A. of, Sciences, N. A. of, and Science and Public Policy Committee on, E. (2009). *On Being a Scientist: A Guide to Responsible Conduct in Research*. National Academies Press Available at: https://www.amazon.com/Being-Scientist-Responsible-Research-Foundations/dp/0309119707.

Meehl, G. A., Boer, G. J., Covey, C., Latif, M., and Stouffer, R. J. (2000). The Coupled Model Intercomparison Project (CMIP). *Bull. Am. Meteorol. Soc.* 81, 313–318. doi:10.1175/1520-0477(2000)081<0313:TCMIPC>2.3.CO;2.

Meehl, G. A., Covey, C., Delworth, T., Latif, M., McAvaney, B., Mitchell, J. F. B., et al. (2007a). THE WCRP CMIP3 Multimodel Dataset: A New Era in Climate Change Research. *Bull. Am. Meteorol. Soc.* 88, 1383–1394. doi:10.1175/BAMS-88-9-1383.

Meehl, G. A., Stocker, T. F., Collins, W. D., Friedlingstein, P., Gaye, A. T., Gregory, J. M., et al. (2007b). Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.

Meinshausen, M., Raper, S. C. B., and Wigley, T. M. L. (2011a). Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – Part 1: Model description and calibration. *Atmos. Chem. Phys.* 11, 1417–1456. doi:10.5194/acp-11-1417-2011.

Meinshausen, M., Smith, S. J., Calvin, K., Daniel, J. S., Kainuma, M. L. T., Lamarque, J.-F., et al. (2011b). The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. *Clim. Change* 109, 213–241. doi:10.1007/s10584-011-0156-z.

Meinshausen, M., Vogel, E., Nauels, A., Lorbacher, K., Meinshausen, N., Etheridge, D. M., et al. (2017). Historical greenhouse gas concentrations for climate modelling (CMIP6). *Geosci. Model Dev.* 10, 2057–2116. doi:10.5194/gmd-10-2057-2017.

Meinshausen, M., Wigley, T. M. L., and Raper, S. C. B. (2011c). Emulating atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – Part 2: Applications. *Atmos. Chem. Phys.* 11, 1457–1471. doi:10.5194/acp-11-1457-2011.

Members WAIS Divide Project, Buizert, C., Adrian, B., Ahn, J., Albert, M., Alley, R. B., et al. (2015). Precise interpolar phasing of abrupt climate change during the last ice age. *Nature* 520, 661–665. doi:10.1038/nature14401.

Meredith, E. P., Semenov, V. A., Maraun, D., Park, W., and Chernokulsky, A. V. (2015). Crucial role of Black Sea warming in amplifying the 2012 Krymsk precipitation extreme. *Nat. Geosci.* 8, 615.

Milankovich, M. (1920). *Théorie mathématique des phénomènes thermiques produits par la radiation solaire*. Paris: Gauthier-Villars et Cie.

Millar, R. J., Fuglestvedt, J. S., Friedlingstein, P., Rogelj, J., Grubb, M. J., Matthews, H. D., et al. (2017). Emission budgets and pathways consistent with limiting warming to 1.5 °C. *Nat. Geosci.* 10, 741–747. doi:10.1038/ngeo3031.

Mills, M. J., Toon, O. B., Lee-Taylor, J., and Robock, A. (2014). Multidecadal global cooling and unprecedented ozone loss following a regional nuclear conflict. *Earth's Futur.* 2, 161–176. doi:10.1002/2013EF000205.

Mitchell, J. F. B., Johns, T. C., Ingram, W. J., and Lowe, J. A. (2000). The effect of stabilising atmospheric carbon dioxide concentrations on global and regional climate change. *Geophys. Res. Lett.* 27, 2977–2980. doi:10.1029/1999GL011213.

Mitchell, T. D. (2003). Pattern Scaling: An Examination of the Accuracy of the Technique for Describing Future Climates. *Clim. Change* 60, 217–242. doi:10.1023/A:1026035305597.

Moezzi, M., Janda, K. B., and Rotmann, S. (2017). Using stories, narratives, and storytelling in energy and climate change research. *Energy Res. Soc. Sci.* 31, 1–10. doi:10.1016/j.erss.2017.06.034.

Morgenstern, O., Hegglin, M. I., Rozanov, E., O&apos;Connor, F. M., Abraham, N. L., Akiyoshi, H., et al. (2017). Review of the global models used within phase 1 of the Chemistry–Climate Model Initiative (CCMI). *Geosci. Model Dev.* 10, 639–671. doi:10.5194/gmd-10-639-2017.

Mori, M., Kosaka, Y., Watanabe, M., Nakamura, H., and Kimoto, M. (2019). A reconciled estimate of the influence of Arctic sea-ice loss on recent Eurasian cooling. *Nat. Clim. Chang.* 9, 123–129. doi:10.1038/s41558-018-0379-3.

Morice, C. P., Kennedy, J. J., Rayner, N. A., and Jones, P. D. (2012). Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: The HadCRUT4 data set. *J. Geophys. Res. Atmos.* doi:10.1029/2011JD017187.

Mormino, J., Sola, D., and Patten, C. (1975). Climatic Impact Assessment Program: Development and Accomplishments, 1971-1975. U. S. Dept. of Transportation, Climatic Impact Assessment Program Office Available at: hdl.handle.net/2027/mdp.39015039968873.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., et al. (2010). The next generation of scenarios for climate change research and assessment. *Nature* 463, 747. Available at: http://dx.doi.org/10.1038/nature08823.

Moss, R. H., and Schneider, S. H. (2000). Uncertainties in the IPCC TAR: Recommendations to lead authors for more consistent assessment and reporting. In: Guidance Papers on the Cross Cutting Issues of the Third Assessment Report of the IPCC. 33–51.

Mote, P. W., Allen, M. R., Jones, R. G., Li, S., Mera, R., Rupp, D. E., et al. (2015). Superensemble Regional Climate Modeling for the Western United States. *Bull. Am. Meteorol. Soc.* 97, 203–215. doi:10.1175/BAMS-D-14-00090.1.

Mueller, B. L., Gillett, N. P., Monahan, A. H., and Zwiers, F. W. (2018). Attribution of Arctic Sea Ice Decline from 1953 to 2012 to Influences from Natural, Greenhouse Gas, and Anthropogenic Aerosol Forcing. *J. Clim.* 31, 7771–7787. doi:10.1175/JCLI-D-17-0552.1.

Muller-Karger, F. E., Miloslavich, P., Bax, N. J., Simmons, S., Costello, M. J., Sousa Pinto, I., et al. (2018). Advancing Marine Biological Observations and Data Requirements of the Complementary Essential Ocean Variables (EOVs) and Essential Biodiversity Variables (EBVs) Frameworks. *Front. Mar. Sci.* 5. doi:10.3389/fmars.2018.00211.

Muller, R. A., Rohde, R., Jacobsen, R., Muller, E., and Wickham, C. (2013). A New Estimate of the Average Earth Surface Land Temperature Spanning 1753 to 2011. *Geoinformatics Geostatistics An Overv.* 01. doi:10.4172/2327-4581.1000101.

Myhre, G., Forster, P. M., Samset, B. H., Hodnebrog, Ø., Sillmann, J., Aalbergsjø, S. G., et al. (2017). PDRMIP: A Precipitation Driver and Response Model Intercomparison Project—Protocol and Preliminary Results. *Bull. Am. Meteorol. Soc.* 98, 1185–1198. doi:10.1175/BAMS-D-16-0019.1.

Myhre, G., Shindell, D. T., Breon, F.-M., Collins, W. J., Fuglestvedt, J. S., Huang, J., et al. (2013). "Anthropogenic and Natural Radiative Forcing - Supplementary Material," in *Climate Change 2013 - The Physical Science Basis*, 44.

Nabat, P., Somot, S., Mallet, M., Sanchez-Lorenzo, A., and Wild, M. (2014). Contribution of anthropogenic sulfate aerosols to the changing Euro-Mediterranean climate since 1980. *Geophys. Res. Lett.* 41, 5605–5611. doi:10.1002/2014GL060798.

Nakashima, D. J., United Nations University. Traditional Knowledge Initiative., K., Unesco., H., Ramos-Castillo, A., and Rubis, J. (2012). *Weathering uncertainity : traditional knowledge for climate change assessment and adaptation*. UNESCO Available at: https://collections.unu.edu/view/UNU:1511 [Accessed March 21, 2019].

Nakicenovic, N., Lempert, R. J., and Janetos, A. C. (2014). A Framework for the Development of New Socio-economic Scenarios for Climate Change Research: Introductory Essay. *Clim. Change* 122, 351–361. doi:10.1007/s10584-013-0982-2.

Nakicenovic, N., and Swart, R. (2000). IPCC Special Report on Emissions Scenarios: A special report of Working Group III of the Intergovernmental Panel on Climate Change. *Emiss. Scenar.*, 608.

Nash, D. J., De Cort, G., Chase, B. M., Verschuren, D., Nicholson, S. E., Shanahan, T. M., et al. (2016). African hydroclimatic variability during the last 2000 years. *Quat. Sci. Rev.* 154, 1–22. doi:10.1016/j.quascirev.2016.10.012.

National Academies of Sciences Engineering and Medicine (2016). *Attribution of Extreme Weather Events in the Context of Climate Change*. doi:10.17226/21852.

National Research Council; Ad Hoc Study Group on Carbon Dioxide and Climate (1979). Carbon Dioxide and Climate. Washington, D.C.: National Academies Press doi:10.17226/12181.

Navarro, L. M., Fernández, N., Guerra, C., Guralnick, R., Kissling, W. D., Londoño, M. C., et al. (2017). Monitoring biodiversity change through effective global coordination. *Curr. Opin. Environ. Sustain.* 29, 158–169. doi:10.1016/j.cosust.2018.02.005.

Nebeker, F. (1995). *Calculating the Weather: Meteorology in the 20th Century*. New York: Academic Press.

Neukom, R., and Gergis, J. (2012). Southern Hemisphere high-resolution palaeoclimate records of the last 2000 years. *The Holocene* 22, 501–524. doi:10.1177/0959683611427335.

Neukom, R., Gergis, J., Karoly, D. J., Wanner, H., Curran, M., Elbert, J., et al. (2014). Inter-hemispheric temperature variability over the past millennium. *Nat. Clim. Chang.* 4, 362–367. doi:10.1038/nclimate2174.

Newman, T. P. (2017). Tracking the release of IPCC AR5 on Twitter: Users, comments, and sources following the release of the Working Group I Summary for Policymakers. *Public Underst. Sci.* 26, 815–825. doi:10.1177/0963662516628477.

Nordhaus, W. D. (1977). Strategies for the control of carbon dioxide. Cowles Foundation Discussion Paper No. 443. New Have: Yale University Available at: https://ideas.repec.org/p/cwl/cwldpp/443.html.

Notz, D., Jahn, A., Holland, M., Hunke, E., Massonnet, F., Stroeve, J., et al. (2016). The CMIP6 Sea-Ice Model Intercomparison Project (SIMIP): understanding sea ice through climate-model simulations. *Geosci. Model Dev.* 9, 3427–3446. doi:10.5194/gmd-9-3427-2016.

Notz, D., and Stroeve, J. (2016). Observed Arctic sea-ice loss directly follows anthropogenic CO2 emission. *Science (80-.).* doi:10.1126/science.aag2345.

Notz, D., and Stroeve, J. (2018). The Trajectory Towards a Seasonally Ice-Free Arctic Ocean. *Curr. Clim. Chang. Reports* 4, 407–416. doi:10.1007/s40641-018-0113-2.

Nowicki, S. M. J., Payne, A., Larour, E., Seroussi, H., Goelzer, H., Lipscomb, W., et al. (2016). Ice Sheet Model Intercomparison Project (ISMIP6) contribution to CMIP6. *Geosci. Model Dev.* 9, 4521–4545. doi:10.5194/gmd-9-4521-2016.

Nunan, F. (2017). *Making Climate Dompatible Development Happen*. doi:10.4324/9781315621579.

O'Connor, F. M., Boucher, O., Gedney, N., Jones, C. D., Folberth, G. A., Coppell, R., et al. (2010). Possible role of wetlands, permafrost, and methane hydrates in the methane cycle under future climate change: A review. *Rev. Geophys.* 48, RG4005. doi:10.1029/2010RG000326.

O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., et al. (2017a). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Glob. Environ. Chang.* 42, 169–180. doi:10.1016/j.gloenvcha.2015.01.004.

O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., et al. (2017b). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Glob. Environ. Chang.* 42, 169–180. doi:10.1016/j.gloenvcha.2015.01.004.

O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., et al. (2014). A new scenario framework for climate change research: The concept of shared socioeconomic pathways. *Clim. Change* 122, 387–400. doi:10.1007/s10584-013-0905-2.

O'Neill, B. C., Oppenheimer, M., Warren, R., Hallegatte, S., Kopp, R. E., Pörtner, H. O., et al. (2017c). IPCC reasons for concern regarding climate change risks. *Nat. Clim. Chang.* 7, 28–37. doi:10.1038/nclimate3179.

O'Neill, S., Williams, H. T. P., Kurz, T., Wiersma, B., and Boykoff, M. (2015). Dominant frames in legacy and social media coverage of the IPCC Fifth Assessment Report. *Nat. Clim. Chang.* 5, 380–385. doi:10.1038/nclimate2535.

O&apos;Neill, B. C., Tebaldi, C., van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., et al. (2016). The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geosci. Model Dev.* 9, 3461–3482. doi:10.5194/gmd-9-3461-2016.

Oppenheimer, M., Campos, M., Warren, R., Birkmann, J., Luber, G., O'Neill, B., et al. (2014). "Emergent risks and key vulnerabilities," in *Climate Change 2014 Impacts, Adaptation and Vulnerability: Part A: Global and Sectoral Aspects* doi:10.1017/CBO9781107415379.024.

Oppenheimer, M., Little, C. M., and Cooke, R. M. (2016). Expert judgement and uncertainty quantification for climate change. *Nat. Clim. Chang.* 6, 445–451. doi:10.1038/nclimate2959.

Orlove, B., Roncoli, C., Kabugo, M., and Majugu, A. (2010). Indigenous climate knowledge in southern Uganda: the multiple components of a dynamic regional system. *Clim. Change* 100, 243–265. doi:10.1007/s10584-009-9586-2.

Orr, J. C., Najjar, R. G., Aumont, O., Bopp, L., Bullister, J. L., Danabasoglu, G., et al. (2017). Biogeochemical protocols and diagnostics for the CMIP6 Ocean Model Intercomparison Project (OMIP). *Geosci. Model Dev.* 10, 2169–2199. doi:10.5194/gmd-10-2169-2017.

Otto, A., Otto, F. E. L., Boucher, O., Church, J., Hegerl, G., Forster, P. M., et al. (2013). Energy budget constraints on climate response. *Nat. Geosci.* 6, 415–416. doi:10.1038/ngeo1836.

Otto, F. E. L. (2017). Attribution of Weather and Climate Events. *Annu. Rev. Environ. Resour.* 42, 627–646. doi:10.1146/annurev-environ-102016-060847.

Otto, F. E. L., Boyd, E., Jones, R. G., Cornforth, R. J., James, R., Parker, H. R., et al. (2015a). Attribution of extreme weather events in Africa: a preliminary exploration of the science and policy implications. *Clim. Change* 132, 531–543. doi:10.1007/s10584-015-1432-0.

Otto, F. E. L., Haustein, K., Uhe, P., Coelho, C. A. S., Aravequia, J. A., Almeida, W., et al. (2015b). Factors Other Than Climate Change, Main Drivers of 2014/15 Water Shortage in Southeast Brazil. *Bull. Am. Meteorol. Soc.* 96, S35–S40. doi:10.1175/BAMS-D-15-00120.1.

Otto, F. E. L., Van Der Wiel, K., Van Oldenborgh, G. J., Philip, S., Kew, S. F., Uhe, P., et al. (2018). Climate change increases the probability of heavy rains in Northern England/Southern Scotland like those of storm Desmond - A real-time event attribution revisited. *Environ. Res. Lett.* 13, 024006. doi:10.1088/1748-9326/aa9663.

Otto, F. E. L., van Oldenborgh, G. J., Eden, J., Stott, P. A., Karoly, D. J., and Allen, M. R. (2016). The attribution question. *Nat. Clim. Chang.* 6, 813–816. doi:10.1038/nclimate3089.

Paeth, H., Pollinger, F., and Ring, C. (2017). Detection and attribution of multivariate climate change signals using discriminant analysis and Bayesian theorem. *J. Clim.* 30, 7757–7776. doi:10.1175/JCLI-D-16-0850.1.

PAGES 2k Consortium (2013). Continental-scale temperature variability during the past two millennia. *Nat. Geosci.* 6, 339–346. doi:10.1038/ngeo1797.

PAGES Hydro2k Consortium (2017). Comparing proxy and model estimates of hydroclimate variability and change over the Common Era. *Clim. Past* 13, 1851–1900. doi:10.5194/cp-13-1851-2017.

Painter, J. (2015). Disaster, uncertainty, opportunity or risk? Key messages from the television coverage of the IPCC's 2013/2014 reports. *Mètode Rev. difusió la Investig.* doi:10.7203/metode.85.4179.

Palanisamy, H., Meyssignac, B., Cazenave, A., and Delcroix, T. (2015). Is anthropogenic sea level fingerprint already detectable in the Pacific Ocean? *Environ. Res. Lett.* 10. doi:10.1088/1748-9326/10/8/084024.

Palmer, J. G., Cook, E. R., Turney, C. S. M., Allen, K., Fenwick, P., Cook, B. I., et al. (2015). Drought variability in the eastern Australia and New Zealand summer drought atlas (ANZDA, CE 1500–2012) modulated by the Interdecadal Pacific Oscillation. *Environ. Res. Lett.* 10, 124002. doi:10.1088/1748-9326/10/12/124002.

Palmer, M. D., Roberts, C. D., Balmaseda, M., Chang, Y.-S., Chepurin, G., Ferry, N., et al. (2017). Ocean heat content variability and change in an ensemble of ocean reanalyses. *Clim. Dyn.* 49, 909–930. doi:10.1007/s00382-015-2801-0.

Palmer, T. N., Doblas-Reyes, F. J., Weisheimer, A., and Rodwell, M. J. (2008). Toward Seamless Prediction: Calibration of Climate Change Projections Using Seasonal Forecasts. *Bull. Am. Meteorol. Soc.* 89, 459–470. doi:10.1175/BAMS-89-4-459.

Panel on Weather and Climate Modification, N. A. of S. (1966). *Weather and Climate Modification: Problems and Prospects*. Washington D.C.: National Academy of Sciences, National Research Council.

Parajuli, S. P., Yang, Z.-L., and Lawrence, D. M. (2016). Diagnostic evaluation of the Community Earth System Model in simulating mineral dust emission with insight into large-scale dust storm mobilization in the Middle East and North Africa (MENA). *Aeolian Res.* 21, 21–35. doi:10.1016/j.aeolia.2016.02.002.

Parker, H. R., Boyd, E., Cornforth, R. J., James, R., Otto, F. E. L., and Allen, M. R. (2017). Stakeholder perceptions of event attribution in the loss and damage debate. *Clim. Policy* 17, 533–550. doi:10.1080/14693062.2015.1124750.

Parker, W. S., and Winsberg, E. (2018). Values and evidence: how models make a difference. *Eur. J. Philos. Sci.* 8, 125–142. doi:10.1007/s13194-017-0180-6.

Parrenin, F., Masson-Delmotte, V., Kohler, P., Raynaud, D., Paillard, D., Schwander, J., et al. (2013). Synchronous Change of Atmospheric CO2 and Antarctic Temperature During the Last Deglacial Warming. *Science (80-.).* 339, 1060–1063. doi:10.1126/science.1226368.

Past Interglacials Working Group of PAGES (2016). Interglacials of the last 800,000 years. *Rev. Geophys.* 54, 162–219. doi:10.1002/2015RG000482.

Pattyn, F. (2018). The paradigm shift in Antarctic ice sheet modelling. *Nat. Commun.* 9, 2728. doi:10.1038/s41467-018-05003-z.

Paulsen, H., Ilyina, T., Six, K. D., and Stemmler, I. (2017). Incorporating a prognostic representation of marine nitrogen fixers into the global ocean biogeochemical model HAMOCC. *J. Adv. Model. Earth Syst.* 9, 438–464. doi:10.1002/2016MS000737.

Pearce, W., Holmberg, K., Hellsten, I., and Nerlich, B. (2014). Climate Change on Twitter: Topics, Communities and Conversations about the 2013 IPCC Working Group 1 Report. *PLoS One* 9, e94785. doi:10.1371/journal.pone.0094785.

Pearce, W., Niederer, S., Özkula, S. M., and Sánchez Querubín, N. (2019). The social media life of climate change: Platforms, publics, and future imaginaries. *Wiley Interdiscip. Rev. Clim. Chang.* 10, e569. doi:10.1002/wcc.569.

Pecl, G. T., Araújo, M. B., Bell, J. D., Blanchard, J., Bonebrake, T. C., Chen, I.-C., et al. (2017). Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. *Science (80-.).* 355, eaai9214. doi:10.1126/science.aai9214.

Pedro, J. B., Jochum, M., Buizert, C., He, F., Barker, S., and Rasmussen, S. O. (2018). Beyond the bipolar seesaw: Toward a process understanding of interhemispheric coupling. *Quat. Sci. Rev.* 192, 27–46. doi:10.1016/j.quascirev.2018.05.005.

Peel, M. C., Finlayson, B. L., and McMahon, T. A. (2007). Updated world map of the Köppen-Geiger climate classification. *Hydrol. Earth Syst. Sci.* 11, 1633–1644. doi:10.5194/hess-11-1633-2007.

Pendergrass, A. G., and Deser, C. (2017). Climatological Characteristics of Typical Daily Precipitation. *J. Clim.* 30, 5985–6003. doi:10.1175/JCLI-D-16-0684.1.

Pepler, A., Dowdy, A., and Hope, P. (2018). A global climatology of surface anticyclones, their variability, associated drivers and long-term trends. *Clim. Dyn.* doi:10.1007/s00382-018-4451-5.

Persad, G. G., Paynter, D. J., Ming, Y., and Ramaswamy, V. (2017). Competing atmospheric and surface-driven impacts of absorbing aerosols on the East Asian summertime climate. *J. Clim.* 30, 8929–8949. doi:10.1175/JCLI-D-16-0860.1.

Peterson, T. C., Stott, P. A., and Herring, S. (2012). Explaining extreme events of 2011 from a climate perspective. *Bull. Am. Meteorol. Soc.* 93, 1041–1067. doi:10.1175/BAMS-D-12-00021.1.

Peterson, T., Hoerling, M., Stott, P., and Herring, S. (2013). Explaining extreme events of 2012 from a climate perspective. *Bull. Am. Meteorol. Soc.* 94, S1–S74. Available at: http://journals.ametsoc.org/doi/pdf/10.1175/BAMS-D-13-00085.1.

Pfeffer, W. T., Arendt, A. A., Bliss, A., Bolch, T., Cogley, J. G., Gardner, A. S., et al. (2014). The Randolph Glacier Inventory: a globally complete inventory of glaciers. *J. Glaciol.* 60, 537–552. doi:10.3189/2014JoG13J176.

Pfister, P. L., and Stocker, T. F. (2016). Earth system commitments due to delayed mitigation. *Environ. Res. Lett.* 11, 014010. doi:10.1088/1748-9326/11/1/014010.

Pfister, P. L., and Stocker, T. F. (2017). State-Dependence of the Climate Sensitivity in Earth System Models of Intermediate Complexity. *Geophys. Res. Lett.* 44, 10,643-10,653. doi:10.1002/2017GL075457.

Pfister, P. L., and Stocker, T. F. (2018). The realized warming fraction: a multi-model sensitivity study. *Environ. Res. Lett.* 13, 124024. doi:10.1088/1748-9326/aaebae.

Pfleiderer, P., Schleussner, C.-F., Mengel, M., and Rogelj, J. (2018). Global mean temperature indicators linked to warming levels avoiding climate risks. *Environ. Res. Lett.* doi:10.1088/1748-9326/aac319.

Philip, S., Kew, S. F., Jan van Oldenborgh, G., Otto, F., O'Keefe, S., Haustein, K., et al. (2018a). Attribution Analysis of the Ethiopian Drought of 2015. *J. Clim.* 31, 2465–2486. doi:10.1175/JCLI-D-17-0274.1.

Philip, S., Sparrow, S., Kew, S. F. F., van der Wiel, K., Wanders, N., Singh, R., et al. (2018b). Attributing the 2017 Bangladesh floods from meteorological and hydrological perspectives. *Hydrol. Earth Syst. Sci. Discuss.* 2018, 1–32. doi:10.5194/hess-2018-379.

Phillips, A. S., Deser, C., and Fasullo, J. (2014). Evaluating Modes of Variability in Climate Models. *Eos, Trans. Am. Geophys. Union* 95, 453–455. doi:10.1002/2014EO490002.

Phillips, N. A. (1956). The general circulation of the atmosphere: A numerical experiment. *Q. J. R. Meteorol. Soc.* 82, 123–164. doi:10.1002/qj.49708235202.

Phillips, T. J., Potter, G. L., Williamson, D. L., Cederwall, R. T., Boyle, J. S., Fiorino, M., et al. (2004). Evaluating Parameterizations in General Circulation Models: Climate Simulation Meets Weather Prediction. *Bull. Am. Meteorol. Soc.* 85, 1903–1916. doi:10.1175/BAMS-85-12-1903.

Pielke, R., Wigley, T., and Green, C. (2008). Dangerous assumptions. *Nature* 452, 531–532. doi:10.1038/452531a.

Pincus, R., Forster, P. M., and Stevens, B. (2016). The Radiative Forcing Model Intercomparison Project (RFMIP): experimental protocol for CMIP6. *Geosci. Model Dev.* 9, 3447–3460. doi:10.5194/gmd-9-3447-2016.

Plass, G. N. (1961). The Influence of Infrared Absorptive Molecules on the Climate. *Ann. N. Y. Acad. Sci.* 95, 61–71. doi:10.1111/j.1749-6632.1961.tb50025.x.

Plattner, G.-K., Knutti, R., Joos, F., Stocker, T. F., von Bloh, W., Brovkin, V., et al. (2008). Long-Term Climate Commitments Projected with Climate–Carbon Cycle Models. *J. Clim.* 21, 2721–2751. doi:10.1175/2007JCLI1905.1.

Poli, P., Hersbach, H., Dee, D. P., Berrisford, P., Simmons, A. J., Vitart, F., et al. (2016). ERA-20C: An atmospheric reanalysis of the twentieth century. *J. Clim.* 29, 4083–4097. doi:10.1175/JCLI-D-15-0556.1.

Popper, S. K. R. (1959). *The Logic of Scientific Discovery*. New York: Basic Books.

Porter, C., Morin, P., Howat, I., Noh, M.-J., Bates, B., Peterman, K., et al. (2018). *ArcticDEM*. V1 ed. Harvard Dataverse doi:10.7910/DVN/OHHUKH.

Poulsen, M. B., Jochum, M., and Nuterman, R. (2018). Parameterized and resolved Southern Ocean eddy compensation. *Ocean Model.* 124, 1–15. doi:https://doi.org/10.1016/j.ocemod.2018.01.008.

