Annex VII: Climatic Impact Driver Indices

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AVII.1 Introduction

This Annex provides background information on hazard indices used within Chapter 11, Chapter 12, and the Atlas, including technical details of calculation, underlying data and models, bias adjustment procedures, and related references. It helps understanding the information processing behind some of the numbers and figures provided in these chapters.

In the climate science literature, a number of indices have been used in order to characterize and quantify one or several aspects of climate phenomena occurring due to natural variability or due to long-term changes in the system. There is an extremely large number of examples. One can cite mean global climate indices, such as global mean sea level rise or global mean temperature, which characterize the state of the climate system and act as a shifting baseline for regional changes. One can also examine mean regional trends, for example in mean springtime precipitation, which reflect large-scale patterns and alter the background conditions within which episodic hazards may occur. One can also calculate indices of extremes characterizing episodic events within the tail of the distributions of specific variables within their variability range, for instance the annual maximal temperature at a given location or the 100-year return value of river discharge characterizing extreme floods. Such extreme indices have been the subject of a number of studies and have been used to characterize how climate change modifies extreme values of climate variables and subsequent impacts in the Special IPCC Report on "Managing the risks of Extreme Events and Disasters to Advance Climate Change Adaptation" (IPCC, 2012), as well other recent IPCC reports.

Indices can also characterize aspects of hazards or, more generally, climatic impact drivers (see Chapter 1 and Chapter 12 for definitions) that are key to impacts and risks to society and ecosystems. Chapter 12 proposes a definition of "climatic impact drivers indices": "numerically computable indices using one or a combination of essential climate variables (ECVs) designed to measure the severity of the climatic impact driver, or the probability of exceedance of a threshold. The change in climatic impact drivers can be measured via these indices in terms of magnitude (or intensity), duration, frequency, timing, and spatial extent".

Climatic impact drivers, as defined in Chapter 1, may not be related only to extremes, and therefore require a different set of indices. For instance, the rate of coastline recession, due to sea level rise, used in Chapter 12, is involved in the risk of damage and losses in coastal settlements and infrastructures. Mean trends and changes themselves are considered throughout the report as climatic impact drivers. For instance, beyond the warming trend which has a large number of consequences, changes in other indices such 'snow season length' is often used to study economic impacts on winter tourism (Damm et al., 2017). To characterize broad threats to societies Mora et al. (2018) used a set of 11 very different key hazard indices among which about half are related to extremes. This highlights the need of having a set of indices larger than only extremes for regional climate information for climate change risks and impacts reduction. Section 12.3 in Chapter 12 reviews the hazards described in the literature to characterize impacts and risks, and reveal the wide variety of indices used to characterize such hazards

Indices are, in principle, computable from observations, re-analyses or model simulations, although it is important to consider scale in comparing across datasets. For example, an extreme precipitation event has a lower magnitude across a large grid cell than it would at a single station within that grid cell. In many cases, hazards are simply characterized by the exceedance of a threshold for an ECV. For instance, the probability of crop failure dramatically increases as temperature rises above certain thresholds, which may differ from one species to another (Hatfield and Prueger, 2015; Grotjahn, in press) heat stress on outdoor workers is often expressed as a combination of humidity and temperature, such as found for instance in the classical wet bulb temperature with typical thresholds characterizing the stress on work in different categories of activities and human adaptability (Pal and Eltahir, 2015; Im et al., 2017). Because of biases in model climatologies, to assess the effect of climate change on threshold-type of indices (e.g., the change in the number of days with maximum temperature above 35°C), a bias adjustment of model outputs is often desirable (see Chapter 10 for assessment of bias adjustment). In some of the indices used in Chapter 12, bias adjustment is used and methods are described here.

Both regional indices (with time-varying values depending on location) and global indices (single integrated value at each time) are considered. Some of the latter are identified in Chapter 4 as iconic measures of global climate change, like global surface air temperature (GSAT), global land monsoon precipitation, the global monsoon circulation index, the Arctic sea ice area, the Atlantic Meridional Overturning Circulation (AMOC), global mean sea level (GMSL). Others include modes of internal climate variability such as the Southern Annual Mode (SAM), the North Atlantic Oscillation (NAO), and the El Niño–Southern Oscillation (ENSO). Some of these global quantities have been connected by literature and past assessment to risks relevant for the characterization of Reasons for Concern (O'Neill et al., 2017). In that context, the relation of these indices' evolution to global drivers, especially GMST at increasing warming levels, is of interest.

Indices are used in many chapters of the IPCC AR6 report: in Chapter 4 for assessing changes in the global climate, in Chapter 8 for water cycle changes assessment, in Chapter 9 for oceans and the cryosphere, in Chapter 11 for assessing changes in extreme conditions and in Chapter 12 for assessing climatic impact drivers and their changing characteristics due to climate change. In the online Atlas, a number of such indices are displayed with possibility of changing several aspects of the extreme or hazard characteristics (threshold, duration, magnitude, etc.).

AVII.2 Extreme indices selection

In Chapter 11, extreme indices are assessed and studied based on available literature and data. Two approaches are usually used to define extreme indices, namely, non-parametric and parametric. In the non-parametric approach, the indices are estimated using the empirical distribution of daily data. These indices characterize moderate temperature and precipitation extremes with re-occurrence times of a year or shorter (Klein Tank et al., 2009). The Expert Team on Climate Change Detection and Indices (ETCCDI -https://www.wcrp-climate.org/etccdi) defined 27 indices that characterize different aspects of temperature and precipitation and are described by Frich et al. 2002; Alexander et al. 2006; Donat et al. 2013. In this chapter a subset of these indices is assessed in detail. The parametric approach complements the moderate indices and is based on extreme value theory (EVT) (Coles, 2001) in order to evaluate the intensity and frequency of rare events with longer return periods, such as events that occur once in 20 years. This approach has been used and adopted in the literature (e.g. Kharin and Zwiers 2000; Brown et al. 2008; Kharin et al. 2013). These types of events are also assessed in the Chapter 11. Aside from temperature and precipitation the chapter also assesses indices used to characterize droughts. Table AVII.1 list the indices used.

