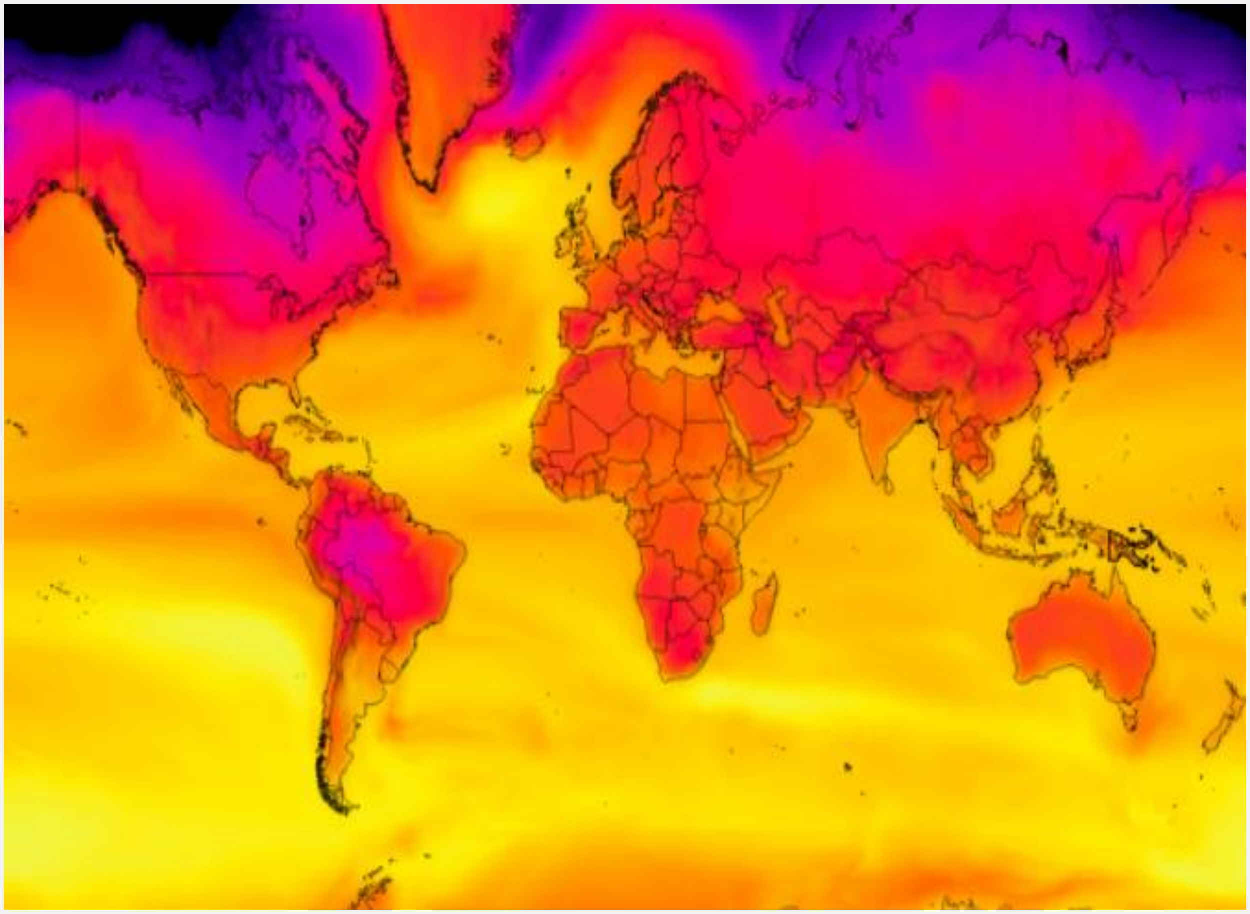
METADATA

CLIMATE CHANGE KNOWLEDGE PORTAL (CCKP)



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

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OBSERVED CLIMATE DATA

DATA SOURCE: CRU TS V.4.08

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 TS4.08 0.5-Degree, DOI: https://doi.org/10.57966/tw2k-9h36

Description: 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 4.08 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 (annually) to reflect data corrections and improvements as well as extensions of the record towards the present.

Summary of data available at CCKP:
Presented at monthly, seasonal, and annual scale
Time period: 1901-2023
Spatial resolution: 0.5º x 0.5º
Historical Climatologies: 1901-1930, 1931-1960, 1961-1990, 1985-2014, 1986-2005, 1991-2020, 1995-2014

Recommended Use: CRU data is suitable for historical averaged climate and trend analysis. However, users should be aware that data quality varies over time, and areas with limited station coverage, especially from the early 20th century, will default to climatology values. CCKP uses CRU data to derive data presentations shown on the Current Climatology Tab

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

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

global climate. Copernicus Climate Change Service (C3S) Data Store (CDS).
DOI: [10.24381/cds.143582cf](https://doi.org/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

Description: 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. Data are updated annually.

Summary of data available at CCKP:
Presented at monthly, seasonal, and annual scale
Time period: 1950-2023
Spatial resolution: 0.25º x 0.25º
Historical Climatologies (20-year or 30-year periods used for climatologies and natural variability): 1986-2005, 1991-2020, 1995-2014
Decadal trends calculated for: 1951-2020, 1971-2020, 1991-2020

Recommended Use: ERA5 is considered one of the top reanalysis products. It provides consistent coverage of all variables found in climate models, making it a valuable reference. In areas with good station coverage, ERA5 closely aligns with CRU data, while in regions lacking stations, it offers reliable estimates and minimizes false trends from short satellite records. Temperature data from ERA5 is highly reliable, but for precipitation, it’s recommended to use multiple datasets due to the challenges in accurately measuring and modeling it.

PROJECTED CLIMATE DATA

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

Description: Modeled climate projections available on CCKP are derived from the multi-model collection of CMIP6 (the Coupled Model Intercomparison Project, Phase 6)[2], the most advanced global climate data projections available. CMIP6 is coordinated by the international modeling community using coupled climate and Earth system models, under the leadership of the World Climate Research Program. The CCKP-CMIP6 dataset includes the historical simulation and four future scenarios (**Table 1**) for up to 30 models (**Table 2**). Original CMIP6 outputs are provided on the Earth System Grid in their native low-resolution grids (~1° resolution). To enhance usability, CCKP re-gridded the models to a unified 1°x1° grid, and then bias-corrected and downscaled the collection to a 0.25°x0.25° resolution. See below for an extended description.

Summary of data available at CCKP:
Presented at monthly, seasonal, and annual scale and for daily thresholds
Data investigation by multi-model ensemble or individual model.
Time period: 1950-2100 (historical scenario - 1950-2014, future scenarios - 2015-2100)
Historical Reference Period: 1995-2014
Future projected Scenarios: SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5
Projected Climatologies: 2020-2039, 2040-2059, 2060-2079, 2080-2099
Multi-Model Ensemble range: 50th (median), 10th, 90th percentiles
Spatial resolution: 0.25° x 0.25° (1° x 1° for extreme precipitation events variables)
Decadal trends calculated for: 1971-2020, 2001-2050, 2051-2100

Recommended Use: To investigate future changes due to global warming.

