Physical Hazard Models: Scientific Principles, Technical Methods and Validation

Methodology

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Executive Summary

This document provides an overview of how the Climate Center of Excellence (CCOE) develops and defends its physical climate hazard metrics. It explains the scientific foundation for each metric, the end-to-end methodology used to translate climate information into hazard measures, and the validation and quality controls applied to ensure results are credible and fit for use. The CCOE covers **12 key physical hazards**: coastal flooding, drought, extreme cold, extreme heat, fluvial flooding, heat stress, landslides, pluvial flooding, subsidence, surface wind, tropical cyclone, and wildfires.

For each hazard, the document describes how metrics are computed and evaluated, including how model outputs are tested against observations or reanalysis products, screened for errors and outliers, and assessed for consistency with established physical relationships. The methodology is anchored in peer-reviewed scientific literature to support transparency and defensibility.

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Introduction

This document explains the scientific basis, methodology, and validation approach used by the Climate Center of Excellence (CCOE) to produce its physical climate hazard metrics. It is intended to help business users understand what the metrics represent, how they are constructed, and how we assess their validity.

CCOE hazard metrics are designed to quantify how climate-driven changes may affect the frequency, intensity, and spatial patterns of key physical hazards. For each hazard, we summarize (1) the scientific rationale for the metric, (2) the core modeling and data-processing steps used to generate it, and (3) the checks performed to confirm that the metric is fit for use across geographies and time periods.

In this document, validation means evaluating whether a model or metric credibly represents the real-world hazard it is intended to simulate. Validation methods vary by hazard and may include comparison of modeled results with observations or reanalysis products (datasets that blend observations with physics-based models), targeted quality-control screening to identify outliers or erroneous values, and consistency checks against established physical relationships. Where appropriate, we also document the rationale for key modeling choices by referencing methods supported in the peer-reviewed scientific literature.

This document is structured in three sections to guide readers through the complete methodology and validation framework. It begins with the climate model foundation and methodologies used across all hazard models, explaining the CMIP6 climate model datasets that underpin many hazard assessments and outlining the critical considerations for their use. This section also discusses data preparation. Namely, the processing and preparation steps applied before hazard modeling, including harmonization, conditioning, and screening procedures. The core of the document highlights hazard-specific methods and evaluation, offering a hazard-by-hazard breakdown of each metric—explaining how it is computed, how performance is assessed, and what quality checks are applied. Finally, the document concludes with references, compiling hazard-specific citations at the end for easy access to supporting literature and technical documentation.

This document provides an overview of CCOE methodology and validation practices. More detailed methodological decisions, sensitivity testing, and implementation specifics are available through your Climanomics representative. For a product-level overview of how these hazards are used in Climanomics, readers should consult the Climanomics Methodology document.

Common Methodologies and Data Inputs

Climate Model Data

For most terrestrial physical hazard assessments, we utilize the downscaled NEX-GDDP CMIP6 dataset. This dataset offers high-resolution daily climate projections for key variables, including relative humidity, precipitation, shortwave radiation, surface wind speed, average temperature, and the daily maximum and minimum temperatures. The data have been bias-corrected and spatially downscaled to a 0.25-degree resolution using the Bias-Correction Spatial Disaggregation (BCSD) method, as described by Thrasher et al. (2012). These datasets are produced and distributed by NASA and are widely regarded as the leading source for high-resolution climate projections.

Additionally, further bias correction procedures are performed by S&P Global for select variables, utilizing various target datasets. Predominantly, these target datasets originate from the European Centre for Medium-Range Weather Forecasts' (ECMWF) ERA5 and ERA5-Land reanalysis datasets. ERA5 is a comprehensive global atmospheric reanalysis that integrates model outputs with observational data to provide detailed climate and weather information over the historical period. ERA5-Land, a higher-resolution land surface dataset, is generated by forcing a land surface model with ERA5 atmospheric data without additional data assimilation. Both datasets are extensively used for climate monitoring and research, with ERA5 offering a broad atmospheric perspective and ERA5-Land providing detailed land surface variables. The use of these target datasets ensures that the absolute values of climate variables from the CMIP6 models align as closely as possible with observed data, which is particularly critical when assessing the severity of the projected hazards.