[START TABLE AVII.1 HERE]

Table AVII.1: Table listing extreme indices used in Chapter 11

Extreme	Label	Index name	Units	Variable
Temperature	TXx	Monthly maximum value of daily maximum temperature	°C	Maximum temperature
	TXn	Monthly minimum value of daily maximum temperature	°C	Maximum temperature
	TNn	Monthly minimum value of daily minimum temperature	°C	Minimum temperature
	TNx	Monthly maximum value of daily minimum temperature	°C	Minimum temperature
	TX90p	Percentage of days when daily maximum temperature is greater than the 90th percentile	%	Maximum temperature
	TX10p	Percentage of days when daily maximum temperature is less than the 10th percentile	%	Maximum temperature
	TN90p	Percentage of days when daily minimum temperature is greater than the 90th percentile	%	Minimum temperature
	TN10p	Percentage of days when daily minimum	%	Minimum

		temperature is less than the 10th percentile		temperature
	ID	Number of icing days: Annual count of days when TX (daily maximum temperature) < 0°C	days	Maximum temperature
	FD	Number of frost days: Annual count of days when TN (daily minimum temperature) < 0°C	days	Minimum temperature
	WSDI	Warm spell duration index: Annual count of days with a least 6 consecutive days when TX >90th percentile	days	Maximum temperature
	CSDI	Cold spell duration index: Annual count of days with a least 6 consecutive days when TN <10th percentile	Days	Minimum temperature
	SU	Number of summer days: Annual count of days when TX (daily maximum temperature) > 25°C	Days	Maximum temperature
	TR	Number of tropical nights: Annual count of days when TN (daily minimum temperature) > 20°C	Days	Minimum temperature
	DTR	Daily temperature range: Monthly mean difference between TX and Tn	°C	Maximum and minimum temperature
	GSL	Growing season length: Annual (1st Jan to 31st Dec in Northern Hemisphere (NH), 1st July to 30th June in Southern Hemisphere (SH)) count between first span of at least 6 days with daily mean temperature TG>5oC and first span after July 1st (Jan 1st in SH) of 6 days with TG<5oC	Days	Mean temperature
	20TXx	one-in-20 year return value of monthly maximum value of daily maximum temperature	°C	Maximum temperature
	20TXn	one-in-20 year return value of monthly minimum value of daily maximum temperature	°C	Maximum temperature
	20TNn	one-in-20 year return value of monthly minimum value of daily minimum temperature	°C	Minimum temperature
	20TNn	one-in-20 year return value of monthly maximum value of daily minimum temperature	°C	Minimum temperature
Precipitation	Rx1day	Maximum 1-day precipitation	mm	Precipitation
	Rx5day	Maximum 5-day precipitation	mm	Precipitation
	R5mm	Annual count of days when precipitation is greater than or equal to 5mm	days	Precipitation
	R10mm	Annual count of days when precipitation is greater than or equal to 10mm	days	Precipitation
	R20mm	Annual count of days when precipitation is greater than or equal to 20mm	days	Precipitation
	R50mm	Annual count of days when precipitation is greater than or equal to 50mm	days	Precipitation
	CDD	maximum number of consecutive days with less than 1 mm of precipitation	days	Precipitation
	CWD	maximum number of consecutive days with more than or equal 1 mm of precipitation	days	Precipitation
	R95p	annual total precipitation when the daily precipitation exceeds the 95th percentile of the wet-day precipitation	mm	Precipitation
	R99p	annual total precipitation when the daily precipitation exceeds the 99th percentile of the wet-day precipitation	mm	Precipitation
	SDII	Simple precipitation intensity index	mm/day	Precipitation
	20Rx1d	one-in-20 year return value of maximum 1-day	mm/day	Precipitation

	ay	precipitation		
	20Rx5day	one-in-20 year return value of maximum 5-day precipitation	mm/day	Precipitation
Drought	SPI	Standardized Precipitation Index	months	Precipitation
	EDDI	Potential evaporation, Evaporative Demand Drought Index	months	Evaporation
	SMA	Soil moisture anomalies	months	Soil moisture
	SSMI	Standardized Soil Moisture Index	months	Soil moisture
	SRI	Standardized Runoff Index	months	Stream flow
	SSI	Standardized Streamflow Index	months	Stream flow
	PDSI	Palmer drought severity index	months	Precipitation, Evaporation
	SPEI	Standardized precipitation evapotranspiration index	months	Precipitation, Evaporation, Temperature

[END TABLE AVII.1 HERE]

AVII.3 Climatic impact drivers indices selection

In Chapter 12, 31 climatic impact drivers types are identified on the basis of relevance for risks and available literature. They were classified into 7 categories: heat and cold, wet and dry, wind, snow and ice, coastal, oceanic, and other (see Tables 12.1 and 12.2). It would be impossible to cover all indices that have been developed in the literature. However, in order to illustrate how indices can inform on future regional climate, Chapter 12 and the Atlas use a limited number of indices to illustrate the main hazards and their evolution with climate change.