Downscaling and bias-correction:
CCKP re-gridded each model output to a common 1x1-degree grid, which was then bias-corrected and downscaled the multi-model collection to a common 0.25 x 0.25-degree resolution, as described in Thrasher et al. (2012)[3]. Global climate models often have biases when compared to observed climate data due to various limitations (e.g., spatial resolution, parameterizations). These biases can be particularly pronounced in the tails of the distributions, which represent the extremes. Thrasher et al. (2012) uses quantile mapping for bias correction, which involves transforming the simulated data so that its statistical distribution matches the observed data. To achieve this higher resolution, daily output from individual models was processed using a quantile-based bias correction and spatial disaggregation (BCSD) over a historical reference period (1961-2014). Note that this new product was mostly enabled by further improved reanalysis products that served as reference. It is important to note, hence, 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. Note, the temperature trends of the original model simulations are

[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] 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

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. All analyses and data products within the CMIP6 distributions of CCKP exclusively utilize these downscaled and bias-corrected data as input.

Historical simulations

Historical simulations, driven by observed radiative forcings, were 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)[4] use a compromise of **20-year intervals** to better reflect the speed of the changing climate. In AR5, the historical reference period was 1986–2005, with scenarios diverging in 2006. For AR6 and CMIP6, the historical reference period is 1995–2014, after which the SSP scenarios begin. CCKP also applies a consistent 20-year climatological window for future projections: 2020–2039, 2040–2059, 2060–2079, and 2080–2099.

Future projections - Shared socioeconomic pathways SSPs:

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 "ScenarioMIP" 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 to offer a continuous perspective from the past, through the present, and into the future to study possible magnitudes and characteristics of climate change.

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 and land use scenarios produced with a collection of integrated assessment models (IAMs) based on new future pathways of societal development, the SSPs. To preserve some important consistency, the selected emission levels in the new SSPs retain important relations with the RCPs[5]. 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

[4] 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.

[5] 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.

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[6]), 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[7]. 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 (**Table 1**).

Table 1. *List of future scenarios used in CCKP CMIP6-x0.25 compilation[8]*

Scenario Name	Description
SSP1-1.9	**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	**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	**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	**SSP3-7.0** represents a polarized world in which regional conflicts endure and emissions continue to climb, roughly doubling from current levels by 2100.
SSP5-8.5	**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.

Scenario SSP1-1.9:
Because only a few climate modeling centers 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 mean temperature differences were established in the CMIP6

[6] 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

[7] 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.

[8] 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.

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 models:

The CCKP-CMIP6 collection consists of up to 30 models (**Table 2**) that submitted data across the SSPs. All data were processed using an updated version of the Climate Risk Management engine (CRMe) infrastructure[9] and formatted using ArcGIS and functions offered through the Open Geospatial Consortium (http://www.opengeospatial.org/). **Caveats:** Note that several models did not perform simulations for all of the SSPs. The number of available models may vary for different climate indicators. 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, a different numbers of models 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 considered useful.

Table 2. 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

[9] 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

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.

Multi-model variability in comparison to natural variability for CMIP6 models:
The CMIP6 models offer a range of methods to explore multi-model variability. The median value across individual model projections is used as the primary representation of the ensemble, with additional metrics at the 90th (high) and 10th (low) percentiles to illustrate the range of possible outcomes. These values highlight the uncertainty caused by different climate sensitivities and internal climate variability across models. The spread of the ensemble tends to increase over time as the projections diverge, reflecting these uncertainties. Users can examine each model separately to explore the full distribution of outcomes, comparing individual anomalies with the ensemble range. To distinguish multi-model variability from natural variability, users can calculate the multi-model average and standard deviation for a specific variable, region, and time period (at least 20 years). This allows for an assessment of the range of variability across models. Additionally, calculating the standard deviation within each model (using a detrended time series) helps estimate natural interannual variability. Comparing the model variability with natural variability provides insight into how much of the variation is due to model differences versus inherent climate fluctuations. Alternatively, users can visualize the "natvar" variable, representing standard deviation during the historical period, and compare it to the multi-model ensemble percentiles (p10, median, p90) for a clearer understanding of both inter-model and natural variability.

Data use:
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.

DATA PROCESSING STEPS

WORKFLOW FOR CRU

a. Download latest CRU-TS version: select full timeseries of gridded data at 0.5-degrees resolution for all available variables.
b. Processing of monthly temperature variables and precipitation into monthly and annual timeseries.
c. Spatially aggregate timeseries to ADM0, ADM1, and RiverBasins.
d. Compute annual average (temperatures) and annual sum (precipitation) climatologies for same periods.
e. Aggregate climatologies spatially.

WORKFLOW FOR ERA5

a. Download ERA5 daily global.
b. Processing of daily timeseries and form list of variables and derived indicators at monthly or annual resolution.
c. Aggregate timeseries to various spatial products (ADM0, ADM1, and RiverBasins).
d. Generate climatologies for select periods at both gridded and aggregated levels.
e. Compute trends over select period for both gridded and aggregated products.
f. From aggregated outcomes, compute heatplot (10-yr climatologies as anomalies to the common reference of 1995-2014).

WORKFLOW FOR CMIP6 MULTI-MODEL ENSEMBLES

a. For each model, bias-correction and Spatial Desegregation (BCSD) to 0.25 x 0.25-degrees
b. Calculation of climate indicators: The collection of daily model output was processed for calculation of the climate indicators (see **Table 3**).
c. Climatologies: For each model, and for each of the climate variables and indicators, 20-year climatologies were formed from their corresponding time series for historical simulations and future periods for all five SSPs. 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).

d. Anomalies: For each model, each variable, each of the four future time windows, and each scenario, 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.

e. Ensemble Information: Ensemble values were calculated from the individual model series and their anomalies from each of the models in the collection for every 20-year climatological period in the future and each scenario. These ensembles describe how the collection of up to 30 CMIP6 models, on average, project climatologies or their 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 (90^{th} percentile) and low (10^{th} percentile) values for all the climatological quantities 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 a 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 climatological information and anomalies can be compared with the provided ensemble description that encompasses the range between high (90^{th} percentile) and low (10^{th} percentile) levels of the underlying distribution.

f. Quality Control: Due to the large data volume, not every field of every model could be inspected visually. Rather, the CCKP Team implements 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 are flagged and ultimately a few individual models or specific products are 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.

WORKFLOW FOR SPATIAL AGGREGATION

a. High-Resolution Intersection: Each type of global data grids was intersected with high-resolution polygon boundaries (e.g., ADM0, ADM1, River Basins, or other feature zones). The fractional overlap of each grid cell with the polygon was calculated.

b. Fractional Weighting: Weights were assigned to each grid cell based on the fraction of the cell that lay within a particular polygon. This ensured that partially overlapping cells contributed proportionally to the aggregation.

c. Latitudinal Area Weighting: Latitudinal weighting was applied to account for the varying areas of grid cells resulting from the Earth's curvature. The cosine of latitude was used to adjust for the convergence of grid cells toward the poles.

d. Variable Aggregation: The weighted mean, sum, or other statistical measures were computed for each polygon, with weights combining both fractional overlap and latitudinal adjustments.

e. Sum or Mean: For most climate variables, the weighted mean of the gridded data was calculated. For aggregations involving additive variables, such as population counts, the weighted contributions of all grid cells within the polygon were summed.
f. Output and Validation: The final aggregated statistics were generated at the desired resolution (e.g., national or sub-national) and validated against expected values to ensure accuracy.

