Annex VII: Hazard and Extreme Indices

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AVII.1 Introduction

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.

[*Placeholder paragraph on extreme indices*]

Indices can also characterize aspects of hazards (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 "hazard indices": "numerically computable indices using one or a combination of essential climate variables (ECVs) designed to measure the severity of the climate hazard, or the probability of exceedance of a threshold. The change in hazard can be measured via these indices in terms of magnitude (or intensity), duration, frequency, timing, and spatial extent".

Hazards, 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. Trends and changes themselves are considered throughout the report as potential hazards. 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, submitted); heat stress on outdoor workers is often express 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 (Im et al., 2017; Pal and Eltahir, 2015). Because model climatologies bear unavoidable biases, 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 mean surface temperature (GMST), 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), and 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 hazards 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…).

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 particular, Figures 12.5-7 and 12.10-13 are based on the analysis described here, although many additional indices are assessed throughout the WGI report.

AVII.2 Extreme indices selection

[*Placeholder: This section will include the description of indices used in Chapter 11*]

[START TABLE AVII.1 HERE]

Table AVII.1: Table listing extreme indices used in Chapter 11, models used and observations

[END TABLE AVII.1 HERE]

AVII.3 Hazard indices selection

In Chapter 12, 28 main hazard types are identified on the basis of relevance for risks and available literature. Hazards were classified into 8 categories: heat, cold, wet, dry, wind and storms, snow and ice, coastal, 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 hazard 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 24 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.

[*Placeholder: in the FOD only a limited subset of these indices were processed, the list of intended other indices for final draft is indicated in Table AVII.2*]

AVII.3.1 Regional hazard indices used in Section 12.4

Hazard indices

Mean temperature (MT): The most commonly used index of warming across all IPCC reports is simply the mean temperature, which is calculated from the daily mean surface air temperature (variable named *tas* from climate models), and averaged over a given time period. Regional mean temperature change is often the basis of attribution of observed impacts (Hansen et al., 2016). In Chapter 12, mean annual temperature change is shown in all hazard indices figures (12.5-7 and 12.10-13).

Sea Surface Temperature (SST): Within the Reasons for Concern framework global annual average SSTs were identified as a driver for impacts on marine ecosystems. [*Placeholder: SST will be developed in the Atlas in the SOD*]

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 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, max and min daily temperature with the formula taken from this reference :

$$CDD_i = \begin{cases} 0 \\ \dfrac{T_X - T_b}{4} \\ \dfrac{T_X - T_b}{2} - \dfrac{T_b - T_N}{4} \\ T_M - T_b \end{cases} \quad if \quad \begin{cases} T_X \le T_b \\ T_M \le T_b < T_X \\ T_N \le T_b < T_M \\ T_N \ge T_b \end{cases} \tag{43}$$

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 head upward. Changes in climatic conditions could influence de behavior 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 (Blanford et al., 2013; Lambrechts et al., 2011; 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, submitted). Three thresholds are used in the Atlas (30°C, 35°C and 40°C). Chapter 12 uses the 35°C threshold for most regions, which was identified as a critical temperature for maize pollination and production (Deryng et al., 2014; Gourdji et al., 2013; Hatfield et al., 2011, 2014; Hatfield and Prueger, 2015; Lobell et al., 2013; Lobell and Gourdji, 2012; Schauberger et al., 2017; Schlenker and Roberts, 2009; Tesfaye et al., 2017; Tripathi et al., 2016; Wolfe et al., 2008) 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.

The heat wave magnitude index (HWMId): [*Placeholder: the heat wave magnitude index will be developed in the SOD*]

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):

WBGT(°C) = 0.567 Ta + 0.393 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; Cradock-Henry, 2017; Crimp et al., 2016; 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).

Cold wave magnitude index (CWMId): [*Placeholder: the cold wave magnitude index will be developed in the SOD*]

Mean precipitation (MP): changes in mean precipitation affects a number of sectors (see Chapter 12 Section 12.3). In Chapter 12, mean regional precipitation changes are shown in all regional figures (Figures 12.5-7 and 12.10-13). Mean precipitation is calculated from the daily amounts (variable named *pr* from climate models), and averaged over a given time period.

