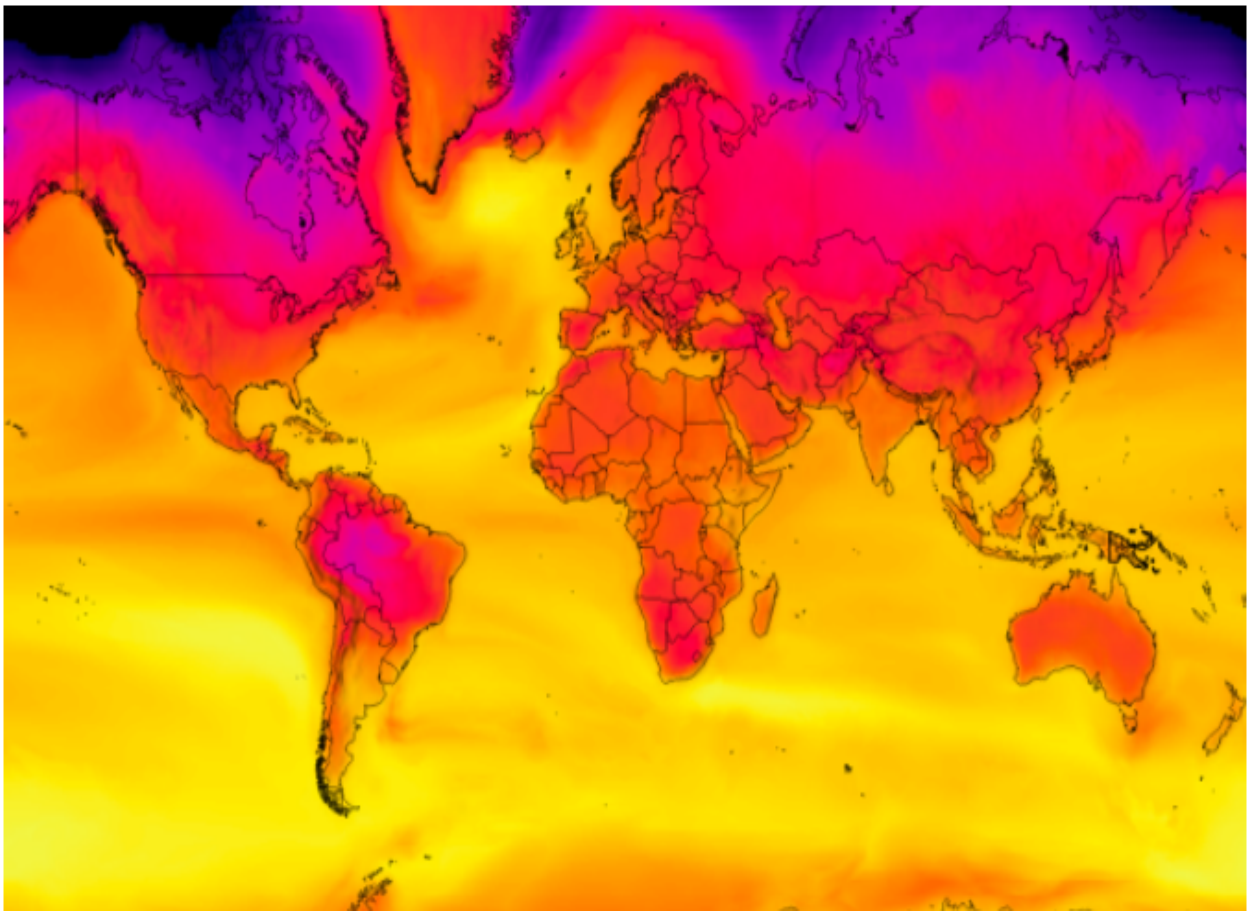
METADATA

CLIMATE CHANGE KNOWLEDGE PORTAL (CCKP)



WORLD BANK GROUP | Climate Change Knowledge Portal
For Development Practitioners and Policy Makers

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CLIMATE DATA

OBSERVED CLIMATE DATA

DATA SOURCE: CRU TS V.4.07

Original Citation: Harris, I., et al. (2020): Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. Sci Data 7, 109. https://doi.org/10.1038/s41597-020-0453-3

Original data access:
https://crudata.uea.ac.uk/cru/data/hrg/

CCKP Data Reference: Climate Change Knowledge Portal: Observed Climate Data, CRU TS4.07 0.5-Degree, DOI: https://doi.org/10.57966/tw2k-9h36

CRU TS (Climatic Research Unit gridded Time Series) is an observational climate dataset represented on a 0.5 x 0.5-degree grid over all land domains except Antarctica and derived by spatial analysis and interpolation from an extensive network of weather station observations collected at the Climatic Research Unit at the University of East Anglia (UEA)[1]. The CRU TS version 4.07 gridded dataset provides quality-controlled temperature and rainfall values from thousands of weather stations worldwide, as well as derivative products, including monthly climatologies and long term historical climatologies. CRU TS has formed the historical foundation used by CCKP and is updated on a regular basis to reflect data corrections and improvements as well as extensions of the record towards the present.

CRU TS v.4.07 are available from 1901-2022 and are used to derive current climatology on CCKP. Data are updated annually.

DATA SOURCE: ERA5

Original Citation: Hersbach H. et al., (2020): The ERA5 global reanalysis. Quart. Journal of the Royal Meteorol. Society, 146: 1999-2049. DOI: 10.1002/qj.3803, and Hersbach, H. et al., (2017): Complete ERA5 from 1940: Fifth generation of ECMWF atmospheric reanalyses of the global climate. Copernicus Climate Change Service (C3S) Data Store (CDS). DOI: 10.24381/cds.143582cf (Accessed on 22-April-2022 and 10-Jan-2024)

Original data access:
https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-complete

CCKP Data Reference: Climate Change Knowledge Portal: Observed Climate Data, ERA5 0.25-Degree, DOI: https://doi.org/10.57966/128g-6s70

[1] University of East Anglia. 2020: Climatic Research Unit. URL:http://www.cru.uea.ac.uk/about-cru

The historical climate reanalysis data from ERA5 are offered at 0.25 x 0.25-degree resolution over the entire globe. ERA5 is the fifth generation ECMWF atmospheric reanalysis of the global climate covering the period from January 1940 to the present. ERA5 uses a broad collection of observational data, including various satellite-derived products in multivariate data assimilation mode to capture global variability and change. The data are offered through the Copernicus Climate Change Service (C3S) as a public good and are updated operationally. CCKP holdings cover 1950-2022 to present and are used to derive historical trends and variability. Data are updated annually.

CLIMATE PROJECTION DATA

Modeled climate projections available on CCKP are derived from the multi-model collection of CMIP6 (the Coupled Model Intercomparison Project, Phase 6)[2]. CMIP offers a standardized experimental framework for studying climate change. The coordinated experiments are conducted by the international modeling community using coupled climate and Earth system models under the leadership of the . World Climate Research Program.

There are many components to the model intercomparison efforts, each of which is an attempt to advance understanding of particular aspects of the climate system. The key intercomparison effort used for the broad climate projections used in CCKP is the "Scenario MIP" activity, subsequently labeled in simplified form as "CMIP6". This activity expands on the historical climate (1850-2014) into the future using various emission and other development metrics as described in the Shared Socioeconomic Pathways (SSPs). These pathways were developed along a collection of plausible story lines of societal development[3] to offer a continuous perspective from the past, through the present, and into the future to study possible magnitudes and characteristics of climate change. CMIP6 also contains activities that utilize idealized experiments to increase understanding of the model responses to specific disturbances or of select model components; these results are currently not part of CCKP. Finally, there are also experiments that are performed to investigate the predictability of the climate system on various temporal (i.e. seasonal to decadal) and spatial scales, including some that are initialized with observed climate states. These "forecasts" are under scientific development and not yet operationally used in CCKP.