WORKFLOW FOR EXTREME PRECIPITATION EVENTS

Extreme Precipitation events (currently available at 1.0-deg, 0.25-deg production in process) Extreme events are often responsible for some of the largest climate 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 fitted to the data using L-Moments for more robust results within 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 (problem of including the values of 0). We apply the methodology described in Naveau et al. (2016)[1] in which precipitation distributions 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 mevR package[2]. To Note, these products are currently being updated.

Variables used for extreme precipitation statistics: Largest 1-Day Precip, Largest 5-Day Cumulative Precip, Largest Monthly Cumulative Precip
Time periods:

- Historical: 1985-2014 (center 2000)
- Projections: 2010-2039 (center 2025), 2035-2064 (center 2050), 2060-2089 (center 2075), 2070-2099 (center 2085)

Statistics available for precipitation extremes:
Historical

- Return Level (5yr, 10yr, 25yr, 50yr, 100yr) e.g. returnlevel5yr
- Return Period (25mm, 50mm, 100mm, 150mm, 200mm) e.g. returnperiod25mm
- Annual Exceedance Probability (25mm, 50mm 100mm, 150mm, 200mm) e.g. aep25mm

Projections

- Future Return Period (5yr, 10yr, 25yr, 50yr, 100yr) e.g. frp5yr

- Future Annual Exceedance Probability (5yr, 10yr, 25yr, 50yr, 100yr) e.g. faep10yr
- Change factor (5yr, 10yr, 25yr, 50yr, 100yr) e.g. changefactorfaep100yr

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.

TROPICAL CYCLONES

Cyclones are powerful, rotating storms that form over warm tropical and subtropical oceans and generally move from East to West before turning towards higher latitudes. These cyclones are known as Hurricanes in the Atlantic and Northeast Pacific basins, and as Typhoons in the Northwest Pacific. Cyclones pose a significant threat upon landfall, causing heavy rain, strong winds, flooding, and widespread damage, which can degrade water quality, spread disease, and destroy infrastructure. In addition to the immediate physical destruction, the aftermath often leads to long-term challenges, such as disruption of essential services, economic loss, and environmental degradation. To mitigate these impacts and support recovery, building broad resilience is essential. In most tropical places the occurrence of these storms in any one place is still rare. Therefore, the historical record, commonly going back several decades to a century, is generally too short to allow for a robust estimation of recurrence intervals of these storms. Such historical uncertainty can be reduced somewhat using models, where large ensembles of tropical cyclones can be generated. CCKP is offering these products as first examples that are designed to assist the stakeholder community in engaging with Tropical Cyclone data, forming a better understanding of their statistical properties today, and then working in a scenario context to consider possible changes in the future.

OBSERVED CYCLONES

DATA SOURCE: IBTRACS

Original Citations:

Knapp, K. R., M. C. Kruk, D. H. Levinson, H. J. Diamond, and C. J. Neumann, 2010: The International Best Track Archive for Climate Stewardship (IBTrACS): Unifying tropical cyclone best track data. Bulletin of the American Meteorological Society, 91, 363-376. doi:10.1175/2009BAMS2755.1

Gahtan, J., K. R. Knapp, C. J. Schreck, H. J. Diamond, J. P. Kossin, M. C. Kruk, 2024: International Best Track Archive for Climate Stewardship (IBTrACS) Project, Version 4r01. since1980. NOAA National Centers for Environmental Information. doi:10.25921/82ty-9e16 [access date 24th of October 2024].

Original data access: NOAA's International Best Track Archive for Climate Stewardship (IBTrACS) data, https://www.ncei.noaa.gov/products/international-best-track-archive accessed on 24th of October 2024

Description: The International Best Track Archive for Climate Stewardship (IBTrACS) offers a global historical reference dataset for observed tropical cyclones around the world (Knapp et al. 2010). While the archive contains entries in some basins going back over 100 years, the period after 1980 – the satellite era – offers a more stationary observing system across all tropical ocean basins. The data selected here covers the period 1980-2023 (see Gahtan et al., 2024), drawing on wind speed data provided by the USA National Hurricane Center (1-minute sustained wind speed). 'USA_wind' combines data from the National Hurricane Center (NHC), the Join Typhoon Warning Center (JTWC), the Central Pacific Hurricane Center (CPHC), and includes data for the WMO Regional Specialised Meteorological Center at Miami and Honolulu (operated by NOAA).

Summary of data available at CCKP:
Currently, CCKP only displays IBTrACS data. Products are not available for download. Please use this link for data access: https://www.ncei.noaa.gov/products/international-best-track-archive

The historical record, commonly going back several decades to a century, is generally too short to allow for a robust estimation of proper recurrence intervals. Using probabilistic products based on large numbers of model simulated cyclones can help fill gaps in the record (see CHAZ data below).

MODELLED CYCLONES

DATA SOURCE: CHAZ MODEL

Original Citation:
Lee, C.-Y., Tippett, M. K., Sobel, A. H., & Camargo, S. J. (2018). An Environmentally Forced Tropical Cyclone Hazard Model. Journal of Advances in Modeling Earth Systems, 10(1), 223–241. https://doi.org/10.1002/2017MS001186

Lee, C.-Y., S.J. Camargo, A.H. Sobel, and M.K. Tippett (2020). Statistical-dynamical downscaling projections of tropical cyclone activity in a warming climate: Two diverging genesis scenarios. J. Climate, 33, 4815-4834. http://doi.org/10.1175/JCLI-D-19-0452.1

Original data access: October 2023 (provided directly by Columbia University)

Description:
The Columbia HAZard Model (CHAZ, Lee et al., 2018) simulates potential cyclone distributions across ocean basins and their landfall by generating a comprehensive synthetic catalog of cyclone tracks based on outputs from 12 CMIP6 models, thus offering a broader perspective than observational data alone. Additionally, CHAZ was used to project future cyclone activity based on outputs from the same 12 CMIP6 models under the SSP2-4.5 scenario, centering a 30-year projection period around the year 2050. The CHAZ products used here are based on the genesis configuration using column relative humidity (CRH, see Lee et al. 2020). CCKP is offering these products as first examples that are designed to assist users in engaging with Tropical Cyclone data, forming a better understanding of their statistical properties today, and then working in a scenario context to consider possible changes in the future. CCKP plans to integrate additional models, scenarios, and time periods in the future.

Summary of data available at CCKP:
Presented at grid-level, and aggregated by ocean basin, exclusive economic zone, and by territory/country representing landfall. For ocean basins, a time series and daily climatology of storm occurrence within the seasonal cycle is available.