The selection of indices, as displayed in Chapter 12 and the Atlas, is based on expert judgement using the following guiding principles. The set of indices should:

(i) describe the evolution of a manageable and illustrative number of indices,
(ii) cover these categories, while giving more weight to those with a higher number of potential impacts as described in the literature,
(iii) be used broadly in the literature
(iv) allow easy computation from publicly available model outputs and observations, or be accessible from published material through contact with the authors
(v) be well-evaluated in model simulations, or based on ECVs that are well-evaluated in model simulations
(vi) represent hazards of interest to regional impact and risk assessment.

The selection resulted in 16 regional indices which are reported in Table AVII.2. The description of the formula used or processing is described below. In addition, 12 global hazard indices were used in Chapter 12 in relation to reasons for concerns as indices that were calculated for different warming levels.

AVII.3.1 Regional hazard indices used in Section 12.4

Climatic impact drivers indices

Length of frost-free period (LFFP): Many ecosystems and crops are sensitive to frost conditions, and can only develop over a frost-free period (e.g., (Wolfe et al., 2018)); the length of the frost-free period is calculated in Chapter 12 and the Atlas as in (McCabe et al., 2015) by counting the number of days between the last spring frost and first fall frost using 0°C as a threshold for the daily minimum temperature and adjusting for season between hemispheres (from January to December in the Northern Hemisphere and from

July to June in the Southern Hemisphere).

Growing degree-days (GDD): Ecosystems and crop growth is often linked to a widely used index of thermal conditions, the cumulative number of degrees above a threshold (often between 0 and 10 °C, depending on species and farming system) during a given growing period. In Chapter 12 and the Atlas we use 5 °C as an indicative threshold, which was also used in Ruosteenoja et al. (2016), and the calculation is taken from this reference. GDD calculations sometimes include a high temperature threshold above which plant development does not occur (e.g., (Mu et al., 2017)), but no cap was employed for our calculations. The GDD index used here is therefore the accumulated sum of the difference between daily mean temperature and the threshold (when higher than the threshold) over the April-September months that forms the primary growing season for mid-latitude agricultural areas in the northern Hemisphere.

Cooling degree-days (CDD): Energy consumption in hot environments typically depends on the excess of temperature above a given threshold, where cooling is required. In Chapter 12 and the Atlas we used the formulation of (Spinoni et al., 2015), which uses the mean, maximum and minimum daily temperature with the formula taken from this reference :

$$CDD_i = \begin{cases} 0 \\ \dfrac{T_X - T_b}{4} \\ \dfrac{T_X - T_b}{2} - \dfrac{T_b - T_N}{4} \\ T_M - T_b \end{cases} \quad if \quad \begin{cases} T_X \le T_b \\ T_M \le T_b < T_X \\ T_N \le T_b < T_M \\ T_N \ge T_b \end{cases}$$

With T_b=22°C, then

$$CDD = \sum_{i=1}^{365} CDD_i$$

The difference between Chapter 12, Atlas, and the previous reference is that in this report the sum is cumulated over the year instead of 6 months so it applies to all hemispheres.

Number of days with mean daily temperature above threshold (Tnn): Climate change is driving changes in the incidence and spatial distribution of climate-sensitive vector-borne diseases. Malaria, dengue fever, leishmaniasis, yellow fever, chikungunya, and zika are among those diseases considered most likely to increase as global temperatures increase. Changes in climatic conditions could influence the behaviour of vectors (proliferation and frequency of blood meal feedings), their geographical distribution (expansion into formerly vector-free territories), and the development rate at which pathogens (viruses and parasites) inside the mosquitoes mature. Air temperature is an important determinant of the transmission of vector-borne diseases. Several research efforts suggest that the optimal malaria transmission takes place at around 25°C, and that the transmission of Zika, dengue and chikungunya can occur between 18 and 34°C and peak at 26–29°C. The basic reproduction rate of these diseases declines to zero for temperatures below 16-18°C, thresholds at which the pathogen development ceases, and above 31.6-35°C, which are the thresholds at which death of mosquitoes occurs. The sudden increase from a zero basic reproduction rate to non-zero levels commonly takes place at air temperatures around 21.5°C. See details in (Lambrechts et al., 2011; Blanford et al., 2013; Mordecai et al., 2013, 2017; Ruiz et al., 2014).

Number of days with maximum daily temperature above threshold (TXnn): The number of days with maximum temperature above a threshold can be critical for human health, infrastructure, ecosystems, and agriculture. Different thresholds are used for different crops, generally varying between 30 degrees and 40 degrees (Hatfield and Prueger, 2015; Grotjahn, in press). Three thresholds are used in the Atlas (30°C, 35°C and 40°C). Chapter 12 uses the 35°C threshold globally (Figure 12.4), which was identified as a critical temperature for maize pollination and production (Wolfe et al., 2008; Schlenker and Roberts, 2009; Hatfield et al., 2011, 2014; Lobell and Gourdji, 2012; Gourdji et al., 2013; Lobell et al., 2013; Deryng et al., 2014; Hatfield and Prueger, 2015; Tripathi et al., 2016; Schauberger et al., 2017; Tesfaye et al., 2017) as well as a notable threshold for human health hazards (Kingsley, Eliot, Gold, Vanderslice, & Wellenius, 2016; Petitti et al., 2016). However, a 30°C threshold was used for Asia as most studies used this threshold in this continent. Figure 12.4 also displays change for the number of days with daily maximum temperature above 40°C in order to see the sensitivity to the threshold.