The climate scenario approach based on SSPs represents a continuation of earlier products on CCKP. Scenarios are used to characterize the range of plausible climate futures and to illustrate the possible consequences of different pathways. The scenarios chosen by the climate research community span a wide range of options without any tie to likelihood. Over the past three decades, the approach to formulating the different scenarios has evolved from a climate-centric approach to an increasingly societal development-centric concept, albeit with the same underlying goal of providing insight into a range of plausible climate outcomes. CMIP6 presents scenarios as the Shared Socioeconomic Pathways (SSPs), instead of the Representative Concentration Pathways (RCPs) that were used in CMIP5. CMIP6 climate projections are driven by a new set of emissions

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[2] Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. Geoscientific Model Development, 9(5), 1937–1958. https://doi.org/10.5194/gmd-9-1937-2016.

[3] O'Neill, B., Tebaldi, C., Van Vuuren, D., et al., 2016: The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6, Geoscience Model Development 9, 3461–3482. DOI:doi:10.5194/gmd-9-3461-2016

and land use scenarios produced with a collection of integrated assessment models (IAMs) based on new future pathways of societal development, the SSPs. For the purpose of preserving some important consistency, the selected emission levels in the new SSPs retain important relations with the RCPs[4]. While the outputs are similar, CMIP6 climate projections will differ from those in CMIP5 not only because they are produced with updated versions of climate models, but also because they are driven with SSP-based scenarios produced with updated versions of forcings and boundary conditions generated by IAMs and based on updated data on recent emissions trends. Unlike in CMIP3 and CMIP5, where climate model projections were part of the core experiments, in CMIP6 the relevant projection exercises were part of a dedicated intercomparison exercise (one of the CMIP6-Endorsed MIPs[5]), namely the Scenario-MIP.

At the core of the Scenario-MIP activity of CMIP6 are the five primary societal development pathways for which several climate change projections are being conducted. Each represents a *possible* societal development and policy path for meeting designated radiative forcing by the end of the century. They were not meant to be interpreted as the only possible paths to get to the specific forcing levels, but they are selected as representative examples. In addition to the more traditional spread of paths, **SSP1-1.9** represents the most optimistic scenario and was added to offer insight into a climate response that would be expected if emissions would globally adhere to the Paris-Accord emission target of average global mean temperature rise limited to 1.5°C by 2100. Its end-of-century radiative forcing over preindustrial conditions is 1.9 watts per meter squared (W/m^2), thus SSP1 with the label 1.9 (SSP1-1.9). **SSP1-2.6**, which is also derived within SSP1, also aims at sustainable outcomes, with global emissions cut severely and a target global average mean temperature rise likely limited to 2°C by 2100. However, its end-of-century forcing level is a reflection of the earlier scenario RCP-2.6, where net-zero emissions are reached after 2050. **SSP2-4.5** represents a 'middle of the road' scenario in which emissions remain around current levels before starting to fall around mid-century. Net-zero in that pathway is not reached until after 2100. **SSP3-7.0** represents a polarized world in which regional conflicts endure and emissions continue to climb, roughly doubling from current levels by 2100. Finally, **SSP5-8.5** represents a future based on an intensified exploitation of fossil fuel resources where global markets are increasingly integrated, leading to innovations and technological progress. The radiative forcing associated with this scenario is the highest, again in line with earlier RCP-8.5 to preserve continuity in the projections.

Individual model output products **on CCKP** had previously been re-gridded to a common 1x1-degree grid. For the latest version of products presented on CCKP, derived from CMIP6, the model output has been bias-corrected and downscaled to a common 0.25 x 0.25-degree grid. To achieve this higher resolution, daily output from individual models was processed using a quantile-based

[4] O'Neill, B. C., Tebaldi, C., van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.-F., Lowe, J., Meehl, G. A., Moss, R., Riahi, K., and Sanderson, B. M., 2016: The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6, Geosci. Model Dev., 9, 3461–3482, https://doi.org/10.5194/gmd-9-3461-2016.

[5] Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., and Taylor, K. E., 2016: Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization, *Geosci. Model Dev*., 9, 1937-1958, DOI: https://doi.org/10.5194/gmd-9-1937-2016

bias correction and spatial disaggregation (BCSD)[6]. Note, this new product is only in small part due to higher resolution climate models. Rather, it was enabled by further improved reanalysis products that served as reference (see below). It is important to note that the CCKP products inherit higher spatial-resolution spatial relations from this reference period without the models themselves actually resolving some of the underlying processes.

DATA SOURCE: CMIP6 - THE COUPLED MODEL INTERCOMPARISON PROJECT, PHASE 6

Original Citation: Eyring, V. et al. (2016): Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization, *Geosci. Model Dev.*, 9, 1937-1958, DOI: https://doi.org/10.5194/gmd-9-1937-2016

Original data access:
https://www.wcrp-climate.org/wgcm-cmip/wgcm-cmip6
https://pcmdi.llnl.gov/CMIP6/Guide/dataUsers.html

CCKP Data Reference: Climate Change Knowledge Portal: Projected Climate Data, CMIP6 0.25-Degree. DOI: https://doi.org/10.57966/b54h-7s87

The downscaled daily surface fields from CMIP6 in CCKP are a collection of 0.25-degree resolution daily products from thirty models using their historical simulations and up to four SSP experiments (SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5) covering the period from 1950 to 2100. The data are based on the Bias-Correction-Spatial-Disaggregation (BCSD) method that uses quantile mapping over a historical reference period (1961-2014). Note, the temperature trends of the original model simulations are explicitly preserved during bias correction. The spatial disaggregation is based on the reference period spatial structure derived using a scaling approach based on three harmonics of the Fast Fourier Transforms. The underlying reference dataset is the 0.25-degree ERA5 output over the reference period.

The daily data form the foundation from which CCKP generated a broad set of climate indicators that are offered in monthly, seasonal, and/or annual resolution as time series, as well as the different climatology periods used within CCKP. All data are available as globally gridded products using netCDF format and in spatially aggregated form reflecting World Bank shapefiles for national (Admin-0) and sub-national units (Admin-1), as well as for global watersheds (HydroBasins v4)[7].

Because most climate modeling centers performed the above mentioned four standard scenarios, and only few offer daily data for SSP1-1.9, CCKP chose a global mean-temperature-change-based scaling approach to estimate the ensemble outcomes for the SSP1-1.9 scenario. First, the global

[6] Thrasher, B., Maurer, E. P., McKellar, C., and Duffy, P. B. Technical Note: Bias correcting climate model simulated daily temperature extremes with quantile mapping. Hydrol. Earth Syst. Sci., 16, 3309–3314 (2012). https://doi.org/10.5194/hess-16-3309-2012

[7] Lehner, B., Grill G. (2013). Global river hydrography and network routing: baseline data and new approaches to study the world’s large river systems. Hydrological Processes, 27(15): 2171–2186. https://doi.org/10.1002/hyp.9740

mean temperature differences were established in the CMIP6 1-degree datasets between each of the ensemble medians of SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 with the available ensemble of SSP1-1.9 (with reduced number of models). The average of these differences was used to establish a linear scaling factor at each time point between the global-mean temperature outcomes of the four available scenarios and SSP1-1.9 to estimate the equivalent anomalies of all different ensemble products. Because the conversion is only robust at the ensemble level (where internal variability is minimized), no estimates for individual models of SSP1-1.9 are currently available.

CMIP6 model data were originally licensed under a Creative Commons Attribution-ShareAlike 4.0 International License (CC BY-SA 4.0). However, in June 2022, the CMIP6 community updated their underlying licenses, relaxing them to CC BY 4.0 (https://wcrp-cmip.github.io/CMIP6_CVs/docs/CMIP6_source_id_licenses.html) and thereby allowing the distribution of derivative products .

The World Bank makes data publicly available according to open data standards and licenses datasets under the Creative Commons Attribution 4.0 International license (CC-BY 4.0). The Creative Commons Attribution 4.0 International license allows users to copy, modify and distribute data in any format for any purpose, including commercial use. Users are only obligated to give appropriate credit (attribution) and indicate if they have made any changes, including translations. CC-BY 4.0 is the default license for all datasets produced by the World Bank itself and distributed as open data. All CCKP data adhere to CC-BY 4.0.

CCKP acknowledges the World Climate Research Programme, which, through its Working Group on Coupled Modelling, coordinated and promoted CMIP6. We thank the climate modeling groups for producing and making available their model output through the Earth System Grid, the Earth System Grid Federation (ESGF) for archiving the data and providing access, and the multiple funding agencies who support CMIP6 and ESGF.