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 the Euro-CORDEX regional model 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.

[*Placeholder: this will be replaced by flood modeling in the SOD: For CMIP5-based figures in Chapter 12,* *for the sake of simplicity, we use instead 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-6): The SPI is a statistical index that compares cumulated precipitation for *n* months with the long term precipitation distribution for the same location and cumulation period. The SPI-6 months has been computed that is considered to be a medium-term cumulated value and 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 6-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-6 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). This has to be taken into account when interpreting figures of the SPI index in Chapter 12 and its Supplementary online material.

Mean Precipitation-Evapotranspiration: This index is used for the analysis of changes in the water cycle (Byrne and O'Gorman, 2015) and as an index for freshwater resource. This index is shown in one figure of Chapter 12 and the Atlas. It is calculated as the mean difference between precipitation and evapotranspiration.

SPEI accumulated over 6 months (SPEI-6): [*Placeholder: this index will be developed in the SOD*]

Normalized Soil Moisture (NSM): [*Placeholder: this index will be developed in the SOD*]

98th percentile of daily maximum wind speed: 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. In Chapter 12 and the Atlas this index is used. 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 (SSL): 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. In several figures of Chapter 12 and the Atlas, the snow season length is calculated then 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.

Freezing level height (FLH): Freezing level, the height above ground level where the 0°C isotherm lies, is used as an index for melting of snow and glaciers in mountainous areas (Vuille et al., 2018). [*Placeholder: this index will be developed in SOD*]

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) resulting from a fully probabilistic model that incorporating SLR from 7 GCMs and structural function uncertainty 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 for FOD and italicized indices are not considered in the Atlas or Chapter 12 for FOD, but will be in SOD.

Hazard category	**Manifested hazard (from Table 12.1) and potential affected sectors**	**Hazard Index**	**Required ECVs**	**Way to calculate**	**Bias adjustment**	**References**
Heat	**Warming, key to many sectors**	**Mean Temperature (MT)**	**tas**	**from projections**	**yes**	**IPCC AR6 Chapter 4**
Heat	*Warming*	*SST change (SST)*	*tos*	*from projections*	*no*	**IPCC AR6 Chapter 4**
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 Tx>30, 35, 40 (TX35)**	**tasmax**	**from projections**	**yes**	**(Hatfield and Prueger, 2015) (Grotjahn, submitted)**
Heat	*Heat Wave index accounting for duration, link to health*	*Mean annual area fraction with HWMId>= 6, 10, 15 HWMId*	*tasmax*	*from projections*	*no*	**(Forzieri et al., 2016; Russo et al., 2015)**
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)**

Heat	*Marine heat wave index for coral bleaching*	*#days SST>28.7*	*tos*	*from projections*	*yes*	*[Placeholder: to be developed]*
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)**
Cold	*Cold snap*	*CWMId*	*tasmin*	*from projections*	*no*	**(Forzieri et al., 2016; Russo et al., 2015)**
Wet	**Wet or dry trend in precipitation**	**Mean Precipitation (MP)**	**pr**	**from proejctions**	**No**	**IPCC AR6, Chapter 4**
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**	**(Alfieri et al., 2017; Forzieri et al., 2016)**
Drought	**drought**	**SPI accumulated over 6 month (SPI-6)**	**pr**	**from projections**	**yes**	**(Naumann et al., 2018)**
Drought	**drought**	**P-E**	**pr, evspsbl**	**from projections**	**no**	**(Byrne and O'Gorman, 2015)**
Drought	*drought*	*SPEI acc over 6 months*		*from projections*		**(Arnell et al., 2018)**
Drought	*drought*	*Normalized Soil Moisture*	*mrso/ mrsos*	*from projections*	*no*	*[Placeholder : to be developed]*
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. (SSL)**	**snw**	**from projections**	**no**	(Damm et al., 2017; Wobus et al., 2017)
Snow/Ice	*Glacier melt*	*Freezing Level Height (FLH)*	*3D data (Z,T)*	*from projections*	*no*	***(Vuille et al., 2018)***
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**	*[Placeholder : to be developed]*