The S&P Global CCOE conducts additional quality assurance procedures on these datasets to develop robust and reliable physical hazard metrics.

Extraction of the Climate-Forced Signal

Due to the limited number of climate models available and the variation in output from these climate models, we developed a method to smooth over natural variability and extract the climate-forced signal from the final hazard metrics. To do this, we regress the annual hazard time series at any location onto time series of annual Global Surface Air Temperature (GSAT).

The steps below are repeated for each model and each location. We start with the annual hazard time series that we calculated for each scenario and model.

1. Linearly regress the annual hazard metric (y) across all years and scenarios on the corresponding values of annual GSAT (x). The resulting regression model has two coefficients, one for the slope (m) of and one for the y-intercept (b). These coefficients do not vary by scenario (SSP), i.e. the same coefficients are used to derive the forced response for each scenario. What varies by scenario is simply the GSAT. The model captures the relation between GSAT and the metric such that:

$$metricforced = m(GSATscenario) + b$$

   The metric represents the forced response; the component of the metric linked to climate change as captured by GSAT.

2. For each model, isolate the forced response of the metric by evaluating the linear regression model at the GSAT values for each scenario for each year. The result is a set of four forced annual time series for each model.
   a. *Note that if the hazard metric is frequency based (and thus bounded between 0 and 1), then this simple linear regression model could theoretically yield results below 0 or above 1. Values outside those bounds, however, would have no physical meaning, therefore results are bounded at 0 and 1.*

Individual Hazard Metrics

All methodologies are developed using the latest peer-reviewed research, cited for each hazard at the end of this document. All hazards undergo extensive quality control by numerous independent scientists within the S&P Global CCOE, followed by external quality assurance (QA) prior to release. Unless otherwise noted, the hazard metrics are available as decadal ensemble averages from the 2020s to the 2090s for four IPCC emission scenarios (SSP 1.2-6, SSP 2.4-5, SSP 3.7-0, and SSP 5.8-5) for each grid point location and a historical baseline.

Coastal Flooding

Motivation

Flooding driven by storm surge and tides is a significant hazard for coastal populations and infrastructure. Strong storms, such as intense tropical cyclones (TCs), can increase water levels at the coast by many meters, especially when coincident with high tides. These extreme water levels propagate inland from the coast, depending on local topography, potentially flooding roads and houses. The hazard becomes worse as sea levels rise, as the surge and tide propagate on a higher background sea level. Thus, projecting hazard and risk from coastal floods in future decades and climate scenarios is a critical part of climate risk analysis.

Metrics

Two hazard metrics from the coastal flood model are currently provided: 1. The future projected frequency of the baseline 1-in-100-year (i.e., 0.01/year) flood depth. This is a relative change metric, as the baseline 100-year flood depth is not specified. 2. Flood depth (meters) at nine return periods: 2, 5, 10, 20, 50, 100, 200, 500, 1000 years. This is an absolute metric. For both metrics, values are provided for the baseline period (1979-2014) and each decade from the 2020s to the 2090s for four IPCC scenarios. The geographic domain is near coastal regions, typically extending from the coast to 12 km inland, and the spatial resolution is 1-arc-second (~30 m) in the contiguous US and 3-arcseconds (~90 m) elsewhere.

Methods

The flood model begins with storm tide levels (storm surge and tides) at the coast at multiple return periods, as calculated by Muis et al (2016; 2020) using the Global Tide and Surge Reanalysis (GTSR) hydrodynamic ocean model driven by observational reanalysis wind data. The storm tides are provided along the global coastline at varying resolution, from several to tens of kilometers. The storm tides are generally biased low in active TC regions, as the reanalysis wind data at 25 km does not adequately resolve the wind fields of intense TCs. We apply a statistical debiasing analysis in these regions based on historical TC activity and direct tide gauge storm tide measurements to more closely match direct observational measurements.