The CCKP-CMIP6 collection consists of up to 30 models (**Table 1**) that submitted data across the SSPs. All data were processed using an updated version of the Climate Risk Management engine (CRMe) infrastructure[8] and formatted using ArcGIS and functions offered through the Open Geospatial Consortium (http://www.opengeospatial.org/).

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[8] Ammann et al. 2016: An Efficient Workflow Environment to Support the Collaborative Development of Actionable Climate Information Using the NCAR Climate Risk Management Engine (CRMe). AGU Fall Meeting. 12 December, 2016. URL: https://agu.confex.com/agu/fm16/meetingapp.cgi/Paper/197594

__Table 1.__ List of models used in CCKP CMIP6-x0.25 compilation

Model Name	Modeling Center
access-cm2	CSIRO (Commonwealth Scientific and Industrial Research Organization, Australia), and ARCCS (Australian Research Council Centre of Excellence for Climate System Science, Australia
access-esm1.5	CSIRO (Commonwealth Scientific and Industrial Research Organization, Australia), and ARCCS (Australian Research Council Centre of Excellence for Climate System Science, Australia
bcc-csm2-mr	Beijing Climate Center, China Meteorological Administration, China
canesm5	Canadian Centre for Climate Modeling and Analysis, Canada
cmcc-esm2	Euro-Mediterranean Center on Climate Change
cnrm-cm6-1	Centre National de Recherches Meteorologiques, France
cnrm-esm2-1	Centre National de Recherches Meteorologiques / Centre Européen de Recherche et Formation Avancées en Calcul Scientifique, France
ec-earth2	EC-Earth-Consortium
ec-earth3-veg-lr	EC-Earth-Consortium
fgoals-g3	China Academy of Sciences, China
gfdl-cm4	Geophysical Fluid Dynamics Laboratory, NOAA, USA
gfdl-esm4	Geophysical Fluid Dynamics Laboratory, NOAA, USA
giss-e2-1-g	Goddard Institute of Space Studies, NASA, USA
hadgem3-gc31-ll	UK Met Office Hadley Centre, U.K.
hadgem3-gc31-mm	UK Met Office Hadley Centre, U.K.
inm-cm4-8	Institute for Numerical Mathematics, Russia
inm-cm5-0	Institute for Numerical Mathematics, Russia
ipsl-cm6a-lr	The Institute Pierre Simon Laplace, France
kace-1-0-g	National Institute of Meteorological Research, Republic of Korea
kiost-esm	Korea Institute of Ocean Science and Technology, Republic of Korea
miroc6	Atmosphere and Ocean Research Institute, The University of Tokyo, Japan
miroc-es2l	Atmosphere and Ocean Research Institute, The University of Tokyo, Center for Climate system Research - National Institute for Environmental Studies, Japan
mpi-esm1-2-hr	Max Planck Institute for Meteorology (MPI-M), Germany
mpi-esm1-2-lr	Max Planck Institute for Meteorology (MPI-M), Germany
mri-esm2-0	Meteorological Research Institute, Japan
nesm3	Nanjing University of Information Science and Technology, China
noresm2-lm	Norwegian Climate Centre, Norway
noresm2-mm	Norwegian Climate Centre, Norway
taiesm1	Research Center for Environmental Changes, Academia Sinica, Taiwan
ukesm1-0-ll	U.K.'s Met Office and Natural Environment Research Council (NERC), U.K.

For each model, a section of the *historical* simulations was required to form each model's own historical reference period. While the World Meteorological Organization generally prefers reference periods that span 30 years (i.e., 1971-2000, 1981-2010, and 1991-2020), the IPCC-Assessment Reports(ARs)[9] use a compromise of **20-year intervals** to better reflect the speed of

[9] IPCC, 2021: *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V., P. Zhai, et al. (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2391 pp. doi:10.1017/9781009157896.

the changing climate. The historical reference in AR5 was 1986-2005 with scenarios branching off at the beginning of 2006. In AR6, based on the CMIP6 experimental design, the historical reference used is **1995-2014** after which the SSP scenarios diverge. This period covers the final 20 years of the *historical* simulations that were driven with observed radiative forcings. As previously, a 20-year window also corresponds to the CCKP standard 20-year climatological windows for the future, **specifically the time periods: 2020-2039, 2040-2059, 2060-2079, and 2080-2099.** For each of these future time windows, simulations from all four SSPs were obtained at 0.25 x 0.25-degree resolution and processed as input into the calculation of **climate variables** and **derived climate indices** (**Table 2**).

ESSENTIAL CLIMATE VARIABLES

The essential climate variables of temperature (mean, min and max) and precipitation were produced with the objective of providing the most robust comparison possible between different SSPs. They were processed separately from the climate indicators. This most basic climate change projection information was restricted to a fixed collection of those models that provided output for all of the SSPs, thereby making a direct comparison between SSPs most robust.

CLIMATE INDICATORS

Climate indicators are designed to capture a specific characteristic of weather and climate that can have specific impacts on the ground. Some indicators are logical general statistical summaries of basic climate variables, others can reflect the frequency of exceedance over select thresholds with meaning for one or more applications. CCKP offers multiple indicators (**Table 2**) that have been implemented on request; new indicators are added regularly. An important part of the collection is derived from the list prepared by the joint CCl/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI) (see: http://etccdi.pacificclimate.org/ list_27_indices.shtml), now under CLIMDEX (WEB-REF). Further indicators include different heat-hazard indicators, drought-related indicators, and various extreme event quantities.[10] New are also CCKP computed categorical products that relate climate with non-climate categories to reflect exposure to inform analyses of vulnerability and risk.

CCKP presents all projection indicators as absolute values and/or as anomalies (from the historical reference period: 1995-2014 for CMIP6), with data provided at annual, monthly or seasonal scales. General products are time series, climatologies, and heatplot products that represent decadal average changes of the seasonal cycle. Data are available as globally-gridded NetCDF files for geospatial data as well as for different aggregation units (country, sub-national units one level below country, and a collection of global river basins).

[10] The precipitation return interval calculations are based on the automatic algorithm of Naveau et al. 2016 (Modeling jointly low, moderate, and heavy rainfall intensities without a threshold selection, Water Resour. Res., 52, 2753– 2769, doi:10.1002/2015WR018552) that does not require local *a priori* specification of a threshold beyond which precipitation would be considered as distributed following an extreme value distribution. The results presented thus far are the mean expected outcome

Table 2. *List of climate indicators*
Definitions for most indicators are sourced from the ETCCDI consortium (Expert Team on Climate Change Detection and Indices) and can now be found under www.climdex.org,; specifically: https://www.climdex.org/learn/indices.
CCKP uses these definitions unless otherwise stated under "Calculation Details / Reference".

Indicator Name	Indicator code	Description	Unit	Calculation Details/ Reference
Annual Drought Index, SPEI (12-month)	spei12	The annual Standardized Precipitation Evapotranspiration Index (SPEI) represents a measure of the integrated water deficit in a location, taking into account the contribution of temperature-dependent evapotranspiration (computed using method by Hargreaves). The integration period for this production is 12 months.	SPEI Index	PYTHON-package climate_indices, James Adams (2017):[11] after Vicente-Serrano et al. 2010 (J Climate)[12]
Average Largest 1-Day Precipitation	rx1day	The average highest precipitation amount in a 1-day period during each month in the data period.	mm	CLIMDEX
Average Largest 5-Day Cumulative Precipitation	rx5day	The average highest precipitation amount over a consecutive 5-day period during each month in the data period.	mm	CLIMDEX
Average Surface Air Temperature	tas	Average temperature over the aggregation period	°C	model variable
Average daily Maximum Surface Air Temperature	tasmax	Average daily maximum temperature over the aggregation period	°C	model variable
Average daily Minimum Surface Air Temperature	tasmin	Average daily minimum temperature over the aggregation period	°C	model variable
Cooling Degree Days (ref-65°F)	cdd65	The cumulative number of degrees that the daily average temperature over a given period is above a specified threshold (here 65°F), which is a measurement designed to quantify the demand for energy needed to cool a building.	degF	CLIMDEX under CDDcoldn using a threshold with Fahrenheit
Cold Spell Duration Index	csdi	The number of days each year in a sequence of at least six consecutive days during which the value of the daily minimum temperature is less than the 10th percentile of daily minimum temperature calculated for a five-day window centered on each calendar day, using all data for the given calendar day-pentad from the data period for a	days	CLIMDEX