[END TABLE AVII.2 HERE]

AVII.3.2 Hazard indices used in Section 12.5.1

[*Placeholder: Section 12.5.1 uses in FOD different indices than Sections 12.4 ; these indices are described below ; they will also be replaced by indices calculated from CMIP6*]

Heat extremes: days with Tmax > 35°C
Global average annual number of days with Tmax greater than 35°C, averaged over grid cells with more than 1000 people in 2010.

Heat stress: days with WBGT>32°C
Global average annual number of days with WBGT greater than 32°C, averaged over grid cells with more than 1000 people in 2010. [*Placeholder: the thresholds for WBGT will be harmonized in the SOD*]

Average annual number of frost-days
Global average annual number of days with Tmin less than 0°C, averaged over grid cells with more than 1000 people in 2010.

Average annual number of heating degree-days

Global average annual number of degree-days above 15.5ºC, averaged over grid cells with more than 1000 people in 2010.

Frequency of 1981-2010 50-year return period river flood
River flood frequency is estimated at each 0.5x0.5ºC grid cell using global hydrological model, and the frequency of the reference period (1981-2010) 50-year flood with climate change is calculated. Global average frequency is averaged over grid cells with more than 1000 people in 2010.

Proportion of time in drought: SPI
Drought is characterised by the Standardised Precipitation Index (SPI), calculated from 6-month accumulated precipitation and calibrated over 1981-2010. A drought has a SPI of less than -1.5 (approximately 6.5% of the time in the 1981-2010 reference period). The global average proportion is weighted by cropland area.

Proportion of time in drought: SPEI
Drought is characterised by the Standardised Precipitation Evaporation Index (SPEI), calculated from the 6-month accumulated difference between precipitation and potential evaporation, calibrated over 1981-2010. A drought has a SPEI of less than -1.5 (approximately 6.5% of the time in the 1981-2010 reference period). The global average proportion is weighted by cropland area.

All these indicators are calculated at the 0.5x0.5ºC scale and aggregated to the global scale. In the plots, the dashed line shows the reference period (1981-2010) indicator, and the solid line shows the median estimate under each climate forcing. The shaded area shows the 10th to 90th percentile range, representing uncertainty in the spatial pattern of climate change as represented by 23 CMIP5 models, and uncertainty in the projected increase in temperature for each RCP. The bars on the right of each plot show the impact in 2100 under four RCPs. See (Arnell et al., 2019) for method.

Area below 100-year coastal flood level
The area below the 100-year coastal flood level is estimated using the DIVA model, which combines projections of sea-level rise with estimated local depth-frequency relationships and a coastal-zone digital elevation model. A globally-uniform sea level rise is assumed, but DIVA incorporates local changes in the relative elevation of land and sea due to tectonic activity and local subsidence. The depth-frequency relationships assume no change in the frequency and characteristics of storms. See Arnell et al. (2019) for method.

AVII.3.3 Global indices

[START TABLE AVII.3 HERE]

Table AVII.3: List and characteristics of global indices used in Chapter 12

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	(Bell et al., 2013; Donner et al., 2005, 2007; Frieler et al., 2013; Gattuso et al., 2015)
Ocean acidification	Global average pH	Ocean pH	From projections/Assessment by Chapter 5	(Bell et al., 2013; Donner et al., 2005, 2007; 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	(Bell et al., 2013; Donner et al., 2005, 2007; 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 permafrost melting	Land area with permafrost	From projections/Assessment by Chapter 9	(Slater and Lawrence, 2013)
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 extreme indices

[*Placeholder: to be developed in SOD*]

