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Annex VI: Climatic Impact-driver and Extreme Indices

Coordinating Lead Authors:
José M. Gutiérrez (Spain), Roshanka Ranasinghe (The Netherlands/Sri Lanka, Australia), Alex C. Ruane (United States of America), Robert Vautard (France)

Lead Authors:
Nigel Arnell (United Kingdom), Erika Coppola (Italy), Izidine Pinto (South Africa/Mozambique), Daniel Ruiz Carrascal (United States of America/Colombia), Jana Sillmann (Norway/Germany), Claudia Tebaldi (United States of America)

Contributing Author:
Clemens Schwingshackl (Norway, Germany/Italy)

Chapter Scientists:
Mathias Hauser (Switzerland), Carley E. Iles (Norway, France/United Kingdom), Maialen Iturbide (Spain)

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AVI.1 Introduction

This annex provides background information on indices used within Chapter 11, Chapter 12 and the Atlas, including technical details of calculation and related references.

In the climate science literature, a number of indices are used 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 surface 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 spring 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 IPCC Special 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 climatic impact-drivers (CIDs; see Chapter 1 for the definition) that are key to impacts and risks to society and ecosystems. Chapter 12 proposes a definition of 'climatic impact-driver indices' as 'numerically computable indices using one or a combination of climate variables designed to measure the intensity of the climatic impact-driver, or the probability of exceedance of a threshold. For instance, an index of heat inducing human health stress is the Heat Index (HI) that combines temperature and relative humidity (e.g., Burkart et al., 2011; Lin et al., 2012; Kent et al., 2014) and is used by the US National Oceanic and Atmospheric Administration (NOAA) for issuing heat warnings'.

Climatic impact-drivers may not be related only to extremes, and therefore require a much broader set of indices. For instance, the rate of coastline recession, due to sea level rise, assessed 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 CIDs. For instance, beyond the warming trend that has a large number of consequences, changes in other indices such as 'snow season length' are often used to study economic impacts on winter tourism (Damm et al., 2017). Furthermore, Mora et al. (2018) used a set of 11 very different key CID indices, among which about half are related to extremes to characterize broader threats to society. Section 12.3 in Chapter 12 reviews the CIDs described in the literature which drive impacts and risks, and reveal the wide variety of indices used to characterize them.

Indices are, in principle, computable from observations, reanalyses 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, CIDs are simply characterized by the exceedance of a threshold for an Essential Climate Variable (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, 2021). To assess the effect of climate change on threshold-based indices (e.g., the change in the number of days with maximum temperature above 35°C), a bias adjustment of model outputs should be considered where sensible as model simulations can have biases compared to observations and reanalyses (Section 10.3.1.3 and Cross-Chapter Boxes 10.2).

Indices are used in many chapters of this 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 CIDs and their changing characteristics due to climate change. The Atlas assesses changes in mean variables/indices (temperature, precipitation and snow). The Interactive Atlas includes indices of mean changes (for temperatures, precipitation, snowfall and wind) and a number of extreme indices and CIDs, allowing for flexible spatial and temporal analysis of the results.

AVI.2 Extreme Indices Selection

In Chapter 11, extreme weather and climate events (collectively referred to as extremes) are assessed and the main focus is on extreme events over land. Since the analysis of extremes often involves the examination of the tails of the statistical distributions, a parametric or non-parametric approach can be used to define extremes. The non-parametric approach is largely adopted in most of the literature to characterize moderate temperature and precipitation extremes with shorter return periods. The Expert Team on Climate Change Detection and Indices (ETCCDI; https://www.wcrp-climate.org/etccdi) defined 27 indices to characterize different aspects of moderate temperature and precipitation extremes, which are described by Frich et al. (2002), Alexander et al. (2006), Zhang et al. (2011), Donat et al. (2013), and Sillmann et al. (2013), and were also extensively used in previous IPCC reports. In Chapter 11, a subset of these indices is assessed in detail (Sections 11.3 and 11.4). For events with longer return periods (e.g., events that occur once in 20 years or even more rarely), the parametric approach based on Extreme Value Theory (EVT; Coles, 2001) is used and adopted in the literature (e.g., Kharin and Zwiers, 2000; Brown et al., 2008; Kharin et al., 2013). These events are also assessed throughout the chapter. Aside from temperature and precipitation, the chapter also assesses indices used to characterize droughts. Table AVI.1 lists the indices used.