We then add to the debiased storm tides IPCC6-generation local sea level rise (SLR) projections from Kopp et al (2023), based on CMIP6 inputs, as well as process models (e.g., glacier melt, ice sheet melt, local land subsidence). These SLR data are provided at 1° resolution. The Kopp et al (2023) SLR data are probabilistic; for each decade and scenario a range of SLR values is provided determined by uncertainty analysis. These uncertainty distributions are fully incorporated into the model. That is, at each baseline storm tide return period, an SLR distribution is added, which generally shifts to higher values with increasing decades.

The storm tides with SLR are propagated inland from the local coastline using a path finding algorithm that accounts for local land elevation variation, the Dijkstra algorithm, as implemented by Grady and Xingong (2018). Given a geographic distribution of land elevation, the algorithm computes at each inland pixel the minimum water level at the local coastline that is needed to inundate the pixel. The minimum water level may simply be the elevation of the pixel above mean sea level, if no intermediate elevation barriers are present. However, elevation above the pixel elevation may be present between the pixel and the local coast, in which case, if no circumventing path is available, the minimum water level is the intermediate elevation. In either case, if the minimum water level is exceeded, then the flood depth at the pixel is the water level minus the pixel elevation. This is sometimes called a ‘modified bathtub model’. It represents possible water flow paths, from the coast to inland pixels, but is not dynamic. (Storm surge information is summarized by the storm tide return periods, rather than being explicitly simulated by storm events.)

At an inland pixel, there may be several possible water flow paths available from different nearby coastal regions. To account for this possibility, the path-finding algorithm is applied in overlapping 25 km square regions centered every 12.5 km along the coast. 25 km square regions were chosen to prioritize the highest resolution analysis that could be completed with the available computational resources. The minimum water level at an inland pixel with respect to the different coastal sections is compared, and the least minimum water level (i.e. easiest to result in flooding) is selected for the pixel.

The grid resolution (pixel size) is determined by the land elevation data, called the Digital Elevation Model (DEM). For the contiguous United States, we use USGS DEM at 1-arc-second (~30m), and for the rest of the global coastlines we use the MERIT DEM at 3-arcseconds (~90m).

Because SLR is represented by an uncertainty distribution, the flood depth at a pixel at each return period is also an uncertainty distribution. It has the shape of the SLR distribution, except often truncated at lower values that don’t exceed the pixel’s minimum water level. The mean of the truncated distributions is taken as the flood depth metric at each return period. This integration for SLR uncertainty has key consequences: It may be that the storm tide plus mean SLR does not result in flooding at a pixel. However, the upper tails of the distribution (small chance that SLR is much higher than its best estimate) may still result in flooding.

The flood depth return period values are archived at decades and scenarios for subsequent analysis and use on delivery platforms. In the case of the relative frequency change metric, projected flood depths are first referred to baseline 100-year values to compute the projected frequencies.

Validation

We built the coastal flooding hazard metric with multiple QA, validation, and bias-reduction checks embedded in the workflow. We start with highly resolved extreme coastal water levels from surge and tide ("storm tide") computed by the Global Tide and Surge Reanalysis (GTSR), a hydrodynamic ocean model driven by ERA5 meteorological reanalysis data (Muis et al, 2016; 2020). Muis et al (2016; 2020) have performed extensive comparisons of GSTR storm tides to direct station observations. We reduce known storm tide biases in active tropical cyclone regions by applying a statistical debiasing model developed with direct tide gauge measurements as the observational target (this model can then be applied to areas without direct tide gauge measurements as well). We then combine the corrected storm tides with local probabilistic sea-level rise (SLR) projections from Kopp et al. (2023) across the four SSP scenarios, explicitly propagating SLR uncertainty distributions into projected storm tide estimates rather than relying on a single deterministic SLR value.