Wet Bulb Globe Temperature (WBGT): This index, together with the Wet Bulb Temperature and other indices, have widely been used to characterize the effect of temperature on health and outdoor work conditions (Lemke and Kjellstrom, 2012; Zhao et al., 2015). Thresholds have been defined as recommendations for workers (Kjellstrom et al., 2009). It is calculated in the Atlas and Chapter 12 using the simplified formula of the Australian Bureau of Meteorology (http://www.bom.gov.au/info/thermal_stress/) assuming constant radiation as taken from (Lemke and Kjellstrom, 2012):

$$\mathrm{WBGT}(°\mathrm{C}) = 0.567\ \mathrm{Ta} + 0.393\ \mathrm{r} + 3.94$$

Where Ta is the atmospheric temperature and r (hPa) is the partial water vapor pressure, calculated either from relative humidity or from absolute humidity, depending on availability of variables for each model.

Heating Degree Day (HDD): symmetrical to the Cooling Degree Day index, the HDD index is used for illustrating energy demand for heating. It has been used in several studies of impacts of climate change on the energy sector. Chapter 12 and the Atlas follow the formulation proposed by (Spinoni et al., 2015). The calculation follows:

$$HDD_i = \begin{cases} T_b - T_M \\ \dfrac{T_b - T_N}{2} - \dfrac{T_X - T_b}{4} \\ \dfrac{T_b - T_N}{4} \\ 0 \end{cases} \quad if \quad \begin{cases} T_X \le T_b \\ T_M \le T_b < T_X \\ T_N \le T_b < T_M \\ T_N \ge T_b \end{cases}$$

With T_b=15.5°C, then

$$HDD = \sum_{i=1}^{365} HDD_i$$

To account for various geographic zones, however, the HDD index is cumulated over the year instead of 6 months as in the previous reference.

Number of frost days: Frost affects crops (Barlow et al., 2015; Crimp et al., 2016; Cradock-Henry, 2017; Mäkinen et al., 2018), and there has been a number of studies investigating changes in the number of frost days, with various thresholds, mostly between -10°C and 2°C. In Chapter 12 and the Atlas, we use the simple threshold of 0°C for the daily minimum temperature to define frost days as in Rawlins et al. (2016).

99th percentile of daily precipitation (R99): this index is an extreme index used to measure extreme precipitations which can cause pluvial flooding. This index is used in several Figures of Chapter 12 and in the Atlas. It is calculated as the 99th percentile of the daily amounts at each grid point.
River flood index using runoff (FI): As a flood indicator, the 100-year return value of discharge value (Q) has been used. The computation of the index follows Alfieri et al., (2015):

1. Annual maximum river discharges are selected and a Gumbel distribution is fitted on time slices of

30 years and an analytical function is obtained.

2. The analytical function is used to estimate extreme discharge peaks with chosen return period Q(RP), by inverting the formulation of the Gumbel distribution:

$$Q(\mathrm{RP}) = \xi - \alpha \ln\left(-\ln\left(1 - \frac{1}{\mathrm{RP}}\right)\right)$$

where α and ξ are the scale and location parameters of the analytical Gumbel distributions.

3. The peak discharge corresponding to the 100-year return period, Q(RP=100), is then calculated.

For Euro-CORDEX regional models the total runoff of each of the models has been used as an input of the hydrological model CHyM (Coppola et al., 2007, 2018) to produce the river discharge for all the European network. The Q(RP=100) value has been computed for each of the river segment and for each of the 29 CHyM simulations.

This index is used for EURO-CORDEX data in Figure 12.12, while in other figures it is temporarily replaced by the mean 100-year return value of the runoff variable for some continents. The interpretation between the two indices should be different, and they are not directly comparable.

Standardized Precipitation Index (SPI): The SPI is a statistical index that compares cumulated precipitation for *n* months (*n*=6 or *n*=12 in the SOD) with the long term precipitation distribution for the same location and cumulation period. The SPI months have been computed and are considered to be a medium-term cumulated value that can be used to measure the medium term impact on river flow and reservoir storage (Mckee et al., 1993).

The index is computed in this way:

1. A monthly precipitation time series is selected (at least 30 years).
2. The running average for the *n*-months window is computed.
3. The Gamma distribution is used to fit the data. The fitting can be achieved through the maximum likelihood estimation of the gamma distribution parameters.
4. The values from this probability distribution are then transformed into a normal distribution, so that the mean SPI for the location and desired period is zero and the standard deviation is 1 (Edwards and McKee, 1997).

Once SPI has been computed, the calculation of the Drought Frequency (DF) follows the method in (Naumann et al., 2013): a drought event starts in the month when SPI falls below −1 and it ends when SPI returns to positive values, for at least two consecutive months.

It has to be noted that the SPI index has been recognized to be difficult to interpret in high latitudes and in arid areas due to statistical issues linked to inaccuracies in the estimation of the Gamma function (Spinoni et al., 2014). Two durations are considered in Figure 12.6 (6 and 12 months).

SPEI accumulated over 6 months (SPEI-6):

98th percentile of daily maximum wind speed (P98wind): This high-percentile index is used in several studies to characterize extreme winds (Klawa and Ulbrich, 2003; Martius et al., 2016), but other studies use other high percentiles in the same range from the 95th to 99th. This index is used in Chapter 12 and the Atlas. It is calculated using the maximum daily wind speed and its 98th percentile over reference and future periods. Importantly, wind speed modelled distribution can depend on resolution since highest wind speeds can be found in small spatial structures.