Prabhat, Rübel, O., Byna, S., Wu, K., Li, F., Wehner, M., et al. (2012). TECA: A Parallel Toolkit for Extreme Climate Analysis. *Procedia Comput. Sci.* 9, 866–876. doi:10.1016/j.procs.2012.04.093.

Rahmstorf, S., Crucifix, M., Ganopolski, A., Goosse, H., Kamenkovich, I., Knutti, R., et al. (2005). Thermohaline circulation hysteresis: A model intercomparison. *Geophys. Res. Lett.* 32, L23605. doi:10.1029/2005GL023655.

Raper, S. C. B., Gregory, J. M., and Osborn, T. J. (2001). Use of an upwelling-diffusion energy balance climate model to simulate and diagnose A/OGCM results. *Clim. Dyn.* 17, 601–613. doi:10.1007/PL00007931.

Rasmussen, R. A., and Khalil, M. A. K. (1981). Atmospheric methane (CH 4): Trends and seasonal cycles. *J. Geophys.*

Res. 86, 9826. doi:10.1029/JC086iC10p09826.

Rasool, S. I., and Schneider, S. H. (1971). Atmospheric Carbon Dioxide and Aerosols: Effects of Large Increases on Global Climate. *Science (80-.).* 173, 138–141. doi:10.1126/science.173.3992.138.

Rehfeld, K., Marwan, N., Breitenbach, S. F. M., and Kurths, J. (2013). Late Holocene Asian summer monsoon dynamics from small but complex networks of paleoclimate data. *Clim. Dyn.* 41, 3–19. doi:10.1007/s00382-012-1448-3.

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., et al. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature* 566, 195–204. doi:10.1038/s41586-019-0912-1.

Renault, L., Molemaker, M. J., Gula, J., Masson, S., and McWilliams, J. C. (2016). Control and Stabilization of the Gulf Stream by Oceanic Current Interaction with the Atmosphere. *J. Phys. Oceanogr.* 46, 3439–3453. doi:10.1175/JPO-D-16-0115.1.

Rennie, J. J., Lawrimore, J. H., Gleason, B. E., Thorne, P. W., Morice, C. P., Menne, M. J., et al. (2014). The international surface temperature initiative global land surface databank: monthly temperature data release description and methods. *Geosci. Data J.* 1, 75–102. doi:10.1002/gdj3.8.

Revelle, R., and Suess, H. E. (1957). Carbon Dioxide Exchange Between the Atmosphere and Ocean and the Question of an Increase of Atmospheric CO2 during the Past Decades. *Tellus* 9, 18–27. doi:10.1111/j.2153-3490.1957.tb01849.x.

Rhein, M., Rintoul, S. R., Aoki, S., Campos, E., Chambers, D., Feely, R. A., et al. (2013). "Observations: Ocean," in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, et al. (Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press), 255–316. doi:10.1017/CBO9781107415324.010.

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., et al. (2017a). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Glob. Environ. Chang.* 42, 153–168. Available at: https://www.sciencedirect.com/science/article/pii/S0959378016300681 [Accessed March 18, 2019].

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., et al. (2017b). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Glob. Environ. Chang.* 42, 153–168. doi:10.1016/j.gloenvcha.2016.05.009.

Ribes, A., Azaís, J.-M., and Planton, S. (2009). Adaptation of the optimal fingerprint method for climate change detection using a well-conditioned covariance matrix estimate. *Clim. Dyn.* 33, 707–722. doi:10.1007/s00382-009-0561-4.

Ribes, A., Planton, S., and Terray, L. (2013). Application of regularised optimal fingerprinting to attribution. Part I: method, properties and idealised analysis. *Clim. Dyn.* 41, 2817–2836. doi:10.1007/s00382-013-1735-7.

Ribes, A., and Terray, L. (2013). Application of regularised optimal fingerprinting to attribution. Part II: application to global near-surface temperature. *Clim. Dyn.* 41, 2837–2853. doi:10.1007/s00382-013-1736-6.

Richardson, L. F. (1922). *Weather Prediction by Numerical Process*. Cambridge: Cambridge University Press.

Riedlinger, D., and Berkes, F. (2001). Contributions of traditional knowledge to understanding climate change in the Canadian Arctic. *Polar Rec. (Gr. Brit).* 37, 315–328.

Rignot, E., and Kanagaratnam, P. (2006). Changes in the Velocity Structure of the Greenland Ice Sheet. *Science (80-.).* 311, 986–990. doi:10.1126/science.1121381.

Rind, D., and Peteet, D. (1985). Terrestrial Conditions at the Last Glacial Maximum and CLIMAP Sea-Surface Temperature Estimates: Are They Consistent? *Quat. Res.* 24, 1–22. doi:10.1016/0033-5894(85)90080-8.

Ritchie, P., Karabacak, Ö., and Sieber, J. (2019). Inverse-square law between time and amplitude for crossing tipping thresholds. *Proc. R. Soc. A Math. Phys. Eng. Sci.* 475, 20180504. doi:10.1098/rspa.2018.0504.

Roberts, M. J., Vidale, P. L., Senior, C., Hewitt, H. T., Bates, C., Berthou, S., et al. (2018). The benefits of global high-resolution for climate simulation: process-understanding and the enabling of stakeholder decisions at the regional scale. *Bull. Am. Meteorol. Soc.* 0, null. doi:10.1175/BAMS-D-15-00320.1.

Robock, A., Oman, L., and Stenchikov, G. L. (2007). Nuclear winter revisited with a modern climate model and current nuclear arsenals: Still catastrophic consequences. *J. Geophys. Res. Atmos.* 112, n/a-n/a. doi:10.1029/2006JD008235.

Rodas, C. D., and Giulio., G. M. Di (2017). Brazilian Media and Climate Change: Analysis of Media Coverage Trends, Approaches and Criteria of Newsworthiness. *Desenvolv. E Meio Ambient.* 40, 101–124.

Rodgers, K. B., Lin, J., and Frölicher, T. L. (2015). Emergence of multiple ocean ecosystem drivers in a large ensemble suite with an Earth system model. *Biogeosciences* 12, 3301–3320. doi:10.5194/bg-12-3301-2015.

Rogelj, J., Den Elzen, M., Höhne, N., Fransen, T., Fekete, H., Winkler, H., et al. (2016). Paris Agreement climate proposals need a boost to keep warming well below 2 °c. *Nature*. doi:10.1038/nature18307.

Rogelj, J., Shindell, D., Jiang, K., Fifita, S., Forster, P., Ginzburg, V., et al. (2018). "Mitigation Pathways Compatible with 1.5°C in the Context of Sustainable Development," in *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission* *pathways, in the context of strengthening the global response to the threat of climate change,* eds. V. Masson-Delmotte, P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P. R. Shukla, et al. (In Press).

Rogers, J. C., and van Loon, H. (1982). Spatial Variability of Sea Level Pressure and 500 mb Height Anomalies over the Southern Hemisphere. *Mon. Weather Rev.* 110, 1375–1392. doi:10.1175/1520-0493(1982)110<1375:SVOSLP>2.0.CO;2.

Rohde, R., Muller, R., Jacobsen, R., Perlmutter, S., and Mosher, S. (2013). Berkeley Earth Temperature Averaging Process. *Geoinformatics Geostatistics An Overv.* 01. doi:10.4172/2327-4581.1000103.

Rojas, M., Lambert, F., Ramirez-Villegas, J., and Challinor, A. J. (2019). Emergence of robust precipitation changes across crop production areas in the 21st century. *Proc. Natl. Acad. Sci.* 116, 6673–6678. doi:10.1073/pnas.1811463116.

Rose, S. K., Richels, R., Blanford, G., and Rutherford, T. (2017). The Paris Agreement and next steps in limiting global warming. *Clim. Change* 142, 255–270. doi:10.1007/s10584-017-1935-y.

Rosenblum, E., and Eisenman, I. (2016). Faster Arctic Sea Ice Retreat in CMIP5 than in CMIP3 due to Volcanoes. *J. Clim.* 29, 9179–9188. doi:10.1175/JCLI-D-16-0391.1.

Rosenblum, E., and Eisenman, I. (2017). Sea Ice Trends in Climate Models Only Accurate in Runs with Biased Global Warming. *J. Clim.* 30, 6265–6278. doi:10.1175/JCLI-D-16-0455.1.

Rothrock, D. A., Yu, Y., and Maykut, G. A. (1999). Thinning of the Arctic sea-ice cover. *Geophys. Res. Lett.* 26, 3469–3472. doi:10.1029/1999GL010863.

Rotmans, J. (1990). *Image: An Integrated Model to Assess the Greenhouse Effect*. Dordrecht: Springer Netherlands doi:10.1007/978-94-009-0691-4.

Rounsevell, M. D. A., and Metzger, M. J. (2010). Developing qualitative scenario storylines for environmental change assessment. *Wiley Interdiscip. Rev. Clim. Chang.* 1, 606–619. doi:10.1002/wcc.63.

Rovere, A., Raymo, M. E., Vacchi, M., Lorscheid, T., Stocchi, P., Gómez-Pujol, L., et al. (2016). The analysis of Last Interglacial (MIS 5e) relative sea-level indicators: Reconstructing sea-level in a warmer world. *Earth-Science Rev.* 159, 404–427. doi:10.1016/j.earscirev.2016.06.006.

Ruane, A. C., Teichmann, C., Arnell, N. W., Carter, T. R., Ebi, K. L., Frieler, K., et al. (2016). The Vulnerability, Impacts, Adaptation and Climate Services Advisory Board (VIACS AB v1.0) contribution to CMIP6. *Geosci. Model Dev.* 9, 3493–3515. doi:10.5194/gmd-9-3493-2016.

Rubel, F., Brugger, K., Haslinger, K., and Auer, I. (2017). The climate of the European Alps: Shift of very high resolution Köppen-Geiger climate zones 1800?2100. *Meteorol. Zeitschrift* 26, 115–125. doi:10.1127/metz/2016/0816.

Rubel, F., and Kottek, M. (2010). Observed and projected climate shifts 1901-2100 depicted by world maps of the Köppen-Geiger climate classification. *Meteorol. Zeitschrift* 19, 135–141. doi:10.1127/0941-2948/2010/0430.

Runge, J., Petoukhov, V., Donges, J. F., Hlinka, J., Jajcay, N., Vejmelka, M., et al. (2015). Identifying causal gateways and mediators in complex spatio-temporal systems. *Nat. Commun.* 6, 8502. doi:10.1038/ncomms9502.

Runge, J., Petoukhov, V., and Kurths, J. (2014). Quantifying the Strength and Delay of Climatic Interactions: The Ambiguities of Cross Correlation and a Novel Measure Based on Graphical Models. *J. Clim.* 27, 720–739. doi:10.1175/JCLI-D-13-00159.1.

Ruppel, C. D., and Kessler, J. D. (2017). The interaction of climate change and methane hydrates. *Rev. Geophys.* 55, 126–168. doi:10.1002/2016RG000534.

Sammonds, P. R., Hatton, D. C., and Feltham, D. L. (2017). Micromechanics of sea ice frictional slip from test basin scale experiments. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* 375, 20150354. doi:10.1098/rsta.2015.0354.

Sanderson, B. M., Knutti, R., and Caldwell, P. (2015a). A Representative Democracy to Reduce Interdependency in a Multimodel Ensemble. *J. Clim.* 28, 5171–5194. doi:10.1175/JCLI-D-14-00362.1.

Sanderson, B. M., Knutti, R., and Caldwell, P. (2015b). Addressing Interdependency in a Multimodel Ensemble by Interpolation of Model Properties. *J. Clim.* 28, 5150–5170. doi:10.1175/JCLI-D-14-00361.1.

Sanderson, B. M., Wehner, M., and Knutti, R. (2017). Skill and independence weighting for multi-model assessments. *Geosci. Model Dev* 10, 2379–2395. doi:10.5194/gmd-10-2379-2017.

Sanderson, M. (1999). The Classification of Climates from Pythagoras to Koeppen. *Bull. Am. Meteorol. Soc.* 80, 669–674. doi:10.1175/1520-0477(1999)080<0669:TCOCFP>2.0.CO;2.

Santer, B. D. (2003). Contributions of Anthropogenic and Natural Forcing to Recent Tropopause Height Changes. *Science (80-.).* 301, 479–483. doi:10.1126/science.1084123.

Santer, B. D., Fyfe, J. C., Pallotta, G., Flato, G. M., Meehl, G. A., England, M. H., et al. (2017). Causes of differences in model and satellite tropospheric warming rates. *Nat. Geosci.* 10, 478–485. doi:10.1038/ngeo2973.

Santer, B. D., Painter, J. F., Bonfils, C., Mears, C. A., Solomon, S., Wigley, T. M. L., et al. (2013). Human and natural influences on the changing thermal structure of the atmosphere. *Proc. Natl. Acad. Sci.* 110, 17235–17240. doi:10.1073/pnas.1305332110.

Sapiains, R., Beeton, R. J. S., and Walker, I. A. (2016). Individual responses to climate change: Framing effects on pro-environmental behaviors. *J. Appl. Soc. Psychol.* 46, 483–493. doi:10.1111/jasp.12378.

Scambos, T. A., Bohlander, J. A., Shuman, C. A., and Skvarca, P. (2004). Glacier acceleration and thinning after ice shelf collapse in the Larsen B embayment, Antarctica. *Geophys. Res. Lett.* 31, L18402.

doi:10.1029/2004GL020670.

Schäfer, M. S., and Schlichting, I. (2014). Media Representations of Climate Change: A Meta-Analysis of the Research Field. *Environ. Commun.* 8, 142–160. doi:10.1080/17524032.2014.914050.

Schaller, N., Kay, A. L., Lamb, R., Massey, N. R., van Oldenborgh, G. J., Otto, F. E. L., et al. (2016). Human influence on climate in the 2014 southern England winter floods and their impacts. *Nat. Clim. Chang.* 6, 627–634. doi:10.1038/nclimate2927.

Schaller, N., Sillmann, J., Anstey, J., Fischer, E. M., Grams, C. M., and Russo, S. (2018). Influence of blocking on Northern European and Western Russian heatwaves in large climate model ensembles. *Environ. Res. Lett.* 13, 054015. doi:10.1088/1748-9326/aaba55.

Scheffer, M., Carpenter, S. R., Lenton, T. M., Bascompte, J., Brock, W., Dakos, V., et al. (2012). Anticipating Critical Transitions. *Science (80-.).* 338, 344–348. doi:10.1126/science.1225244.

Schepers, D., de Boisseson, E., Eresmaa, R., Lupu, C., and Rosnay, P. (2018). CERA-SAT: A coupled satellite-era reanalysis.

Schlesinger, M. E., Jiang, X., Schlesinger, M. E., and Jiang, X. (1990). Simple Model Representation of Atmosphere-Ocean GCMs and Estimation of the Time Scale of C0 $_2$ -Induced Climate Change. *J. Clim.* 3, 1297–1315. doi:10.1175/1520-0442(1990)003<1297:SMROAO>2.0.CO;2.

Schleussner, C.-F., Lissner, T. K., Fischer, E. M., Wohland, J., Perrette, M., Golly, A., et al. (2016). Differential climate impacts for policy-relevant limits to global warming: the case of 1.5 &amp;deg;C and 2 &amp;deg;C. *Earth Syst. Dyn.* 7, 327–351. doi:10.5194/esd-7-327-2016.

Schneider, S. H. (1994). Detecting Climatic Change Signals: Are There Any “Fingerprints”? *Science (80-.).* 263, 341–347. doi:10.1126/science.263.5145.341.

Schneider, S. H. (2001). What is “dangerous” climate change? *Nature* 411, 17–19.

Schneider von Deimling, T., Meinshausen, M., Levermann, A., Huber, V., Frieler, K., Lawrence, D. M., et al. (2012). Estimating the near-surface permafrost-carbon feedback on global warming. *Biogeosciences* 9, 649–665. doi:10.5194/bg-9-649-2012.

Scholes, R. J., Montanarella, L., Brainich, E., Brainich, E., Barger, N., ten Brink, B., et al. eds. (2018). *NoIPBES (2018): Summary for policymakers of the assessment report on land degradation and restoration of the Intergovernmental Science- Policy Platform on Biodiversity and Ecosystem Services Title*. Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services.

Schurer, A. P., Mann, M. E., Hawkins, E., Tett, S. F. B., and Hegerl, G. C. (2017). Importance of the pre-industrial baseline for likelihood of exceeding Paris goals. *Nat. Clim. Chang.* 7. doi:10.1038/NCLIMATE3345.

Schwarber, A. K., Smith, S. J., Hartin, C. A., Vega-Westhoff, B. A., and Sriver, R. (2018). Evaluating Climate Emulation: Unit Testing of Simple Climate Models. *Earth Syst. Dyn. Discuss.*, 1–13. doi:10.5194/esd-2018-63.

Scott, D., Iipinge, K., Mfune, J., Muchadenyika, D., Makuti, O., and Ziervogel, G. (2018). The Story of Water in Windhoek: A Narrative Approach to Interpreting a Transdisciplinary Process. *Water* 10, 1366. doi:10.3390/w10101366.

Seneviratne, S. I., Donat, M. G., Pitman, A. J., Knutti, R., and Wilby, R. L. (2016). Allowable CO2 emissions based on regional and impact-related climate targets. *Nature* 529, 477–483. doi:10.1038/nature16542.

Seneviratne, S. I., Wartenburger, R., Guillod, B. P., Hirsch, A. L., Vogel, M. M., Brovkin, V., et al. (2018). Climate extremes, land–climate feedbacks and land-use forcing at 1.5°C. *Philos. Trans. R. Soc. A Math. Eng. Sci.* 376, 20160450. doi:10.1098/rsta.2016.0450.

Serreze, M. C., and Stroeve, J. (2015). Arctic sea ice trends, variability and implications for seasonal ice forecasting. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* 373, 20140159. doi:10.1098/rsta.2014.0159.

Shackleton, N. J., and Opdyke, N. D. (1973). Oxygen Isotope and Palaeomagnetic Stratigraphy of Equatorial Pacific Core V28-238: Oxygen Isotope Temperatures and Ice Volumes on a 105 Year and 106 Year Scale. *Quat. Res.* 3, 39–55. doi:10.1016/0033-5894(73)90052-5.

Shapiro, H. T., Diab, R., de Brito Cruz, C. H., Cropper, M. L., Fang, J., Fresco, L. O., et al. (2010). *Climate change assessments: Review of the processes and procedures of the IPCC*. Available at: http://www.nationalacademies.org/PDFs/shapirostatement.pdf.

Shepherd, A., Ivins, E. R., Geruo A, Barletta, V. R., Bentley, M. J., Bettadpur, S., et al. (2012). A Reconciled Estimate of Ice-Sheet Mass Balance. *Science (80-.).* 338, 1183–1189. doi:10.1126/science.1228102.

Shepherd, T. G., Boyd, E., Calel, R. A., Chapman, S. C., Dessai, S., Dima-West, I. M., et al. (2018). Storylines: an alternative approach to representing uncertainty in physical aspects of climate change. *Clim. Change* 151, 555–571. doi:10.1007/s10584-018-2317-9.

Sheridan, S. C., and Allen, M. J. (2018). Temporal trends in human vulnerability to excessive heat. *Environ. Res. Lett.* 13. doi:10.1088/1748-9326/aab214.

Sherley, C., Morrison, M., Roderick, D., and Paton, K. (2014). Using Segmentation and Prototyping in Engaging Politically-Salient Climate-Change Household Segments. *J. Nonprofit Public Sect. Mark.* 26, 258–280.

Sherwood, S. C., Bony, S., Boucher, O., Bretherton, C., Forster, P. M., Gregory, J. M., et al. (2015). Adjustments in the Forcing-Feedback Framework for Understanding Climate Change. *Bull. Am. Meteorol. Soc.* 96, 217–228. doi:10.1175/BAMS-D-13-00167.1.

Shindell, D. T. (2014). Inhomogeneous forcing and transient climate sensitivity. *Nat. Clim. Chang.* 4, 274–277. doi:10.1038/nclimate2136.

Shiogama, H., Stone, D. A., Nagashima, T., Nozawa, T., and Emori, S. (2013). On the linear additivity of climate forcing-response relationships at global and continental scales. *Int. J. Climatol.* 33, 2542–2550. doi:10.1002/joc.3607.

Siddall, M., Rohling, E. J., Almogi-Labin, A., Hemleben, C., Meischner, D., Schmelzer, I., et al. (2003). Sea-level fluctuations during the last glacial cycle. *Nature* 423, 853–858. doi:10.1038/nature01690.

SIEGENTHALER, U., and JOOS, F. (1992). Use of a simple model for studying oceanic tracer distributions and the global carbon cycle. *Tellus B* 44, 186–207. doi:10.1034/j.1600-0889.1992.t01-2-00003.x.

Simmons, A. J., and Poli, P. (2015). Arctic warming in ERA-Interim and other analyses. *Q. J. R. Meteorol. Soc.* 141, 1147–1162. doi:10.1002/qj.2422.

Singh, D., Ghosh, S., Roxy, M. K., and McDermid, S. (2019). Indian summer monsoon: Extreme events, historical changes, and role of anthropogenic forcings. *Wiley Interdiscip. Rev. Clim. Chang.* 10, e571. doi:10.1002/wcc.571.

Sippel, S., and Otto, F. E. L. (2014). Beyond climatological extremes - assessing how the odds of hydrometeorological extreme events in South-East Europe change in a warming climate. *Clim. Change* 125, 381–398. doi:10.1007/s10584-014-1153-9.

Sippel, S., Walton, P., and Otto, F. E. L. (2015). Stakeholder Perspectives on the Attribution of Extreme Weather Events: An Explorative Enquiry. *Weather. Clim. Soc.* 7, 224–237. doi:10.1175/WCAS-D-14-00045.1.

Skeie, R. B., Berntsen, T., Aldrin, M., Holden, M., and Myhre, G. (2018). Climate sensitivity estimates – sensitivity to radiative forcing time series and observational data. *Earth Syst. Dyn.* 9, 879–894. doi:10.5194/esd-9-879-2018.

Slangen, A. B. A., Church, J. A., Agosta, C., Fettweis, X., Marzeion, B., and Richter, K. (2016). Anthropogenic forcing dominates global mean sea-level rise since 1970. *Nat. Clim. Chang.* 6, 701–705. doi:10.1038/nclimate2991.

Slangen, A. B. A., Church, J. A., Zhang, X., and Monselesan, D. (2014). Detection and attribution of global mean thermosteric sea level change. *Geophys. Res. Lett.* 41, 5951–5959. doi:10.1002/2014GL061356.

Smith, C. J., Forster, P. M., Allen, M., Leach, N., Millar, R. J., Passerello, G. A., et al. (2018). FAIR v1.3: a simple emissions-based impulse response and carbon cycle model. *Geosci. Model Dev.* 11, 2273–2297. doi:10.5194/gmd-11-2273-2018.

Smith, D. M., Screen, J. A., Deser, C., Cohen, J., Fyfe, J. C., García-Serrano, J., et al. (2019). The Polar Amplification Model Intercomparison Project (PAMIP) contribution to CMIP6: investigating the causes and consequences of polar amplification. *Geosci. Model Dev.* 12, 1139–1164. doi:10.5194/gmd-12-1139-2019.

Snyder, C. W. (2016). Evolution of global temperature over the past two million years. *Nature* 538, 226–228. doi:10.1038/nature19798.

Spratt, R. M., and Lisiecki, L. E. (2016). A Late Pleistocene sea level stack. *Clim. Past* 12, 1079–1092. doi:10.5194/cp-12-1079-2016.

Spreen, G., Kwok, R., Menemenlis, D., and Nguyen, A. T. (2017). Sea-ice deformation in a coupled ocean–sea-ice model and in satellite remote sensing data. *Cryosph.* 11, 1553–1573. doi:10.5194/tc-11-1553-2017.

Steffen, K., and Box, J. (2001). Surface climatology of the Greenland Ice Sheet: Greenland Climate Network 1995-1999. *J. Geophys. Res. Atmos.* 106, 33951–33964. doi:10.1029/2001JD900161.

Steffen, W., Crutzen, P. J., and McNeill, J. R. (2007). The Anthropocene: Are Humans Now Overwhelming the Great Forces of Nature. *AMBIO A J. Hum. Environ.* 36, 614–621. doi:10.1579/0044-7447(2007)36[614:TAAHNO]2.0.CO;2.

Steffen, W., Rockström, J., Richardson, K., Lenton, T. M., Folke, C., Liverman, D., et al. (2018). Trajectories of the Earth System in the Anthropocene. *Proc. Natl. Acad. Sci.*

Steinhaeuser, K., Chawla, N. V., and Ganguly, A. R. (2011). Complex networks as a unified framework for descriptive analysis and predictive modeling in climate science. *Stat. Anal. Data Min.* 4, 497–511. doi:10.1002/sam.10100.

Steinhaeuser, K., Ganguly, A. R., and Chawla, N. V (2012). Multivariate and multiscale dependence in the global climate system revealed through complex networks. *Clim. Dyn.* 39, 889–895. doi:10.1007/s00382-011-1135-9.

Steinhaeuser, K., and Tsonis, A. A. (2014). A climate model intercomparison at the dynamics level. *Clim. Dyn.* 42, 1665–1670. doi:10.1007/s00382-013-1761-5.

Stephens, G. L. (2005). Cloud Feedbacks in the Climate System: A Critical Review. *J. Clim.* 18, 237–273. doi:10.1175/jcli-3243.1.

Stevenson, S., Powell, B., Cobb, K., Nusbaumer, J., Merrifield, M., and Noone, D. (2018). Twentieth Century Seawater δ 1 8 O Dynamics and Implications for Coral-Based Climate Reconstruction. *Paleoceanogr. Paleoclimatology* 33, 606–625. doi:10.1029/2017PA003304.

Stickler, A., Grant, A. N., Ewen, T., Ross, T. F., Vose, R. S., Comeaux, J., et al. (2010). The Comprehensive Historical Upper-Air Network. *Bull. Am. Meteorol. Soc.* 91, 741–752. doi:10.1175/2009BAMS2852.1.

Stjern, C. W., Samset, B. H., Myhre, G., Forster, P. M., Hodnebrog, Ø., Andrews, T., et al. (2017). Rapid Adjustments Cause Weak Surface Temperature Response to Increased Black Carbon Concentrations. *J. Geophys. Res. Atmos.* 122, 11,462-11,481. doi:10.1002/2017JD027326.

Stock, C. A., Dunne, J. P., and John, J. G. (2014). Global-scale carbon and energy flows through the marine planktonic food web: An analysis with a coupled physical–biological model. *Prog. Oceanogr.* 120, 1–28.

doi:10.1016/j.pocean.2013.07.001.

Stocker, T. F., and Johnsen, S. J. (2003). A minimum thermodynamic model for the bipolar seesaw. *Paleoceanography* 18, n/a-n/a. doi:10.1029/2003PA000920.

Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M. M. B., Allen, S. K., Boschung, J., et al. (2013). *Climate change 2013: The physical science basis-conclusions*. doi:10.5169/seals-391142.