[11] Adams J., 2017: Climate Indices, an open source python library providing reference implementations of commonly used climate indices. Url: https://github.com/monocongo/climate_indices. From : https://www.drought.gov
[12] Vicente-Serrano, S., Begueria, S., and Lopez-Moreno, I. (2010).
A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. Journal of Climate, 23 (7), p. 1696-1718. doi: https://doi.org/10.1175/2009JCLI2909.1

		reference climate (e.g., present-day climate).		
Growing Season Length	gsl	Span in number of days between the days defining the Growing Season Start and Growing Season End (see below) computed across each of the two hemispheres.	days	CLIMDEX
Growing Season Start	gslstart	Annual series with the day of the year (1st Jan to June 30 in Northern Hemisphere, NH, and 1st July to 31st Dec in Southern Hemisphere, SH) that reflects the first span of at least 6 consecutive days with daily mean temperature T >5ºC.	days	CLIMDEX gsl, referring to start day of the growing season
Growing Season End	gslend	Annual series with the day of the year (1st Jan to June 30 in Southern Hemisphere, SH, and 1st July to 31st Dec in Northern Hemisphere, NH) that reflects the first span of at least 6 consecutive days with daily mean temperature T <5ºC.	days	CLIMDEX gsl, referring to end day of the growing season
Heating degree days (ref-65°F)	hdd65	The cumulative number of degrees that the daily average temperature over a given period is below a specified threshold (here 65°F), which is a measurement designed to quantify the demand for energy needed to warm a building.	degF	CLIMDEX under HDDcoldn using a threshold with Fahrenheit
Heat Index Heat Risk Categorization	hicat	Categorization of the occurrence of days above four select thresholds for designated Heat Risk Variable. Heat Index Risk Categorization includes heat index: 35°C, 37°C, 39°C, and 41°C. If at least 0.5 day surpassed the highest threshold, then the highest category is given, reflecting that "at minimum one day of the year experienced the highest heat level". Risk Factor Categorization: 0-4 represents Low - Extreme Risk.	risk category	Direct categorization using four heat index thresholds
Hot Day Heat Risk Categorization	hdcat	Categorization of the occurrence of days above four thresholds for designated Heat Risk Variable. Hot Day Risk Categorization includes daily maximum temperature: 30C, 35°C, 40°C, and 45°C. If at least 0.5 day surpassed the highest threshold, then the highest category is given, reflecting that "at minimum one day of the year experienced the highest heat level". Risk Factor Categorization: 0-4 represents Low - Extreme Risk.	risk category	Direct categorization using four hot-day (tasmax) thresholds

Hot Day and Tropical Nights Heat Risk Categorization	hdtr	Categorization of the occurrence of days above eight thresholds for designated Heat Risk Variable. Hot Day and Tropical Night Risk Categorization includes daily maximum temperature: 30°C, 35°C, 40°C, and 45°C and nighttime minimum temperature: 20°C, 23°C, 26°C, and 29°C. If at least 0.5 day surpass	risk category	Direct categorization by combining four categories of hot day (tasmax) and four hot night (tasmin) categories
Hot Day and Tropical Nights with Humidity Heat Risk Categorization	hdtrhi	Categorization of the occurrence of days above eight thresholds for designated Heat Risk Variable. Hot Day and Tropical Night with Humidity Risk Categorization includes daily maximum temperature: 30°C, 35°C, 40°C, and 45°C; nighttime minimum temperature: 20°C, 23°C, 26°C, and 29°C and heat index: 35°C, 37°C, 39°C, and 41°C. If at least 0.5 day surpassed the highest threshold, then the highest category is given, reflecting that "at minimum one day of the year experienced the highest heat level". Risk Factor Categorization: 0-4 represents Low - Extreme Risk.	risk category	Direct categorization using four categories of hot day (tasmax), four hot night (tasmin), and four heat index categories
Maximum of Daily Max-Temperature	txx	The single-day maximum value of the daily maximum temperatures over the aggregated data period.	°C	CLIMDEX
Minimum of Daily Min-Temperature	tnn	The single-day minimum value of the daily minimum temperatures over the aggregated data period.	°C	CLIMDEX
Number of Frost Days (Tmin < 0°C)	fd	The average aggregated number of days where the daily minimum temperature is < 0°C (= Frost Days) in the data period. A negative value in anomalies of this indicator indicates a reduction in the number of Frost Days.	days	CLIMDEX
Maximum Number of Consecutive Dry Days_Max	cdd	Maximum number of consecutive days over the period with precipitation < 1mm	days	CLIMDEX
Maximum Number of Consecutive Wet Days_Max	cwd	Maximum number of consecutive days over the period with precipitation >= 1mm	days	CLIMDEX
Number of Consecutive Dry Days_Mean	cdd	Monthly, Seasonal or Annual maximum of the maximum number of consecutive days with precipitation < 1mm	days	CLIMDEX
Number of Consecutive Wet Days Mean	cwd	Monthly, Seasonal or Annual mean of the maximum number of consecutive days with precipitation > 1mm	days	CLIMDEX

Heat Index	hi	Heat Index as defined by US-National Weather Service	°C	Steadman, R.G (1979)[13]
Number of Days with Heat Index >= 35°C	hi35	The number of days where the Heat Index >= 35°C over the aggregation period. The Heat Index is a measure of apparent temperature that includes the influence of atmospheric moisture. High temperatures with high moisture lead to high Heat Index.	days	CCKP: days over hi with threshold
Number of Days with Heat Index >= 37°C	hi37	The number of days where the Heat Index >= 37°C over the aggregation period. The Heat Index is a measure of apparent temperature that includes the influence of atmospheric moisture. High temperatures with high moisture lead to high Heat Index.	days	CCKP: days over hi with threshold
Number of Days with Heat Index >= 39°C	hi39	The number of days where the Heat Index >= 39°C over the aggregation period. The Heat Index is a measure of apparent temperature that includes the influence of atmospheric moisture. High temperatures with high moisture lead to high Heat Index.	days	CCKP: days over hi with threshold
Number of Days with Heat Index >= 41°C	hi41	The number of days where the Heat Index >= 41°C over the aggregation period. The Heat Index is a measure of apparent temperature that includes the influence of atmospheric moisture. High temperatures with high moisture lead to high Heat Index.	days	CCKP: days over hi with threshold
Number of Hot Days (Tmax >= 30°C)	hd30	The number of days with daily maximum temperature >= 30°C that occurred during the aggregation period.	days	CCKP: days over tasmax with threshold
Number of Hot Days (Tmax >= 35°C)	hd35	The number of days with daily maximum temperature >= 35°C that occurred during the aggregation period.	days	CCKP: days over tasmax with threshold
Number of Hot Days (Tmax >= 40°C)	hd40	The number of days with daily maximum temperature >= 40°C that occurred during the aggregation period.	days	CCKP: days over tasmax with threshold
Number of Hot Days (Tmax >= 42°C)	hd42	The number of days with daily maximum temperature >= 42°C that occurred during the aggregation period.	days	CCKP: days over tasmax with threshold
Number of Hot Days (Tmax >= 45°C)	hd45	The number of days with daily maximum temperature >= 45°C that occurred during the aggregation period.	days	CCKP: days over tasmax with threshold
Number of Hot Days (Tmax >= 50°C)	hd50	The number of days with daily maximum temperature >= 50°C that occurred during the aggregation period.	days	CCKP: days over tasmax with threshold
Number of Ice Days (Tmax < 0°C)	id	This variable represents the average aggregated number of days where the	days	CLIMDEX