For flood depths at locations interior from the coastline, we avoid a simple approach comparing coastal water level to land elevation ("bathtub" models). Instead, we implement a more physical method that uses a Dijkstra algorithm (Grady and Xingong, 2018) to identify water flow pathways consistent with land elevation. This is effectively a physical validation step that reduces artificial features common in bathtub models, such as ponds of flood water disconnected from the coast. To control data volume and scope, we apply screening filters so that the hazard is only computed where flooding is plausible: we skip pixels that require SLR and storm tide greater than 20m to be inundated, and among the remaining pixels we only consider those whose 1000-year return period flood depth at the 99th percent SLR confidence level for SSP5-8.5 in the 2090s is non-zero.

Data Availability

Both the relative and absolute coastal flooding hazard data are available on Climanomics. The relative coastal flooding hazard data are used in the Physical Risk dataset.

Drought

Motivation

Impacts of drought include significant economic disruptions, such as reduced productivity and yield to agriculture, reduced energy production, and disruptions to supply chains, leading to substantial financial losses. Drought also causes severe water shortages, straining limited water resources and increasing the need for conservation efforts. Overall, drought conditions threaten both economic productivity and stability as well as health and well-being.

Metrics

Currently, the drought hazard is quantified via one absolute metric and one relative metric. Both metrics are based on the Standardized Precipitation Evapotranspiration Index (SPEI-12), which is an indicator of drought conditions based on environmental variables. We use SPEI-12, which accumulates the index over a 12-month period to focus on hydrological drought conditions and is useful for long-term water supply tracking. The absolute metric is defined as the number of months in a year in severe drought (SPEI below -1.5). The relative metric quantifies the number of months where the SPEI is below the historical 10th percentile.

Methods

The drought indicator SPEI-12 is a monthly index that helps characterize meteorological drought conditions to the extent that these conditions are driven by meteorological variables. It is calculated from a combination of temperature, relative humidity, precipitation, shortwave radiation, and surface wind. In short, the SPEI-12 measures the water balance, that is the difference between precipitation and potential evapotranspiration. For our purposes, the water balance is then aggregated over a 12-months period. This hazard metric is computed over land only and available at a spatial resolution of one-quarter degree. The input variables are taken from the downscaled NEX-GDDP CMIP6 data set.

Validation

We implemented careful quality control on the NEX-GDDP based input variables before calculating SPEI-12. During monthly aggregation and unit conversion, we screen the input variables for unrealistic negatives and cap any negative values to zero to prevent physically impossible inputs from propagating into the drought metric. This hazard uses the daily minimum and maximum temperature data that has known errors (as described in Extreme Cold and Extreme Heat sections of this document).

We document missing and failed SPEI-12 computations as a methodological limitation. Specifically, we acknowledge that at some locations the log-logistic distribution fit can fail during SPEI calculation. This issue is well reported in other established SPEI production workflows (e.g. the Spanish National Resource Council SPEI dataset) and especially prevalent in persistently low precipitation regions (e.g., Andes, Sahara, Namib, Southwest Asia, Himalayas). When this occurs, we set the SPEI-12 to NA and then interpolate in time per model and grid cell to fill gaps prior to hazard metric derivation. We examine the scope of this limitation by mapping NA counts over the 1032-month projection series and report the approximate fraction of affected grid cells by scenario (e.g., ~9% in SSP1-2.6 and ~18% in SSP5-8.5 on average per model). For context, even for the most extreme scenario, SSP5-8.5, 95% of grid cells contain less than 5% of missing data and averaged across all models. Separately, we track permanent data dropouts (NA) where SPEI is never computed (including all grid cells south of 87.875°S).