Stolbova, V., Martin, P., Bookhagen, B., Marwan, N., and Kurths, J. (2014). Topology and seasonal evolution of the network of extreme precipitation over the Indian subcontinent and Sri Lanka. *Nonlinear Process. Geophys.* 21, 901–917. doi:10.5194/npg-21-901-2014.

Stolbova, V., Surovyatkina, E., Bookhagen, B., and Kurths, J. (2016). Tipping elements of the Indian monsoon: Prediction of onset and withdrawal. *Geophys. Res. Lett.* 43, 3982–3990. doi:10.1002/2016GL068392.

Stone, D. A., Allen, M. R., Stott, P. A., Pall, P., Min, S.-K., Nozawa, T., et al. (2009). The detection and attribution of human influence on climate. *Annu. Rev. Environ. Resour.* 34, 1–16. doi:10.1146/annurev.environ.040308.101032.

Stone, D., Auffhammer, M., Carey, M., Hansen, G., Huggel, C., Cramer, W., et al. (2013). The challenge to detect and attribute effects of climate change on human and natural systems. *Clim. Change* 121, 381–395. doi:10.1007/s10584-013-0873-6.

Stott, P. A., Gillett, N. P., Hegerl, G. C., Karoly, D. J., Stone, D. A., Zhang, X., et al. (2010). Detection and attribution of climate change: a regional perspective. *Wiley Interdiscip. Rev. Clim. Chang.* 1, 192–211. doi:10.1002/wcc.34.

Stott, P. A., and Jones, G. S. (2012). Observed 21st century temperatures further constrain likely rates of future warming. *Atmos. Sci. Lett.* 13, 151–156. doi:10.1002/asl.383.

Stott, P. A., and Kettleborough, J. A. (2002). Origins and estimates of uncertainty in predictions of twenty-first century temperature rise. *Nature* 416, 723–726. doi:10.1038/416723a.

Stott, P. A., Stone, D. A., and Allen, M. R. (2004). Human contribution to the European heatwave of 2003. *Nature* 432, 610–614. doi:10.1038/nature03089.

Stott, P. A., Tett, S. F. B., Jones, G. S., Allen, M. R., Mitchell, J. F. B., and Jenkins, G. J. (2000). External Control of 20th Century Temperature by Natural and Anthropogenic Forcings. *Science (80-.).* 290, 2133–2137. doi:10.1126/science.290.5499.2133.

Stott, P. A., and Walton, P. (2013). Attribution of climate-related events: Understanding stakeholder needs. *Weather* 68, 274–279. doi:10.1002/wea.2141.

Stott, P., Good, P., Jones, G., Gillett, N., and Hawkins, E. (2013). The upper end of climate model temperature projections is inconsistent with past warming. *Environ. Res. Lett.* 8, 014024. doi:10.1088/1748-9326/8/1/014024.

Stouffer, R. J., and Manabe, S. (2017). Assessing temperature pattern projections made in 1989. *Nat. Clim. Chang.* doi:10.1038/nclimate3224.

Strassmann, K. M., and Joos, F. (2018). The Bern Simple Climate Model (BernSCM) v1.0: an extensible and fully documented open-source re-implementation of the Bern reduced-form model for global carbon cycle-climate simulations. *Geosci. Model Dev* 11, 1887–1908. doi:10.5194/gmd-11-1887-2018.

Study of Critical Environmental Problems (1970). *Man's Impact on the Global Environment: Assessment and Recommendations for Action*. Cambridge: MIT Press.

Study of Man's Impact on Climate (1971). *Inadvertent Climate Modification: Report of the Study of Man's Impact on Climate*. Cambridge: MIT Press.

Stuiver, M. (1965). Carbon-14 Content of 18th- and 19th-Century Wood: Variations Correlated with Sunspot Activity. *Science (80-.).* 149, 533–534. doi:10.1126/science.149.3683.533.

Sun, Y., Frankenberg, C., Wood, J. D., Schimel, D. S., Jung, M., Guanter, L., et al. (2017). OCO-2 advances photosynthesis observation from space via solar-induced chlorophyll fluorescence. *Science (80-.).* 358, eaam5747. doi:10.1126/science.aam5747.

Sunyer, M. A., Madsen, H., Rosbjerg, D., and Arnbjerg-Nielsen, K. (2014). A Bayesian Approach for Uncertainty Quantification of Extreme Precipitation Projections Including Climate Model Interdependency and Nonstationary Bias. *J. Clim.* 27, 7113–7132. doi:10.1175/JCLI-D-13-00589.1.

Sutton, R., Suckling, E., and Hawkins, E. (2015). What does global mean temperature tell us about local climate? *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* doi:10.1098/rsta.2014.0426.

Swales, D. J., Pincus, R., and Bodas-Salcedo, A. (2018). The Cloud Feedback Model Intercomparison Project Observational Simulator Package: Version 2. *Geosci. Model Dev.* 11, 77–81. doi:10.5194/gmd-11-77-2018.

Swart, N. C., Fyfe, J. C., Hawkins, E., Kay, J. E., and Jahn, A. (2015). Influence of internal variability on Arctic sea-ice trends. *Nat. Clim. Chang.* 5, 86–89. doi:10.1038/nclimate2483.

Swart, R., Mitchell, J., Morita, T., and Raper, S. (2002). Stabilisation scenarios for climate impact assessment. *Glob. Environ. Chang.* 12, 155–165. doi:10.1016/S0959-3780(02)00039-0.

Tailleux, R., Hochet, A., Ferreira, D., Kuhlbrodt, T., and Gregory, J. (2017). A new process-based vertical advection/diffusion theoretical model of ocean heat uptake. Available at: https://arxiv.org/abs/1708.02085 [Accessed March 18, 2019].

Tanaka, K., Kriegler, E., Bruckner, T., Hooss, G., Knorr, W., and Raddatz, T. (2007). Aggregated Carbon Cycle, Atmospheric Chemistry and Climate Model (ACC2) - Description of the forward and inverse modes. Hamburg, German Available at: www.mpimet.mpg.de [Accessed March 18, 2019].

Tantet, A., and Dijkstra, H. A. (2014). An interaction network perspective on the relation between patterns of sea surface temperature variability and global mean surface temperature. *Earth Syst. Dyn.* 5, 1–14. doi:10.5194/esd-5-1-2014.

Tardif, R., Hakim, G. J., Perkins, W. A., Horlick, K. A., Erb, M. P., Emile-Geay, J., et al. (2018). Last Millennium Reanalysis with an expanded proxy database and seasonal proxy modeling. *Clim. Past Discuss.*, 1–37. doi:10.5194/cp-2018-120.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. (2012). An Overview of CMIP5 and the Experiment Design. *Bull. Am. Meteorol. Soc.* 93, 485–498. doi:10.1175/BAMS-D-11-00094.1.

Tebaldi, C., and Arblaster, J. M. (2014). Pattern scaling: Its strengths and limitations, and an update on the latest model simulations. *Clim. Change* 122, 459–471. doi:10.1007/s10584-013-1032-9.

Tebaldi, C., and Knutti, R. (2007). The use of the multi-model ensemble in probabilistic climate projections. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* 365, 2053–2075. doi:10.1098/rsta.2007.2076.

Thomason, L. W., Ernest, N., Millán, L., Rieger, L., Bourassa, A., Vernier, J.-P., et al. (2018). A global space-based stratospheric aerosol climatology: 1979–2016. *Earth Syst. Sci. Data* 10, 469–492. doi:10.5194/essd-10-469-2018.

Thorne, P. W., Lanzante, J. R., Peterson, T. C., Seidel, D. J., and Shine, K. P. (2011). Tropospheric temperature trends: history of an ongoing controversy. *Wiley Interdiscip. Rev. Clim. Chang.* 2, 66–88. doi:10.1002/wcc.80.

Thornthwaite, C. W. (1948). An Approach Toward a Rational Classification of Climate. *Geogr. Rev.* 38, 55–94.

Tierney, J. E., Abram, N. J., Anchukaitis, K. J., Evans, M. N., Giry, C., Kilbourne, K. H., et al. (2015). Tropical sea surface temperatures for the past four centuries reconstructed from coral archives. *Paleoceanography* 30, 226–252. doi:10.1002/2014PA002717.

Tirabassi, G., and Masoller, C. (2016). Unravelling the community structure of the climate system by using lags and symbolic time-series analysis. *Sci. Rep.* 6, 29804. doi:10.1038/srep29804.

Trenberth, K. E., Marquis, M., and Zebiak, S. (2016). The vital need for a climate information system. *Nat. Clim. Chang.* doi:10.1038/nclimate3170.

Trewartha, G. T. (1954). *An Introduction to Climate*. 3rd ed. New York: McGraw-Hill.

Tsonis, A. A., and Roebber, P. J. (2004). The architecture of the climate network. *Phys. A Stat. Mech. its Appl.* 333, 497–504. doi:10.1016/j.physa.2003.10.045.

Tsonis, A. A., Swanson, K., and Kravtsov, S. (2007). A new dynamical mechanism for major climate shifts. *Geophys. Res. Lett.* 34, n/a-n/a. doi:10.1029/2007GL030288.

Tsonis, A. A., and Swanson, K. L. (2008). Topology and Predictability of El Niño and La Niña Networks. *Phys. Rev. Lett.* 100, 228502. doi:10.1103/PhysRevLett.100.228502.

Tukey, J. W., Alexander, M., Bennett, H. S., Brady, N. C., Calhoun Jr, J. C., Geyer, J. C., et al. (1965). *Restoring the quality of our environment: Report of the Environmental Pollution Panel, President's Science Advisory Committee*. Washington, DC: US Government Printing Office.

Turner, J., and Comiso, J. (2017). Solve Antarctica's sea-ice puzzle. *Nature* 547, 275–277.

Turner, J., Hosking, J. S., Bracegirdle, T. J., Marshall, G. J., and Phillips, T. (2015). Recent changes in Antarctic Sea Ice. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* 373, 20140163. doi:10.1098/rsta.2014.0163.

Tyndall, J. (1861). I. The Bakerian Lecture.—On the absorption and radiation of heat by gases and vapours, and on the physical connexion of radiation, absorption, and conduction. *Philos. Trans. R. Soc. London* 151, 1–36. doi:10.1098/rstl.1861.0001.

Uhe, P., Sjoukje, P., Sarah, K., Kasturi, S., Joyce, K., Emmah, M., et al. (2017). Attributing drivers of the 2016 Kenyan drought. *Int. J. Climatol.* 38, e554–e568. doi:10.1002/joc.5389.

UNEP (2016). The Montreal Protocol on Substances that Deplete the Ozone Layer - as adjusted and amended up to 15th October 2016 (Kigali Agreement). Kigali, Rwanda Available at: https://ozone.unep.org/sites/default/files/Consolidated-Montreal-Protocol-November-2016.pdf [Accessed March 22, 2019].

UNFCCC (1992). UNITED NATIONS FRAMEWORK CONVENTION ON CLIMATE CHANGE.

UNFCCC (2015). Report of the Conference of the Parties on its twenty-first session, held in Paris from 30 November to 13 December 2015. Addendum. Part two: Action taken by the Conference of the Parties at its twenty-first session. Paris.

UNFCCC (2016). Aggregate effect of the intended nationally determined contributions: an update - Synthesis report by the secretariat. 75. Available at: https://unfccc.int/sites/default/files/resource/docs/2016/cop22/eng/02.pdf [Accessed April 5, 2019].

UNGA (2015). Transforming our world: the 2030 Agenda for Sustainable Development. Resolution adopted by the 70th UN General Assembly. Available at: http://www.un.org/en/ga/search/view_doc.asp?symbol=A/RES/70/1.

UNISDR (2015). Sendai Framework for Disaster Risk Reduction 2015-2030.

United Nations (2017). New Urban Agenda. doi:ISBN: 978-92-1-132757-1.

Uotila, P., Goosse, H., Haines, K., Chevallier, M., Barthélemy, A., Bricaud, C., et al. (2019). An assessment of ten ocean reanalyses in the polar regions. *Clim. Dyn.* 52, 1613–1650. doi:10.1007/s00382-018-4242-z.

van den Hurk, B., Kim, H., Krinner, G., Seneviratne, S. I., Derksen, C., Oki, T., et al. (2016). LS3MIP (v1.0) contribution to CMIP6: the Land Surface, Snow and Soil moisture Model Intercomparison Project – aims, setup and expected outcome. *Geosci. Model Dev.* 9, 2809–2832. doi:10.5194/gmd-9-2809-2016.

van Marle, M. J. E., Kloster, S., Magi, B. I., Marlon, J. R., Daniau, A.-L., Field, R. D., et al. (2017). Historic global biomass burning emissions for CMIP6 (BB4CMIP) based on merging satellite observations with proxies and fire models (1750–2015). *Geosci. Model Dev.* 10, 3329–3357. doi:10.5194/gmd-10-3329-2017.

Van Oldenborgh, G. J., Philip, S., Kew, S., Van Weele, M., Uhe, P., Otto, F., et al. (2018). Extreme heat in India and anthropogenic climate change. *Nat. Hazards Earth Syst. Sci.* 18, 365–381. doi:10.5194/nhess-18-365-2018.

van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., et al. (2011a). The representative concentration pathways: an overview. *Clim. Change* 109, 5–31. doi:10.1007/s10584-011-0148-z.

van Vuuren, D. P., Kriegler, E., O'Neill, B. C., Ebi, K. L., Riahi, K., Carter, T. R., et al. (2014). A new scenario framework for Climate Change Research: scenario matrix architecture. *Clim. Change* 122, 373–386. doi:10.1007/s10584-013-0906-1.

van Vuuren, D. P., Lowe, J., Stehfest, E., Gohar, L., Hof, A. F., Hope, C., et al. (2011b). How well do integrated assessment models simulate climate change? *Clim. Change* 104, 255–285. doi:10.1007/s10584-009-9764-2.

van Vuuren, D. P., and Riahi, K. (2008). Do recent emission trends imply higher emissions forever? *Clim. Change* 91, 237–248. doi:10.1007/s10584-008-9485-y.

Vannière, B., Guilyardi, E., Toniazzo, T., Madec, G., and Woolnough, S. (2014). A systematic approach to identify the sources of tropical SST errors in coupled models using the adjustment of initialised experiments. *Clim. Dyn.* 43, 2261–2282. doi:10.1007/s00382-014-2051-6.

Vidal, J.-P., Martin, E., Franchistéguy, L., Habets, F., Soubeyroux, J.-M., Blanchard, M., et al. (2010). Multilevel and multiscale drought reanalysis over France with the Safran-Isba-Modcou hydrometeorological suite. *Hydrol. Earth Syst. Sci.* 14, 459–478. doi:10.5194/hess-14-459-2010.

Vose, R. S., Arndt, D., Banzon, V. F., Easterling, D. R., Gleason, B., Huang, B., et al. (2012). NOAA's Merged Land–Ocean Surface Temperature Analysis. *Bull. Am. Meteorol. Soc.* 93, 1677–1685. doi:10.1175/BAMS-D-11-00241.1.

Wang, G., Swanson, K. L., and Tsonis, A. A. (2009). The pacemaker of major climate shifts. *Geophys. Res. Lett.* 36, n/a-n/a. doi:10.1029/2008GL036874.

Wang, Q., Danilov, S., Sidorenko, D., Timmermann, R., Wekerle, C., Wang, X., et al. (2014). The Finite Element Sea Ice-Ocean Model (FESOM) v.1.4: formulation of an ocean general circulation model. *Geosci. Model Dev.* 7, 663–693. doi:10.5194/gmd-7-663-2014.

Wang, Y., Gozolchiani, A., Ashkenazy, Y., Berezin, Y., Guez, O., and Havlin, S. (2013). Dominant Imprint of Rossby Waves in the Climate Network. *Phys. Rev. Lett.* 111, 138501. doi:10.1103/PhysRevLett.111.138501.

Warszawski, L., Frieler, K., Huber, V., Piontek, F., Serdeczny, O., and Schewe, J. (2014). The Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP): project framework. *Proc. Natl. Acad. Sci. U. S. A.* 111, 3228–32. doi:10.1073/pnas.1312330110.

Wartenburger, R., Hirschi, M., Donat, M. G., Greve, P., Pitman, A. J., and Seneviratne, S. I. (2017). Changes in regional climate extremes as a function of global mean temperature: an interactive plotting framework. *Geosci. Model Dev.* 10, 3609–3634. doi:10.5194/gmd-10-3609-2017.

Webb, M. J., Andrews, T., Bodas-Salcedo, A., Bony, S., Bretherton, C. S., Chadwick, R., et al. (2017). The Cloud Feedback Model Intercomparison Project (CFMIP) contribution to CMIP6. *Geosci. Model Dev.* 10, 359–384. doi:10.5194/gmd-10-359-2017.

Webster, M., Forest, C., Reilly, J., Babiker, M., Kicklighter, D., Mayer, M., et al. (2003). Uncertainty Analysis of Climate Change and Policy Response. *Clim. Change* 61, 295–320. doi:10.1023/B:CLIM.0000004564.09961.9f.

Wenzel, S., Eyring, V., Gerber, E. P., and Karpechko, A. Y. (2016). Constraining Future Summer Austral Jet Stream Positions in the CMIP5 Ensemble by Process-Oriented Multiple Diagnostic Regression*. *J. Clim.* 29, 673–687. doi:10.1175/JCLI-D-15-0412.1.

Whan, K., Zscheischler, J., Orth, R., Shongwe, M., Rahimi, M., Asare, E. O., et al. (2015). Impact of soil moisture on extreme maximum temperatures in Europe. *Weather Clim. Extrem.* 9, 57–67. doi:10.1016/j.wace.2015.05.001.

White, S., Pfister, C., and Mauelshagen, F. eds. (2018). *The Palgrave Handbook of Climate History*. London: Palgrave Macmillan UK doi:10.1057/978-1-137-43020-5.

Whitmarsh, L. (2011). Scepticism and uncertainty about climate change: Dimensions, determinants and change over time. *Glob. Environ. Chang.* 21, 690–700. doi:10.1016/j.gloenvcha.2011.01.016.

Wieczorek, S., Ashwin, P., Luke, C. M., and Cox, P. M. (2011). Excitability in ramped systems: the compost-bomb instability. *Proc. R. Soc. A Math. Phys. Eng. Sci.* 467, 1243–1269. doi:10.1098/rspa.2010.0485.

Wigley, T. M. L., Clarke, L. E., Edmonds, J. A., Jacoby, H. D., Paltsev, S., Pitcher, H., et al. (2009). Uncertainties in climate stabilization. *Clim. Change* 97, 85–121. doi:10.1007/s10584-009-9585-3.

Wigley, T. M. L., Richels, R., and Edmonds, J. A. (1996). Economic and environmental choices in the stabilization of atmospheric CO2concentrations. *Nature* 379, 240–243. doi:10.1038/379240a0.

Williams, H. T. P., McMurray, J. R., Kurz, T., and Hugo Lambert, F. (2015). Network analysis reveals open forums and echo chambers in social media discussions of climate change. *Glob. Environ. Chang.* 32, 126–138. doi:10.1016/j.gloenvcha.2015.03.006.

Williams, K. D., Bodas-Salcedo, A., Déqué, M., Fermepin, S., Medeiros, B., Watanabe, M., et al. (2013). The

Transpose-AMIP II Experiment and Its Application to the Understanding of Southern Ocean Cloud Biases in Climate Models. *J. Clim.* 26, 3258–3274. doi:10.1175/JCLI-D-12-00429.1.

Williams, K. D., and Webb, M. J. (2009). A quantitative performance assessment of cloud regimes in climate models. *Clim. Dyn.* 33, 141–157. doi:10.1007/s00382-008-0443-1.

Williams, M., and Eggleston, S. (2017). Using indicators to explain our changing climate to policymakers and the public. *WMO Bull.*

Winkler, H., Mantlana, B., and Letete, T. (2017). Transparency of action and support in the Paris Agreement. *Clim. Policy* 17, 853–872. doi:10.1080/14693062.2017.1302918.

Winsberg, E. (2018). *Philosophy and Climate Science*. Cambridge University Press Available at: https://www.amazon.com/Philosophy-Climate-Science-Eric-Winsberg/dp/1316646920.

WMO (2014a). *Assessment for Decision-Makers: Scientific Assessment of Ozone Depletion*. Available at: https://www.esrl.noaa.gov/csd/assessments/ozone/2014/assessment_for_decision-makers.pdf [Accessed April 5, 2019].

WMO (2014b). *Implementation plan of the global framework for climate services*. Geneva.

WMO (2016). Climate Services for Supporting Climate Change Adaptation: Supplement to the Technical Guidelines for The National Adaptation Plan Process.

WMO (2017). *WMO Guidelines on the Calculation of Climate Normals (WMO 1203)*. Geneva, Switzerland.

Woodruff, S. D., Diaz, H. F., Elms, J. D., and Worley, S. J. (1998). COADS Release 2 data and metadata enhancements for improvements of marine surface flux fields. *Phys. Chem. Earth* 23, 517–526. doi:10.1016/S0079-1946(98)00064-0.

Woodruff, S. D., Diaz, H. F., Worley, S. J., Reynolds, R. W., and Lubker, S. J. (2005). Early Ship Observational Data and Icoads. *Clim. Change* 73, 169–194. doi:10.1007/s10584-005-3456-3.

Woodruff, S. D., Slutz, R. J., Jenne, R. L., and Steurer, P. M. (1987). A Comprehensive Ocean-Atmosphere Data Set. *Bull. Am. Meteorol. Soc.* 68, 1239–1250. doi:10.1175/1520-0477(1987)068<1239:ACOADS>2.0.CO;2.

Wu, C., Lin, Z., He, J., Zhang, M., Liu, X., Zhang, R., et al. (2016). A process-oriented evaluation of dust emission parameterizations in CESM: Simulation of a typical severe dust storm in East Asia. *J. Adv. Model. Earth Syst.* 8, 1432–1452. doi:10.1002/2016MS000723.

Xi, X. (2014). A Review of Water Isotopes in Atmospheric General Circulation Models: Recent Advances and Future Prospects. *Int. J. Atmos. Sci.* 2014, 1–16. doi:10.1155/2014/250920.

Yamasaki, K., Gozolchiani, A., and Havlin, S. (2008). Climate Networks around the Globe are Significantly Affected by El Niño. *Phys. Rev. Lett.* 100, 228501. doi:10.1103/PhysRevLett.100.228501.

Yamasaki, K., Gozolchiani, A., and Havlin, S. (2009). Climate Networks Based on Phase Synchronization Analysis Track El-Niño. *Prog. Theor. Phys. Suppl.* 179, 178–188. doi:10.1143/PTPS.179.178.

Yan, X., DelSole, T., and Tippett, M. K. (2016). What surface observations are important for separating the influences of anthropogenic aerosols from other forcings? *J. Clim.* 29, 4165–4184. doi:10.1175/JCLI-D-15-0667.1.

Yang, X., Tang, J., Mustard, J. F., Lee, J.-E., Rossini, M., Joiner, J., et al. (2015). Solar-induced chlorophyll fluorescence that correlates with canopy photosynthesis on diurnal and seasonal scales in a temperate deciduous forest. *Geophys. Res. Lett.* 42, 2977–2987. doi:10.1002/2015GL063201.

Zaehle, S., Jones, C. D., Houlton, B., Lamarque, J.-F., and Robertson, E. (2014). Nitrogen Availability Reduces CMIP5 Projections of Twenty-First-Century Land Carbon Uptake. *J. Clim.* 28, 2494–2511. doi:10.1175/JCLI-D-13-00776.1.

Zalasiewicz, J., Waters, C., and Head, M. J. (2017). Anthropocene: its stratigraphic basis. *Nature* 541, 289. Available at: http://dx.doi.org/10.1038/541289b.

Zanchettin, D., Khodri, M., Timmreck, C., Toohey, M., Schmidt, A., Gerber, E. P., et al. (2016). The Model Intercomparison Project on the climatic response to Volcanic forcing (VolMIP): experimental design and forcing input data for CMIP6. *Geosci. Model Dev.* 9, 2701–2719. doi:10.5194/gmd-9-2701-2016.

Zaval, L., Keenan, E. A., Johnson, E. J., and Weber, E. U. (2014). How warm days increase belief in global warming. *Nat. Clim. Chang.* 4, 143–147. doi:10.1038/nclimate2093.

Zemp, M., Frey, H., Gärtner-Roer, I., Nussbaumer, S. U., Hoelzle, M., Paul, F., et al. (2015). Historically unprecedented global glacier decline in the early 21st century. *J. Glaciol.* 61, 745–762. doi:10.3189/2015JoG15J017.

Zhang, Y., Xie, S., Klein, S. A., Marchand, R., Kollias, P., Clothiaux, E. E., et al. (2018). The ARM Cloud Radar Simulator for Global Climate Models: Bridging Field Data and Climate Models. *Bull. Am. Meteorol. Soc.* 99, 21–26. doi:10.1175/BAMS-D-16-0258.1.

Zhao, M., Golaz, J.-C., Held, I. M., Guo, H., Balaji, V., Benson, R., et al. (2018). The GFDL Global Atmosphere and Land Model AM4.0/LM4.0: 1. Simulation Characteristics With Prescribed SSTs. *J. Adv. Model. Earth Syst.* 10, 691–734. doi:10.1002/2017MS001208.

Zheng, B., Tong, D., Li, M., Liu, F., Hong, C., Geng, G., et al. (2018). Trends in China's anthropogenic emissions since 2010 as the consequence of clean air actions. *Atmos. Chem. Phys.* 18, 14095–14111. doi:10.5194/acp-18-14095-2018.

Zhou, L., Dai, A., Dai, Y., Vose, R. S., Zou, C. Z., Tian, Y., et al. (2009). Spatial dependence of diurnal temperature range trends on precipitation from 1950 to 2004. *Clim. Dyn.* 32, 429–440. doi:10.1007/s00382-008-0387-5.

Zhou, T., Turner, A. G., Kinter, J. L., Wang, B., Qian, Y., Chen, X., et al. (2016). GMMIP (v1.0) contribution to CMIP6: Global Monsoons Model Inter-comparison Project. *Geosci. Model Dev.* 9, 3589–3604. doi:10.5194/gmd-9-3589-2016.

Zickfeld, K., Eby, M., Weaver, A. J., Alexander, K., Crespin, E., Edwards, N. R., et al. (2013). Long-Term Climate Change Commitment and Reversibility: An EMIC Intercomparison. *J. Clim.* 26, 5782–5809. doi:10.1175/JCLI-D-12-00584.1.

Zscheischler, J., Westra, S., van den Hurk, B. J. J. M., Seneviratne, S. I., Ward, P. J., Pitman, A., et al. (2018). Future climate risk from compound events. *Nat. Clim. Chang.* 8, 469–477. doi:10.1038/s41558-018-0156-3.

Appendix 1.A

[START TABLE 1.A.1 HERE]

Table 1.A.1: Historical overview of major conclusions of IPCC assessment reports. The table repeats Table 1.1 from the IPCC Fifth Assessment Report (AR5; IPCC, 2013) and extends it with the AR5 and AR6 key findings. The table provides a non-comprehensive selection of key statements from previous assessment reports—IPCC First Assessment Report (FAR; IPCC, 1990), IPCC Second Assessment Report (SAR; IPCC, 1996), IPCC Third Assessment Report (TAR; IPCC, 2001), IPCC Fourth Assessment Report (AR4; IPCC, 2007), IPCC Fifth Assessment Report (AR5; IPCC, 2013), and the IPCC Sixth Assessment Report (AR6; 202X) —with a focus on global mean surface air temperature and sea level change as two policy relevant quantities that have been covered in IPCC since the first assessment report.