[13] Steadman R.G., 1979: The assessment of sultriness, Part I: A temperature-humidity index based on human physiology and clothing science. J. Appl. Meteorol., 18, 861-873, doi: http://dx.doi.org/10.1175/1520-0450

		daily maximum temperature is < 0°C in the data period.		
Number of Days with Precipitation >= 20mm	r20mm	The number of heavy precipitation days during the aggregation period. A heavy precipitation day is defined as any day in which the daily accumulated precipitation is ≥= 20 mm.	days	CLIMDEX
Number of Days with Precipitation >= 50mm	r50mm	The number of very heavy precipitation days during the aggregation period. A very heavy precipitation day for r50mm is defined as any day in which the daily accumulated precipitation is ≥= 50 mm.	days	CLIMDEX
Number of Summer Days (Tmax >= 25°C)	sd	The number of days where the daily maximum temperature is >= 25°C in the aggregation period. A positive value indicates an increase in the number of Summer Days.	days	CLIMDEX
Number of Tropical Nights (T-min >= 20°C)	tr	The number of days where the daily minimum temperature remained >= 20°C over the aggregation period.	days	CLIMDEX
Number of Tropical Nights (T-min >= 23°C)	tr23	The number of days where the daily minimum temperature remained >= 23°C over the aggregation period.	days	CCKP: days over tasmin with threshold
Number of Tropical Nights (T-min >= 26°C)	tr26	The number of days where the daily minimum temperature remained >= 26°C over the aggregation period.	days	CCKP: days over tasmin with threshold
Number of Tropical Nights (T-min >= 29°C)	tr29	The number of days where the daily minimum temperature remained >= 29°C over the aggregation period.	days	CCKP: days over tasmin with threshold
Number of Tropical Nights (T-min >=32°C)	tr32	The number of days where the daily minimum temperature remained >= 32°C over the aggregation period.	days	CCKP: days over tasmin with threshold
Percentage of Population below $1.90/day	pov190	Poverty as a percent of population below a given poverty classification: $1.90/day, as per World Bank definitions.	% of population	Worldbank data integrating GDP, Population, Ginis; See Rao et al (2018)[14]
Percentage of Population below $3.20/day	pov320	Poverty as a percent of population below a given poverty classification: $3.20/day, as per World Bank definitions.	% of population	Worldbank data integrating GDP, Population, Ginis; See Rao et al (2018)
Percentage of Population below $5.50/day	pov550	Poverty as a percent of population below a given poverty classification: $5.50/day, as per World Bank definitions.	% of population	Worldbank data integrating GDP, Population, Ginis; See Rao et al (2018)
Population Count	popcount	Population Count	population	Source: Global Population of the World, v.4[15]
Population Density	popdensit y	Population Density	population_ density	Calculated from: Global Population of the World, v.4

[14] Rao N.D., et all. Income inequality projections for the Shared Socioeconomic Pathways. Futures, doi: 10.1016/j.futures.2018.07.001

[15] Jones B. and B.C. O'Neill, 2016: Spatially Explicit Global Population Scenarios Consistent with the Shared Socioeconomic Pathways. Env. Res. Lett., 11, 084003, doi: 10.1088/1748-9326/11/8/084003

Precipitation	pr	Aggregated accumulated precipitation.	mm	model variable
Precipitation Percent Change	prpercnt	Projected percent change in total precipitation; anomaly only.	%	percent of pr in historical reference period
Precipitation Amount during Wettest Days	r95ptot	This series measures the accumulated precipitation amount during the 5% wettest days over the data period.	mm	CLIMDEX
Relative Humidity	hurs	Based on daily mean relative humidity at 2m as reported by climate models, or derived from specific humidity reported by climate models.	percent	model variable
Temperture-based Excess Mortality Risk	tx84rr	Excess mortality risk factor for daily maximum temperatures > 84th percentile of maximum temperatures in reference period.	factor	Honda et al. 2014[16]
Temperature-Based Heat + Population Risk Categorization	hdtrpopdensitycat	Temperature-Based Heat + Population Risk Categorization is calculated to account for both climate conditions and high population densities. Categorization was established relative to the highest threshold: daily maximum temperature: 30°C, 35°C, 40°C, and 45°C and nighttime minimum temperature: 20°C, 23°C, 26°C, and 29°C, leading to categories 0, 1, 2, 3, 4. If at least 0.5 days surpassed the highest threshold, then the highest categorization is given. Areas with extreme heat but no population are considered less 'risky' for a country, than areas with only high to very high heat conditions but with high population density.	risk factor	CCKP: Direct categorization using two different heat categories (hdcat and trcat) and intersected with population density category
Temperature and Humidity-Based Heat + Population Risk Categorization	hdtrhipopdensitycat	Temperature and Humidity-Based Heat + Population Risk Categorization is calculated to account for both climate conditions and high population densities. Categorization was established relative to the highest threshold: daily maximum temperature: 30°C, 35°C, 40°C, and 45°C; nighttime minimum temperature: 20°C, 23°C, 26°C, and 29°C, and heat index: 35°C, 37°C, 39°C, and 41°C, leading to categories 0, 1, 2, 3, 4. If at least 0.5 days surpassed the highest threshold, then the highest categorization is given. Areas with extreme heat but no population are considered less 'risky' for a country, than areas with only high to very high	risk factor	CCKP: Direct categorization using three different heat categories (hdcat, trcat, and hicat) and intersected with population density category

[16] Honda Y, Kondo M, McGregor G, Kim H, Guo YL, Hijioka Y, Yoshikawa M, Oka K, Takano S, Hales S, Kovats RS. Heat-related mortality risk model for climate change impact projection. Environ Health Prev Med. 2014 Jan;19(1):56-63. doi: 10.1007/s12199-013-0354-6. Epub 2013 Aug 9. PMID: 23928946; PMCID: PMC3890078.

		heat conditions but with high population density.		
Tropical Night Heat Risk Categorization	trcat	Categorization of the occurrence of days above four thresholds for designated Heat Risk Variable. Tropical Night Risk Categorization includes nighttime minimum temperature: 20°C, 23°C, 26°C, and 29°C. If at least 0.5 day surpassed the highest threshold, then the highest category is given, reflecting that "at minimum one day of the year experienced the highest heat level". Risk Factor Categorization: 0-4 represents Low - Extreme Risk.	risk factor	Direct categorization using four minimum temperature thresholds
Warm Spell Duration Index	wsdi	The number of days in a sequence of at least six consecutive days during which the value of the daily maximum temperature is greater than the 90th percentile of daily maximum temperature calculated for a five-day window centered on each calendar day, using all data for the given calendar day-pentad from the data period for a reference climate		CLIMDEX
Wet Bulb temperature	wbt	Temperature measured if a thermometer is covered by a wet cloth		Wet Bulb Temperature formulation by Stull (2011)[17]
Wet Bulb Temperature > 25°C	wbt25	The number of days where the daily wet bulb temperature >= 25°C over the aggregation period.		CCKP: days over wbt with threshold
Wet Bulb Temperature > 27°C	wbt27	The number of days where the daily wet bulb temperature >= 27°C over the aggregation period.		CCKP: days over wbt with threshold
Wet Bulb Temperature > 29°C	wbt29	The number of days where the daily wet bulb temperature >= 29°C over the aggregation period.		CCKP: days over wbt with threshold
Wet Bulb Temperature > 31°C	wbt31	The number of days where the daily wet bulb temperature >= 31°C over the aggregation period.		CCKP: days over wbt with threshold

[17] Stull R., 2011: Wet-bulb temperature from relative humidity and air temperature. J. Appl. Meteorol. Climatol., 50(11), 2267-2269, doi: 10.1175/JAMC-D-11-0143-1

DATA PROCESSING STEPS AND EVALUATION PROTOCOL

Essential Climate Variables

CMIP6 model simulations were processed individually to establish a common dataset for which both absolute climatologies for the present and future 20-year intervals (2020-2039, 2040-2059, 2060-2079, and 2080-2099), as well as their relative changes (anomalies) in comparison to their common reference period of 1995-2014, could be computed. While the base-data were obtained as daily mean/sum and converted into monthly time series, the climatology products were to represent 20-year. Because of internal climate variability, the 20-year intervals at the grid level (or at aggregation levels of relatively small domains) become more useful when looking at the progressive changes throughout the 21st century with its continuously shifting climate. Each 20-year time window can therefore be compared to the standard "present day" reference period of 1995-2014 (CMIP6). The resulting anomalies also correspond to results presented in the IPCC[18,19]. All models used in the calculations were chosen to offer exactly the same suite of experiments and represented time periods. The only exception was humidity, as a few models failed to provide these daily fields. Equally, several models did not perform simulations for all of the SSPs.