Table AVI.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 temperature is less than the 10th percentile	%	Minimum 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 at least six consecutive days when TX >90th percentile	Days	Maximum temperature
	CSDI	Cold spell duration index: annual count of days with at least six 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 (1 Jan to 31 Dec in Northern Hemisphere (NH), 1 July to 30 June in Southern Hemisphere (SH)) count between first span of at least six days with daily mean temperature TG >5°C and first span after July 1 (Jan 1 in SH) of six days with TG <5°C	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
	20TNx	One-in-20 year return value of monthly maximum value of daily minimum temperature	°C	Minimum temperature
Precipitation	Rx1day	Maximum one-day precipitation	mm	Precipitation
	Rx5day	Maximum five-day precipitation	mm	Precipitation
	R5mm	Annual count of days when precipitation is greater than or equal to 5 mm	Days	Precipitation
	R10mm	Annual count of days when precipitation is greater than or equal to 10 mm	Days	Precipitation
	R20mm	Annual count of days when precipitation is greater than or equal to 20 mm	Days	Precipitation
	R50mm	Annual count of days when precipitation is greater than or equal to 50 mm	Days	Precipitation
	CDD	Maximum number of consecutive days with less than 1 mm of precipitation per day	Days	Precipitation
	CWD	Maximum number of consecutive days with more than or equal to 1 mm of precipitation per day	Days	Precipitation
	R95p	Annual total precipitation when the daily precipitation exceeds the 95th percentile of the wet-day (>1 mm) precipitation	mm	Precipitation
	R99p	Annual precipitation amount when the daily precipitation exceeds the 99th percentile of the wet-day precipitation	mm	Precipitation
	SDII	Simple precipitation intensity index	mm day^{-1}	Precipitation
	20Rx1day	One-in-20 year return value of maximum one-day precipitation	mm day^{-1}	Precipitation
	20Rx5day	One-in-20 year return value of maximum five-day precipitation	mm day^{-1}	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	Streamflow
	SSI	Standardized streamflow index	Months	Streamflow
	PDSI	Palmer drought severity index	Months	Precipitation, evaporation
	SPEI	Standardized precipitation evapotranspiration index	Months	Precipitation, evaporation, temperature

Some of these indices are included in the Interactive Atlas allowing further analysis (seasons, regions, baselines and future periods – using both time slices/scenarios and global warming levels): TXx, TNn, Rx1day, Rx5day, FD, CDD and SPI.

AVI.3 Selection of Climatic Impact-drivers Indices

In Chapter 12, 33 CID categories are identified on the basis of relevance for risks and impacts and available literature. They are classified into seven types: heat and cold, wet and dry, wind, snow and ice, coastal, open ocean, 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 provide information about future regional climate, Chapter 12 and the Atlas use a limited number of indices to illustrate the main CIDs 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; and
vi) represent CIDs of interest to regional impacts and risk assessments.

The selection results in 13 regional indices that are reported in Table AVI.2. The description of the formulae used for processing is described below.

AVI.3.1 Regional CID Indices Used in Chapter 12 and the Atlas

Climatic Impact-drivers Indices

Cooling degree days (CD): 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 (T_M), max (T_X) and min daily (T_N) temperature with the formula taken from this reference:

$$CD_i = \begin{cases} 0 \\ \dfrac{T_X - T_b}{4} \\ \dfrac{T_X - T_b}{2} - \dfrac{T_b - T_N}{4} \\ T_M - T_b \end{cases} \quad if \quad \begin{cases} T_X \leq T_b \\ T_M \leq T_b < T_X \\ T_N \leq T_b < T_M \\ T_N \geq T_b \end{cases}$$

With $T_b = 22°C$, then

$$CD = \sum_{i=1}^{365} CD_i$$

The difference between Chapter 12, the Atlas and the previous reference is that in this Report the sum is cumulated over the entire year instead of six months, so it applies to all hemispheres. This index is included in the Interactive Atlas.

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°C and 40°C (Hatfield and Prueger, 2015; Grotjahn, 2021). 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 et al., 2016; Petitti et al., 2016). The Interactive Atlas includes both TX35 and TX40 (both raw and bias adjusted; see Atlas 1.4.5).

NOAA heat index (HI): HI is used by the US National Oceanic and Atmospheric Administration (NOAA) for issuing heat warnings and was applied in several studies that investigated adverse health impacts due to heat stress (e.g., Burkart et al., 2011; Lin et al., 2012; Kent et al., 2014). HI is calculated as multiple linear regression with