Snow season length (SWE100): Several studies use the Snow Water Equivalent (SWE) variable (variable *snw* in model outputs) in order to define a "snow season length" as the number of days with enough snow on the ground. This index is particularly important for the winter tourism sector (Damm et al., 2017; Jacob et al., 2018). Several thresholds are used to define a day with "enough snow on the ground", with (Wobus et al., 2017) marking 100mm as a key threshold for skiing. However this index is not only important for winter tourism but also in other sectors such as water management. In several figures of Chapter 12 and the Atlas, the snow season length is calculated as the number of days with SWE > 100mm, following the definition of (Damm et al., 2017; Wobus et al., 2017). Seasonal limits are given (November through March) for studies in the Northern Hemisphere, and the index for the Southern Hemisphere is taken over the opposite season (May through September). SWE was assessed in several studies and its simulation depends on the representation of surface processes dealing with snow. Despite limitations, SWE was found to be useful in giving insight on the sign of changes (McCrary et al., 2017). When interpreting the figures shown in Chapter 12 and the Atlas, one should also keep in mind that altitudes are model altitudes and may not correspond to real ones due to the coarse resolution, and the changes can be quite sensitive to such effects.

Extreme Sea Level (ESL): Factors contributing to extreme sea levels (ESL), are sea level rise, storm surge (e.g. associated with TCs and ETCs), tide, and extreme waves (resulting in high wave setup at the shoreline). The ESL used here is the summation of the aforementioned factors (Vitousek et al., 2017; Vousdoukas et al., 2018) and the commonly used 1 :100yr ESL is adopted here as the index relevant to episodic coastal flooding.

Coastline Recession (CR): Coastline recession is the slow and continuous landward movement of the coastline in response to Sea level rise (Bruun, 1962). Historically, the most commonly used coastline recession index is the (deterministic) recession amount due to a mid-high SLR by a pre-determined planning horizon, commonly 50 years or 100 years into the future (Ranasinghe, 2016). However, probabilistic coastline recession estimates are becoming more and more sought after and available (Jongejan et al., 2016; Toimil et al., 2017; Dastgheib et al., 2018). Here the median coastline recession (0.5 exceedance probability), together with the associated 5-95 % confidence interval, resulting from a fully probabilistic model that incorporates SLR from 7 GCMs is used as the index relevant for coastline recession.

[START TABLE AVII.2 HERE]

Table AVII.2: Regional Hazard indices table. Boldfaced are indices considered presented in the SOD, whilst other indices are not considered in the Atlas or Chapter 12 for SOD, but will be in the FGD.

Hazard category	**Climatic impact driver (from Table 12.1) and potential affected sectors**	**Index**	**Required ECVs**	**Way to calculate**	**Bias adjustment**	**References**
Heat	Warming indicator for crops, ecosystems and hydrosystems	Length of Frost-Free period (LFFP)	Tasmin	from projections	yes	(Kunkel et al., 2004; McCabe et al., 2015; Wolfe et al., 2018)
Heat	Warming indicator for agriculture and ecosystems	yearly cumulated GDD over 5°C	Tas	from projections	yes	(Bonhomme, 2000; Cayton et al., 2015; Ruosteenoja et al., 2016)
Heat	Change in cooling demand for energy demand and building consumption	CDD above 22°C	tas, tasmin, tasmax	from projections	yes	(Spinoni et al., 2015, 2018)
Heat	**Warming**	**Tmean>21.5°C (T21.5)**	**Tas**	**from projections**	**yes**	**(Ruiz et al., 2014)**
Heat	**Heat, with thresholds important for agriculture**	**#days Tmax>35, 40 (TX35, TX40)**	**Tasmax**	**from projections**	**yes**	(Hatfield and Prueger, 2015; Hatfield et al., 2015; Grotjahn, in press)
Heat	**Heat stress index combining humidity used in occupational and industrial health**	**#days WBGT>28, 31, 35**	**tas hurs ps**	**from projections**	**yes**	**(Lemke and Kjellstrom, 2012; Zhao et al., 2015)**
Cold	Heating Degree Day for Energy consumption	HDD below 15.5°C	tas, tasmin, tasmax	from projections	yes	(Spinoni et al., 2015, 2018)
Cold	Frost	#Frost days below 0°C (FD)	Tasmin	from projections	yes	(Barlow et al., 2015; Rawlins et al., 2016)
Wet	**Pluvial flooding**	**99th percentile of daily amounts (R99)**	**Pr**	**from projections**	**No**	**(Houston et al., 2011)**
Wet	**River flooding**	**Flood index (FI)**	**srroff/ mrro**	**from projections and simplified routing model**	**No**	(Forzieri et al., 2016; Alfieri et al., 2017)
Drought	**drought**	**SPI accumulated over 6 months and 12 months (SPI-6 and SPI-12)**	**Pr**	**from projections**	**yes**	**(Naumann et al., 2018)**
Drought	*drought*	*SPEI acc over 6 months*		*from projections*		**(Arnell et al., 2018)**
Wind & storm	**Extreme wind, affecting key infrastructure**	**P98 of the daily max wind (W98)**	**sfcWindmax**	**from projections**	**yes**	**(Klawa and Ulbrich, 2003; Martius et al., 2016)**
Snow/ice	**Snow season length**	**Number of days with Snow water equivalent > 100 mm. (SWE100)**	**snw**	**from projections**	**no**	(Damm et al., 2017; Wobus et al., 2017)
Coastal	**Extreme Sea level (ESL) inducing storm surges**	**100-year Return level (ESL)**		**data from authors**	**no**	(Vousdoukas et al., 2018)
Coastal	**Coastal Recession inducing threats to infrastructures**	**coastal recession**		**data from authors**	**no**	(Vousdoukas et al., in press)

[END TABLE AVII.2 HERE]

AVII.3.2 Hazard indices used in Section 12.5.1

Heatwaves
Average annual likelihood of at least two consecutive days with Tmax greater than the 1981-2010 warm season 98th percentile of daily Tmax, averaged over grid cells with more than 1000 people in 2010 (see Arnell et al. 2019 ERL). CMIP5 climate model patterns, to be replaced with CMIP6 results.