Derived Indicators

Sector-oriented climate indicators often build on daily rather than monthly data. A collection of daily model output was processed for calculation of the climate indicators (see **Table 2**). Depending on the indicator, monthly, seasonal, and/or annual products were generated for the SSPs and time intervals. For example, some GCM and/or IAM groups did not store or report humidity, pressure, or wind fields on a daily basis, and thus not all indicators could be computed for all models. Therefore, for some indicators there are different numbers of models that contributed to the various ensembles. *This can introduce some inconsistencies when comparing different scenarios, though the direction and even the relative magnitude of the changes should still be useful.*

The following steps describe how each of the models (listed in **Table 1**) were processed:

a. Bias-correction and Spatial Desegregation (BCSD) to 0.25 x 0.25-degrees: Initially, because all original model output is offered on the Earth System Grid on their own native low-resolution grids, the multi-model collection was bias corrected and downscaled to a chosen 0.25 x 0.25-degree resolution. The process is described in Thrasher et al. (2012). All analyses and data products within the CCKP distributions exclusively utilize these downscaled and bias-corrected data as input.

b. Climatologies: For each model, and for each of the climate variables and indicators, 20-year climatologies were formed. For CMIP6, the 'baseline' interval (1995-2014) was derived from the *historical* simulations ("*historical*"), while the future climatologies (2020-2039, 2040-2059, 2060-2079, 2080-2099) were computed for all five SSPs ("SSP1-

[18] Stocker, T. et al, (2013). Climate Change 2013 – The Physical Science Basis. Working Group I Contribution to the Fifth Assessment Report of the IPCC. URL: https://www.ipcc.ch/site/assets/uploads/2017/09/WG1AR5_Frontmatter_FINAL.pdf

[19] IPCC, 2021: Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Masson-Delmotte, V., P. et al. Cambridge University Press. In Press. URL: https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_Full_Report.pdf

1.9", "SSP1-2.6", "SSP2-4.5", "SSP3-7.0", "SSP5-8.5", see comments above). These climatologies consist of twelve-monthly average values, four seasonal average values, and one annual mean value established over the respective time windows (sums for precipitation).

c. Anomalies: For each model, each variable, and each of the four future time windows, anomalies for each month as well as the seasonal and annual values were computed relative to their corresponding *historical* reference period. In contrast to the climatologies, these values are well suited for model-to-model intercomparisons as they always refer to the change simulated by each model.

d. Ensemble Information: Ensemble values were calculated from the anomalies from each of the models in the collection, and for every 20-year climatological period in the future. These ensembles describe how the collection of up to 30 CMIP6 models, on average, project climatological changes. Different ways of exploring the ensemble distribution are possible. Here, the median across the individual model values was used as the main representation. Next to that central value of the ensemble, ensemble high (90th percentile) and low (10th percentile) values for all the climatological anomalies were generated to help users recognize the range of likely outcomes driven by the different sources of uncertainty. Values are available for each model separately, and thus the user could explore the distribution in more detail. Because each model has slightly different climate sensitivity and simulated different internal climate variability, the projections increasingly diverge into the future. Therefore, the ensemble spread generally increases with time. Note, each individual model's anomalies can be compared with the provided ensemble description that encompasses the range between high (90th percentile) and low (10th percentile) levels of the underlying distribution.
(**Note**: the number of available models may vary for different climate indicators.)

e. Quality Control: Due to the large data volume, not every field of every model could be inspected visually. Rather, the CCKP Team implemented an automated final quality control algorithm on the publication-ready data to identify odd outliers in both absolute and anomaly fields. Suspicious values and potentially suspicious model simulations were flagged and ultimately a few individual models or specific products were excluded from the results. Once implemented into the CCKP, thorough visual inspection was performed to identify any remaining issues. Reported data issues are addressed quickly.

EXTREME PRECIPITATION EVENTS

Extreme events are often responsible for some of the largest impacts. Despite limitations using relatively coarse resolution climate models, general tendencies can be identified in the climate model simulations and their projections of climate change. In fact, sometimes the change in the extremes might be more significant against the background noise than the change in the means. The calculation of extremes uses analyses of block maxima of either monthly or annual maximum values covering a period of at least 30 years (longer is better to increase sample size). A Generalized Extreme Value distribution (GEV) is then fit to the data using a scalable python code drawing from the scipy.stats library. Based on the returned parameters of location, scale and shape, *return levels* for a given suite of *return periods* are computed.

For the case of precipitation, the process is more difficult because it describes a discontinuous field. We apply the methodology described in Naveau et al. (2016)[20] in which precipitation time series are automatically split into different parts and extreme value theory is only applied to the tail. An automated procedure to determine the different sections of the distribution is highly advantageous in large, gridded datasets where individual time series cannot be inspected. An implementation of the code by Naveau et al. is available as the *fit.extgp* function as part of the *mev* R package (https://cran.r-project.org/web/packages/ mev/mev.pdf).

CCKP DATA VISUALIZATIONS

Geospatial Presentation (Maps)

Maps show the geospatial expression of different climate fields. Globally, temperature change varies primarily by latitude and elevation, but proximity to oceans also moderate this. Due to the absence of sunlight in winters, seasonality is particularly high in polar regions, and also increases in the interiors of continents. In the tropics, seasonality is minimized and often more easily recognizable through precipitation (e.g., a rainy season and a dry season). However, the lack of strong seasonal oscillations and often a muted year-to-year variability cause the tropics to be much more sensitive to changes than areas at higher latitudes where ecosystems are used to large intra- and inter-annual variations so that small changes in temperature have often quite small environmental impacts.

While temperatures vary spatially only gradually (or due to topography), precipitation is often highly variable. This is often caused by the fact that precipitation is not a “continuous” field but represents intermittent processes with rainfall only occurring occasionally (with a few exceptions). Daily cycles as well as seasonal shifts of zones where precipitation occurs more systematically often lead to complex and often, quite strongly varying fields over a range of time scales. The only locations where precipitation is more regular is in the inner tropics as well as on the windward side of mountain ranges where orographic lift leads to condensation and precipitation. Therefore, maps of precipitation are often much less smooth than temperature or other fields, even when looking at climatologies that average precipitation over 20 or 30 years.

These general differences between temperature- and moisture-related fields can also be observed at the level of climate indicators. However, more generally, information from individual grid-cells should always be looked at in context of their broader spatial fields. This is partially due to the spatial variations described above. Spatial variability (or “noise”), particularly when looking at model-based climate projections, arises also in gridded data when small scale processes are averaged over the full grid cell. As models represent the underlying surface slightly differently, they will not reproduce the same details of the climate processes. Particularly in the moisture fields, namely precipitation, this will lead to model-to-model differences, further affecting the spatial coherence. Therefore, maps in the CCKP offer the user the broader context of a climate field to allow for a better interpretation of the robustness of a grid-based measure of the climatology or of

[20] Naveau, P., Huser, R., Ribereau, P Pierre, and Hannart, A. Modeling jointly low, moderate, and heavy rainfall intensities without a threshold selection. *Water Resources Research*, 2016, 52 (4), pp.2753-2769. ⟨10.1002/2015WR018552⟩. ⟨hal-02078026⟩

a signal of change. Geospatial presentations, maps, use a Web Mapping Service (WMS) to visualize data and indicators on a map service, as shown in **Figure 1.**

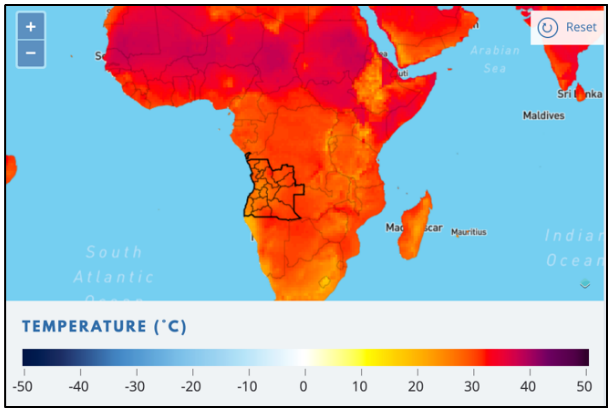

Figure 1. *Observed, maximum temperature of Angola for the latest climatology, 1991-2020)*

Observed data for the latest climatology, 1991-2020, are presented using the Köppen-Geiger Climate Classifications to support broader conceptualization of current climate contexts for a specific area (**Figure 2**). The underlying dataset for this presentation is CRU, and calculations follow identified Köppen-Geiger classification methodology. Data are presented at 0.5 x 0.5-degree spatial resolution. For more information on Köppen-Geiger Climate Classifications, see here.