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temperature (T_F in °F) and relative humidity (RH) as input variables (Steadman, 1979; Rothfusz, 1990):

$$\mathrm{HI} = \begin{cases} \mathrm{HI}_1 + \mathrm{HI}_{\mathrm{A1}}, & \text{if RH} < 13\,\% \text{ and } 80\,°\mathrm{F} < T_F < 112\,°\mathrm{F} \\ \mathrm{HI}_1 + \mathrm{HI}_{\mathrm{A2}}, & \text{if RH} > 85\,\% \text{ and } 80\,°\mathrm{F} < T_F < 87\,°\mathrm{F} \\ \mathrm{HI}_1, & \text{otherwise} \end{cases}$$

with:

$$\mathrm{HI}_1 = c_0 + c_1 \cdot T_F + c_2 \cdot \mathrm{RH} + c_3 \cdot T_F \cdot \mathrm{RH} + c_4 \cdot T_F^2 + c_5 \cdot \mathrm{RH}^2 + c_6 \cdot T_F^2 \cdot \mathrm{RH} + c_7 \cdot T_F \cdot \mathrm{RH}^2 + c_8 \cdot T_F^2 \cdot \mathrm{RH}^2$$

$$\mathrm{HI}_{\mathrm{A1}} = (13 - \mathrm{RH})/4 \cdot \sqrt{(17 - |T_F - 95\,°\mathrm{F}|)/17}$$

$$\mathrm{HI}_{\mathrm{A2}} = (\mathrm{RH} - 85)/10 \cdot (87\,°\mathrm{F} - T_F)/5$$

c_0 = –42.379 °F, c_1 = 2.04901523, c_2 = 10.14333127 °F,
c_3 = –0.22475541, c_4 = –0.00683783 °F^{-1}, c_5 = –0.05481717 °F,
c_6 = 0.00122874 °F^{-1}, c_7 = 0.00085282, c_8 = –0.00000199 °F^{-1}

If HI < 80 °F, the following equation is used:

$$\mathrm{HI} = 0.5 \cdot (T_F + 61\,°\mathrm{F} + 1.2 \cdot (T_F - 68\,°\mathrm{F}) + 0.094\,°\mathrm{F} \cdot \mathrm{RH})$$

The calculated HI is converted into °C.

HI is calculated for CMIP5, CMIP6 and CORDEX using daily mean near-surface specific humidity, daily mean surface pressure, and daily maximum near-surface air temperature. For CMIP5 and CMIP6, daily mean surface pressure is calculated from daily mean sea level pressure by applying a height adjustment (see Schwingshackl et al. (2021) for details). Additionally, HI is calculated for WFDE5, which is a bias-adjusted version of the ERA5 reanalysis (Cucchi et al., 2020). Daily maximum temperature is calculated as the maximum of the hourly WFDE5 near-surface temperature values. Relative humidity is calculated using daily means of the hourly WFDE5 variables for near-surface air temperature, near-surface specific humidity, and surface air pressure.

To quantify heat stress, yearly numbers of daily HI-threshold exceedances are calculated using a threshold of 41°C, which corresponds to conditions that the US National Weather Service classifies into the category of 'Danger' (Blazejczyk et al., 2012). Bias-adjusted model simulations are used for calculating threshold exceedances of HI, employing the quantile delta mapping (QDM) approach as described by Cannon et al. (2015). The QDM approach adjusts the model data in the application period to fit the reference data in the reference period (using quantile mapping). Subsequently, the climate change signal is added for each quantile by considering the change between the model's reference and application periods. QDM is directly applied to the HI data using WFDE5 as the reference dataset and 1981–2010 as the reference period. WFDE5 HI data are conservatively remapped to each model's grid before bias adjustment is performed. QDM is applied on each grid point individually and for each month separately. The application periods are the IPCC periods 1995–2014, 2041–2060 and 2081–2100, and 20-year periods for specific warming levels (1.5°C, 2°C, 3°C and 4°C).

Heating degree days (HDD): symmetrical to the cooling degree days index, the HDD index is used for illustrating energy demand for heating. It has been used in several studies of the impacts of climate change on the energy sector. The Atlas follows 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

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

Where T_M, T_X and T_N correspond to daily mean, maximum and minimum temperature, respectively.

To account for various geographic zones, however, the HDD index is cumulated over the entire year, instead of six months, as in the previous reference. This index is included in the Interactive Atlas.

Number of frost days (FD): 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 Table AVI.1. This index is included in the Interactive Atlas.

River flood index using runoff (FI): As a flood indicator, the 100-year return value of discharge value (Q100) has been used. The computation of the index follows Alfieri et al. (2015):

1. Annual maximum river discharges are selected and an Extreme Value Type I (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:

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

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

3. The peak discharge corresponding to the 100-year return period, Q100=Q(RP=100), is then calculated.

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For 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. The Q(RP=100) value has been computed for each of the river segments and each of the 29 CHyM simulations. The results are shown in the regional figures in Section 12.4.

Standardized precipitation index (SPI): The SPI is a statistical index that compares cumulated precipitation for *n* months ($n = 6$) with the long-term precipitation distribution for the same location and cumulation period. The SPI months have been selected so that SPI represents the 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 *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 Spinoni et al. (2014): 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 arid areas due to statistical issues linked to inaccuracies in the estimation of the Gamma function (Spinoni et al., 2014). The duration of six months is considered in Figure 12.4. This index is included in the Interactive Atlas.