Major heatwaves
Average annual likelihood of at least four consecutive days with Tmax greater than the 1981-2010 warm season 99th percentile of daily Tmax, averaged over grid cells with more than 1000 people in 2010 (see Arnell et al. 2019 ERL). CMIP5 climate model patterns, to be replaced with CMIP6 results.

Average annual number of cooling degree-days
Global average annual number of cooling degree-days relative to 18ºC, averaged over grid cells with more than 1000 people in 2010. CMIP5 model patterns, to be replaced with CMIP6 results.

Average annual number of heating degree-days
Global average annual number of heating degree-days relative to 15.5ºC, averaged over grid cells with more than 1000 people in 2010. CMIP5 model patterns, to be replaced with CMIP6 results.

River floods
Global average change in magnitude of the 100-year river flood. River flood index is defined in AVII.3.1. Global average weighted by grid cell area. This is based on available CMIP6 results

Droughts
Global average number of droughts per decade, based on Standardised Precipitation Index SPI (as defined in AVII.3.1). Global average weighted by grid cell area. This is based on available CMIP6 results

Extreme coastal sea level
Global average height of the 100-year extreme sea level, as defined in AVII.3.1 ((Vousdoukas et al., 2018).

AVII.3.3 Global indices

[START TABLE AVII.3 HERE]

Table AVII.3: List and characteristics of global indices used in Chapter 12 (also in Chapter 2)

Manifested hazard (from Table 12.1) and potential affected sectors	Hazard Index	Required ECVs	Way to calculate	References
Warming	**Global average SSTs**	**tas**	**From projections**	(Donner et al., 2005, 2007; Bell et al., 2013; Frieler et al., 2013; Gattuso et al., 2015)
Ocean acidification	**Global average pH**	**Ocean pH**	**From projections/Assessment by Chapter 5**	(Donner et al., 2005, 2007; Bell et al., 2013; Frieler et al., 2013; Gattuso et al., 2015)
Deoxygenation	**Global average Oxygen content of the ocean**	**Ocean Oxygen content**	**From Projections/Assessment by Chapter 5**	(Donner et al., 2005, 2007; Bell et al., 2013; Frieler et al., 2013; Gattuso et al., 2015)
Permanent inundation	**Global Mean Sea Level Rise**	**Sea Level Rise**	**From Projections/Assessment by Chapter 9**	**(Kopp et al., 2014)**
Warming	**Arctic sea ice extent in September**	**Arctic sea ice area in September**	**From Projections/Assessment by Chapter 4**	**(Jahn et al., 2016)**
Warming	**Equilibrium Mass Balance of Glaciers**	**Equilibrium Mass Balance of Glaciers**	**From projections/Assessment by Chapter 9**	**(Marzeion et al., 2014)**
Warming	**Land area with**	**Land area with**	**From**	**(Slater and Lawrence, 2013)**

	permafrost melting	**permafrost**	**projections/Assessment by Chapter 9**	
Warming	**Snow extent in Northern Hemisphere**	**Snow cover**	**From projections/Assessment by Chapter 9**	**Chapter 9 and references therein**
Air Pollution/Allergens	**Atmospheric CO2 concentrations**	**Atmospheric CO2 concentrations**	**From Scenarios forcings input**	**(Singer et al., 2005)**
Variability changes	**El-Nino3.4 standard deviation**	**SSTs**	**From Projections/Assessment of Chapter 4**	**(Drijfhout et al., 2015)**
Sea Level Rise	**WAIS/GIS ice volume changes**	**Ice volume**	**From Projections/Assessment by Chapter 9**	**(DeConto and Pollard, 2016)**
Variability/Circulation Changes	**AMOC strength**	**Maximum meridional streamfunction below 400m. depth**	**From Projections/Assessment by Chapter 4**	**(Collins et al., 2013)**

[END TABLE AVII.3 HERE]

AVII.4 Models, Scenarios and reference periods used

AVII.4.1 Models used to calculate hazard indices

The models used in Chapter 12 and the Atlas are subsets of the full CMIP5 ensemble and CMIP6 ensemble, selected based on availability in the Atlas database, and from a few other sources. In three regions, Europe, Africa and North America, Chapter 12 used ensembles of regional simulations with high resolution. Associated regional figures were designed to compare these ensembles. However, different GCMs were used in both cases (see below). No model weighting is applied.

In Chapter 12, only results for Scenario (SSP5-8.5 for CMIP6, RCP8.5 for CORDEX) are shown as maps. Figures 12.4 – 12.13 show the differences between results obtained for each index between statistics calculated over two periods: mid-century (2041-2060) and a reference period (1995-2014). Satellite plots show regional mean values and the 5-95th percentiles of model ensemble spread for the AR6 regions (see Chapter 1) for the above periods, ensembles and scenarios with the addition of a further scenario (SSP1-2.6 for CMIP6), ensemble (CMIP5 RCP8.5) and time period (end of century 2081-2100).

[START TABLE AVII.4 HERE]

Table AVII.4: List of CMIP5 (Taylor et al., 2012) models used for each index. The indices are grouped when the same subset of models is used; "85" stands for "RCP8.5.