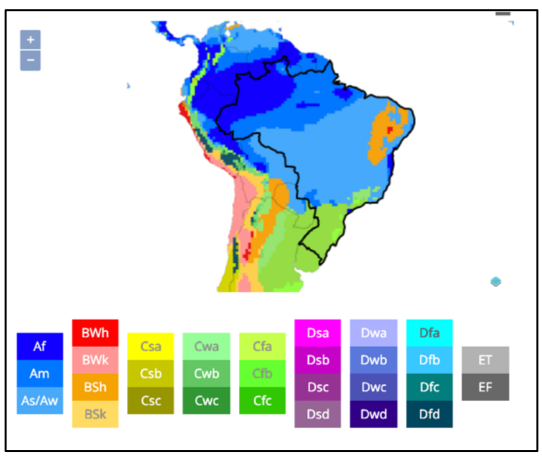

Figure 2. *Köppen-Geiger Climate Classifications of Brazil for the latest climatology, 1991-2020*

Seasonal Cycle

The seasonal cycle enables precipitation and temperature data to be charted to illustrate seasonality for a defined climatology. **Figure 3a** shows the seasonal cycle for the latest climatology, 1991-2020, presenting observational data for mean, min, and max temperatures, and precipitation. **Figure 3b** shows the projected maximum temperature anomaly across the seasonal cycle. This can be compared to the projected mean, which is presented in relation to the Historical Reference Period (**Figure 3c**). The shading area represents the range of model outputs, with the 10th and 90th percentiles and median (solid blue line).

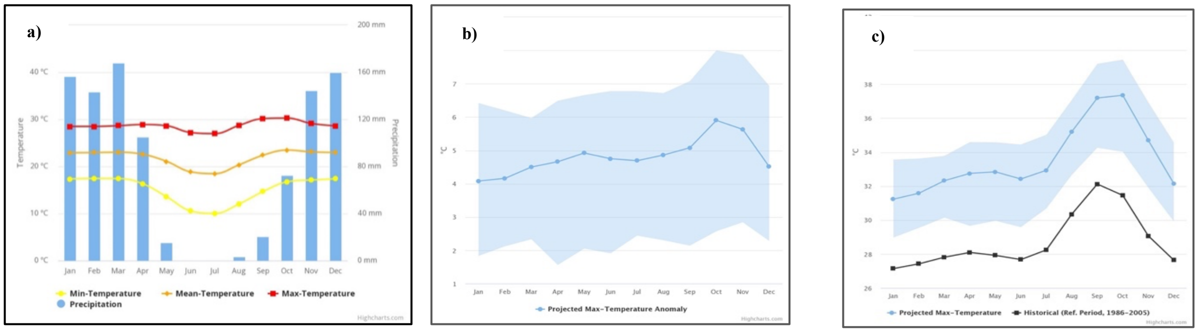

Figure 3. *Seasonal cycle showing (a) the current climatology for observed data; (b) projected anomaly; (c) projected mean in relation to the historical reference period*

Time Series

Time series provide insight into longer-term trends. **Figure 4a** shows the historical time series of the observed annual average temperatures, 1901 to 2020, with a smoothed trendline. **Figure 4b** shows the projected climatological average of mean temperature for each SSP, including the range.

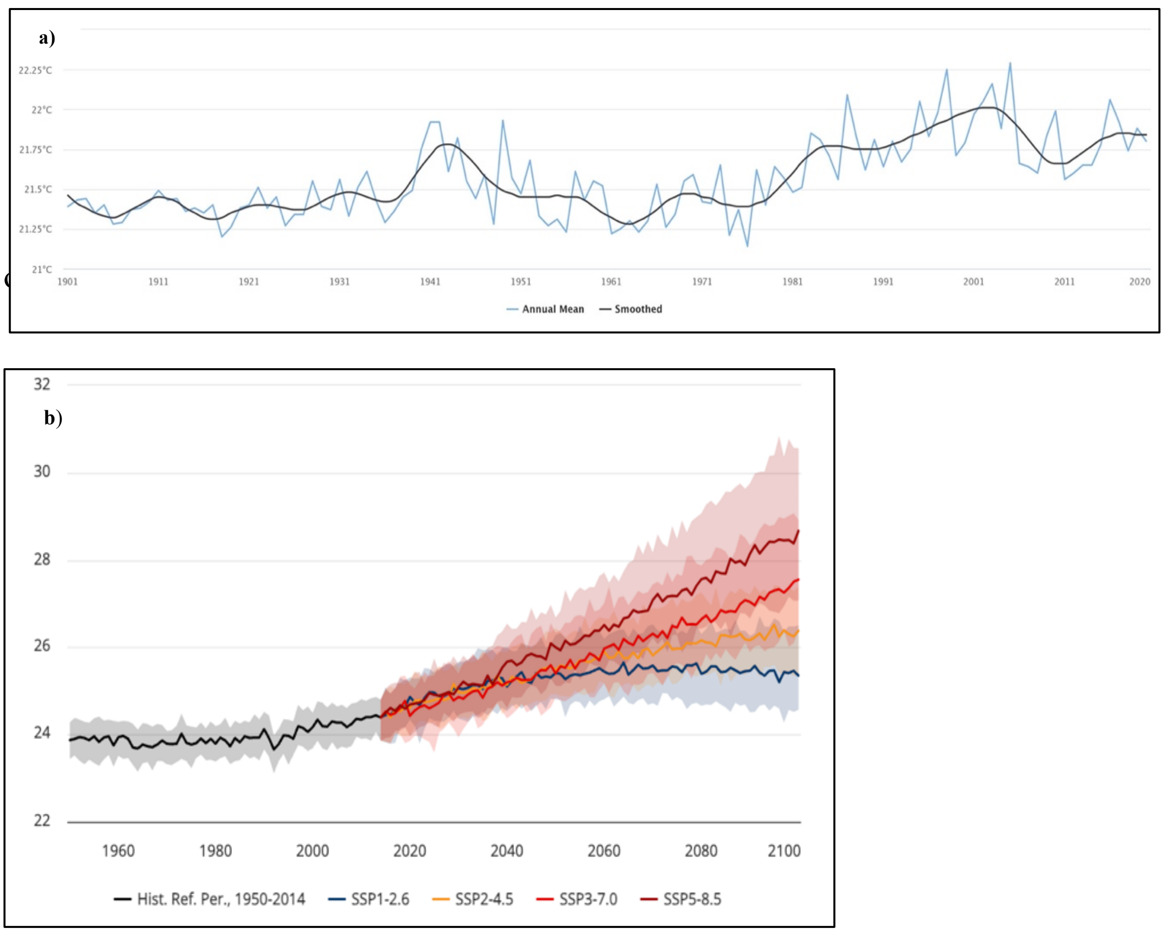

Figure 4. *Time series representing observed data (a); projected data across each SSP (b)*

Heatplot
Heatplots show seasonal anomalies across longer-term time horizons. CCKP heatplots are created using CMIP6 projection data, with historical simulations from 1951 and projections through the end of the century. Monthly data are averaged across each ten-year period from 1951 to 2100. **Figure 5** shows the emerging seasonal anomalies of Tropical Nights for September to April increasing in magnitude from the 2050s.

Figure 5. *Heatplot presenting changes in occurrence of Tropical Night (Tmin>20C)*

Distributions
These distribution graphs reflect the projected shifts in the selected variable, including their variability across different climatology periods. Users can identify shifts in changing temperature or precipitation dynamics by understanding the ranges in the temperature or precipitation outcomes.