AVII.4.2 Models used to calculate hazard indices

[*Placeholder: In SOD, this section will change as model ensembles will likely be different, using a mix of CORDEX, CORDEX-CORE, CMIP5 and CMIP6 data; this section describes the approach and model lists taken in the FOD; the "flat averaging" strategy used for statistics way also be revised*]

The models used in Chapter 12 and the Atlas are subsets of the full CMIP5 ensemble, selected based on availability in the Atlas database, and from a few other sources. In one region, Europe, Chapter 12 used a large ensemble of 34 regional simulations with high resolution (Jacob et al., 2014). Associated regional figures (Figs 12.11 and 12.12, see also the Supplementary Material) for Europe were designed to be compared. However, different GCMs were used in both cases (see below). No model weighting is applied.

In Chapter 12, only results for Scenario RCP8.5 are shown as maps. Figures 12.5-6, and 12.9-13 show the differences between results obtained for each index between statistics calculated over two reference periods: mid-century (2041-2060) and a reference period (1995-2014).

[START TABLE AVII.4 HERE]

Table AVII.4: List of CMIP5 models used for each index. The indices are grouped when the same subset of models is used

CMIP5 Simulation	MT, LFFP, GDD, CDD, T21.5, TX35, HDD, FD, MP, R99WD, P-E	WBGT	SPI	FI	P98WIND	SWE100	ESL
CanESM2	X	X	X	X	X	X	
CNRM-CM5	X	X	X	X	X	X	
EC-EARTH	X (r12 for MT Tx35/30,, T21.5, r8 for MP, R99, P-E;; r1 for SPI)		X (r1)				x
GFDL-ESM2M	X	X	X	X	X	X	x
HadGEM2-ES	X	X	X		X	X	
IPSL-CM5A-MR	X	X	X		X		
MIROC-ESM	X	X		X	X	X	
MPI-ESM-LR	X		X	X	X	X	
NorESM1-M	X	X	X	X			
MIROC5			X	X			x
MPI-ESM-MR				X			
GFDL-ESM2G							x
ACCESS 1							x
ACCESS 3							x
CSIRO Mk3							x

[END TABLE AVII.4 HERE]

[START TABLE AVII.5 HERE]

Table AVII.5: List of EURO-CORDEX models used for each index, for the Figure 12.4.11. 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). [*Placeholder: The simulation list and data analysis is taken from the synthesis work of the Copernicus Climate Change Service on regional simulations for Europe, Contract #D34b_Lot2.4.3.1.*]

GCM	RCM	MT, TX35	WBGT	PR, SPI, FI	P98WIND	SWE100
CANESMr1	CCLM	X	X	X		X
	REMO2015	X		X		
CNRMr1	ALADIN63	X	X	X	X	X
	RACMO	X	X	X	X	X
ECEARTHr12	CCLM	X		X	X	X
	HIRHAM	X	X	X	X	X
	RACMO	X	X	X	X	X
	REMO2015	X		X		X
	RCA	X	X	X	X	
ECEARTHr1	HIRHAM	X	X	X	X	X
	RACMO	X	X	X	X	X
ECEARTHr3	HIRHAM	X	X	X	X	X
	RACMO	X	X	X	X	X
	RCA	X	X	yes for PR and SPI		
HADGEMr1	CCLM	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	

	REMO2015	X		X		X
	WRF361H	X		yes for PR and SPI		
	WRF381P	X	X	yes for PR and SPI	X	
IPSLr1	RCA	X	X	X	X	
	WRF381P	X	X		X	
MIROCr1	CCLM	X	X	X		X
	REMO2015	X		X		X
MPIr1	CCLM	X		X	X	X
	RCA	X	X	X	X	
	REMO	X		X	X	X
	WRF361H	X		yes for PR and SPI		
MPIr2	REMO	X		X	X	X
NORESMr1	HIRHAM	X	X	X	X	X
	RRCA	X	X	X	X	X
	REMO2015	X	X	X	X	X

[END TABLE AVII.5 HERE]

AVII.5 Observations used

Observations are used in two manners: for display for climatologies in the Supplementary Material of Chapter 12 and for bias adjustment. [*Placeholder: for Chapter 11 to input observations used*]

The observations used to compute the mean climatology in Chapter 12 are summarized in Table AVII.6 They are all daily observations for mean, maximum and minimum temperature and mean precipitation.