- Spatial resolution: 0.5° x 0.5° (50km x 50km)
- Time period historical scenario: 1951-2014
- Future scenarios: SSP2-4.5
- Time period projected scenario: 2035-2064

Recommended Use: **To evaluate the probability of cyclones at various wind speed categories and assess how these probabilities are projected to change in the future.** Due to the limited temporal and thus spatial coverage (lots of gaps) of these observational data, we motivate the use of large, model-based ensembles to fill these historical gaps and to provide a more comprehensive view of actual risk distribution. Applying the identical approach to the evolving climate of future climate pathways, here SSP2-4.5, projections are offered of possible future activity. Currently the results are based on a single Tropical Storm and impacts simulation model, albeit driven by a broad array of 12 different GCMs. Caution should be exercised when interpreting future projections.

Cyclones classification:
We classify tropical cyclones using the US National Hurricane Center's Saffir-Simpson Hurricane Scale, based on maximum (sustained) wind speeds. We do not consider storms below 34 knots (often referred to as Tropical Depressions).

Tropical Storm: 34 to <64 knots
Category 1: 64 to <83 knots
Category 2: 83 to <96 knots
Category 3: 96 to <113 knots
Category 4: 113 to <137 knots
Category 5: >=137 knots

Cyclones are classified in 6 categories, as described above, with category names 'tcts' for tropical storms, 'tccat1' for cyclones of category 1, and so on 'tccat2', 'tccat3', 'tccat4', and 'tccat5'.

Caveats for future projections:
CHAZ (Lee et al., 2018) is one model out of a class of statistical-dynamical downscaling tools that are being developed and continuously refined in the scientific community. Ideally, one would use multiple models with a broad array of configurations to fully sample the space of tropical cyclone dynamics and its related statistics. As of now, coordinated collections of projections based on such models in a similar way as the CMIP6 experiments are not available yet. Additionally, there remain significant gaps in the fundamental understanding of various aspects of the science of Tropical Cyclone dynamics as well as global and basin-scale climate change boundary conditions that render any available projections of change fundamentally uncertain. While some derived tendencies might be more robust than others, for example there appears to be reasonably strong agreement that the strongest Tropical Cyclones might become more likely and intense, any projected overall frequency changes in the total occurrence are to be used with caution. Based on potential trends in global dynamics, some basins might see increases while others might experience a decrease in future number of storms. Small differences can potentially lead to a change in sign of outcomes. As with other projections, ensembles might be more robust than individual model outcomes.

It is worth noting that individual CHAZ simulations were based on the projected climate from 12 different global CMIP6 models. Large ensembles were run for both historical and one future period based on SSP2-4.5 boundary conditions. Simulations were performed for different ocean basins where tropical cyclones are occurring today. It might be possible that under future climates, some basins, such as the South Atlantic, might become more or less prone for the occurrence of these storms. However, these were not simulated here, likely because of a lack of opportunity to calibrate the simplified Tropical Cyclone model. Other limitations arise from the uncertainties from within model parameters. For example, the CHAZ model has been used in other configurations in the genesis part of the model (using saturation deficit rather than column relative humidity), which resulted in different outcomes (see Lee et al., 2020; Fosu et al., 2024)[10]. While in some basins the

[10] Fosu, B. O., Sobel, A. H., Lee, C.-Y., Camargo, S. J., Tippett, M. K., Hemmati, M., Drinka, R., Polamuri, S. H., Bowen, S. G., & Bloemendaal, N. (2024). Assessing Future Tropical Cyclone Risk Using Downscaled CMIP6 Projections. Journal of Catastrophe Risk and Resilience, 2024(2), https://doi.org/10.63024/dpva-2pa1

cyclone frequency appears to scale reasonably well with prevalent surface temperatures, in others (especially the Atlantic), the response is more complex as multiple dynamical factors in atmosphere and ocean as well as presence of aerosol can be affecting cyclone formation by enhancing or offsetting each other.

Overall, the user is advised to use the projections with caution and regard the products as possible outcomes. The goal of this collection is to allow users to familiarize themselves with the type of probabilistic data and then to engage with the scientific community to better establish an idea of which elements of projections might be more robust than others in their region of interest.

Caveats in Regional Statistics:
While cyclone counts across ocean basins have been validated and bias-corrected against observed values, regional statistics may still show discrepancies. Models provide greater precision in calculating probabilities, but users should recognize that the numbers may systematically differ from actual occurrences, either higher or lower. Generally, the larger the region, the more accurate the statistics. This is particularly important when considering landfall data, and even more so for small islands, where model uncertainties tend to be more pronounced.

DATA PROCESSING STEPS

WORKFLOW FOR CYCLONES – CHAZ MODEL

a. Original Data: The original CHAZ data was provided with storm locations and maximum winds every six hours.

   Gridded Data: These data points were then projected onto a global grid with a resolution of 0.5x0.5 degrees (approximately 50 km x 50 km).

b. Temporal Interpolation: This data is then interpolated to half-hour intervals to create a continuous center track line on the grid.

c. Footprint: A footprint is subsequently applied to capture the full extent of the cyclones, as cyclones are typically larger than 0.5 degrees (roughly 50 km). Applying the full footprint is particularly important for small islands to avoid underestimating the cyclone's impact. The footprint is based on modeled horizontal wind profiles and latitude, which use a dual-exponential decay function derived from 380 observed storms, as detailed by Willoughby et al. (2006)[11] :

11 Wiloughby, H.E., Darling, R. W. R., and Rahn, M. E. (2006). Parametric Representation of the Primary Hurricane Vortex. Part II: A New Family of Sectionally Continuous Profiles. AMS Monthly Weather Review. 134 (4) 1102-1120. https://doi.org/10.1175/MWR3106.1

$$V_o = V_{\max}\left[(1-A)\exp\left(-\frac{r-R_{\max}}{X_1}\right) + A\exp\left(-\frac{r-R_{\max}}{X_2}\right)\right], \quad (R_1 \leq r),$$

With:

$$R_{\max} = 46.4\exp(-0.0155V_{\max} + 0.0169\varphi),$$

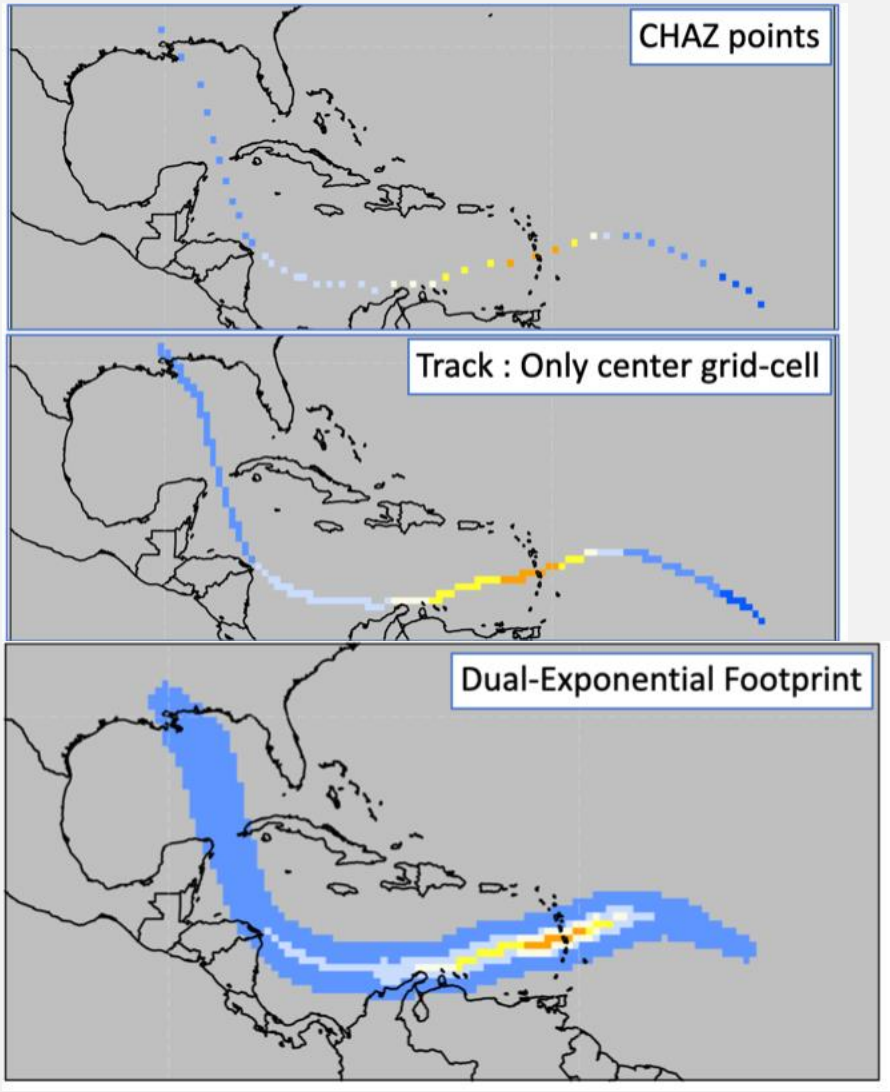
$$X_1 = 317.1 - 2.026V_{\max} + 1.915\varphi,$$

$$n = 0.4067 + 0.0144V_{\max} - 0.0038\varphi,$$

$$A = 0.0696 + 0.0049V_{\max} - 0.0064\varphi, \ (A \geq 0).$$

The resulting *Vo* is the modeled wind maximum velocity at each radius *r* away from the center, calculated on a 7x7 matrix (350km diameter) surrounding the storm's center in our case. If the storm is larger, the outer part of the storm is excluded, though this is rare. The approximation needs two inputs, *Vmax* - the maximum wind speed from CHAZ - and φ - the storm's latitude. *Rmax* represents the radius at which velocity is *Vmax*. Here, we assume that the center grid-cell is the only cell with highest winds of V_{max} even if the radius is >25km (25km refers to half of the 0.5deg pixel), which happens for weaker tropical cyclones. Then, X_2, which refers to the rapid decay length away from the storm's center, is assumed to be fixed at 25 km (deviating from Willoughby et al., 2006). X_1 represents the slower decay length of the wind profile in the outer bands of the tropical cyclone and can be calculated with the formula above.

Here is a schematic illustrating the process of transforming the original CHAZ data into a pixelized version with a footprint: a) the original CHAZ points, b) temporal interpolation to complete the track, c) addition of the footprint, and classification into different categories (represented by colors).



d. Multiple Track Generation: These tracks are generated for all cyclones across each simulation that consist of 6 separate basin results, 40 ensemble members per global driving model (12 CMIP6 models), and future scenario SSP (historical and SSP2-4.5).

e. Bias-Correction: In order to achieve annual counts similar to observations, CHAZ estimates the number of effective years that the simulations cover (as a form of bias correction). Two different numbers are applied: one for the open ocean and a separate number for landfalls.

f. Calculation Of Statistical Products

i. **DENSITY MAP:** For each cyclone, the spatial wind calculations are converted to storm categories using the Saffir-Simpson scale. Then, for each map pixel, we count the number of cases in each storm category across all simulations and divide that count by the number of effective years of simulation, resulting in a map of storm density by category (number of cyclones per pixel per year). Each storm is only counted once per grid cell. Note: For the density map, we apply the ocean basin bias correction, including over land areas.

ii. **SPATIAL STATISTICS**: For each stack of simulated cyclones, we calculate occurrence statistics for each basin, Exclusive Economic Zone (EEZ), and landfall events:

   i. **OCEAN BASINS:** We analyze the peak intensity of each cyclone to determine its timing and ocean basin attribution (so each cyclone is only linked to one ocean basin for statistics). This enables us to count the number of storms per basin per year. The width of the footprint has no impact on basin-level statistics. The effective years of simulation is applied as bias correction for "values per year".

   ii. **EXCLUSIVE ECONOMIC ZONES (EEZs):** We analyze whether a cyclone track intersects with a given EEZ. This includes all grid cells of a cyclone and thus includes the broader footprint of the storms. An EEZ intersection statistic will be determined by the highest storm category from all overlapping cells with the area of an EEZ. The footprint is particularly important here, especially for small EEZs. The effective years are applied as bias-correction.

   iii. **LANDFALL**: Similarly, we count the number of storms that intersect with the official country or territory polygon (ADM0). As with EEZs, the highest category of overlapping grid cells are counted. The footprint is also particularly relevant when calculating landfall statistics. The separate effective years for landfall are applied for bias-correction.

NOTE: The counts and annual exceedance probabilities for ocean basins, EEZs, and landfalls are based on counts of storms. Each storm only gets counted once. Therefore, these products are not spatial averages of the gridded fields shown in maps where the same cyclone may be counted in each pixel it intersects.

g. <u>Ensembles</u>**:** The process is repeated across all simulated tropical cyclones, for each of the 6 basin simulations with CHAZ, and across all 40 ensembles from any single driving GCM. Then, across all 12 CMIP6 models, a multi-model ensemble is formed, which is represented by the median value as well as the 10th and the 90th percentile to reflect cross-model variability.

OUTPUT DATA – CHAZ MODEL

GRIDDED PRODUCTS:

We provide the annual exceedance probability ('aep') and return period ('returnperiod') as multi-model ensemble medians for each of the Saffir-Simpson storm category boundaries. An annual exceedance probability for Tropical Storms of 2.5 means that on average between 2 and 3 tropical storms of ***at least*** 34kn can be expected each year. These counts can include also storms with much higher winds (TS to Cat5). Annual exceedance probabilities of Category 4 storms, however, do only include storms with maximum winds above 113kn. These numbers are computed for the historical period (1951-2014) and a future period based on the SSP2-4.5 scenario (2035-2064) and presented at an interpolated grid of 0.5x0.5 degrees. We also provide the anomaly products between the projected period and the corresponding historical reference ('faep', for median, p10 and p90 to account for uncertainties across models: note because of the current limitation to 12 models, p10 is represented by the second lowest, and p90 by the second highest of the ranked individual model results). The anomaly is expressed as a ratio or fractional change (future period results divided by the corresponding values in the historical run). A fractional change of less than 1 indicates a decrease in probability (a lower annual exceedance probability) or an increase in return period by that factor, while a fractional change greater than 1 indicates an increase in probability or a decrease in return period. One visualization also converts the change into a percent change of counts at each Tropical Cyclone level.