Topic	**FAR SPM Statement**	**SAR SPM Statement**	**TAR SPM Statement**	**AR4 SPM Statement**	**AR5 SPM statement**	**AR6 SPM statement**
Human and Natural Drivers of Climate Change	There is a natural greenhouse effect which already keeps the Earth warmer than it would otherwise be. Emissions resulting from human activities are substantially increasing the atmospheric concentrations of the greenhouse gases carbon dioxide, methane, chlorofluorocarbons and nitrous oxide. These increases will enhance the greenhouse effect, resulting on average in an additional warming of the Earth's surface.	Greenhouse gas concentrations have continued to increase. These trends can be attributed largely to human activities, mostly fossil fuel use, land use change and agriculture.	Emissions of greenhouse gases and aerosols due to human activities continue to alter the atmosphere in ways that are expected to affect the climate. The atmospheric concentration of CO_2 has increased by 31% since 1750 and that of methane by 151%.	Global atmospheric concentrations of carbon dioxide, methane and nitrous oxide have increased markedly as a result of human activities since 1750 and now far exceed pre-industrial values determined from ice cores spanning many thousands of years. The global increases in carbon dioxide concentration are due primarily to fossil fuel use and land use change, while those of methane and nitrous oxide are primarily due to agriculture.	Total radiative forcing is positive, and has led to an uptake of energy by the climate system. The largest contribution to total radiative forcing is caused by the increase in the atmospheric concentration of CO_2 since 1750.	

	Continued emissions of these gases at present rates would commit us to increased concentrations for centuries ahead.	Anthropogenic aerosols are short-lived and tend to produce negative radiative forcing.	Anthropogenic aerosols are short-lived and mostly produce negative radiative forcing by their direct effect. There is more evidence for their indirect effect, which is negative, although of very uncertain magnitude.	Very high confidence that the global average net effect of human activities since 1750 has been one of warming, with a radiative forcing of +1.6 [+0.6 to +2.4] W m–2.	The total anthropogenic RF for 2011 relative to 1750 is 2.29 [1.13 to 3.33] W m−2), and it has increased more rapidly since 1970 than during prior decades. The total anthropogenic RF best estimate for 2011 is 43% higher than that reported in AR4 for the year 2005.	
			Natural factors have made small contributions to radiative forcing over the past century.		The total natural RF from solar irradiance changes and stratospheric volcanic aerosols made only a small contribution to the net radiative forcing throughout the last century, except for brief periods after large volcanic eruptions.	
Observations of Recent Climate Change - Temperature	Global mean surface air temperature has increased by 0.3°C to 0.6°C over the last 100 years, with the five global-average warmest years being in the 1980s.	Climate has changed over the past century. Global mean surface temperature has increased by between about 0.3 and 0.6°C since the late 19th century. Recent years have been among the	An increasing body of observations gives a collective picture of a warming world and other changes in the climate system.	Warming of the climate system is unequivocal, as is now evident from observations of increases in global average air and ocean temperatures, widespread melting of	Warming of the climate system is unequivocal, and since the 1950s, many of the observed changes are unprecedented over decades to millennia. The atmosphere and	

		warmest since 1860, despite the cooling effect of the 1991 Mt. Pinatubo volcanic eruption.		snow and ice, and rising global average sea level.	ocean have warmed, the amounts of snow and ice have diminished, sea level has risen, and the concentrations of greenhouse gases have increased.	
			The global average temperature has increased since 1861. Over the 20th century the increase has been 0.6°C.	Eleven of the last twelve years (1995–2006) rank among the 12 warmest years in the instrumental record of global surface temperature (since 1850). The updated 100-year linear trend (1906 to 2005) of 0.74°C [0.56°C to 0.92°C] is therefore larger than the corresponding trend for 1901 to 2000 given in the TAR of 0.6°C [0.4°C to 0.8°C].	Each of the last three decades has been successively warmer at the Earth's surface than any preceding decade since 1850. The globally averaged combined land and ocean surface temperature data as calculated by a linear trend, show a warming of 0.85 [0.65 to 1.06] °C, over the period 1880 to 2012.	
			Some important aspects of climate appear not to have changed.	Some aspects of climate have not been observed to change.		
Observations of Recent Climate Change - Sea Level	Over the same period global sea level has increased by 10 to 20 cm. These increases have not been smooth with time, nor uniform over the globe.	Global sea level has risen by between 10 and 25 cm over the past 100 years and much of the rise may be related to the	Tide gauge data show that global average sea level rose between 0.1 and 0.2 m during the 20th century.	Global average sea level rose at an average rate of 1.8 [1.3 to 2.3] mm per year over 1961 to 2003. The rate was	The rate of sea level rise since the mid-19th century has been larger than the mean rate during the previous two	

		increase in global mean temperature.		faster over 1993 to 2003: about 3.1 [2.4 to 3.8] mm per year. The total 20th century rise is estimated to be 0.17 [0.12 to 0.22] m.	millennia (*high confidence*). Over the period 1901 to 2010, global mean sea level rose by 0.19 [0.17 to 0.21] m.	
Observations of Recent Climate Change - Ocean Heat Content			Global ocean heat content has increased since the late1950s, the period for which adequate observations of sub-surface ocean temperatures have been available.	Observations since 1961 show that the average temperature of the global ocean has increased to depths of at least 3000 m and that the ocean has been absorbing more than 80% of the heat added to the climate system. Such warming causes seawater to expand, contributing to sea level rise.	Ocean warming dominates the increase in energy stored in the climate system, accounting for more than 90% of the energy accumulated between 1971 and 2010 (*high confidence*). It is virtually certain that the upper ocean (0−700 m) warmed from 1971 to 2010, and it likely warmed between the 1870s and 1971 On a global scale, the ocean warming is largest near the surface, and the upper 75 m warmed by 0.11 [0.09 to 0.13] °C per decade over the period 1971 to 2010. Instrumental biases in upper-ocean temperature records have been identified	

					and reduced, enhancing confidence in the assessment of change.	
Observations of Recent Climate Change - Carbon Cycle / Ocean Acidification				Increasing atmospheric carbon dioxide concentrations lead to increasing acidification of the ocean. Projections based on SRES scenarios give reductions in average global surface ocean pH16 of between 0.14 and 0.35 units over the 21st century, adding to the present decrease of 0.1 units since pre-industrial times.	The atmospheric concentrations of carbon dioxide, methane, and nitrous oxide have increased to levels unprecedented in at least the last 800,000 years. Carbon dioxide concentrations have increased by 40% since pre-industrial times, primarily from fossil fuel emissions and secondarily from net land use change emissions. The ocean has absorbed about 30% of the emitted anthropogenic carbon dioxide, causing ocean acidification	
A Palaeoclimatic Perspective	Climate varies naturally on all timescales from hundreds of millions of years down to the year-to-year. Prominent in the Earth's history have been the 100,000 year glacial–	The limited available evidence from proxy climate indicators suggests that the 20th century global mean temperature is at least as warm as any other	New analyses of proxy data for the Northern Hemisphere indicate that the increase in temperature in the 20th century is likely to have been the largest of any	Palaeoclimatic information supports the interpretation that the warmth of the last half century is unusual in at least the previous 1,300 years.	In the Northern Hemisphere, 1983–2012 was likely the warmest 30-year period of the last 1400 years (*medium confidence*).	

	interglacial cycles when climate was mostly cooler than at present. Global surface temperatures have typically varied by 5°C to 7°C through these cycles, with large changes in ice volume and sea level, and temperature changes as great as 10°C to 15°C in some middle and high latitude regions of the Northern Hemisphere. Since the end of the last ice age, about 10,000 years ago, global surface temperatures have probably fluctuated by little more than 1°C. Some fluctuations have lasted several centuries, including the Little Ice Age which ended in the nineteenth century and which appears to have been global in extent.	century since at least 1400 AD. Data prior to 1400 are too sparse to allow the reliable estimation of global mean temperature.	century during the past 1,000 years. It is also likely that, in the Northern Hemisphere, the 1990s was the warmest decade and 1998 the warmest year. Because less data are available, less is known about annual averages prior to 1,000 years before present and for conditions prevailing in most of the Southern Hemisphere prior to 1861.	The last time the polar regions were significantly warmer than present for an extended period (about 125,000 years ago), reductions in polar ice volume led to 4 to 6 m of sea level rise.	There is *very high confidence* that maximum global mean sea level during the last interglacial period (129,000 to 116,000 years ago) was, for several thousand years, at least 5 m higher than present, and *high confidence* that it did not exceed 10 m above present.	
Understanding and Attributing Climate Change	The size of this warming is broadly consistent with predictions of climate models, but it is also of the same magnitude as natural climate variability. Thus the observed increase could be largely due to this natural variability;	The balance of evidence suggests a discernible human influence on global climate. Simulations with coupled atmosphere–ocean models have provided important information	There is new and stronger evidence that most of the warming observed over the last 50 years is attributable to human activities. There is a longer and more scrutinized temperature record and	Most of the observed increase in global average temperatures since the mid-20th century is very likely due to the observed increase in anthropogenic greenhouse gas	Human influence on the climate system is clear. It is *extremely likely* that more than half of the observed increase in global average surface temperature from 1951 to 2010 was	

	alternatively this variability and other human factors could have offset a still larger human-induced greenhouse warming. The unequivocal detection of the enhanced greenhouse effect from observations is not likely for a decade or more.	about decade to century timescale natural internal climate variability.	new model estimates of variability. Reconstructions of climate data for the past 1,000 years indicate this warming was unusual and is unlikely to be entirely natural in origin.	concentrations. Discernible human influences now extend to other aspects of climate, including ocean warming, continental-average temperatures, temperature extremes and wind patterns.	caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human-induced contribution to warming is similar to the observed warming over this period.	
Projections of Future Changes in Climate - Temperature	Under the IPCC Business-as-Usual emissions of greenhouse gases, a rate of increase of global mean temperature during the next century of about 0.3°C per decade (with an uncertainty range of 0.2°C to 0.5°C per decade); this is greater than that seen over the past 10,000 years.	Climate is expected to continue to change in the future. For the mid-range IPCC emission scenario, IS92a, assuming the 'best estimate' value of climate sensitivity and including the effects of future increases in aerosols, models project an increase in global mean surface air temperature relative to 1990 of about 2°C by 2100.	Global average temperature and sea level are projected to rise under all IPCC SRES scenarios. The globally averaged surface temperature is projected to increase by 1.4°C to 5.8°C over the period 1990 to 2100.	For the next two decades, a warming of about 0.2°C per decade is projected for a range of SRES emission scenarios. Even if the concentrations of all greenhouse gases and aerosols had been kept constant at year 2000 levels, a further warming of about 0.1°C per decade would be expected.	Global surface temperature change for the end of the 21st century is *likely* to exceed 1.5°C relative to 1850 to 1900 for all RCP scenarios except RCP2.6. It is likely to exceed 2°C for RCP6.0 and RCP8.5, and *more likely than not* to exceed 2°C for RCP4.5. Warming will continue beyond 2100 under all RCP scenarios except RCP2.6. Warming will continue to exhibit interannual-to-decadal variability	

					and will not be regionally uniform.	
			Confidence in the ability of models to project future climate has increased.	There is now higher confidence in projected patterns of warming and other regional-scale features, including changes in wind patterns, precipitation and some aspects of extremes and of ice.	Climate models have improved since the AR4. Models reproduce observed continental-scale surface temperature patterns and trends over many decades, including the more rapid warming since the mid-20th century and the cooling immediately following large volcanic eruptions.	
			Anthropogenic climate change will persist for many centuries.	Anthropogenic warming and sea level rise would continue for centuries, even if greenhouse gas concentrations were to be stabilised.	Cumulative emissions of CO_2 largely determine global mean surface warming by the late 21st century and beyond. Most aspects of climate change will persist for many centuries even if emissions of CO_2 are stopped. This represents a substantial multi-century climate change commitment created by past,	

					present and future emissions of CO_2.	
Projections of Future Changes in Climate - Sea Level	An average rate of global mean sea level rise of about 6 cm per decade over the next century (with an uncertainty range of 3 to 10 cm per decade) is projected.	Models project a sea level rise of 50 cm from the present to 2100.	Global mean sea level is projected to rise by 0.09 to 0.88 m between 1990 and 2100.	Global sea level rise for the range of scenarios is projected as 0.18 to 0.59 m by the end of the 21st century.	Global mean sea level rise for 2081–2100 relative to 1986–2005 will *likely* be in the ranges of 0.26 to 0.55 m for RCP2.6, 0.32 to 0.63 m for RCP4.5, 0.33 to 0.63 m for RCP6.0, and 0.45 to 0.82 m for RCP8.5.	
Projections of Future Changes in Climate - AMOC		Most simulations show a reduction in the strength of the north Atlantic thermohaline circulation. Future unexpected, large and rapid climate system changes are difficult to predict. These arise from the non-linear nature of the climate system. Examples include rapid circulation changes in the North Atlantic.	Most models show weakening of the ocean thermohaline circulation which leads to a reduction of the heat transport into high latitudes of the Northern Hemisphere. However, even in models where the thermohaline circulation weakens, there is still a warming over Europe due to increased greenhouse gases. The current projections using climate models do not exhibit a complete shut-down of the thermohaline circulation by 2100. Beyond 2100, the	Based on current model simulations, it is *very likely* that the meridional overturning circulation (MOC) of the Atlantic Ocean will slow down during the 21st century. It is *very unlikely* that the MOC will undergo a large abrupt transition during the 21st century. Longer-term changes in the MOC cannot be assessed with confidence.	It is that the Atlantic Meridional Overturning Circulation (AMOC) will weaken over the 21st century. It is *very unlikely* that the AMOC will undergo an abrupt transition or collapse in the 21st century for the scenarios considered. There is *low confidence* in assessing the evolution of the AMOC beyond the 21st century because of the limited number of analyses and equivocal results. However, a collapse beyond the 21st	

			thermohaline circulation could completely, and possibly irreversibly, shut-down in either hemisphere if the change in radiative forcing is large enough and applied long enough.		century for large sustained warming cannot be excluded.	

[END TABLE 1.A.1 HERE]

Figures:

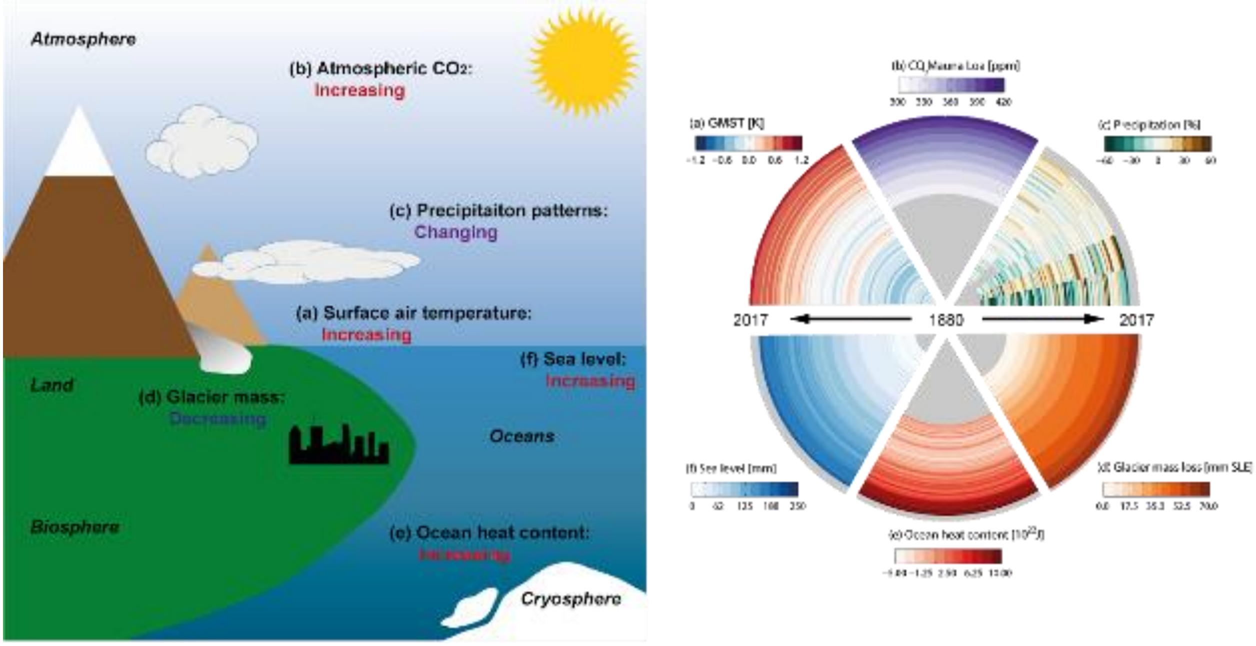


Figure 1.1: The changing state of the physical climate system. Left: Schematic of the components of the climate system, and examples of how key physical observables are changing. Right: Each wedge of the rosette shows annual means of one variable, from 1850 (center) out to 2017 (outer circle). Grey indicates missing data. [To be updated for SOD. All data plotted so far temporary, taken predominantly from AR5.]

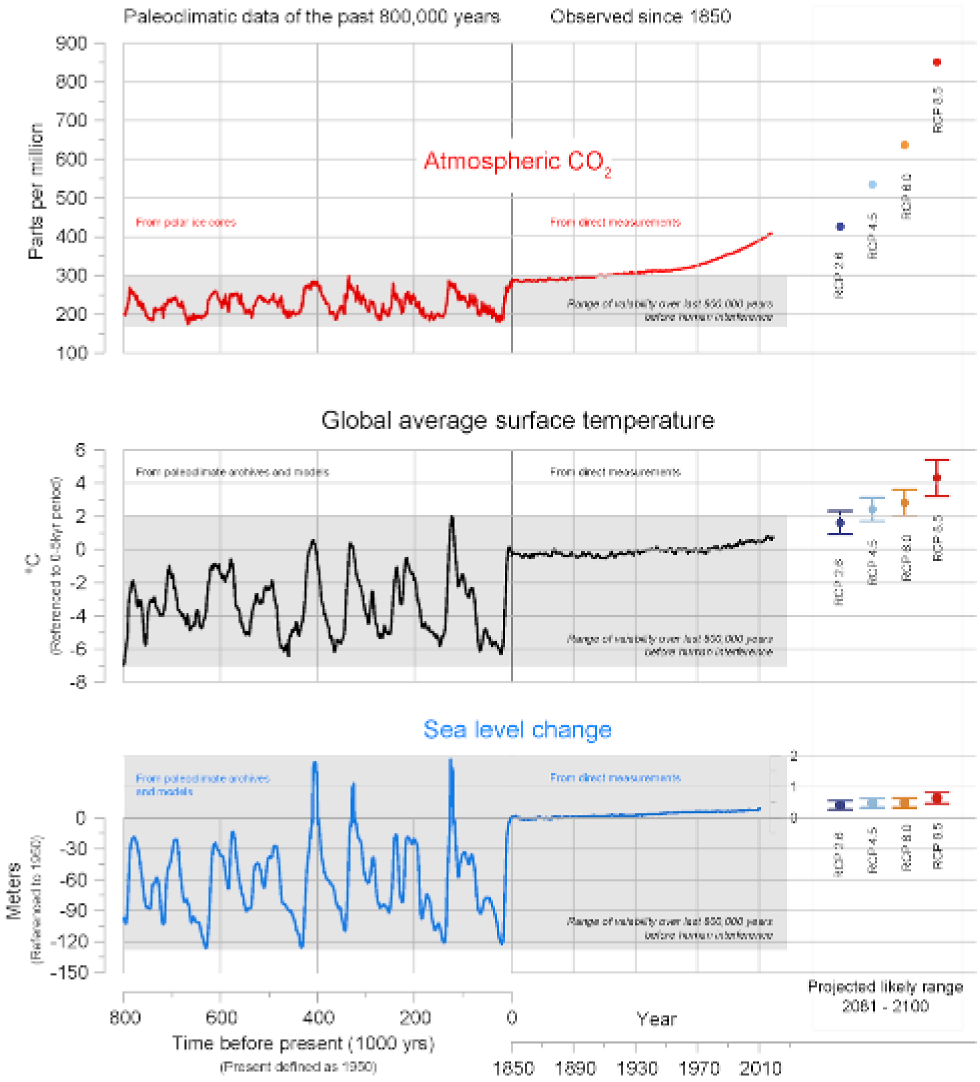


Figure 1.2: Long-term context of anthropogenic climate change based on selected paleoclimatic reconstructions over the past 800,000 years for three key indicators: atmospheric CO_2 concentrations, global mean surface temperature, and sea level. **a)** Measurements of CO_2 in air enclosed in Antarctic ice cores (Lüthi et al., 2008; MacFarling Meure et al., 2006) and direct air measurements (Dlugokenky and Tans, 2019) (Keeling et al., 1976). Inferred CO_2 concentrations for the RCPs are indicated by the bars on the right side of the figure and taken from Zickfeld et al. (2013). Reconstruction of global average surface air temperature based on a combination of several marine paleoclimate proxies and PMIP model simulations (Snyder, 2016). Observed temperature changes since 1850 are from the HadCRUT4 dataset, re-referenced to 1850-1900; bars indicate the projected ranges of warming derived from CMIP5 simulations (IPCC, 2013a) Sea level changes reconstructed from oxygen isotope measurements on several ocean sediment cores (Bintanja and van de Wal, 2008, re-referenced to 1850-1900). The observed sea level record is from Jevrejeva et al. (2014); projections are based on a combination of CMIP5 ensembles and process-based models (IPCC, 2013a). [PLACEHOLDER: projections are based on CMIP5. They will be replaced by CMIP6 in the SOD; uncertainties will be added to the paleoclimate reconstructions in the SOD. Also, SLR projections will likely use Spratt and Lisiecki (2016) (re-referenced to 1850-1900) for the SOD instead of Bintanja and van de Wal (2008).

Cross-Chapter Box 1.2, Figure 1: Schematic of the Risk Framework used in AR6. Risk results from the interaction between hazards, exposure and vulnerability. Vulnerability and exposure are mainly driven by socioeconomic processes. Climate mainly influences hazards through natural climate variability as well as anthropogenic climate change. Risk can be reduced via adaptation and mitigation, thereby constructing resilience.

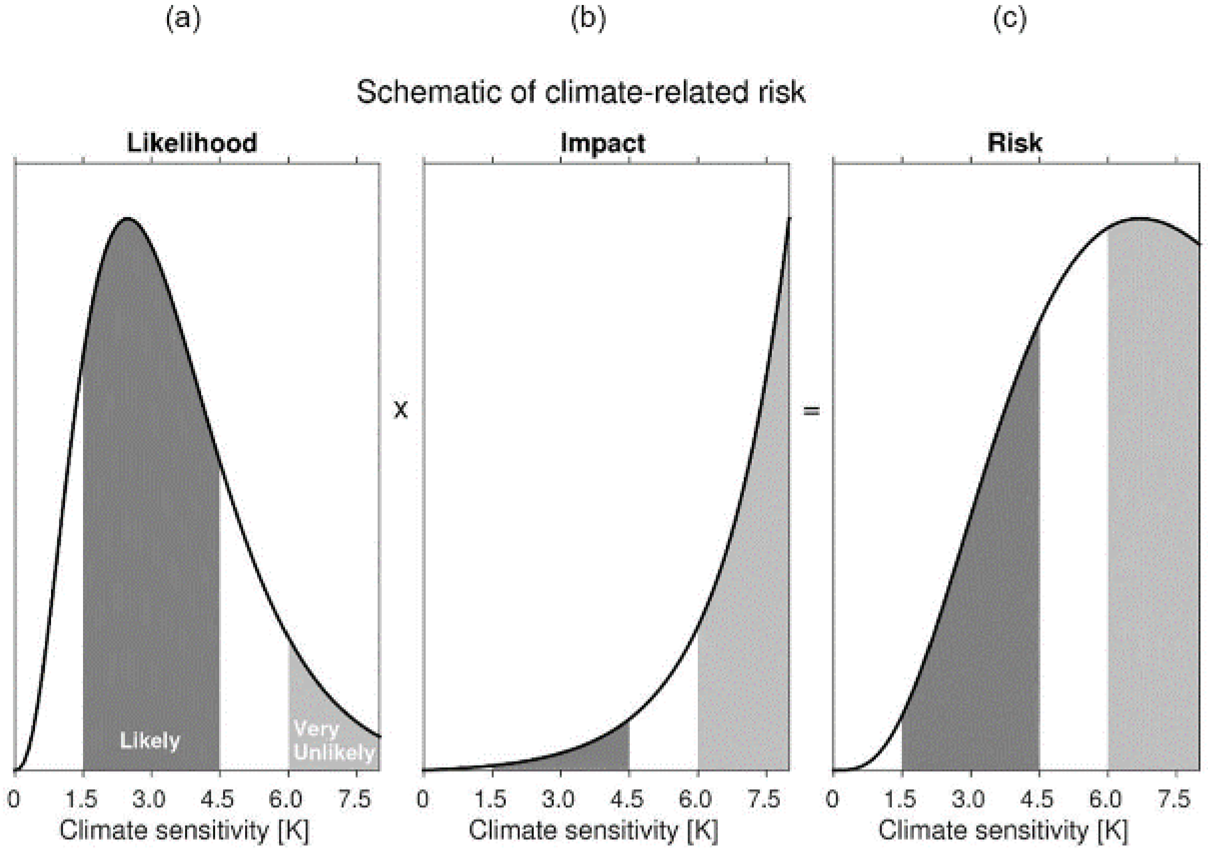


Figure 1.3: A schematic representation of how climate change risk depends on equilibrium climate sensitivity (ECS). (a) A possible likelihood distribution consistent with the IPCC AR5 assessment that “Equilibrium climate sensitivity is likely in the range 1.5 to 4.5°C (high confidence), extremely unlikely less than 1°C (high confidence) and very unlikely greater than 6°C (medium confidence)”. (b) A schematic illustration of the fact that, for a given emissions scenario, the cost of impacts and adaptation rises very rapidly (shown here as an exponential damage function) with ECS. (c) In this example, the resultant risk (quantified here as likelihood × impact) is highest for high ECS values. The precise shape of the risk curve is dependent on assumptions about the shape of the likelihood and damage functions at high sensitivity (Weitzman, 2011). Figure and caption taken from Sutton (2018) [To be updated]