[START TABLE AVII.6 HERE]

Table AVII.6: Observations used to compute mean climatology of hazard indices of Chapter 12.

Observed Datasets	Domain	PRECIP	TEMP	Data type	Spatial Resol.	Time Resol.	Period	Reference
CPC_Global	Global Land	✓ X	✓ (tmax/tmin)	Station based	0.50°	DD	1979-2017	https://www.esrl.noaa.gov/psd/data/gridded/ data.cpc.globalprecip.html data.cpc.globaltemp.html
E_OBS (v19)	Europe Land	✓ X	✓ (tmax/tmin)	Grid	0.25°	DD	1950-2015	(Cornes et al., 2018)
GCOSGHCN	North America	✓ X	✓ (tmax/tmin)	Stations	2551 stations	DD	1961-2000 (1979-2005)	http://www.ncdc.noaa.gov/oa/climate/ghcn-daily
IMD	India	✓ X	✓	Gridded	1.0°	DD	1951-2015	(Rajeevan, et al., 2006)
LIVNEH	Central America	✓ X	✓ (tmax/tmin)	Station based	6 km	DD	1950-2013	(Livneh et al., 2015)
CN05.1	China	X	✓	Station based	0.25°	DD	1961-present	(Wu and Gao, 2013)
EWEMBI	Global	✓	✓	Reanalysis (ERA-Interim) calibrated with observations	0.5°	DD	1979-2016	Lange, S. (2019). EartH2Observe, WFDEI and ERA-Interim data Merged and Bias-corrected for ISIMIP (EWEMBI) [Data set]. GFZ Data Services. https://doi.org/10.5880/pik.2019.004
Coastal Recession	Global			Satellite data	N/A	N/A	1984-2017	(Luijendijk et al., 2018)

[END TABLE AVII.6 HERE]

AVII.6 Bias adjustment

[*Placeholder: In SOD, bias adjustment approach will likely be different building on different approaches (to estimate the uncertainty) and on the recommendations from Chapter 10; this section describes the approach taken in the FOD*]

Some indices in Table A VII.2 are sensitive to model biases and, therefore, have been computed from bias-adjusted data. In particular, minimum, mean and maximum temperatures from CMIP5 models have been bias adjusted using EWEMBI (Table AVII.5; the reference dataset for the ISI-MIP initiative) as observational reference. EWEMBI was interpolated (bi-linearly) to a 2º resolution grid (the same used to interpolate the CMIP5 models in the Interactive Atlas) instead of using the 0.5º original resolution. The main reason was to have a similar resolution for the raw and bias corrected data, thus avoiding "downscaling" artefacts (this is recommended e.g. in IPCC, 2015). Two standard bias adjustment methods representatives of simple and sophisticated bias adjustment methods have been tested:

- PQM: Parametric scaling (correcting the mean and variance).
- EQM: Empirical Quantile Mapping, adjusting percentiles 1 to 99 and linearly interpolating between them (with "constant" extrapolation; i.e. using the P1-P2 and P98-P99 adjustment value for values out of sample; see DEQUE, 2007).

In both cases, adjustments are performed month by month. The two methods have been assessed in the VALUE inter-comparison initiative (codes: RaiRat-M7 and EQM in Gutiérrez et al., (2018), Table 4), obtaining better adjustment for the tails of the distribution with the empirical method [*Placeholder: the EQM method was selected for the FOD*]. However, both approaches have advantages and shortcomings and an ensemble approach (comparing the results from different methods) would be preferable. In the Atlas chapter some comparison results of these two methods for some illustrative index are shown. EQM is implemented in the downscaleR package (biasCorrection function) with the options method = "eqm", extrapolation = "constant" (code for reproducibility of results is provided in the Atlas). Further details are given on Iturbide et al. (2019).

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