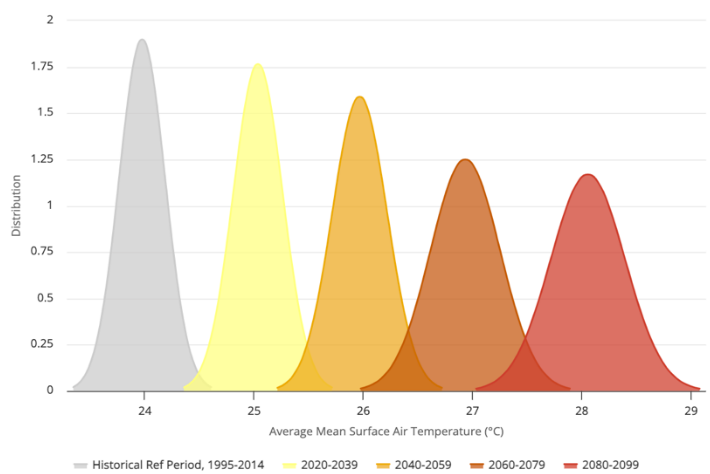

Figure 6. *Distributions presenting Average Mean Surface Air Temperature for different climatology periods, SSP5-8.5*

Bubble Chart
A bubble chart is used to illustrate the much more variable occurrence of short-term weather events (daily scale). A potential climate change signal is often more difficult to recognize in these noisy series. For some variables, a tendency can either be seen through changes in magnitude of events

and/or through changes in frequency of significant events (see temperatures). For other variables, a clear trend might not always be visible. Here, each bubble represents climate extremes in the form of standard deviations (SD) away from the monthly mean determined over the Historical Reference Period, 1995-2014.

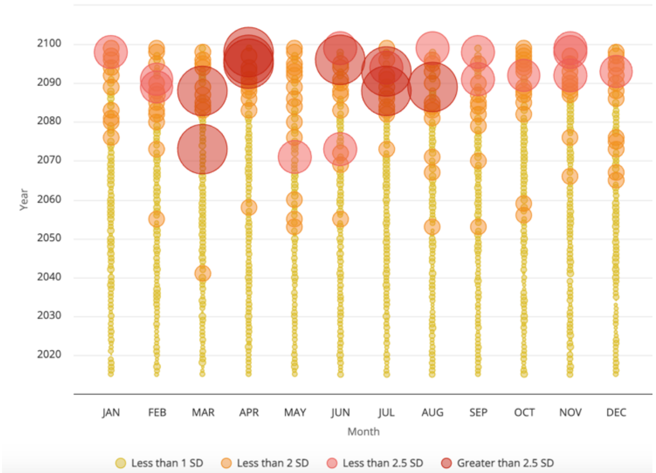

Figure 7. *Bubble Chart presenting the changing event intensities of the maximum of daily maximum temperatures for selected model, SSP5-8.5*

Natural Variability

Variability is an inherent, natural property of climate. Any trend or change needs to be evaluated against this natural background to have meaning. Analyzing the change of evolving climate against the range of natural variability provides a way to identify a time when the series, driven by its underlying trend, departs from historical natural variability, the year of significant change. A period dominated by natural variability (low trend vis-à-vis relatively larger natural variability) can be seen in contrast to a case when a sufficiently large (anthropogenically) forced trend causes the series to depart from the range of variability: emergence of change. Using longer-term time series is useful to identify the changing dynamics of a variable or indicator selected. Climate change can be recognized when there is a statistically significant departure from natural variability bounds after a particular point in time (year of significant change).

In CCKP, each SSP shows the individual models used in the multi-model ensemble, with the dark line indicating the median of the multi-model ensemble. Some variables and regions of the world realize a strong departure from historical natural variability (1995-2014), while some never realize significant departure. For scenarios of strongly reduced emissions, i.e., SSP1-1.9 or SSP1-2.6, some series emerge from variability (indicating change) but can in a few cases dip back into the pre-2015 range of natural variability.

The key for calculating significance of change is that natural variability is determined relative to an evolving climate. When looking at an individual model, CCKP is applying the formulation adopted in the sixth Assessment Report of IPCC (Masson-Delmotte et al, 2021; see Cross-Chapter Box Atlas 1, p. 1945-1948). A detrended annual series (or for each month or season separately) is used to determine the standard deviation, which is then scaled by sqrt(2/20) * 1.645 to get a climatologically (20-yr average oriented) meaningful natural variability threshold.

For ensembles, which are represented by the multi-model median as well as the 10th and 90th percentile across the different model outcomes, the determination is more difficult because the natural variability is essentially removed by building a ~30-model ensemble. CCKP uses a relatively conservative format of the 90th percentile of the natural variability from the multi-model collection as the upper bound and the 10th percentile of the natural variability as the lower bound. This guards against the fact that in the historical period the natural variability is a combination of internal variability and naturally forced deviations, in particular those induced by volcanic eruptions. Compared to the purely internal variability, the historical period experienced an enhanced fluctuation.

The year-of-change is defined as the first year when the 20-yr smoothed time series that represents the evolving climate surpasses (or drops below) the upper (or lower) threshold and stays beyond the natural variability. Transient changes are possible and do occur for low emission SSPs and some regions.

POPULATION AND POVERTY DATA

DATA SOURCE: POPULATION

Population source data:
Historical Reference Period (1995-2014) is derived from:
Center for International Earth Science Information Network - CIESIN - Columbia University. 2018. Gridded Population of the World, Version 4 (GPWv4): Population Density, Revision 11. Palisades, New York: NASA Socioeconomic Data and Applications Center (SEDAC). https://sedac.ciesin.columbia.edu/data/collection/gpw-v4

Projection data is derived from:
Jones, B., and B. C. O'Neill. 2020. Global One-Eighth Degree Population Base Year and Projection Grids Based on the Shared Socioeconomic Pathways, Revision 01. Palisades, New York: NASA Socioeconomic Data and Applications Center (SEDAC). https://doi.org/10.7927/m30p-j498. as an advancement from: Jones, B., and B. C. O'Neill. 2016. Spatially Explicit Global Population Scenarios Consistent with the Shared Socioeconomic Pathways. Environmental Research Letters, 11 (2016): 084003. https://doi.org/10.1088/1748-9326/11/8/084003

CCKP Data Reference: Climate Change Knowledge Portal: Projected Population And Poverty, 0.25-Degree DOI: https://doi.org/10.57966/7r80-cc19

Population data as gridded product or at sub-national level are represented as either population count or population density (persons/km2) for "present" (~2010-2015) and as projected in the SSPs for selected time intervals. Note, the population density is calculated based on the grid size and grid contribution to a sub-national polygon. These calculations might suffer from lack of precision for small spatial entities (particularly small islands).

Thresholds per grid-cell or aggregation area were set by population count or density (count: 1'000, 10'000, 100'000, 1'000'000; density: 1, 10, 100, 1'000).

Age Pyramid source data: Samir, K. C., & Lutz, W. (2014). The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. Global Environmental Change, 378. https://doi.org/10.1016/j.gloenvcha.2014.06.004 issn:09593780

Age- and sex- specific proportions are taken from the IIASA database of human capital reconstruction and projections. The method used for carrying out projections by age, sex, and educational attainment level is a generalization of the standard cohort-component method of population projections. This standard method is based on the fact that the age group a in year t will be a+x in year t+x (it is the same birth cohort, i.e., group of people born in the same year) after adjusting for the effects of mortality and migration and applying fertility rates to derive the number of births (the three components of population change).

DATA SOURCE: POVERTY

Poverty source data: World Bank Data Catalog: International Poverty Line - Global Subnational Poverty Atlas GSPA https://datacatalog.worldbank.org/search/dataset/0042041

Poverty is represented as a percent of population below a given poverty classification: $1.90, $3.20, $5.50/day, as per World Bank definitions.

NATURAL HAZARDS

DATA SOURCE: EM-DAT

Source data: https://www.emdat.be/

Credits: EM-DAT: The OFDA/CRED International Disaster Database – www.emdat.be – Université Catholique de Louvain – Brussels – Belgium.

Description: EM-DAT contains essential core data on the occurrence and effects of over 18,000 mass disasters in the world from 1900 to present. The database is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies.

Variables presented: Top Disasters; Number Killed; Number of Affected; Average Annual Disaster Occurrence by Type.