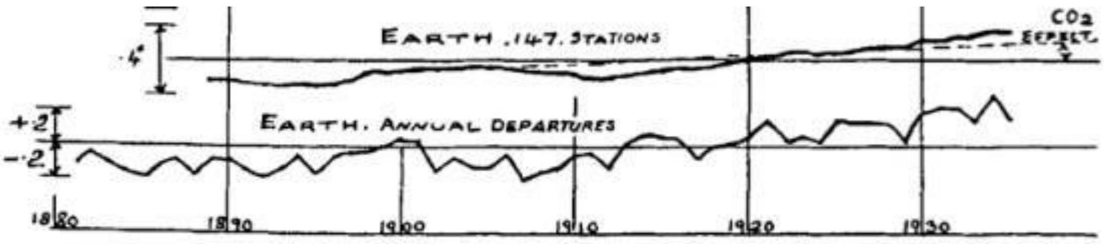
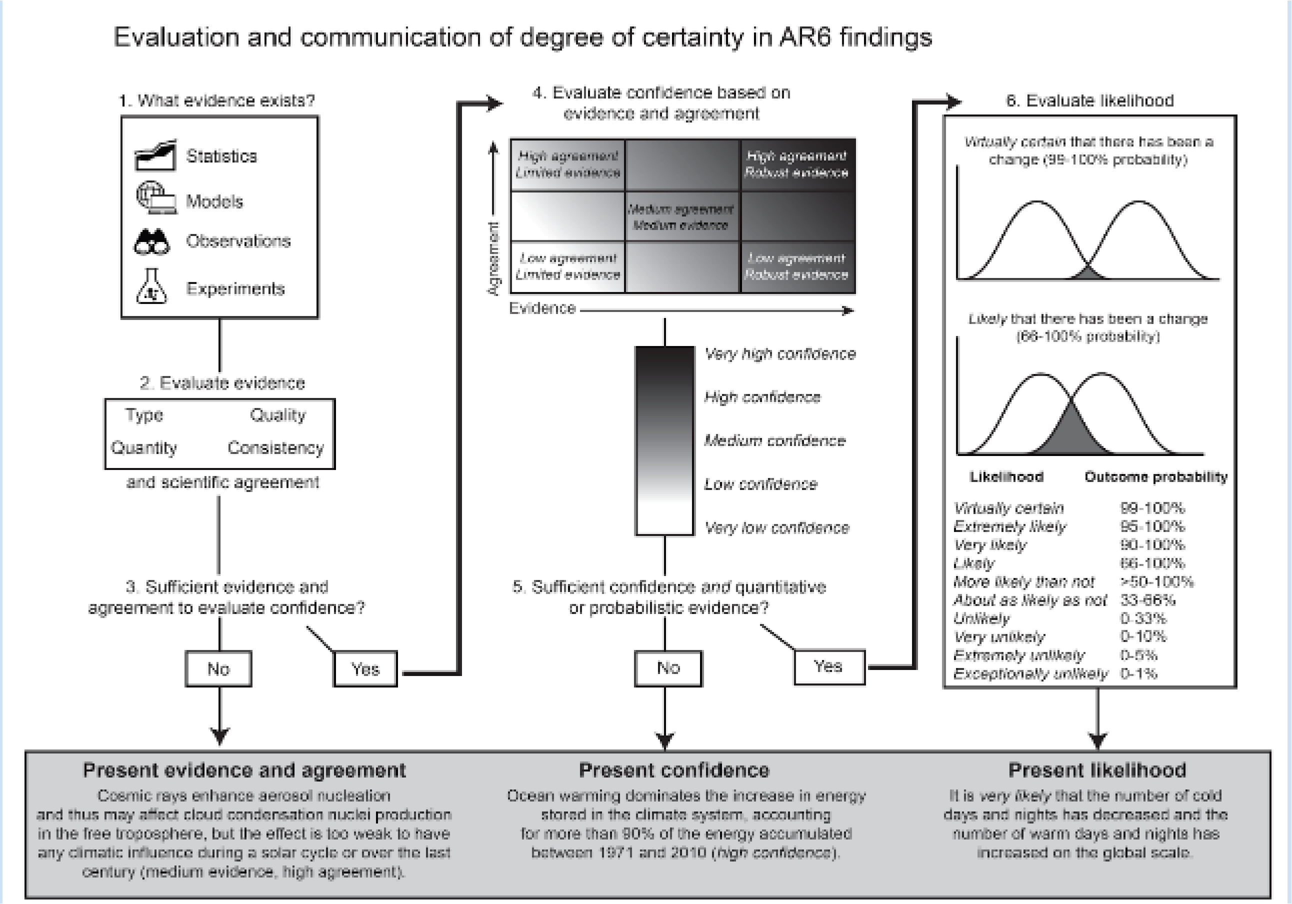


FIG. 4.—Temperature variations of the zones and of the earth. Ten-year moving departures from the mean, 1901-1930, °C.

Figure 1.4: G.S. Callendar's graph of global temperatures from 147 surface stations, 1880-1934. Top: ten-year moving departures from the mean of 1901-1930 (Callendar, 1938). The dashed line represents his estimate of the "CO2 effect" on temperature rise. Bottom: annual departures from the 1901-1930 mean.



Cosmic rays enhance aerosol nucleation and thus may affect cloud condensation nuclei production in the free troposphere, but the effect is too weak to have any climatic influence during a solar cycle or over the last century (*medium evidence, high agreement*).

Ocean warming dominates the increase in energy stored in the climate system, accounting for more than 90% of the energy accumulated between 1971 and 2010 (*high confidence*).

It is *very likely* that the number of cold days and nights has decreased and the number of warm days and nights has increased on the global scale.

Box 1.1, Figure 1.1: The IPCC AR6 approach for characterizing understanding and uncertainty in assessment findings. This diagram illustrates the step-by-step process authors use to evaluate and communicate the state of knowledge in their assessment (Mastrandrea et al., 2010). Authors present evidence/agreement, confidence, or likelihood terms with assessment conclusions, communicating their expert judgments accordingly. Example conclusions are drawn from the IPCC WGI AR5 [adapted, from Mach et al. (2017)].

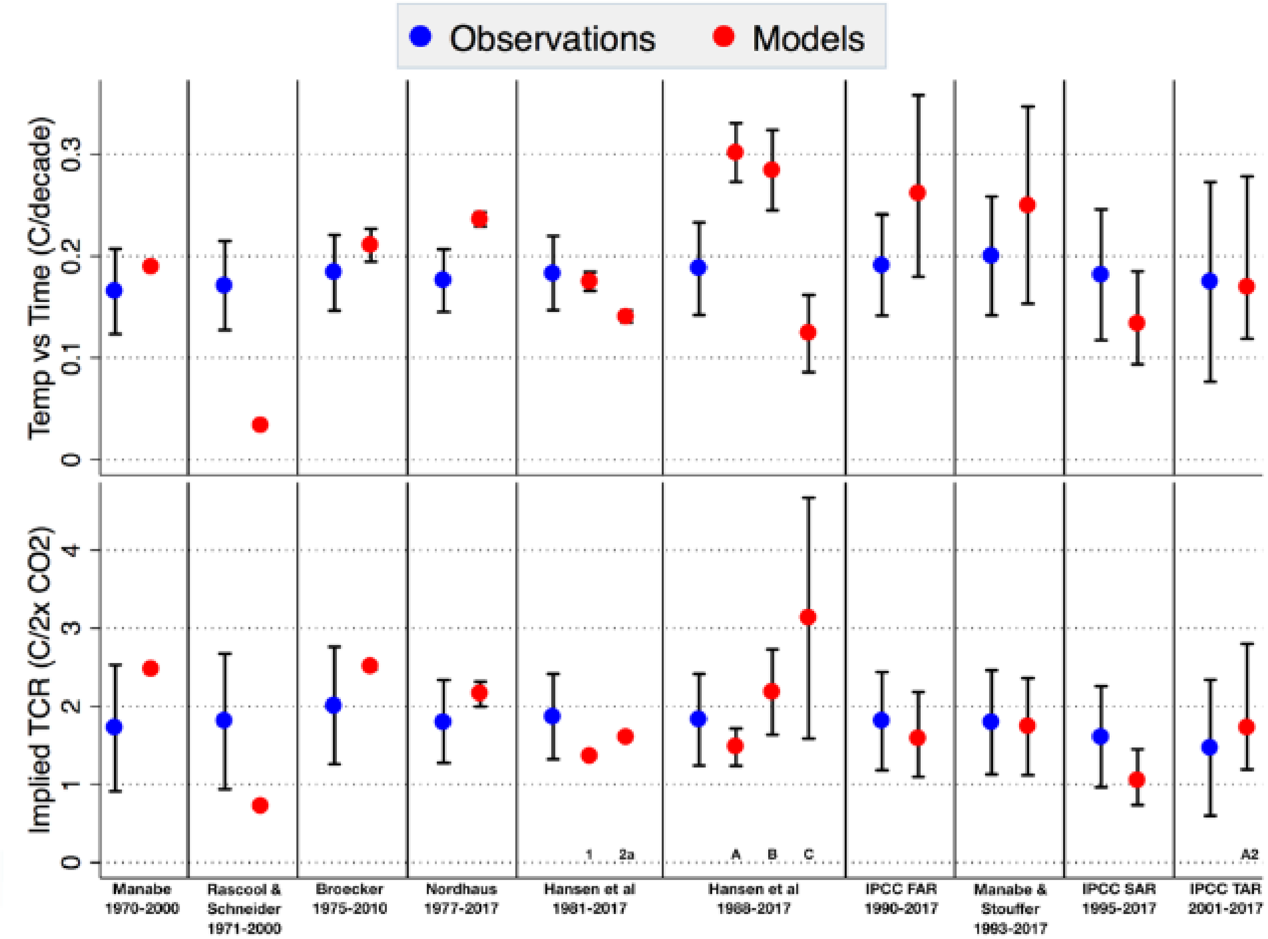


Figure 1.5: Top row: Trend in temperature change over time (°C per decade) for observations (blue) and climate models projections (red) for a selection of prominent past climate model forecasts. Bottom: Implied Transient Climate Response (°C per doubled CO_2) for observations and models based on the ratio of change in temperature to change in anthropogenic radiative forcing. Radiative forcing values are taken from each separate model; observed radiative forcing estimates use a 1000-member ensemble extended from Dessler and Forster (2018). Observed temperatures are based data from five groups: NASA GISTEMP, Hadley/UEA HadCRUT4, NOAA GlobalTemp, Berkeley Earth, and Cowtan and Way. Both modeled and observed trends are shown over the forecast period of each model between date of publication and the end of 2017 (or the last available model forecast year).

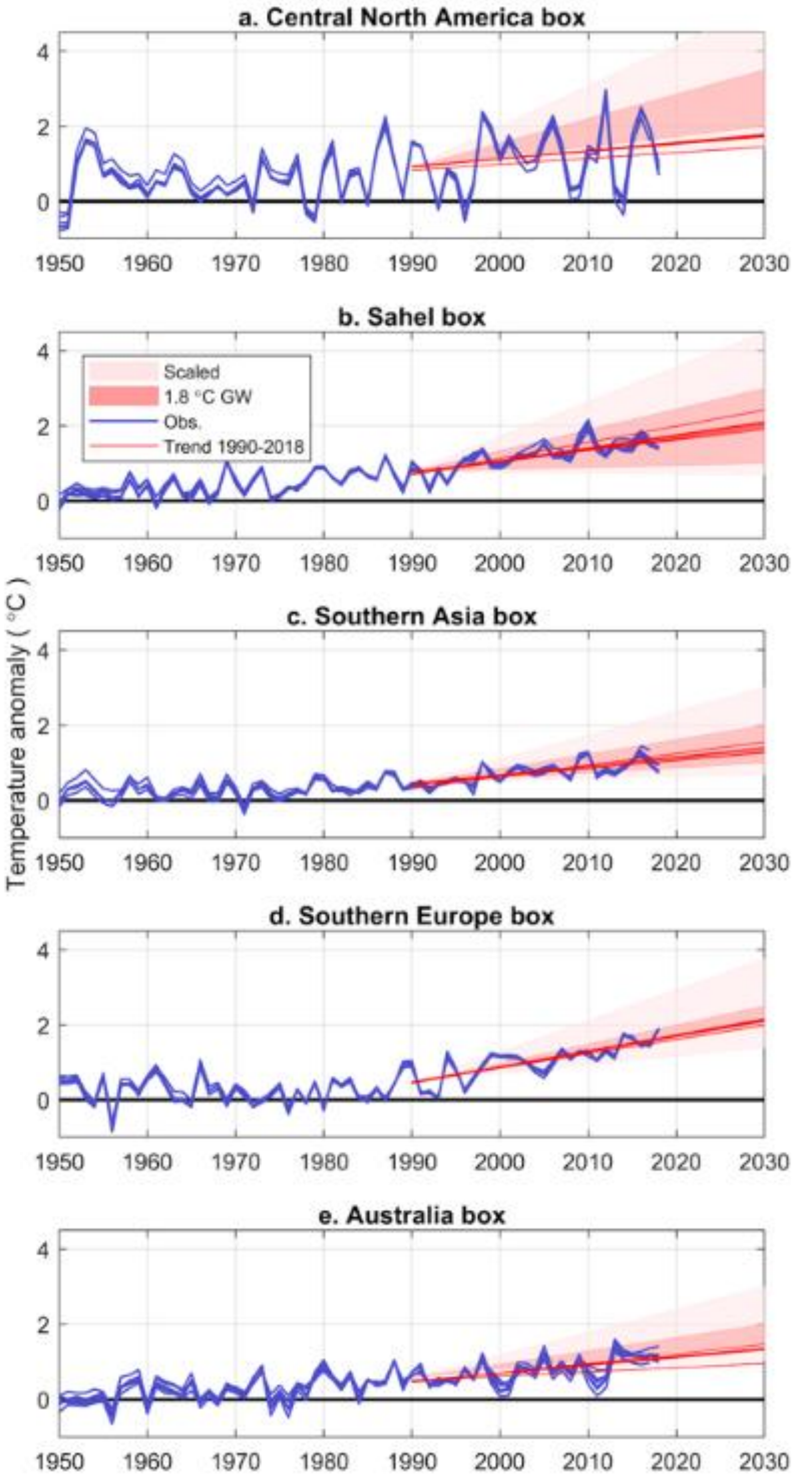


Figure 1.6: Range of projected temperature change for 1990-2030 for regions defined in IPCC FAR (1990). Darker red bands show the range of projected change given for the best estimate of 1.8°C global warming since pre-industrial, faint bands show the range scaled for lower and higher estimates of global warming. Blue lines show the observations from several global temperature gridded datasets, red lines show the linear trends in those datasets for 1990-2018 extrapolated to 2030. Observed datasets are: HadCRUT4.6, Cowtan and Way, GISTEMP, Berkeley Earth and University of Delaware.

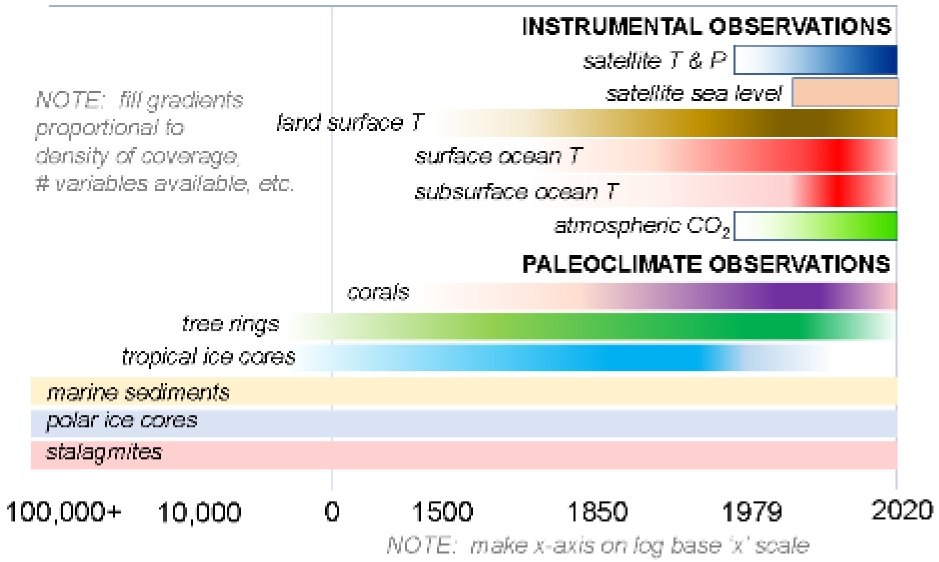


Figure 1.30:

Figure 1.7: Schematic of climate data coverage through time, indicating time span covered by different sources, as well as density of coverage from a given source (i.e. satellite coverage increasing through time, whereas ground-based instrumental coverage is decreasing in recent years, and corals and tropical ice cores are a "vanishing" archive).

Figure 1.31:

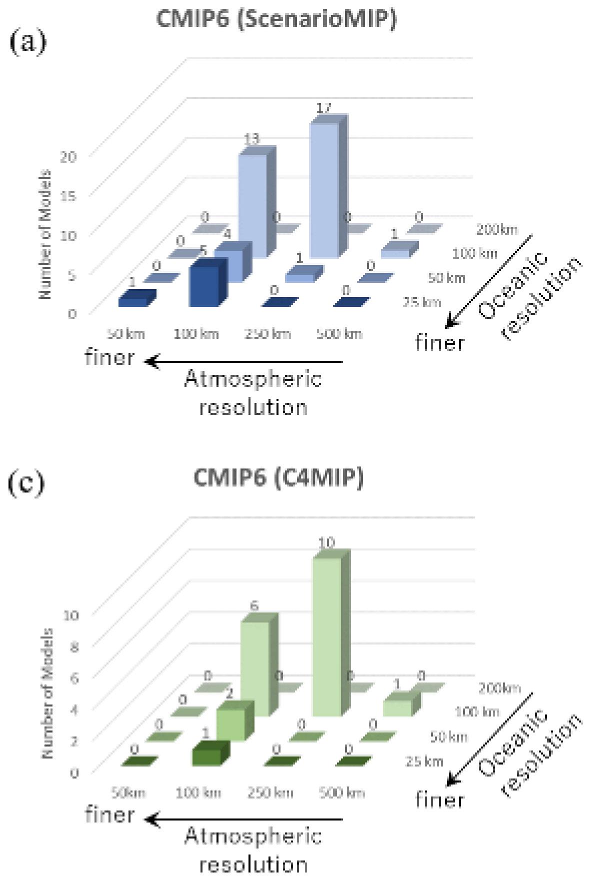


Figure 1.8: The population distributions of global climate models in terms of nominal horizontal atmospheric and oceanic resolutions. (a) (b) Models used for future projection scenario experiments in CMIP6 and CMIP5 model intercomparison projects respectively. (c) (d) Models used for assessing biogeochemical feedbacks in CMIP6 and CMIP5.The CMIP6 models are those registered as of December, 2018 (https://rawgit.com/WCRP-CMIP/CMIP6_CVs/master/src/CMIP6_source_id.html), while the CMIP5 models are those available at the IPCC Data Distribution Centre AR5 Reference Snapshot (http://www.ipcc-data.org/sim/gcm_monthly/AR5/Reference-Archive.html). [To be updated].

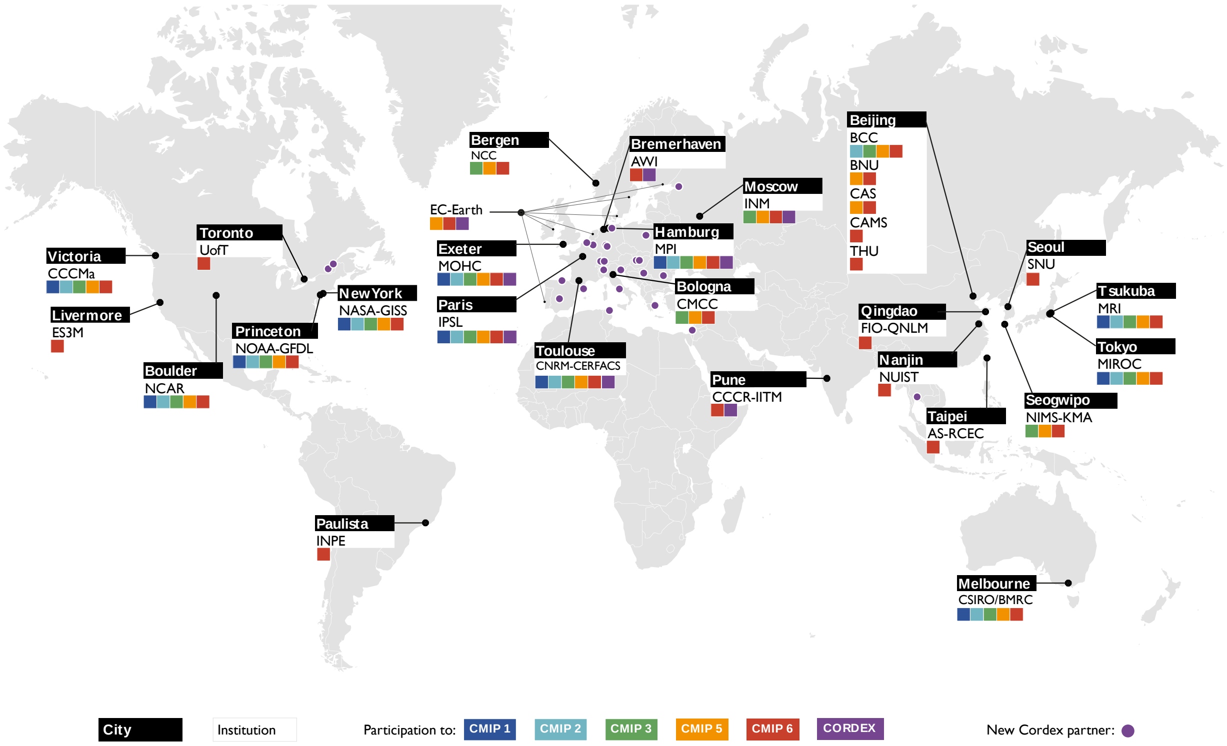


Figure 1.9: A world map showing the increased diversity of modelling centres contributing to CMIP (idea, use different symbols or colors or sizes for climate centres that participated in CMIP3, CMIP5, CMIP6), and also modelling contributions to CORDEX. [TO BE UPDATED, CORDEX information is incomplete]

Figure 1.32:

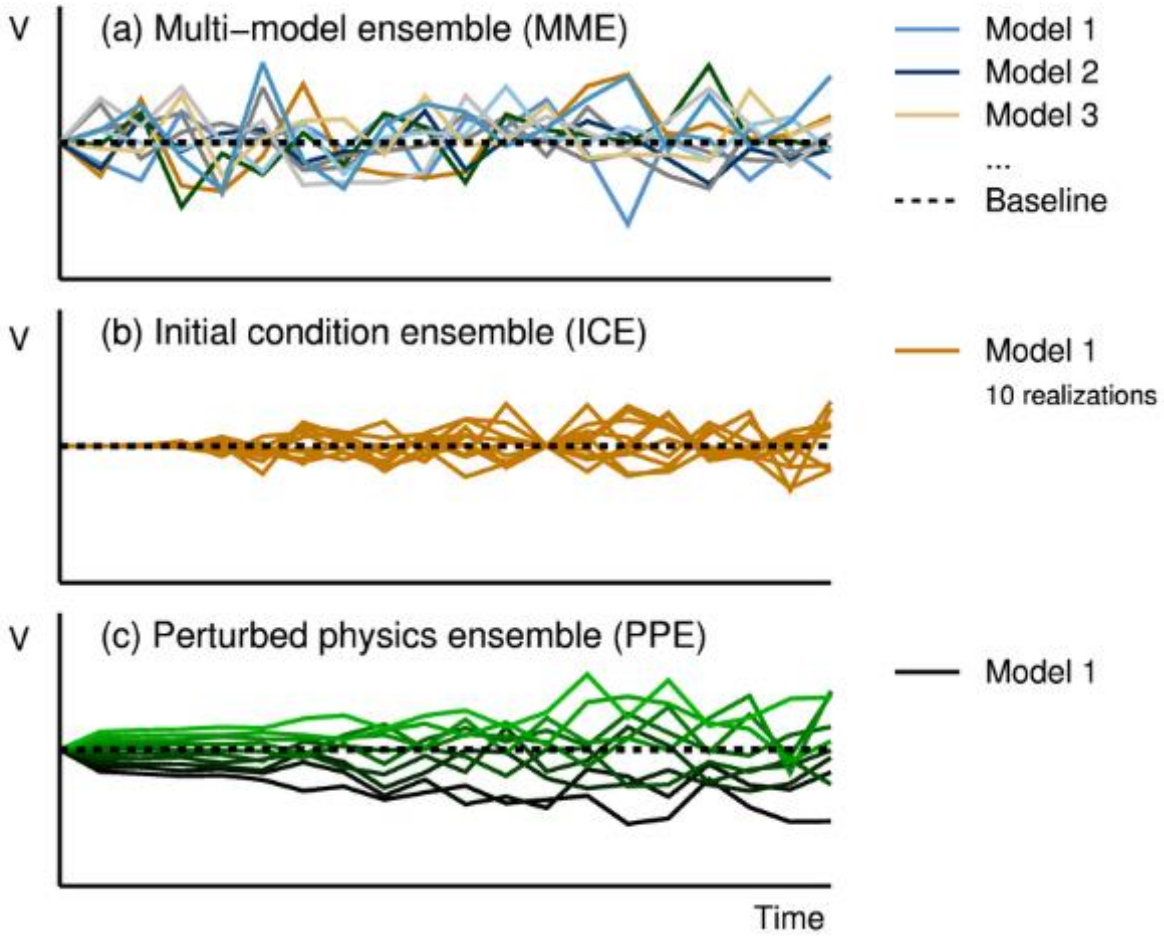


Figure 1.10: Illustration of common types of model ensemble, simulating the time evolution of a quantity V (such as surface temperature or precipitation). (a) Multi-model ensemble, where each model has its own realization of the processes affecting V, and its own internal variability around the baseline value (dashed line). (b) Initial condition ensemble, where several realizations from a single model are compared. These differ only by minute perturbations to the initial conditions of the simulation, such that over time, internal variability will progress differently in each ensemble member. (c) Perturbed physics ensemble, which also compares realizations from a single model, but where one or more quantities that may affect V are systematically changed to allow for a quantification of the impact of those quantities on the model results.