CMIP5 Simulations	TX35, TX40, R99	T21.5	WBGT	SPI	FI	P98WIND	SWE100
ACCESS1-0	85	85	85	85		85	
ACCESS1-3	85	85	85	85		85	
bcc-csm1-1	85	85	85	85			85
bcc-csm1-1-m	85	85	85	85			85
BNU-ESM	85	85	85	85		85	85
CanESM2	85	85	85	85	85	85	85
CCSM4	85	85		85			
CESM1-BGC	85	85		85			
CMCC-CESM						85	
CMCC-CM	85	85		85	85	85	

CMCC-CMS	85	85		85	85	85	
CNRM-CM5	85	85	85	85	85	85	85
CSIRO-Mk3-6-0	85	85	85	85	85	85	85
EC-EARTH	85*	85*		85*			
FGOALS-g2	85			85	85		85
GFDL-CM3	85	85	85	85	85	85	85
GFDL-ESM2G	85	85	85	85	85	85	85
GFDL-ESM2M	85	85	85	85	85	85	85
HadGEM2-CC	85	85	85	85		85	85
HadGEM2-ES	85	85	85	85		85	85
inmcm4	85	85	85	85	85		85
IPSL-CM5A-LR	85	85	85	85		85	
IPSL-CM5A-MR	85	85	85	85		85	
IPSL-CM5B-LR	85	85	85	85		85	
MIROC5	85	85	85	85	85	85	85
MIROC-ESM	85	85	85	85	85	85	85
MIROC-ESM-CHEM	85	85	85	85		85	85
MPI-ESM-LR	85	85		85		85	85
MPI-ESM-MR	85	85		85	85	85	85
MRI-CGCM3	85	85	85	85	85	85	85
MRI-ESM1			85		85	85	85
NorESM1-M	85	85	85	85	85		85

*r12
** r1,r2,r3

[END TABLE AVII.4 HERE]

[START TABLE AVII.5 HERE]

Table AVII.5: List of CMIP6 (Eyring et al., 2016) models used for each index. The indices are grouped when the same subset of models is used; "85" stands for SSP5-8.5 and "26" stands for SSP1-2.6.

CMIP6 Simulations	TX35, TX40, R99	T21.5	WBGT	SPI	FI	P98WIND	SWE100
AWI-CM-1-1-MR						85, 26	
BCC-CSM2-MR			85, 26	85, 26	85, 26	85, 26	85, 26
CAMS-CSM1-0				85, 26			
CanESM5	85, 26	85, 26	85, 26	85††, 26††	85	85, 26	85, 26
CESM2				85, 26			
CESM-WACCM				85, 26			
CNRM-CM6-1	85, 26	85, 26	85, 26	85, 26		85, 26	
CNRM-CM6-1-HR						85	
CNRM-ESM2-1	85, 26	85, 26	85, 26	85, 26		85, 26	
EC-Earth3	85*, 26*	85*, 26*	85, 26	85*, 26*	85, 26	85*, 26*	85*, 26*
EC-Earth3-Veg	85, 26	85, 26	85, 26	85, 26		85, 26	
FGOALS-g3			85, 26	85, 26			

GFDL-CM4	85	85	85	85	85	85	85
GFDL-ESM4	26	85, 26	26	85, 26		26	85, 26
INM-CM4-8						85, 26	
INM-CM5-0						85, 26	
IPSL-CM6A-LR	85, 26	85, 26	85	85, 26	85, 26	85, 26	85, 26
MIROC-ES2L				85, 26			
MIROC6				85, 26	85, 26	85, 26	85, 26
MPI-ESM1-2-HR			85, 26		85, 26	85, 26	85, 26
MRI-ESM2-0	85, 26	85, 26	85, 26	85, 26	85, 26	85, 26	85, 26
NESM3	85, 26	85, 26		85, 26	85, 26	85, 26	85, 26
UKESM1-0-LL	85, 26	85, 26	85, 26		85, 26	85, 26	85, 26

All r1i1p1f1 where available, r1i1p1f2 otherwise except :
* r4i1p1f1
† r6i1p1f1
†† r1i1p2f1

[END TABLE AVII.5 HERE]

[START TABLE AVII.6 HERE]

Table AVII.6: List of EURO-CORDEX models used for each index, Figures 12.4-12.6 and 12.12 (Vautard et al., submitted). The indices are grouped when the same subset of models is used. GCM and RCMs used are specified. For GCMs a simplified simulation name was taken (GCMrN, where N is the member). All simulations are for RCP8.5.

GCM	RCM	TX35, TX40	WBGT	PR, SPI, FI	P98WIND	SWE100
CANESMr1	CCLM	X	X	X		X
	REMO	X	X	X	X	X
CNRMr1	ALADIN63	X	X		X	X
	ALADIN53	X	X			X
	CCLM	X	X	X	X	X
	HIRHAM	X	X	X	X	X
	RACMO	X	X	X	X	X
	RCA	X	X	X	X	
	REMO	X	X	X	X	X
	WRF381P	X	X	X	X	X
ECEARTHr12	CCLM	X	X	X	X	X
	COSMO-crCLIM	X	X		X	
	HIRHAM	X	X	X	X	X
	RACMO	X	X	X	X	X
	RCA	X	X	X	X	
	REMO	X	X	X	X	X
	WRF361H	X				X
ECEARTHr1	HIRHAM	X	X	X	X	X
	RACMO	X	X	X	X	X
	RCA	X	X	X	X	X
ECEARTHr3	HIRHAM	X	X	X	X	X
	RACMO	X	X	X	X	X
	RCA	X	X		X	X
HADGEMr1	ALADIN63	X	X		X	X
	CCLM	X	X	X	X	X
	HIRHAM	X	X	X	X	X
	RACMO	X	X	X	X	X
	RCA	X	X	X	X	
	REGCM	X	X	X	X	X
	REMO	X	X	X	X	X