SPATIALLY AGGREGATED PRODUCTS:
The following spatially aggregated products can be download by users:

- Cyclone occurrence as number counts per year ('counts') and percentages ('tcfraction') for each storm category, as well as annual exceedance probability ('aep') for each category and above (at least this category) as spatially aggregated to global, ocean basin, Exclusive Economic Zone (EEZ), and country/territory (landfalls) for historical and projected SSP2-4.5.

- Annual timeseries of counts over the historical period (1951-2014) have been generated for three broader intensity groups (annual temporal aggregation): tropical storms, minor cyclones (cat 1 and cat 2, 'tcminor') and major cyclones (cat 3 and above, 'tcmajor').

- As a representation of the seasonal cycle of "presence of tropical cyclone activity" in all of the ocean basins, the 5-day moving averaged daily storm counts (normalized to per 100 years) have been aggregated for tropical storms, minor cyclones, and major cyclones.

SEA LEVEL CHANGE

Rising sea levels contribute to coastal flooding, erosion, and the loss of habitat for both human populations and wildlife. As the climate warms, thermal expansion of seawater and the melting of land-based ice sources - such as glaciers and the Greenland and Antarctic ice sheets - are the primary drivers of sea level rise. In addition, regional variations in sea level are influenced by local factors, such as vertical land motion and oceanic processes like ocean current changes, making it essential to study both global and localized trends. These drivers of sea level change are explained in more detail below.

Understanding past and present sea level changes is crucial for projecting future risks and for developing adaptation and resilience strategies for affected communities. By analyzing historical sea level records and reconstructions (data which combines observed tide gauge measurements with satellite altimetry data to create longer records of sea level changes), scientists are able to track the rate of change and identify trends in different regions of the world. This information can help policymakers and planners understand changing ocean dynamics and anticipate the impacts of future sea level rise to guide decisions on coastal infrastructure, conservation, and disaster preparedness.

Sea Level Change Measurement Methods

The data used to study sea level change is derived from multiple sources, each offering unique insights into global and regional trends.

1. **Satellite Altimetry**
   Since 1992, satellite altimeters, such as those on NASA's TOPEX/Poseidon, Jason-1, and Jason-2 satellites, have provided precise global measurements of sea surface height. Using radar pulses, they track changes in sea level across remote and coastal areas, revealing long-term trends and patterns on a global scale.
2. **Tide Gauges**
   Tide gauges, in use for over a century, measure sea level relative to fixed land points at coastal locations. While geographically limited, these instruments provide valuable local data on sea level trends and complement satellite observations by capturing regional variations due to land subsidence or ocean dynamics.
3. **Probabilistic Reconstruction**
   By combining tide gauge records, satellite data, and geophysical models, researchers create probabilistic reconstructions of sea level changes. These account for uncertainties and quantify contributions from key factors like ice melt, ocean warming, and land motion, producing a comprehensive long-term record.

Key Drivers of Sea Level Change

Sea level rise is driven by several interconnected processes that shape both regional and global patterns. The main drivers include:

1. **Ice Sheets and Glaciers**
   - **Greenland and Antarctic Ice Sheets**: Major contributors to global sea level rise as warmer temperatures accelerate ice melting, releasing freshwater into the oceans.
   - **Mountain Glaciers**: Their retreat adds additional freshwater to the seas, further amplifying global sea level trends.
2. **Vertical Land Motion** can lead to localized sea level changes and can either exaggerate or mitigate the effects of global sea level rise.
   - **Natural Causes**: Tectonic shifts or sediment settling can cause the land to rise or sink.
   - **Human Activities**: Groundwater extraction or resource removal exacerbates subsidence.
3. **Sterodynamics**
   - **Thermal Expansion**: Oceans absorb heat from global warming, causing water to expand and raise sea levels.
   - **Ocean Currents**: Altered by freshwater input from melting ice and changing heat distribution, these shifts create regional sea level variations.
4. **Terrestrial Water Storage**
   - **Groundwater Depletion**: Pumping groundwater adds water to the ocean, increasing sea levels.

- **Land Retention**: Water stored in reservoirs, soils, or other terrestrial systems can offset sea level rise temporarily.

Together, these drivers interact to produce the observed trends and regional variations in sea level rise, highlighting the complex dynamics of Earth's changing climate system.

HISTORICAL SEA LEVEL CHANGE

ORIGINAL DATASETS (consolidated by NASA and made available via NASA Global Sea Level Change):

1. Tide gauge data: Permanent Service for Mean Sea Level (PSMSL)
2. Altimetry data: NASA - Integrated Multi-Mission Ocean Altimeter Data for Climate Research (NASA-SSH)
3. Reconstruction product: Kalman Smoother Sea Level Reconstruction
    - This data product offers a near-global, probabilistic analysis of sea level changes from 1900 to present, combining tide gauge records, satellite data, and geophysical models to fill gaps in long-term observations. By resolving individual processes like ice melt, land motion, and ocean dynamics, it provides valuable insights into historical trends and regional variations, aiding coastal communities in understanding and adapting to rising sea levels.
    - Citation: Dangendorf, S., Sun, Q., Wahl, T., Thompson, P., Mitrovica, J. X., and Hamlington, B.: Probabilistic reconstruction of sea-level changes and their causes since 1900, Earth Syst. Sci. Data, 16, 3471–3494, https://doi.org/10.5194/essd-16-3471-2024, 2024.

AGGREGATED DATASETS FOR CCKP USERS

1. Global Mean Sea Level
2. Gridded Sea Level
3. Tide Gauge Sea Level
4. EEZ Sea Level

For each of the above, the following are available via API:

1. Reconstructed sea level data (annual): 1970 - 2021, baseline 2005
2. Satellite altimetry data (monthly): 1993 - present, baseline 2005
3. Tide gauge data (monthly): 1993 - present, baseline 2005
4. High Tide Flooding (HTF) data: 1970 - present
    - Tracks the number of days per year where sea levels exceed set thresholds (40cm[400mm], 60cm[600mm], 80cm[800mm] above average high tide), indicating increasing flood risk. These thresholds provide a standardized way to assess changes in coastal flooding potential over time. Exceeding thresholds signals higher flood risk, but impacts vary by location. This dataset tracks trends but doesn't confirm flooding on HTF days.
5. Percent contribution of various processes to total sea level change (average from 1993 - present)

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 3**) 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)[12], now under CLIMDEX. Further indicators include different heat-hazard indicators, drought-related indicators, and various extreme event quantities[13]. CCKP has also computed categorical products that relate climate with non-climate categories such as population to reflect exposure to inform analyses of vulnerability and risk.

***Table 3**. 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". Note that we also include here population variables, used to characterize climate vulnerability and exposure (the dataset used is described below in the document). The CRU dataset is only produces at monthly scales and thus only offered for mean, minimum and maximum temperatures and precipitation (sum).