Soil moisture (SM): The soil moisture index is used in Chapter 12 figures. It is using the total soil moisture content integrated over the soil depth, normalized by the recent past climatological values at each grid point.

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 100 mm as a key threshold for skiing. However, this index is important not only for winter tourism but also in other sectors such as water management. In several figures of Chapter 12, the snow season length is calculated then as the number of days with SWE > 100 mm, following the definition of Damm et al. (2017) and 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 into the sign of changes (McCrary et al., 2017). When interpreting the figures shown in Chapter 12, 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 Total Water Level (ETWL): Factors contributing to extreme sea levels (ETWL) are sea level rise, storm surge (e.g., associated with tropical cyclones and extratropical cyclones), tide, and extreme waves (resulting in high-wave setup at the shoreline). The ETWL used here is the summation of the aforementioned factors (Vitousek et al., 2017; Vousdoukas et al., 2018) and the commonly used 1-in-100-year ETWL (the 100-year ETWL return value) is adopted here as the index relevant to episodic coastal flooding. Here, the median ETWL, together with the associated 5–95% confidence interval, resulting from a fully probabilistic model that incorporates storm surge and waves derived from models forced by an ensemble of six GCMs, is used as the index relevant for long-term coastal erosion.

Coastal erosion (CE): Coastal erosion is generally accompanied by shoreline retreat, which can occur as a gradual process (e.g., due to sea level rise) or as an episodic event due to storm surge and/or extreme waves, especially when combined with high tide (Ranasinghe, 2016). The most commonly used shoreline retreat index is the magnitude of shoreline retreat by a predetermined planning horizon such as 50 or 100 years into the future. Here, the median shoreline retreat, together with the associated 5–95% confidence interval, resulting from a fully probabilistic model that incorporates storm surge and waves derived from models forced by an ensemble of six GCMs, is used as the index relevant for long-term coastal erosion.

Some of these indices are included in the Interactive Atlas allowing flexible analysis (seasons, regions, baselines and future periods – using both time slices/scenarios and global warming levels): TX35 and TX40 (both raw and bias adjusted; see Atlas 1.4.5), FD, CDD, HDD, SPI-6 (CDD and HDD are labelled as CD and HD, respectively, in the Interactive Atlas).

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Table AVI.2 | Regional CID indices table and relevant references.

CID Category	Climatic Impact-driver (from Table 12.1) and Potential Affected Sectors	Index	Required ECVs	Way to Calculate	Bias Adjustment	References
Heat	Change in cooling demand for energy demand and building consumption	Cooling degree days above 22°C	Tas, tasmin, tasmax	From projections	Yes	Spinoni et al. (2015, 2018)
	Heat, with thresholds important for agriculture	Number of days with Tmax >35°C or 40°C (TX35, TX40)	Tasmax	From projections	Yes	Hatfield and Prueger (2015); Hatfield et al., (2015); Grotjahn (2021)
	Heat stress index combining humidity used in occupational and industrial health	NOAA heat index (HI): number of days above 41°C threshold	Tasmax, huss, ps	From projections	Yes	Burkart et al. (2011); Lin et al. (2012); Kent et al. (2014)
Cold	Heating degree day for energy consumption	Heating degree days below 15.5°C	Tas, tasmin, tasmax	From projections	Yes	Spinoni et al. (2015, 2018)
	Frost	Number of frost days below 0°C (FD)	Tasmin	From projections	Yes	Barlow et al. (2015); Rawlins et al. (2016)
Wet	River flooding	Flood index (FI)	srroff/mrro	From projections and simplified routing model	No	Forzieri et al. (2016); Alfieri et al. (2017)
Drought	Aridity	Soil moisture (SM)	mrso	From projections	No	Cook et al. (2020)
	Droughts	Standardized Precipitation Index accumulated over 6 months (SPI-6)	Pr	From projections	No	Naumann et al. (2018)
Wind & storm	Mean wind speed	Annual mean wind speed	sfcWind	From projections	No	Karnauskas et al. (2018); Li et al. (2018)
Snow/ice	Snow season length	Number of days with snow water equivalent >100 mm (SWE100) over the snow season (Nov–Mar for NH)	Snw	From projections	No	Damm et al. (2017); Wobus et al. (2017)
Coastal	Extreme sea level (ETWL) inducing storm surges	1-in-100-year return period level (ETWL)		Data from authors	No	Vousdoukas et al. (2018)
	Coastal erosion	Shoreline retreat by mid- and end of century		Data from authors	No	Vousdoukas et al. (2020)

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