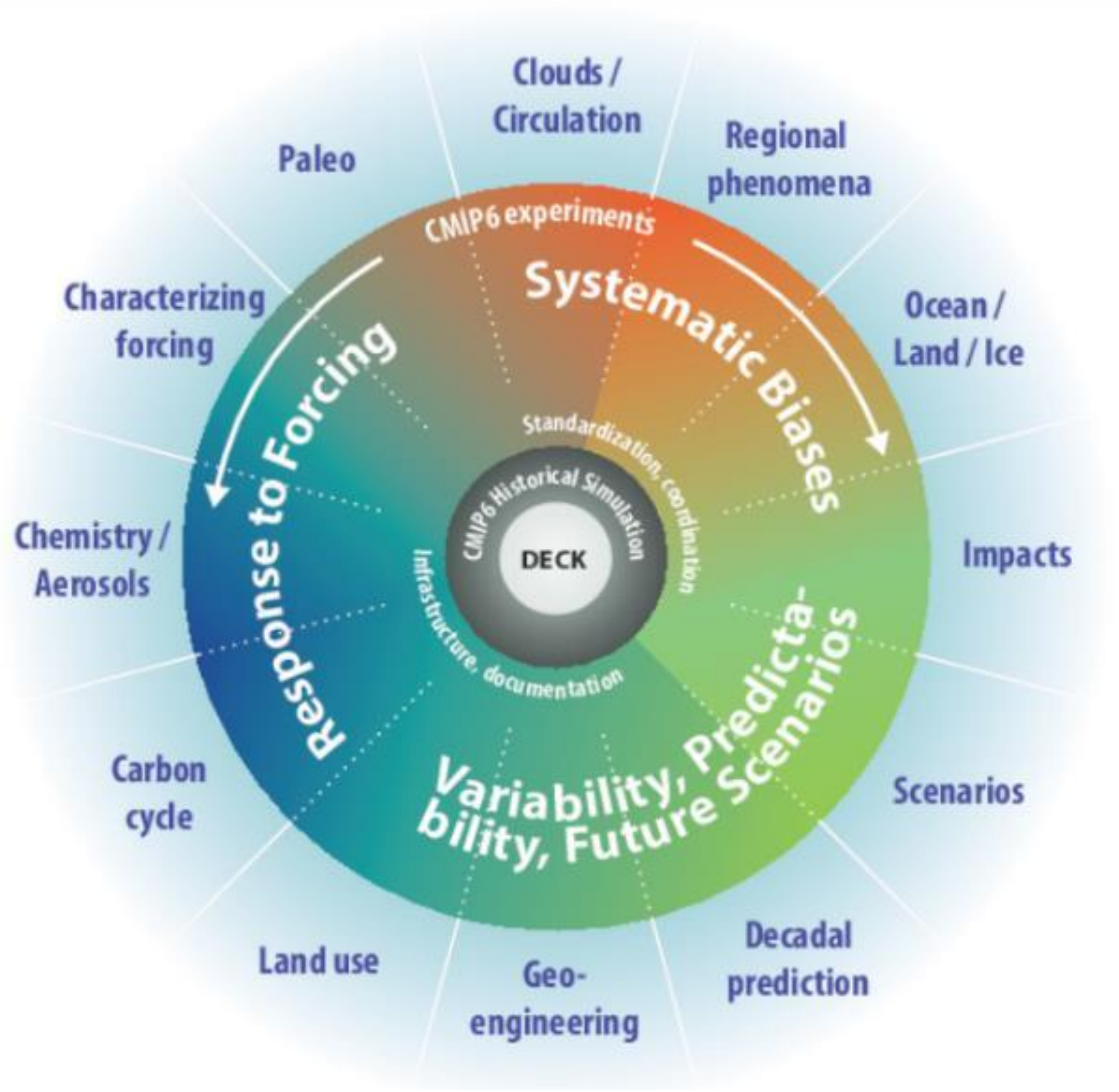


Figure 1.11: Structure of the CMIP6 multi-model intercomparison project (Eyring et al., 2016a). The centre shows the common DECK and historical experiments that all participating models must perform, the outer circle shows the topics covered by the endorsed MIPs.

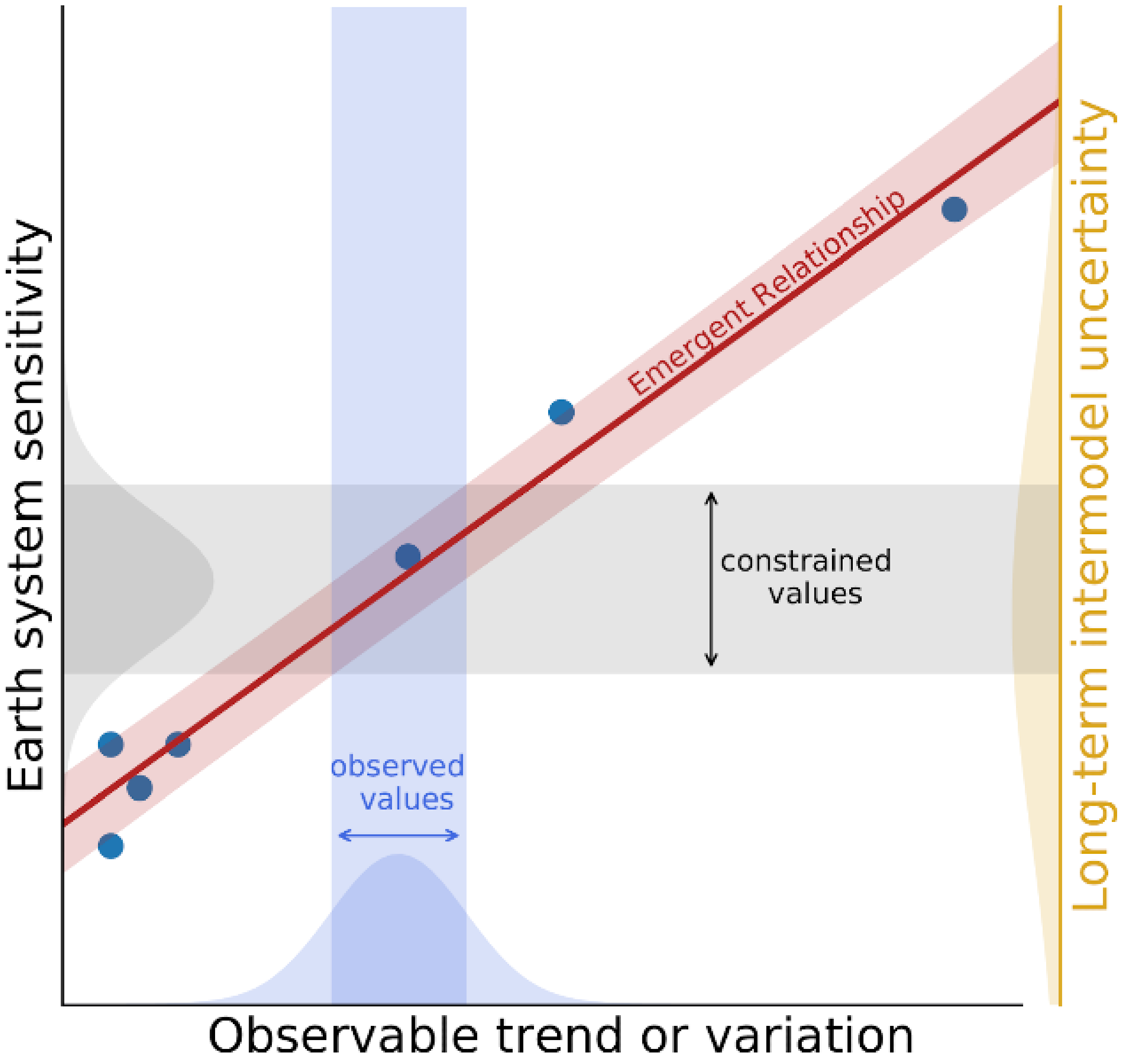
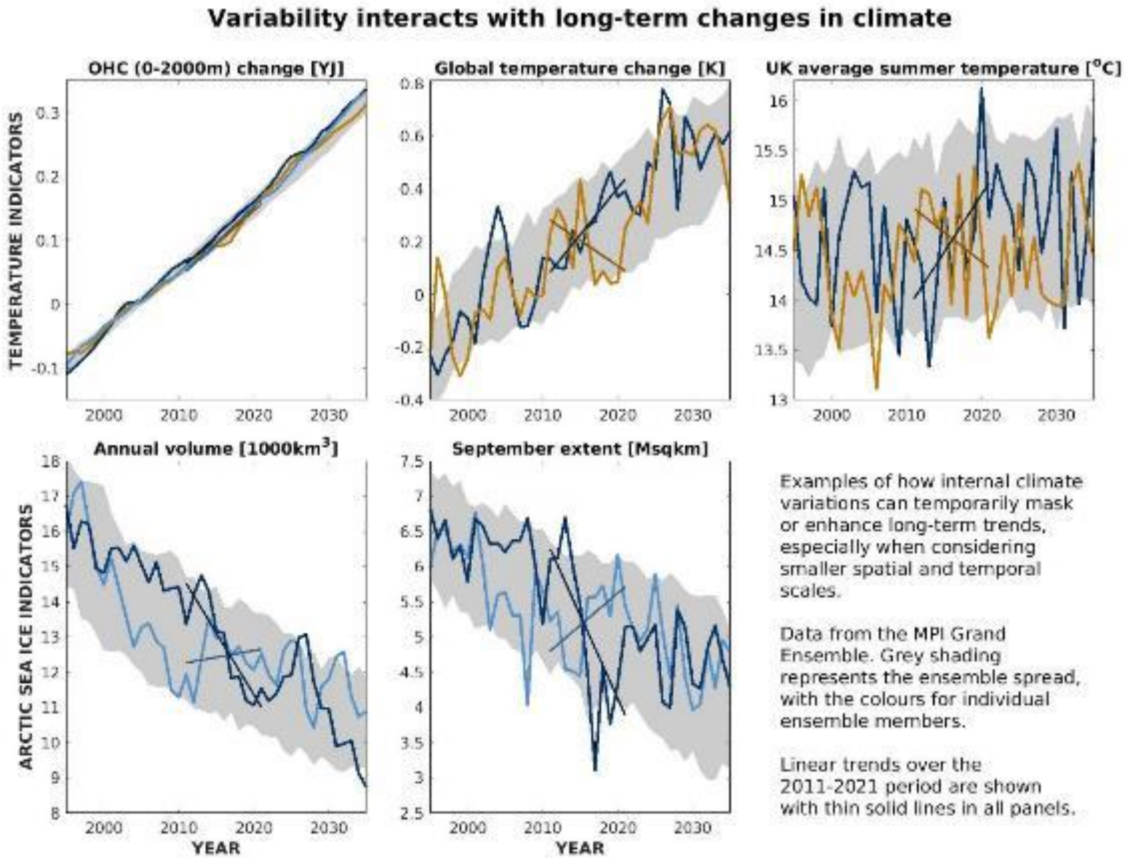


Figure 1.12: The principle of Emergent Constraints. An ensemble of models (blue dots) define a relationship between an observable trend or variation in the climate (x-axis) and an uncertain climate sensitivity or feedback (y-axis). An observation of the x-axis variable can then be combined with the model-derived relationship to provide a tighter estimate of the climate sensitivity or feedback on the y-axis (adapted from Eyring et al. (2019)).


Variability interacts with long-term changes in climate

OHC (0-2000m) change [YJ]

Global temperature change [K]

UK average summer temperature [^{o}C]

Annual volume [1000km^3]

September extent [Msqkm]

Examples of how internal climate variations can temporarily mask or enhance long-term trends, especially when considering smaller spatial and temporal scales.

Data from the MPI Grand Ensemble. Grey shading represents the ensemble spread, with the colours for individual ensemble members.

Linear trends over the 2011-2021 period are shown with thin solid lines in all panels.

Figure 1.13: Simulated changes in various climate metrics using historical and RCP4.5 scenarios using the MPI Grand Ensemble (Maher et al. 2019, in review). The top row shows temperature-related metrics (Ocean Heat Content to 2000m, annual global surface air temperature and UK summer temperatures) and the bottom row shows Arctic sea-ice related metrics (annual ice volume and September sea-ice area). The grey shading shows the 5-95% range from the 100-member ensemble, and the coloured lines represent three individual ensemble members. All three members shown have very similar OHC trends (top left) but vary considerably for other climate metrics (only two are shown for each). Trends are shown with thin solid lines for the 2011-2021 period.

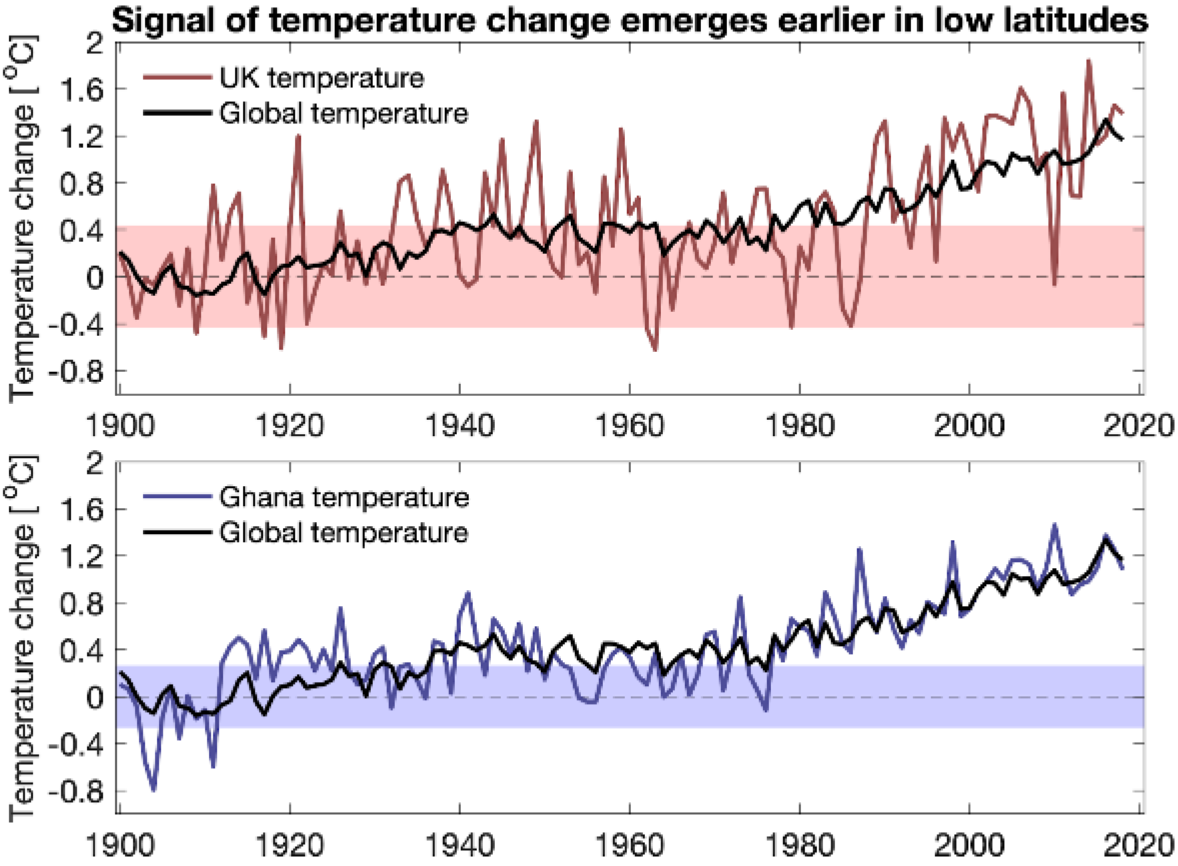


Figure 1.14: Observed temperatures in the UK and Ghana from 1900-2018 in the Berkeley Earth temperature dataset, and GMST from HadCRUT4. The shaded band indicates the amplitude of internal variability [over X year periods] for each region. After Sutton et al. (2016).

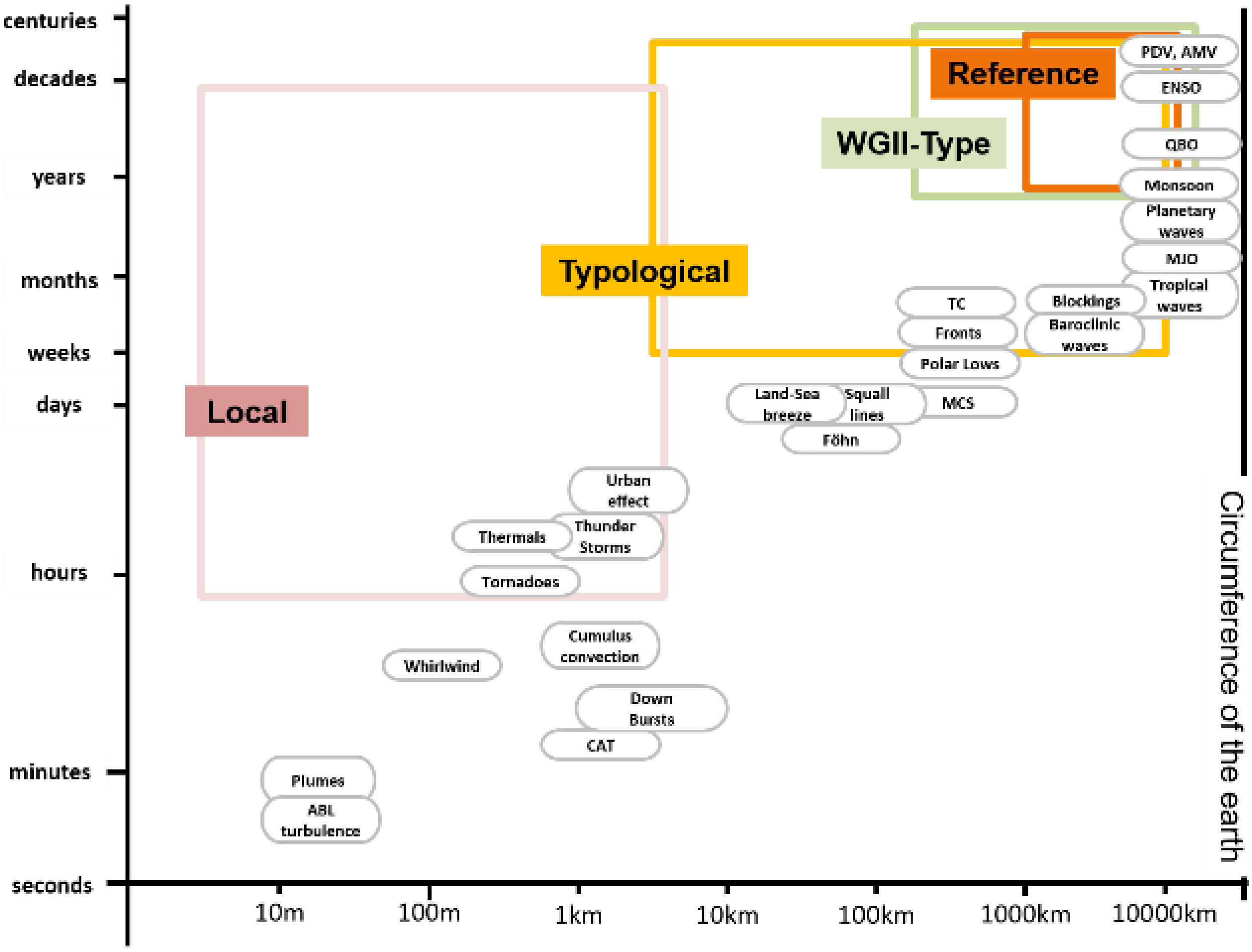


Figure 1.15: Spatial and temporal scales of atmospheric processes and their relations to the region sets used in this report, namely reference land and ocean regions (Reference), WGII-type regions (WGII-Type), and typological land and ocean regions (Typological). The domain "Local" stands for local domains not formally defined but occasionally mentioned in specific situations (see Figure 10.1 in Chapter 10 for a comparison with various modelled processes at regional and global scales. [To be updated]

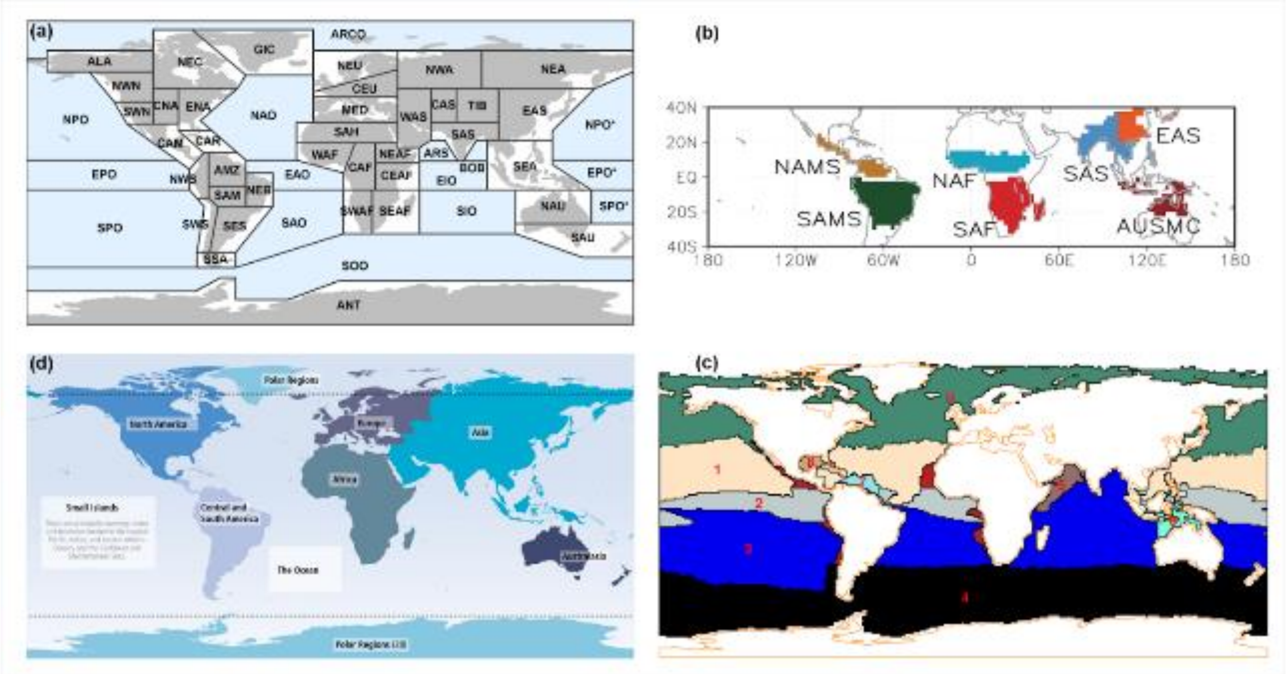


Figure 1.16: Main types of regions used in this report. (a): AR6 WGI reference set of land and ocean regions, used throughout this report. There are 37 land regions and 12 ocean regions in total. Notice that SPO, NPO and EPO continue on the left side of the map, indicated with an asterisk. For the meaning of the acronyms and details of each region, see the Atlas. [The reference set of ocean regions are still tentative and will be confirmed in the SOD]. (b): Example of typological land regions. Land monsoon domains adopted in Chapter 8 [to be updated accordingly with chapter 8], as defined in AR5 WGI. The acronyms stand for North America Monsoon System (NAMS), North Africa (NAF), Southern Asia (SAS), East Asian Summer (EAS), South America Monsoon System (SAMS), South Africa (SAF), and Australian-Maritime Continent (AUSMC). All the regions are within 40°S to 40°N. For further details, see Chap. 8. (c): Example of typological ocean regions. Ocean biome zones used in Chapters 5 and 9, which reflect the historical mean of the dynamics. The following regions are displayed: (0) Northern Hemisphere High Latitudes, (1) Northern Hemisphere Subtropics, (2) Equatorial, (3) Southern Hemisphere Subtropics, (4) Southern Hemisphere High Latitudes, (5) Arabian Sea, (6) Eastern Boundaries, (7) Amazon River, (8) Gulf of Mexico and (9) Indonesian Flowthrough. For more information, see Chapter 5. (d): WGII-type regions used in Chapter 12, as defined in AR5 WGII Part B.

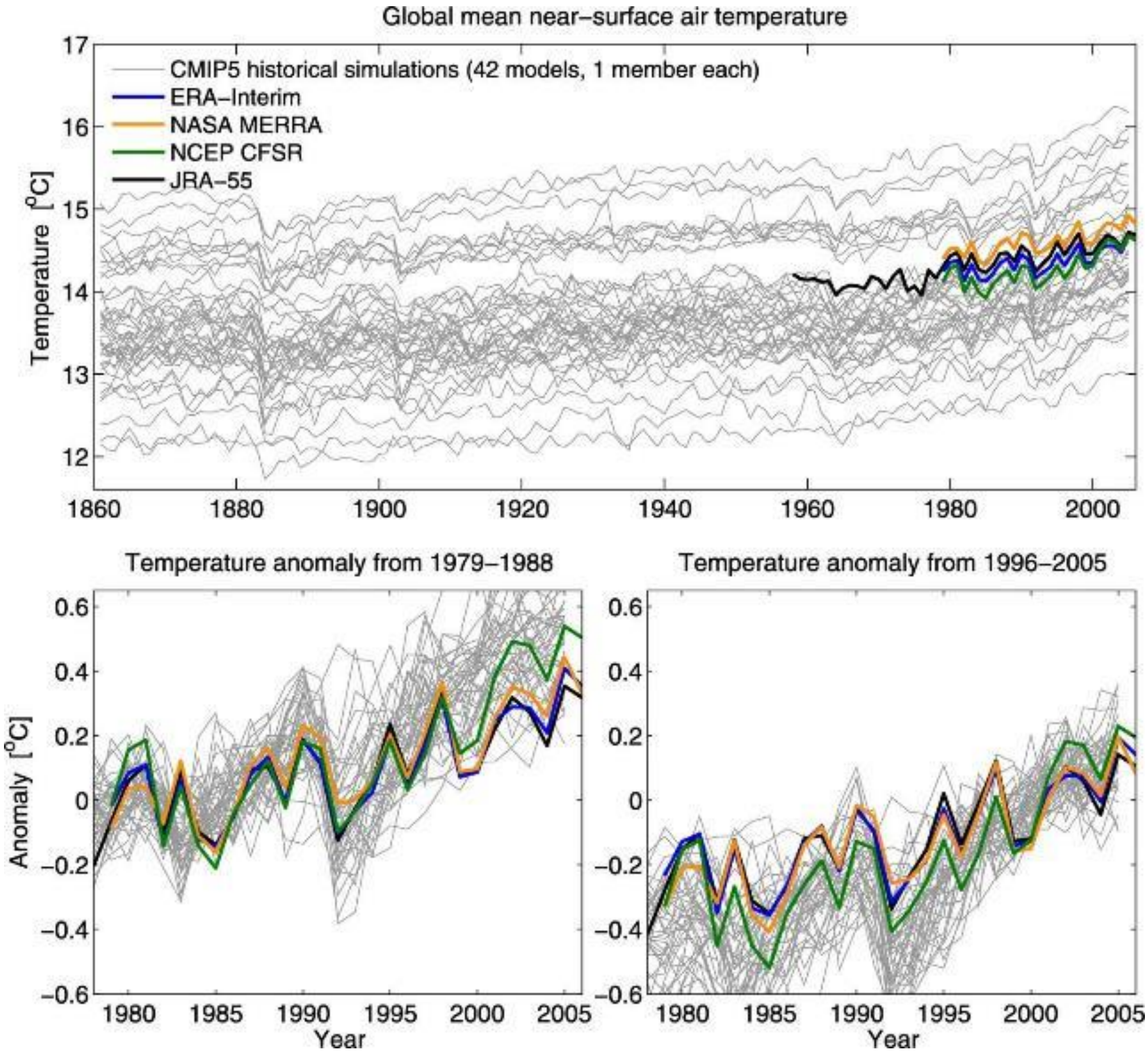


Figure 1.17: Global mean surface air temperature from the range of CMIP5 historical simulations (1861-2005) using absolute values (top) and anomalies relative to two different baselines (bottom). In order to compare the models with each other and with reanalyses and observations (colours), a baseline or reference period has to be chosen, and that choice can affect the comparison. (Taken from Hawkins and Sutton, 2016, and to be updated with CMIP6 data.)