Listed Alphabetically per Section

Indicator Name	**Indicator code**	**Description**	**Unit**	**Calculation Details/ Reference**
TEMPERATURE				
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	degF	CLIMDEX under CDDcoldn using a threshold with Fahrenheit

[12] See http://etccdi.pacificclimate.org/ list_27_indices.shtml

[13] 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

		demand for energy needed to cool a building.		
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 reference climate (e.g., present-day climate).	days	CLIMDEX
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 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	risk category	Direct categorization by combining four categories of hot day (tasmax) and four hot night (tasmin) categories

		Factor Categorization: 0-4 represents Low - Extreme Risk.		
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
Heat Index	hi	Heat Index as defined by US-National Weather Service	°C	Steadman, R.G (1979)[14]
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	days	CCKP: days over hi with threshold

[14] 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

		temperatures with high moisture lead to high Heat Index.		
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 daily maximum temperature is < 0°C in the data period.	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

Temperature-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[15]
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 heat conditions but with high population density.	risk factor	CCKP: Direct categorization using three different heat categories (hdcat, trcat, and hicat) and intersected with population density category
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

[15] 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.

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	days	CLIMDEX
Wet Bulb temperature	wbt	Temperature measured if a thermometer is covered by a wet cloth	days	Wet Bulb Temperature formulation by Stull (2011)[16]. Only available for CMIP6 dataset.
Wet Bulb Temperature > 25°C	wbt25	The number of days where the daily wet bulb temperature >= 25°C over the aggregation period.	days	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.	days	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.	days	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.	days	CCKP: days over wbt with threshold
PRECIPITATION				
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):[17] after Vicente-Serrano et al. 2010 (J Climate)[18]
Average Largest 1-Day Precipitation	rx1day	The average highest precipitation amount in a 1-day period during each data period.	mm	CLIMDEX

[16] 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

[17] 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

[18] 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

Average Largest 5-Day Cumulative Precipitation	rx5day	The average highest precipitation amount over a consecutive 5-day period during each data period.	mm	CLIMDEX
Average Largest Month Cumulative Precipitation	rxmonth	The average highest precipitation amount over a consecutive month period during each data period.	mm	CLIMDEX
Maximum Number of Consecutive Dry Days_Max	cdd	The largest number of consecutive dry days (>1mm) during the considered period.	days	CLIMDEX
Maximum Number of Consecutive Wet Days_Max	cwd	The largest number of consecutive dry days (>1mm) during the considered period.	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
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
Precipitation	pr	Aggregated accumulated precipitation.	mm	model variable
Precipitation Percent Change	prpercnt	Projected percent change in total precipitation; anomaly only. The initial time series from which all calculations derive is calculated as the percent precipitation for each month with respect to the average month during the historical reference period (usually 1995-2014). For example, percent precipitation on January 1999 is the precipitation on January 1999 divided by the average of precipitation over all the Januaries between 1995 and 2014 and multiplied by 100.	%	percent of pr in historical reference period
Precipitation Amount during Wettest Days	r95ptot	The total sum of daily precipitation during wet days that exceed the 95th percentile of wet days determined during the historical reference period.	mm	CLIMDEX
EXTREME PRECIPITATION EVENTS				

Largest 1-day Precipitation	rx1day	The highest precipitation amount in a 1-day period during a period.	mm	Naveau et al. (2016)[19]
Largest 5-day Cumulative Precipitation	rx5day	The highest precipitation amount over a consecutive 5-day period during a period.	mm	Naveau et al. (2016)
Largest Month Cumulative Precipitation	rxmonth	The highest precipitation amount over a consecutive month period during a period.	mm	Naveau et al. (2016)
POPULATION				
Population Count	popcount	Population Count	population	Source: Global Population of the World, v.4[20]
Population Density	popdensity	Population Density	population_density	Calculated from: Global Population of the World, v.4
POVERTY				
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)[21]
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)
OTHER				
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	days	CLIMDEX gsl, referring to end day of the growing season

[19] 4 Modeling jointly low, moderate, and heavy rainfall intensities without a threshold selection, Water Resour. Res.,52, 2753– 2769, doi:10.1002/2015WR018552

[20] 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

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

		reflects the first span of at least 6 consecutive days with daily mean temperature T <5ºC.		
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

DESCRIPTION OF CLIMATE PRODUCTS AND INTERPRETATION

Most CCKP-processed data is available in monthly, seasonal, and annual resolutions as time series, along with various statistical products outlined below. All data are provided as globally gridded products in netCDF format and in spatially aggregated form, reflecting World Bank shapefiles for national (ADM0) and sub-national (ADM1) units, as well as global watersheds (HydroBasins v4). Ocean-related data, such as cyclones and sea level rise, have also been spatially aggregated for Exclusive Economic Zones.

Time series (‘timeseries’) - *available for all datasets.* - The download page offers full time series (‘timeseries’) at the pixel level (raster files) and spatially aggregated, available at various temporal resolutions. The user can calculate their own statistics and temporal and spatial aggregation from those primary time series. Beyond time series, CCKP has calculated standard climate statistical products for standard time periods. See the following definitions.

Table 4. List of products

Product	Recommended use	Description
Anomaly (‘anomaly’, ‘anomalysignificance’, ‘robustchange’, ‘nochange’, ‘conflictingchange’) - *available for CMIP6 future projections*	- The anomalies are used to show the long-term differences between the historical period and a future projected period. 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	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 (starting from a smoothed 20-year running averages). In contrast to climatologies, these values are well suited for model-to-model intercomparisons as they always refer to the change simulated by each model. Hence, we recommend using anomalies when focusing on changes. The ensemble anomaly is calculated by taking the anomalies from individual models and then determining the median, along with the 10th and 90th percentiles. For significance and agreement across models, 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). Anomaly significance is determined at the individual model level and is established by comparing the climatological mean of a future period against the range of natural variability in the historical period. If outside of that range, then the change is determined as significant. The fields 'robust-change,' 'no-change,' and 'conflicting-change' are determined solely at the ensemble level, as they indicate model agreement and areas of discrepancy. The field ‘robust-