	WRF361H	X				X
	WRF381P	X	X		X	X
IPSLr1	RACMO	X	X		X	X
	RCA	X	X	X	X	
	WRF381P	X	X		X	X
MIROCr1	CCLM	X	X	X	X	X
	REMO	X	X	X	X	X
MPIr1	CCLM	X	X	X	X	X
	COSMO-crCLIM	X	X	X	X	
	RACMO	X	X	X	X	X
	RCA	X	X	X	X	
	REGCM	X	X		X	X
	REMO	X	X	X		X
	WRF361H	X				
MPIr2	COSMO-crCLIM	X	X		X	
	REMO	X	X	X		X
MPIr3	COSMO-crCLIM	X	X		X	
	RCA	X	X	X	X	X
	REMO	X	X	X	X	X
NORESMr1	COSMO-crCLIM	X	X		X	
	HIRHAM	X	X	X	X	X
	RACMO	X	X	X	X	X
	RCA	X	X	X	X	X
	REMO	X	X	X	X	X
	WRF381P	X	X	X	X	X

2

[END TABLE AVII.6 HERE]

[START TABLE AVII.7 HERE]

Table AVII.7: List of CORDEX models used for each index for North America for Figures 12.4-12.6 and 12.13. The indices are grouped when the same subset of models is used. GCM and RCMs used are specified. All simulations are for RCP8.5.

GCM	RCM	Resolution	PR	P98WIND	SWE100
GFDL-ESM2M	RegCM4	0.22	x		x
HadGEM2-ES	GERICS	0.22	x	x	x
	RegCM4	0.22	x		x
MPI-ESM-LR	GERICS	0.22	x	x	x
	RegCM4	0.22	x		x
NorESM1-M	GERICS	0.22	x	x	x
CanESM2	CanRCM4	0.44	x		
	CRCM5-UQAM	0.44	x		
	SMHI-RCA4	0.44	x	x	
EC-EARTH	DMI-HIRHAM5	0.44	x	x	x
	SMHI-RCA4	0.44	x	x	
GFDL-ESM2M	RegCM4	0.44	x		
	WRF	0.44	x		
HadGEM2-ES	RegCM4	0.44	x		
	WRF	0.44	x		
	GERICS	0.44	x		
MPI-ESM-LR	CRCM5-UQAM	0.44	x		
	CRCM5-UQAM	0.44	x		
	RegCM4	0.44	x		
	WRF	0.44	x		

[END TABLE AVII.7 HERE]

[START TABLE AVII.8 HERE]

Table AVII.8: List of CORDEX models used for each index for North America for Figures 12.4-12.6 and 12.8. The indices are grouped when the same subset of models is used. GCM and RCMs used are specified. All simulations are for RCP8.5.

GCM	RCM	member	TX35, TX40	WBGT	PR	SPI	P98WIND
CanESM2	RCA4	r1i1p1	x	x	x	x	x
CNRM-CM5	CCLM4-8-17	r1i1p1	x	x	x	x	x
	RCA4	r1i1p1	x	x	x	x	x
CSIRO-Mk3-6-0	RCA4	r1i1p1	x	x	x	x	x
EC-EARTH	CCLM4-8-17	r12i1p1	x	x	x	x	x
	RACMO22T	r1i1p1	x	x		x	x
	HIRHAM5_v2	r3i1p1	x	x	x	x	x
	REMO2009	r12i1p1		x		x	x
	RCA4	r12i1p1		x	x		x
IPSL-CM5A	REMO2009	r1i1p1	x	x		x	x
	RCA4	r1i1p1	x	x		x	x
MIROC5	RCA4	r1i1p1	x	x		x	x
	REMO2009	r1i1p1	x	x		x	x
HadGEM2-ES	CCLM4-8-17	r1i1p1	x	x	x	x	x
	RACMO22T	r1i1p1	x	x		x	x
	RCA4	r1i1p1	x	x		x	x
	REMO2009	r1i1p1	x	x		x	x
	RegCM4	r1i1p1			x		
MPI-ESM-LR	CCLM4-8-17	r1i1p1	x	x	x	x	x
	RCA4	r1i1p1	x	x		x	x
	REMO2009	r1i1p1	x	x		x	x
NorESM1-M	HIRHAM5_v1	r1i1p1	x			x	x
	RCA4	r1i1p1	x	x		x	x
	WRF331	r1i1p1	x			x	
GFDL-ESM2M	RCA4	r1i1p1	x	x		x	x

[END TABLE AVII.8 HERE]

AVII.5 Bias adjustment

The quantile delta mapping approach that is described by (Cannon et al., 2015). It adjusts the model data in the application period to fit the reference data in the base period (using quantile mapping). Afterwards, the climate change signal is added for each quantile by considering the change between the model's reference and application period. This prevents that extremes outside the reference period are always corrected by a constant factor. The bias correction is applied directly onto the heat index. As reference, the ERA5 data is used after re-gridding to the model grid before calculating the heat index. Bias correction is applied on each grid point individually and for each month of the year separately. The reference period is 1981-2010 and the application periods are the IPCC periods 1995-2014, 2041-2060, and 2081-2100.

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