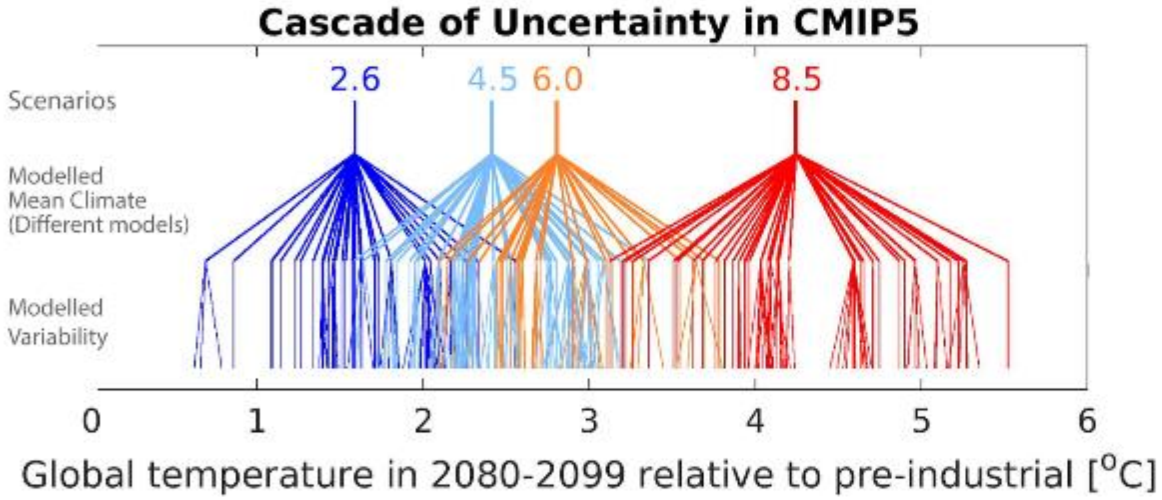


Figure 1.18: The 'cascade of uncertainties' in climate projections of global mean surface temperature change for 2080-2099 from CMIP5. The multi-model mean for each scenario is indicated at the top of the cascade. This branches downwards to show the multi-realisation mean for each model (middle row), and further branches into the individual realisations (bottom row), though often only a single realisation is available. For this time period, the scenario uncertainty and model response uncertainty are larger than the internal variability. (To be updated to CMIP6 and include a near-term regional example to highlight the role of internal variability on smaller spatial and temporal scales.)

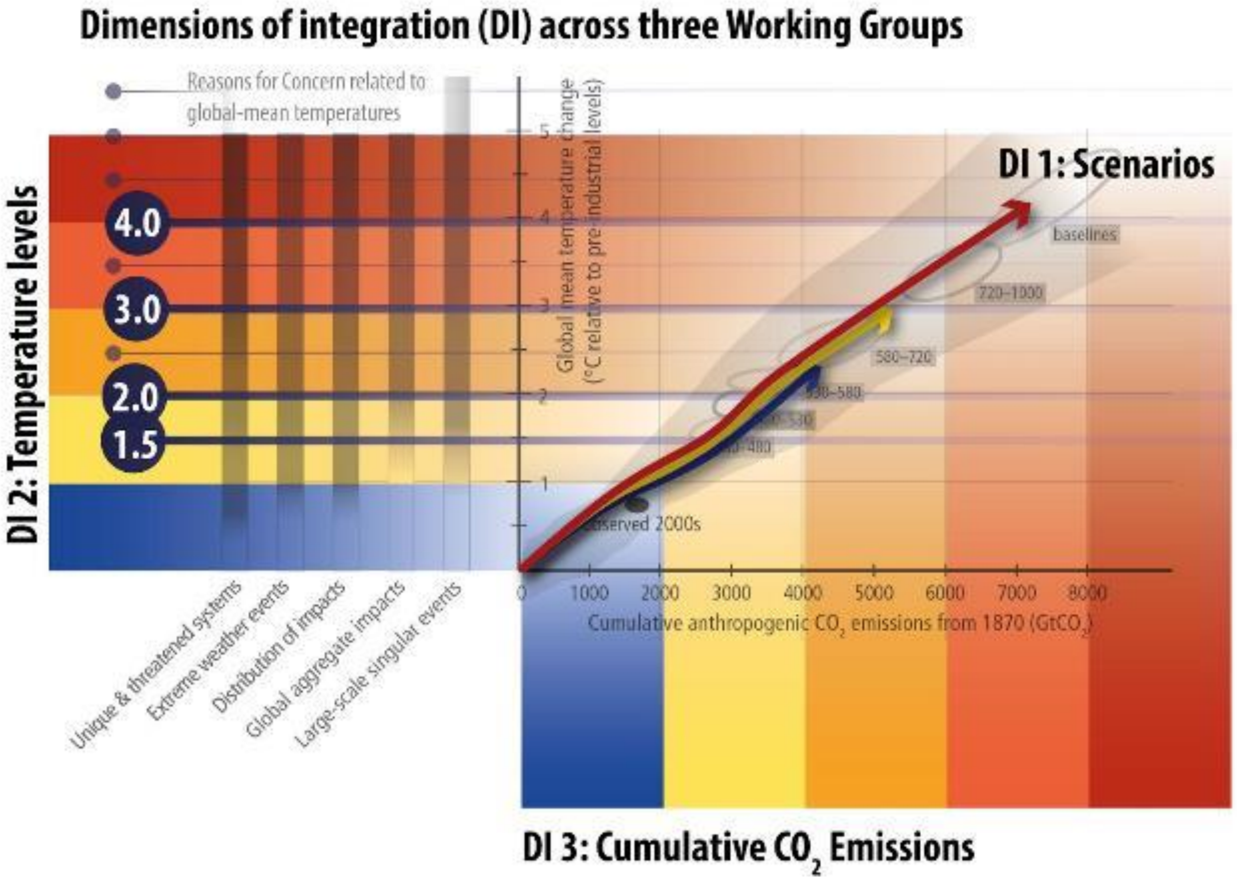


Figure 1.19: The Dimensions of Integration (DI) across Chapters and Working Groups in the IPCC AR6 assessment report. Building on the Synthesis Reports of the Fifth IPCC Assessment report (background image detail) this report adopts three explicit dimensions of integration to integrate knowledge across chapters and Working Groups. The first dimension (DI 1) are scenarios, the second dimension (DI 2) are global-mean temperature levels relative to pre-industrial levels and the third dimension (DI 3) are cumulative CO_2 emissions.

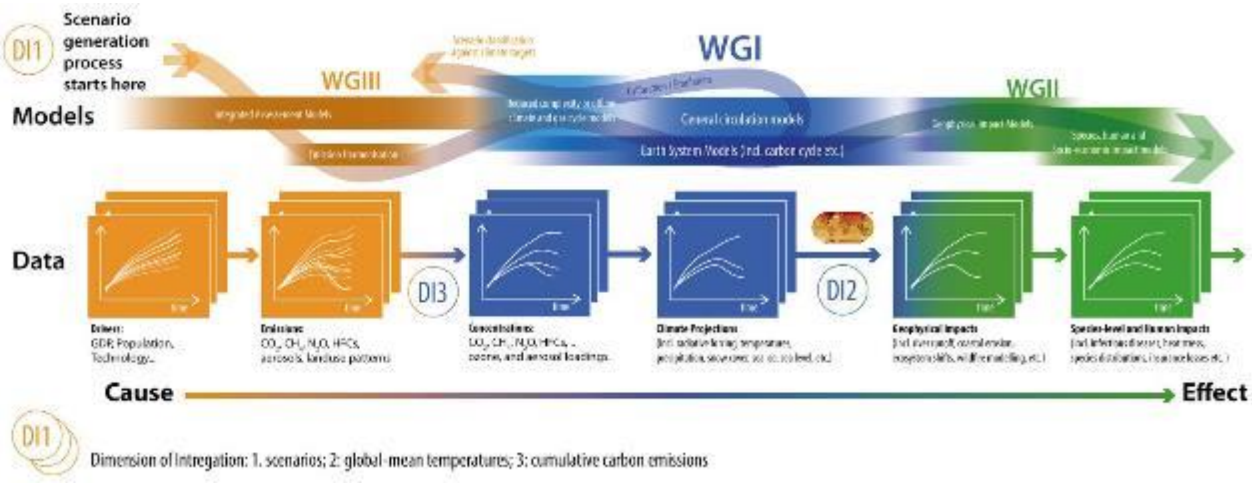


Figure 1.20: The scenario generation process that weaves through the three Working Groups and its scientific communities. The top level indicates the main set of models used in that scenario generation process, with the lower level indicating the datasets. Also, the three dimensions of integration (scenarios, cumulative carbon emissions and global-mean temperature levels) are indicated as open circles, with cumulative emissions sitting at the handover between WGIII (orange) and WGI (blue), and global-mean temperatures sitting - simplified speaking - at the connection point between WGI and WGII (green).

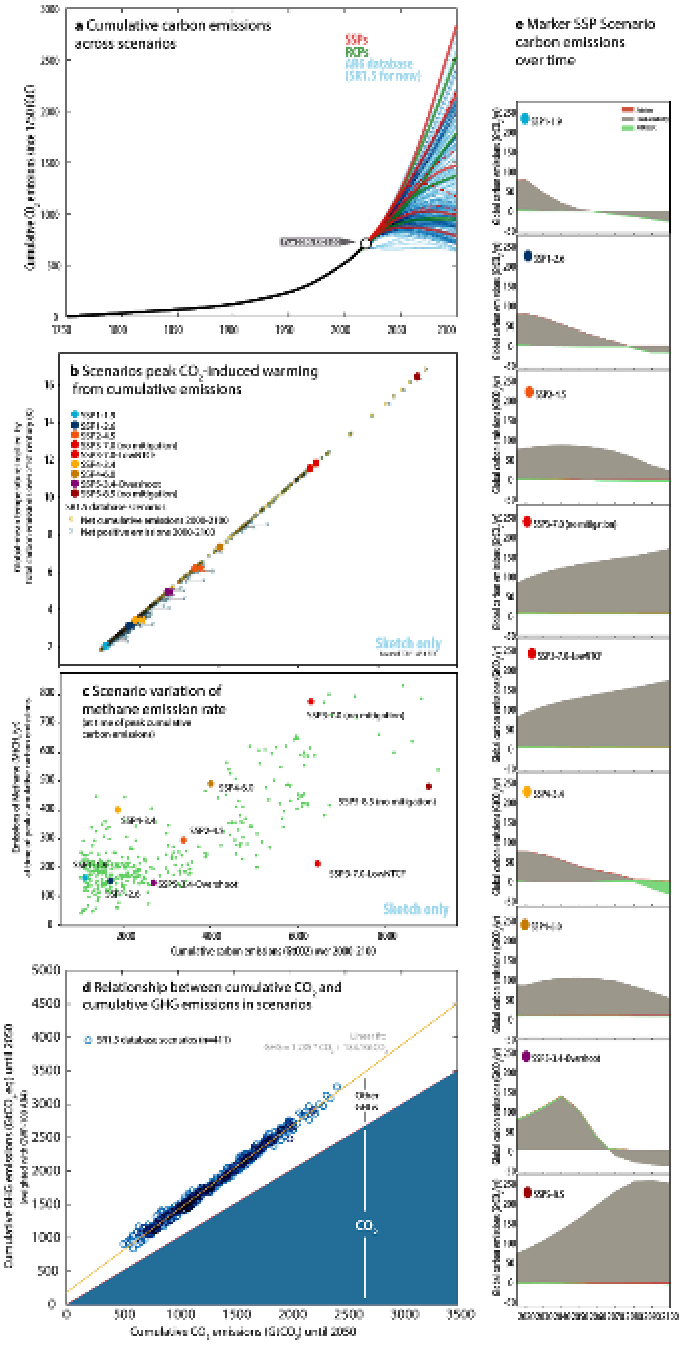


Figure 1.21: Analysis of the marker SSP scenarios, RCP and the wider AR6 scenario database regarding cumulative carbon emissions over time (panel a). The implied CO_2-induced warming given those cumulative emissions and the TCRE is shown for SSP scenarios and SR1.5 emission scenario database (panel b). The variation of non-CO_2 emission rates at the time of peak cumulative emissions is here exemplified with total methane emissions that can substantially influence the remaining carbon budget (cf. Collins et al. (2018)) (panel c). Overall, the GWP-weighted sum of all greenhouse gas emissions is a close indicator of cumulative carbon emissions until 2050 in the literature scenarios, lending some support to policy architectures that address GWP-weighted emission baskets as one of many options (see discussion in Chapter 7) (panel d). The timing of net positive and net negative emissions across the 9 SSP marker scenarios over time (panels e on the right side). [Note: this graph is only a sketch to highlight a few aspects of the AR6 emission database. To be updated]

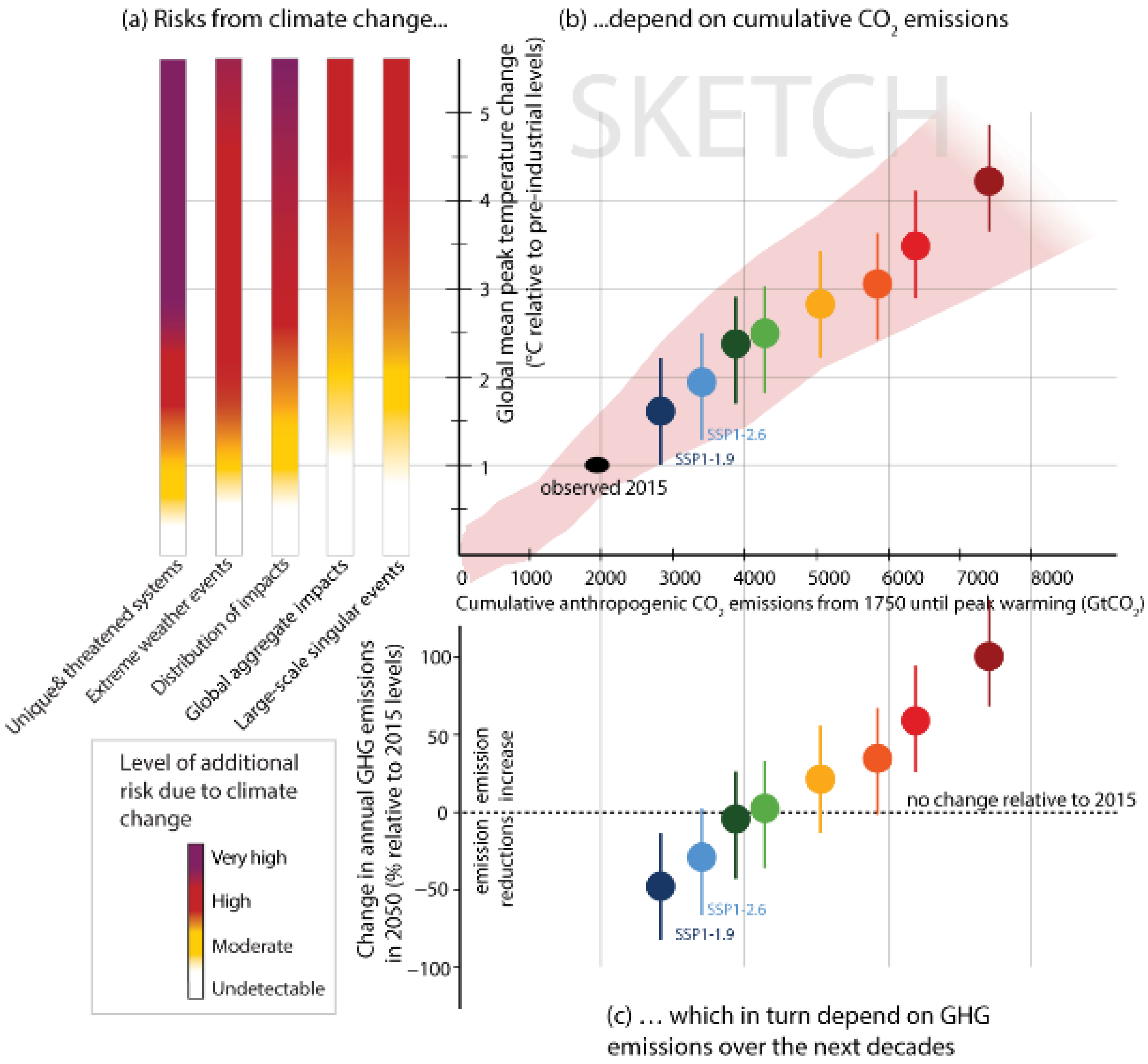


Figure 1.22: The marker SSP scenarios used throughout the AR6 report, their cumulative CO2 emissions and 2050 GHG emission levels in the context of the risks from climate change. Shown is the Synthesis Report Figure SPM.10 from AR5, updated by the 21st century characteristics of the new SSP scenarios in panel b and c. [Note, this is only a hand-drawn sketch].

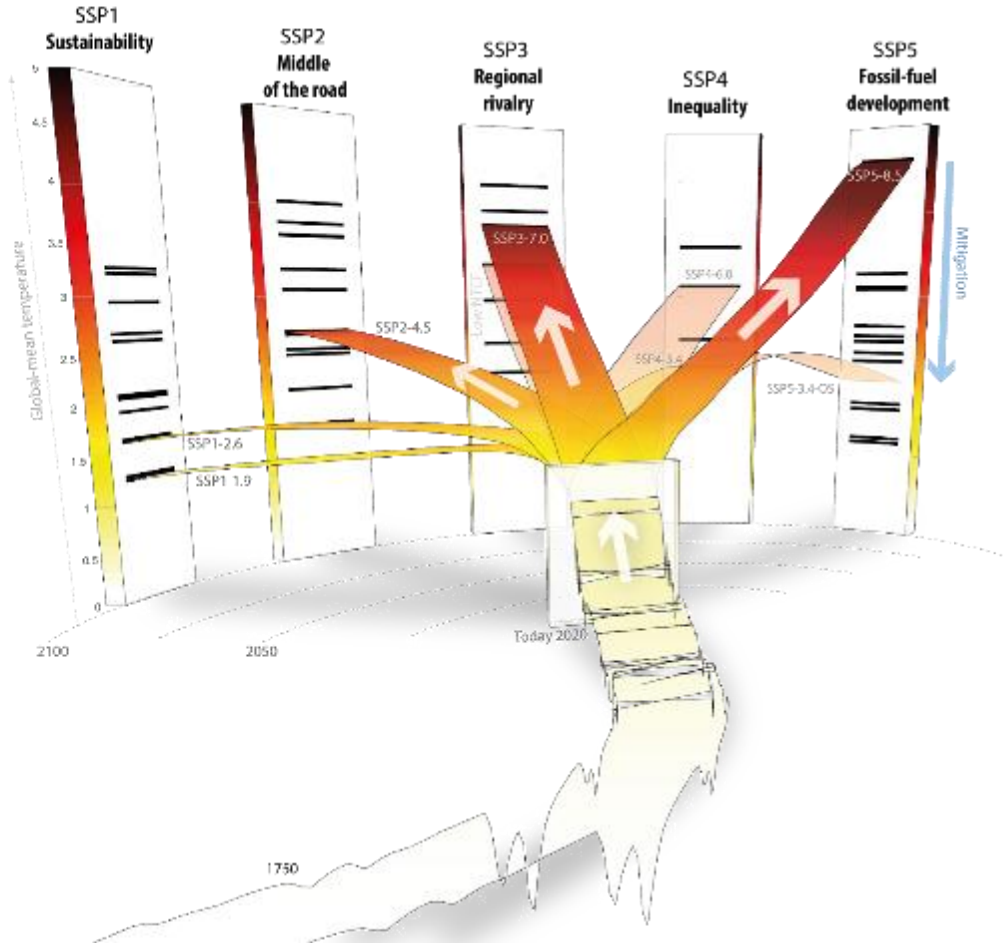


Figure 1.23: The five future shared socio-economic scenarios SSP1 to SSP5, their model-specific reference scenarios and mitigation scenario within each future world. Here, the nine marker SSP scenarios from ScenarioMIP are shown with the higher priority scenarios SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 being shown in higher opaqueness. The illustrative temperature evolution is derived from the default MAGICC 7.0 setting used to produce the greenhouse gas concentrations for those SSP scenarios (greenhousegases.science.unimelb.edu.au). Note that those temperature evolutions are illustrative only and subject to large uncertainties. The black stripes on the respective scenario panels indicate SSP scenarios that were not selected to be marker scenarios, but span the scenario range more fully [Note, this graph is a sketch only. To be updated].

Figure 1.33:

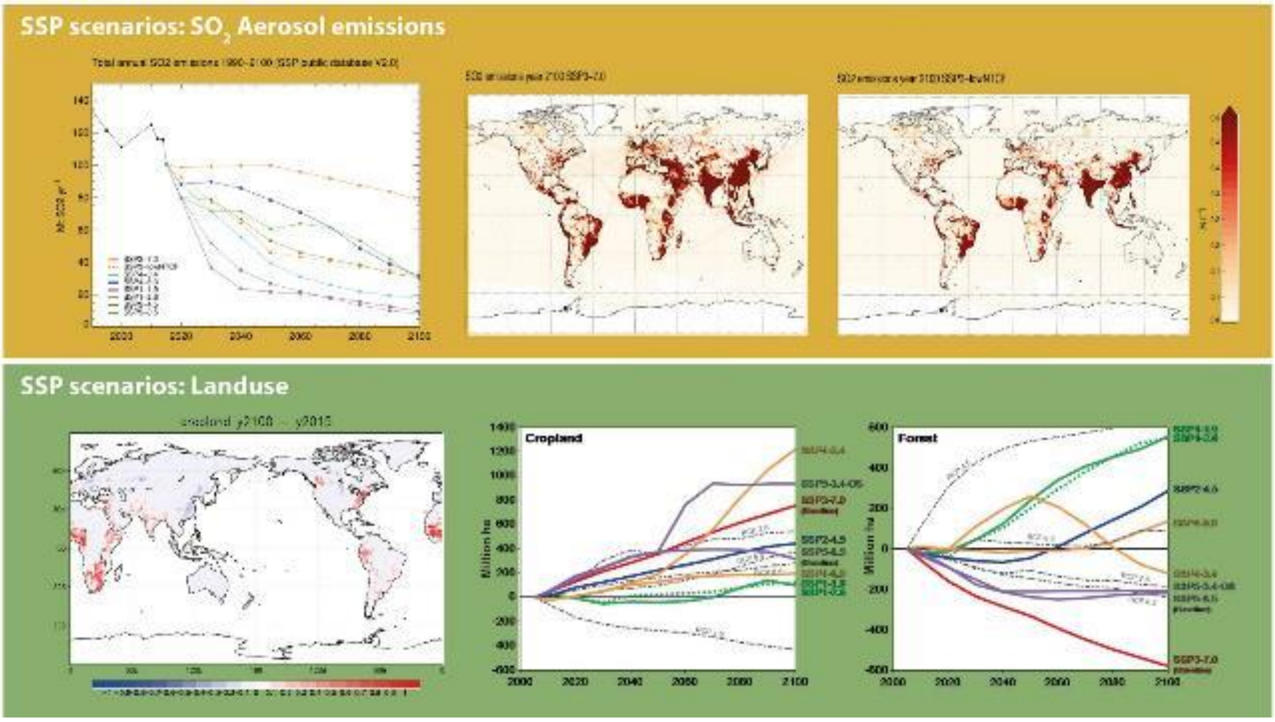


Figure 1.24: Examples for the input datasets for the SSP scenarios, showing the range of SO2 emission scenarios over the 21st century [Note, a future version of this graph will show the RCP range in the background], and also a very high and low spatial emission example from the SSP3.-7.0 and SSP3-7.0-lowNTCF scenarios in 2100, respectively (top row). As landuse examples for the SSP scenarios, the spatial change in cropland cover in year 2100 to year 2015 is shown in the scenario SSP3-7.0 (left panel), the global cropland change over time in all SSP scenarios compared with the RCP scenarios (middle panel) and the change in forest cover - with afforestation and reforestation in the SSP1-1.9 and SSP1-2.6 scenarios indicating the strongest increase in global forest cover (right panel). Source: Top graphs produced by CICERO on the basis of SSP database 2.0. Bottom graphs adapted from Fig 4 in O'Neill et al. (2016) with the cropland cover map being based on the land-cover dataset from LUMIP (Hurtt et al, in preparation - available at: http://luh.umd.edu/).