	to results presented in the IPCC[22,23].	change' indicates a value of 1 when there is a significant change with high agreement across models. Specifically, this requires that more than two-thirds of the models show an anomaly exceeding the natural variability calculated from the historical reference climate, and 80% of these models must agree on the direction of the change. The field 'no change' indicates no significant change or no robust signal. The field indicates a value of 1 wherever fewer than two-thirds of the models show a change that exceeds the historical natural variability. The field 'conflicting change' indicates significant changes but high disagreement among models. The field indicates a value of 1 wherever more than two-thirds of the models show an anomaly above the historical natural variability, but fewer than 80% of these models agree on the direction of the change.
Annual Exceedance Probability ('aep..') - *available for extreme precipitation events and cyclones in CMIP6 models*	Annual exceedance probability represents the probability that an event will exceed a specific value (e.g., flood discharge, rainfall amount, wind speed) in any given year.	For precipitation extremes, we provide AEP for the following thresholds: 25mm, 50mm 100mm, 150mm, 200mm e.g. aep25mm - Number of days per year with precipitation variable exceeding a given threshold. For cyclones, we provide the annual exceedance probability ('aep') for each category and above, as the number of cyclones/year for the given category and higher.
Climatology ('climatology') - *available for all datasets and all time periods*	Climatology is used to characterize the average climate (historically and projected)	Climatology is the annual (1 layer), seasonal (4 layers), or monthly (12 layers) temporal average over a period of time.
Daily Percentiles Percentiles (1 daily, 5 daily, 10 daily, 90 daily, 95 daily, 99 daily) - *available for few variables in ERA5 and CMIP6 (historical scenario)*	Daily percentiles aim to show the day-to-day natural variability.	A percentile is a statistical measure indicating the value below which a given percentage of observations in a dataset falls. In our datasets, different percentiles are calculated from daily data for each season (3 months) for the full historical period.
Future Annual Exceedance Probability and change factor – *available for CMIP6 extreme precipitation events and cyclones*	This product indicates how the extreme events are changing in time	For precipitation extremes: • Future Annual Exceedance Probability (5yr, 10yr, 25yr, 50yr, 100yr) e.g. faep10yr - 10-yr Change in Future Annual Exceedance Probability (occurrence / year) • Change factor (5yr, 10yr, 25yr, 50yr, 100yr) e.g. changefactorfaep100yr - 100-yr Change in Future Annual Exceedance Probability (Change Factor). The factor is expressed as a ratio or fractional change (future period results divided by the corresponding values in the historical run). A fractional change of less than 1 indicates a decrease in probability (a lower annual exceedance probability) or an increase in return period by that

[22] 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
[23] 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

		factor, while a fractional change greater than 1 indicates an increase in probability or a decrease in return period. For cyclones, 'faep' indicates the ratio or fractional change (future period results divided by the corresponding values in the historical run). A fractional change of less than 1 indicates a decrease in probability (a lower annual exceedance probability) or an increase in return period by that factor, while a fractional change greater than 1 indicates an increase in probability or a decrease in return period.
Future Return Period – *available for CMIP6 extreme precipitation events*	The return period (e.g., 100 years) at which an event of a certain intensity, equivalent to the historical return level for that same period, is projected to occur in the future. For example, if a 100-year event historically is projected to occur every 85 years in the future, the future return period for that event has decreased to 85 years.	For precipitation extremes, we provide Future Return Period (5yr, 10yr, 25yr, 50yr, 100yr) e.g. frp5yr - Future return period (years) for extreme precipitation events that correspond to the 100-year return period levels during the historical period.
Heatplot - *available for ERA5 and CMIP6*	Heatplots show monthly anomalies (with respect to an historical reference period) across long-term time horizons.	CCKP heatplots display the monthly anomalies for various 10-year periods, relative to the monthly average over the historical recent period (1995-2014). For example, for ERA5, the value shown under 1980-1990 for March represents the difference between the average March temperature during 1980-1990 and the average March temperature across the reference period (1995-2014).
Natural variability ('natvar', 'natvarhigh', 'natvarlow') - *available for ERA5 and CMIP6 (historical scenario)*	Climate variability is a natural characteristic of the climate system, and any observed trend or change must be assessed against this background to be meaningful. Comparing evolving climate changes with the range of natural variability helps pinpoint when a trend departs from historical variability, marking the "year of significant change." Periods dominated by natural variability (low trends compared to larger variability) can be contrasted with periods where a substantial, often anthropogenic, trend leads to a clear departure from natural variability—this is known as the "emergence of change." Long-term time	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[5]). 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 years) * 1.645 to get a climatologically meaningful natural variability threshold. The number 1.645 corresponds to a 90% confidence level. For historical data (ERA5), 'natvarhigh' refers to the climatological average value plus the natural variability, while 'natvarlow' refers to the climatological value minus the natural variability. For CMIP6 model historical ensembles, the determination of natural variability is more difficult because it 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 ('natvarhigh') and the 10th percentile of the natural variability as the lower bound ('natvarlow'). Note that natural variability can also be calculated for SSP scenarios, but this data is not available for download on CCKP. We rely on natural variability from the historical period.

	series are essential for identifying shifts in the dynamics of a selected variable or indicator.	
Return level (‘returnlevel...’) - *available for extreme precipitation events in CMIP6 models.*	The return level corresponds to the size or intensity of an event that occurs with a given probability over a certain time frame (return period).	For precipitation extremes, we provide Return Level (5yr, 10yr, 25yr, 50yr, 100yr) e.g. returnlevel5yr – Intensity level of extreme events occurring at a given return period.
Return period (‘returnperiod...’) - *available for extreme precipitation events and cyclones in CMIP6 models.*	The return period represents the average time interval between occurrences of a particular event (e.g., a flood with a certain discharge level or a tropical cyclone with a certain intensity).	For precipitation extremes, we provide Return Period (25mm, 50mm, 100mm, 150mm, 200mm) e.g. returnperiod25mm - Average time between extreme events defined as precipitation exceeding different thresholds. Note: 500-year and 1000-year return periods are also available; however, due to high volatility and poor model performance, CCKP does not make these data public. For cyclones, we provide the return period for each category and above.
Trend (‘trend’, ‘trendsignificance’, ‘trendconfidence’) - *available for ERA5 and CMIP6 (ssp scenarios)*	A trend refers to a long-term change in a variable, expressed in the CCKP as change per decade or percent change per decade. Reporting trends with their significance is crucial.	The trend is calculated using regression on an annual time series smoothed with a 20-year running average. For CMIP6 models, the trend is calculated separately for each model. Then, the ensemble trend is calculated by taking the trends from individual models and determining the median, along with the 10th and 90th percentiles. The Theil–Sen estimator, which is robust against outliers, is used to calculate the regression for the median. The CCKP is transitioning to a similarly robust, but faster approach called RANSAC. The confidence and significance of the trend are assessed using the Mann-Kendall test. The significance is determined by calculating a p-value, which represents the probability of observing the data if the null hypothesis (no trend) were true. A low p-value (typically less than 5%) suggests that the trend is unlikely due to random chance and is therefore significant. Significance is then expressed as a binary outcome to support map presentations on the web: locations determined to have a significant trend are marked as “_FillValue” (= missing value) and non-significant locations are marked as = 1. This reflects the mapping convention of not obscuring anomalies that are significant while hatching or stippling areas that are not significant (see IPCC AR6 conventions). The actual level of confidence (1 minus p-value), that is the degree of certainty in the results, is stored in the trend confidence with values >= 95 (%) indicating that the observed trend is real. Trends can be influenced by various factors, including climate change as well as natural variability, but investigating the causes in observed data requires attribution analysis, which is currently outside the scope of CCKP. For the ensemble, confidence and significance are evaluated using the same approach, beginning with the ensemble time series.
Year of change - *available for ERA5 and CMIP6 (ssp scenarios)*	The year-of-change allows the user to predict when the climate signal will likely emerge significantly above the interannual natural	The year-of-change is defined as the first year when the 20-yr smoothed time series that represents the evolving climate (from 2005 to 2100) 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

	variability for the first time.	some regions, meaning that for these scenarios the climate trend surpasses the natural variability for a limited period of time and then falls back within the natural historical variability.