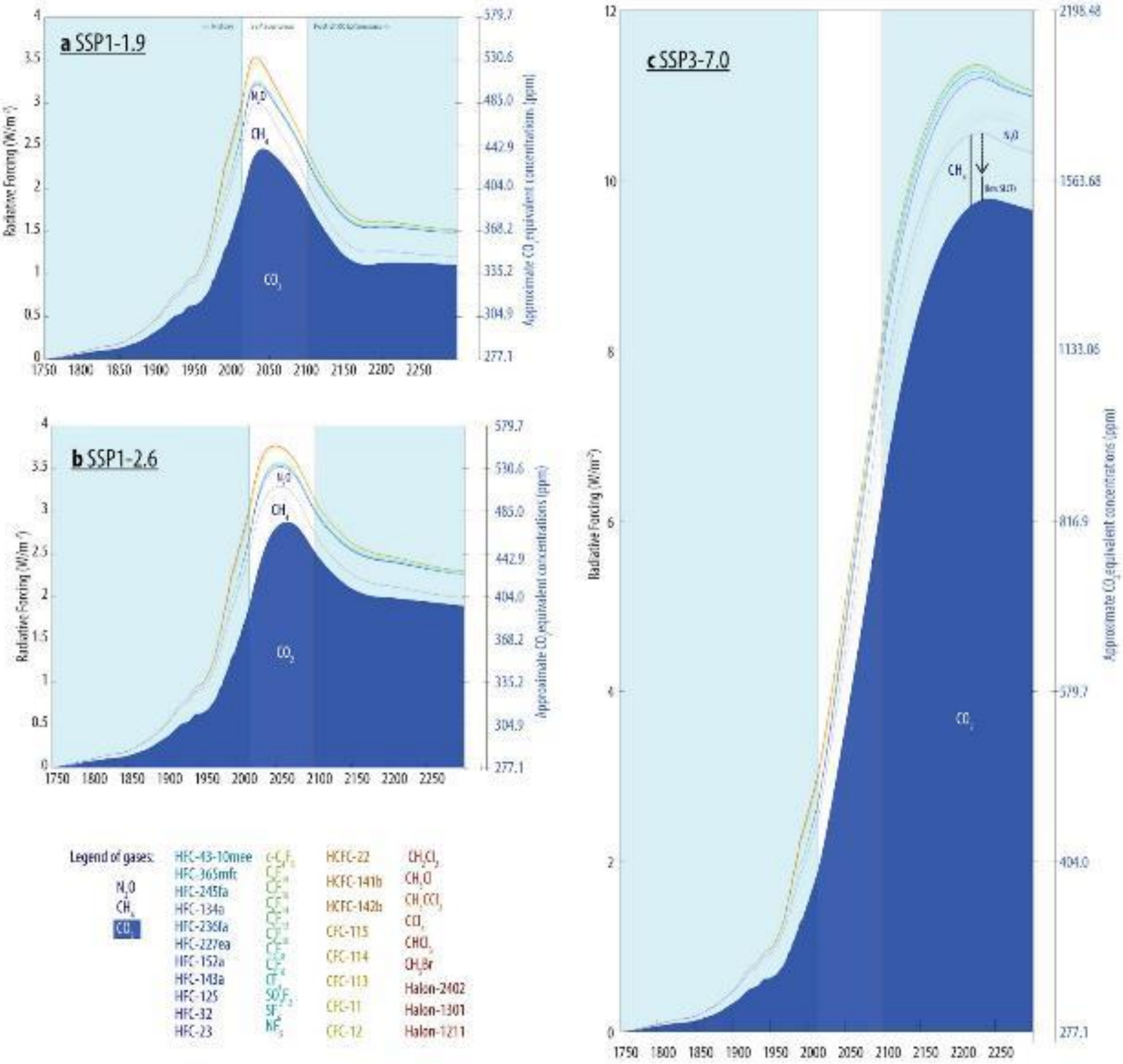


Figure 1.25: An illustrative comparison of the relative importance of greenhouse gas concentrations for projected climate change. The blue shaded area indicates the approximate forcing exerted by CO_2 in three of the SSP scenarios, SSP1-1.9, SSP1-2.6 and SSP3-7.0. The CO_2 concentrations under the SSP1-1.9 scenarios approximately reach 350 ppm after 2150, those of SSP1-2.6 around 400 ppm and the SSP3-7.0 as one of the higher scenarios will reach levels of nearly 1500 ppm CO_2 in the longer term until 2300. Also shown are the effects of reducing short-lived climate forcers in the SSP3-7.0 scenario at the example of methane (panel c, black arrows in the top right), when comparing the SSP3-7.0 scenarios with the AerChemMIP variant SSP3-7.0-lowNTCF [To be updated]

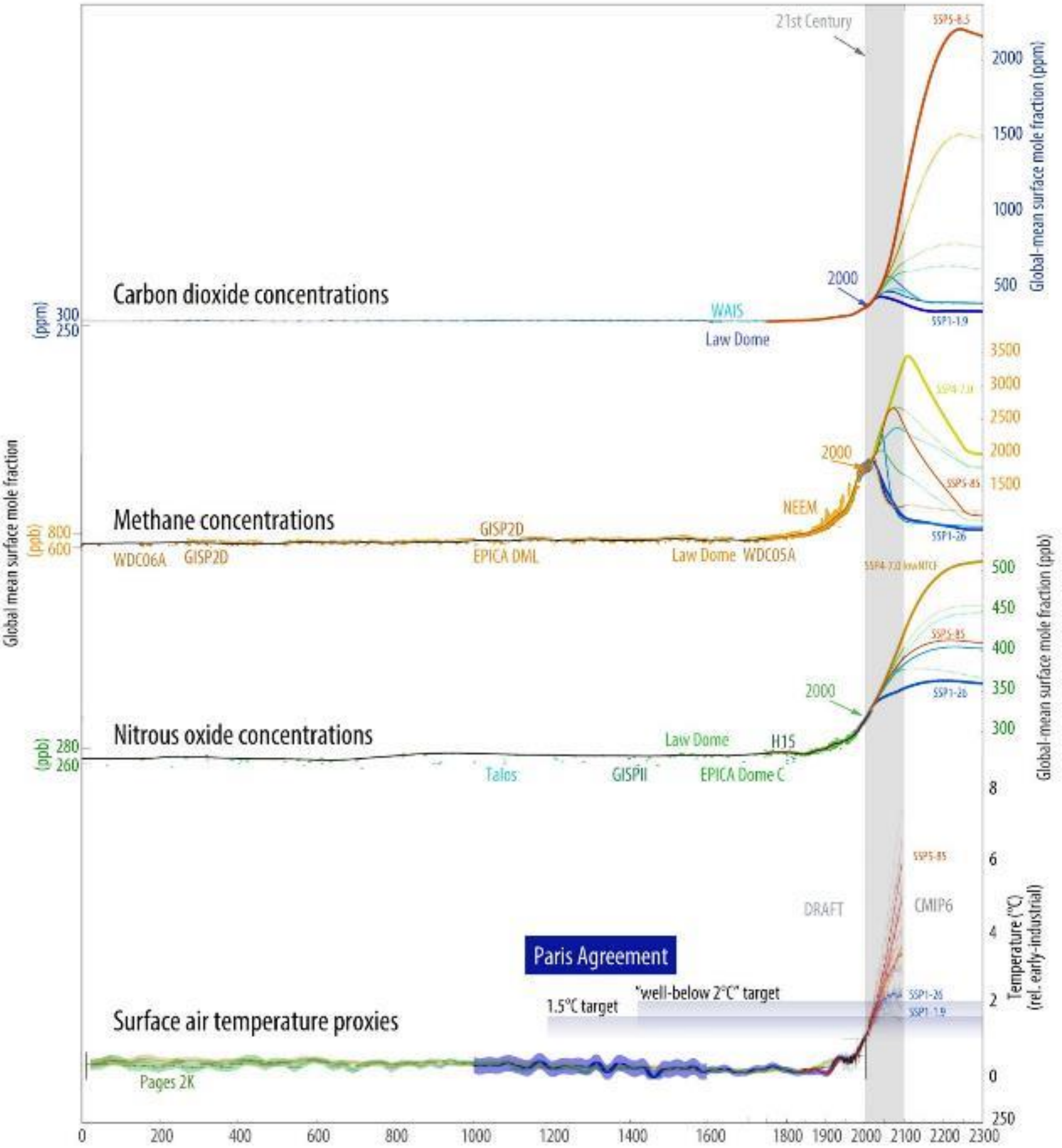
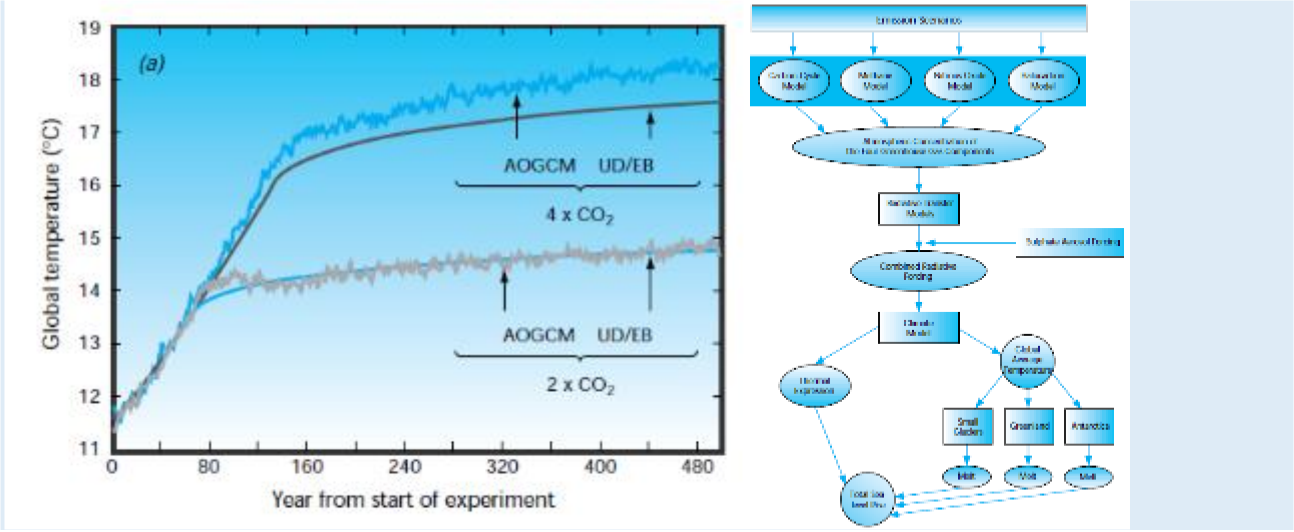


Figure 1.26: Historical concentrations for the past 2000 years of CO_2, CH_4 and N_2O (Meinshausen et al., 2017), and [draft sketch of] temperature reconstructions joined with scenario information up to year 2300. The temperature proxies over the last 2000 years were compiled by the Pages 2K project (Emile-Geay et al., 2017) and also shown are northern hemispheric temperature reconstructions by Mann et al. (1999) (dark blue ranges). Future temperature projections are from the CMIP6 ScenarioMIP experiment, examined in Chapter 4 of this report. The grey vertical band indicates the 21st century. [Note: this is a draft sketch figure only].

[PLACEHOLDER for figure]

Figure 1.27: Illustrative synthesis figure on the “decision power/policy-relevance” of scenarios in the context of the Paris Agreement. The ‘decision power’ for this analysis is here defined as the range between reference and various mitigation scenarios that include shared policy assumptions (SPAs), separated by gases and scenario characteristics in relation to their effect (attributable warming) on peak 21st century temperatures [and end of century sea level rise] (y-axis). The individual elements on the x-axis can be: Next decade cumulative CO_2 emissions, CH_4 emissions, non-methane SLCF, second half of century net negative CO_2 emissions, and GHG emission levels in 2030 (possibly shown by various metrics, (GWP|GTP, and GWP* in some form)). For example, methane emissions, cumulative CO_2 emissions, cumulative GHG emissions (GWP|GTP\GWP* weighted), SLCF emissions and other GHG emissions. [dependent on AR6 scenario database analysis].



Cross-Chapter Box 1.5, Figure 1: Left panel: A comparison between an the global-mean temperature response of an upwelling-diffusion energy balance simple climate model in 1997 to early AOGCM results by by Manabe and Stouffer (1994), reproduced from the IPCC Technical Paper on simple climate models (Houghton et al., 1997). The non-linearity or state-dependency of the climate sensitivity in AOGCMs or ESMs is evident by the difference to a constant-climate sensitivity simple climate model as used in IPCC Second Assessment Report. More advances in simple climate models of similar structure account for those state-dependent climate sensitivities and time-variable effective sensitivities, but an appropriate representation of those effects within the forcing-feedback framework is still an active area of research. Right panel: A depiction of the basic elements of simple climate models in 1997 (Houghton et al., 1997). The new generation of simple climate models includes a number of additional processes and interactions, such as carbon cycle feedbacks, permafrost modules (Schneider von Deimling et al., 2012), absorption spectra overlaps between CO_2, CH_4 and N_2O (Etminan et al., 2016). [Note, will be updated to current generation additional high-level modules].

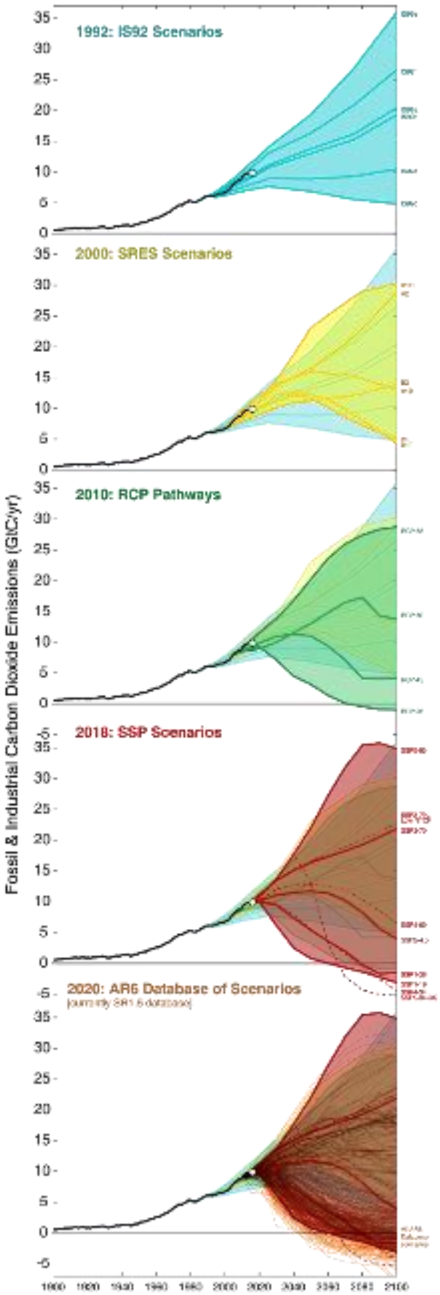


Figure 1.28: Comparison of range of CO_2 emissions from scenarios used in previous assessment up to AR6, namely the IS92 scenarios from 1992 (top panel), the SRES scenarios from year 2000 (second panel), the RCP scenarios designed around 2010 (third panel) and the SSP scenarios (second bottom panel). In addition, the full set of the AR6 set of scenarios is shown in the lower panel [Note: Placeholder dataset from SR1.5 emission database; Other gases methane and nitrous oxide to be added].

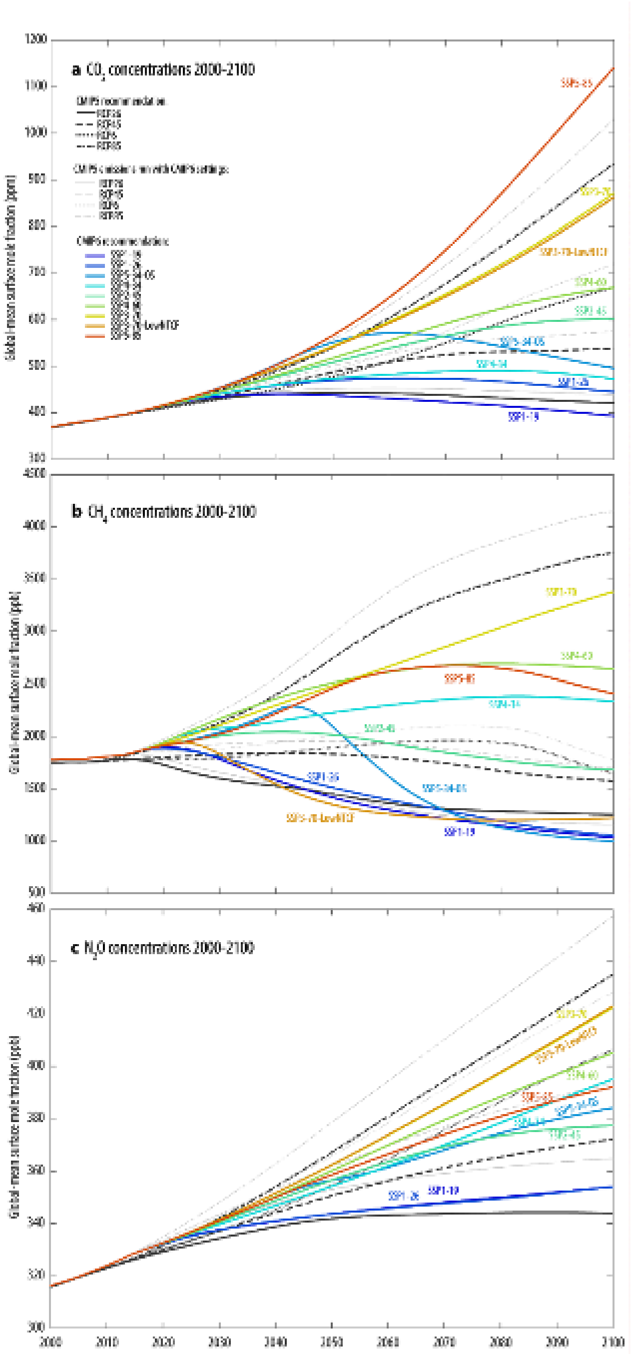
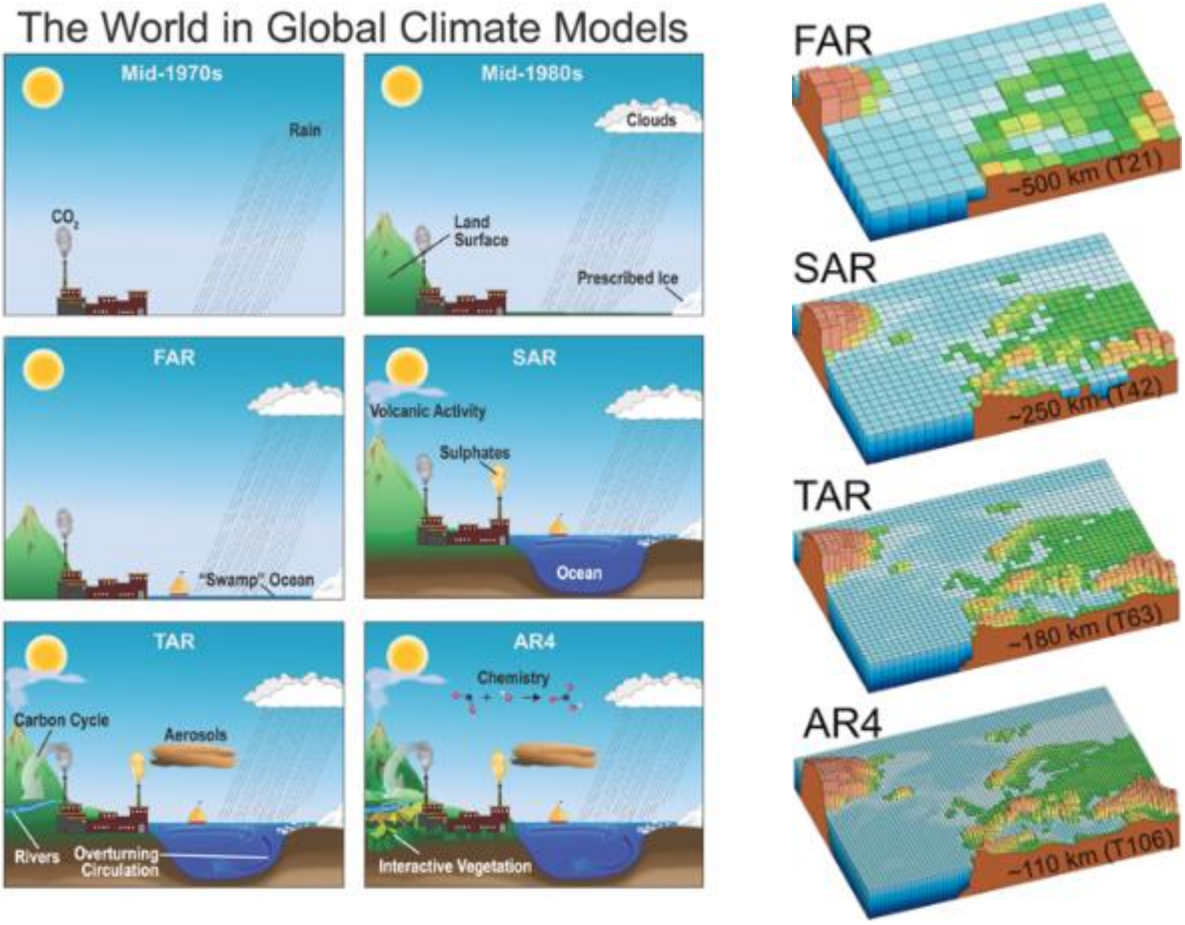
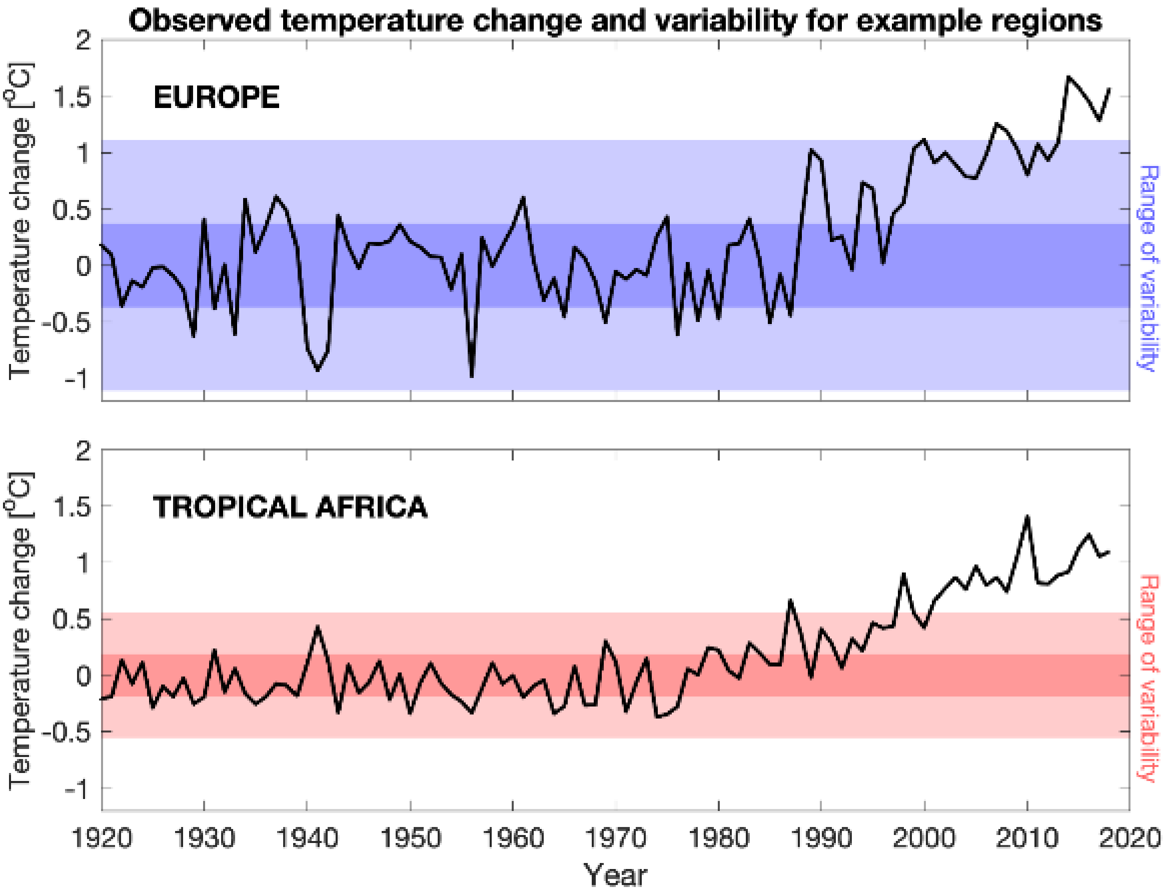


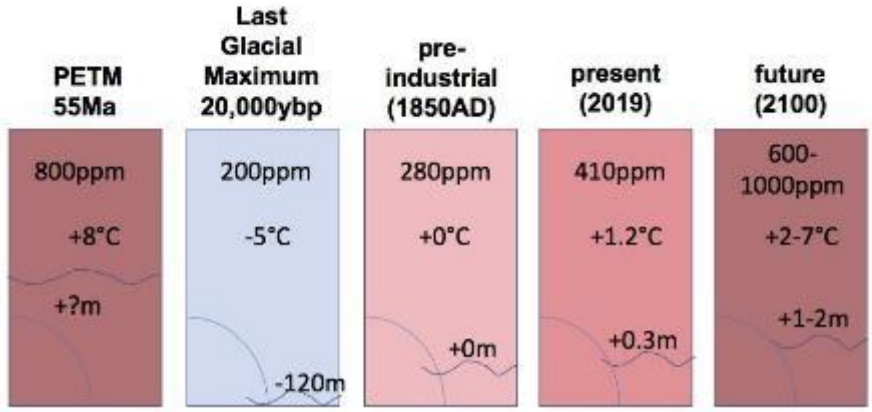
Figure 1.29: Comparison of CO$_2$, methane and nitrous oxide concentration projections under the SSP scenarios and RCP pathways. The SSP scenarios (coloured solid lines) span a wider range than the RCP scenarios for CO$_2$, whereas the top emission levels for CH$_4$ and N$_2$O are somewhat reduced in comparison to the RCP range. That is despite the fact that gas cycles have been adapted in AR6, suggesting higher future carbon, methane and nitrous oxide concentrations for the same RCP set of emissions (compare higher thin dashed lines with the thicker dashed lines).

FAQ 1.1, Figure 1: [PLACEHOLDER]

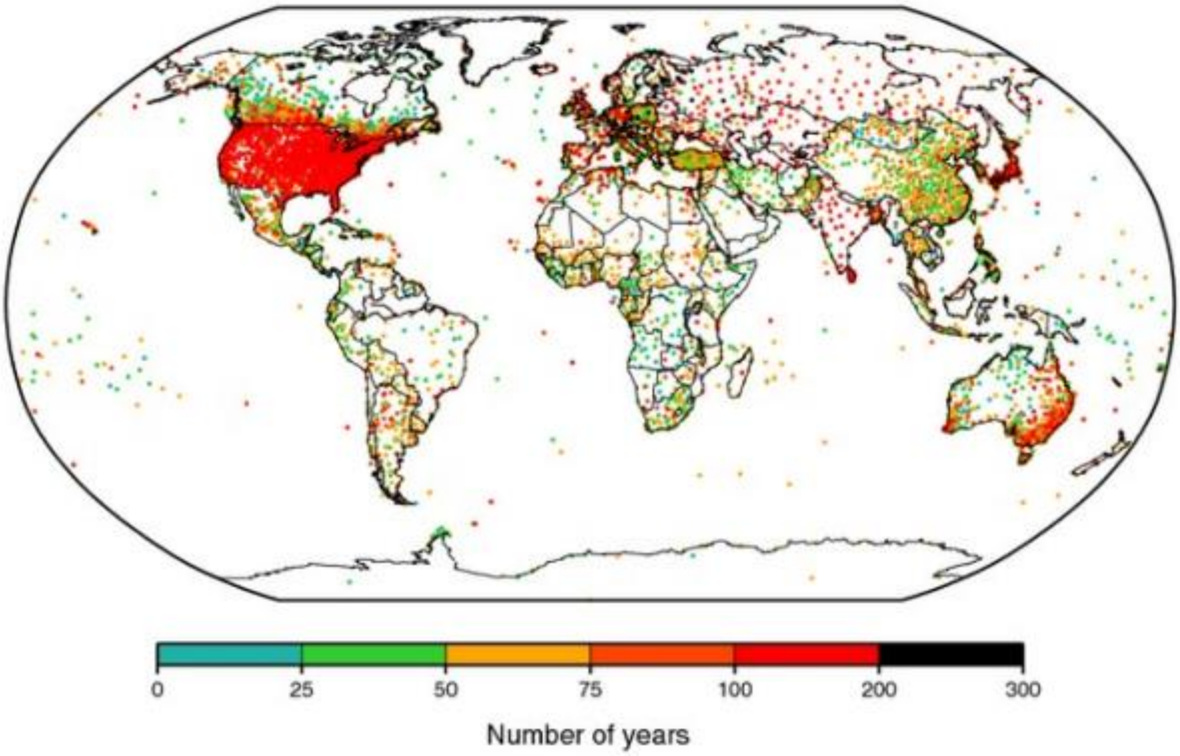




FAQ 1.2, Figure 1: Observed variations in regional temperatures since 1920 from CRUTEM4. Europe has warmed by a larger amount than tropical Africa, but the background variations are also larger (shading represents 1 and 3 standard deviations of background interannual variations). The signal of observed temperature change emerged earlier in tropical Africa than in Europe.



FAQ 1.3, Figure 1: [PLACEHOLDER]



FAQ 1.4, Figure 1: Suggestion: Global map of measurement site/point densities. With a side list of all the different techniques (eg, buoys, satellites, ships etc – could have icons for each?) Present placeholder is from Rennie et al. (2014).