Additionally, we perform qualitative validation by comparing historical CMIP6 derived SPEI trends with reanalysis SPEI trends. We find consistency in the directionality of the trend with variations in the absolute values owing to different standardization windows. We note that different observational SPEI products themselves tend to exhibit substantial spread due to differences in station coverage, precipitation products, and wind inputs. Published peer-reviewed literature finds that CMIP6 based SPEI generally reproduces global patterns meaningfully, though contains some regional over- and underestimates.

We applied additional controls during GSAT regression of annual threshold frequency by capping regressed values between 0 and 1.

Data Availability
Both the relative and absolute drought hazard data are available on Climanomics. Relative drought hazard data are used in the Physical Risk dataset.

Extreme Cold
Motivation
Extreme cold poses significant risks to business operations, shipping, and financial stability. Cold temperatures can lead to operational disruptions by freezing ports, delaying freight shipments, and causing mechanical failures in transportation infrastructure. Infrastructure damage, such as burst pipes and compromised facilities, can incur substantial repair costs and downtime. Additionally, colder conditions place increased strain on the power grid, leading to higher energy costs for heating and insulation for businesses. Furthermore, reduced workforce availability due to unsafe travel conditions or cold-related illnesses (i.e. hypothermia, slips and falls) may impact workforce capacity.

Metrics
The Extreme Cold hazard is quantified by a relative and an absolute metric.

- Extreme cold days (Tn5p): The frequency of days below the historical 5th percentile daily minimum temperature. This metric is dimensionless and bound between 0 and 1.
- Absolute Extreme Cold (Tn5pAbs, Units: degrees Celsius). This metric represents the absolute extreme cold physical hazard and is defined as the absolute 5th percentile daily minimum temperature.

Methods

For the relative hazard metric, we calculated the baseline 5th percentile daily minimum temperatur for each model from the historical period 1950 to 2014 for each model and grid cell. Then, for each model, scenario and grid cell we calculated the number of days annually where the 5th percentile daily minimum temperature is below the historical baseline. Then we divided this number by the total number of days in the year to obtain the frequency of days below the baseline for each year. For the absolute hazard metric, we isolate the absolute 5th percentile daily minimum temperature for each model, grid cell, and climate scenario. For both metrics, these values are GSAT regressed following the methods outlined above, and the new annual time series for each model and grid cell are used to create an annual time series for the scenario by taking the mean value of all the model ensemble members. Finally, these values are converted to a decadal time series by taking the average of the annual time series every 10 years.

Validation
When analyzing our hazard model output, we identified an issue with the minimum temperature (tasmin) NEX-GDDP data through internal QA when we observed erroneous minimum temperature values affecting all CMIP6 models in the SSP1-2.6 and SSP3-7.0 scenarios. After consultation with the NASA product owner of NEX-GDDP, and our own internal investigation, we confirmed that the erroneous data

is only present in the downscaled NEX-GDDP CMIP6 products (not in the original climate model outputs) and is spatially concentrated along parts of the continental coastline and Central Canada. Because the affected tasmin values are biased warm but still physically plausible, we determined that simple threshold screening as described below would be insufficient to reliably flag the issue.

To validate and localize the anomaly, we relied on contextual and comparative diagnostics: we compared impacted grid cells to neighboring regions and generated scenario difference maps between affected and unaffected scenarios. We used ensemble mean tasmin difference maps to show that coastal/Central Canada areas appear as negative differences when comparing SSP1-2.6 or SSP3-7.0 versus SSP5-8.5, which contradicts the expected directionality (tasmin should generally be higher under the higher emissions scenario and hence differences between SSP5-8.5 and other scenarios should be positive). As a control, we also compared SSP2-4.5 versus SSP5-8.5 and observed no negative difference patches, reinforcing that the earlier negative patterns reflect a data error rather than a plausible climate signal. From the difference maps, we generate a string of affected grid cells, which are treated slightly differently in subsequent analysis steps. Specifically, to remedy this issue, when calculating the global surface air temperature (GSAT) regressed extreme cold metric in the locations with this error, we only use data from SSP2-4.5 and SSP5-8.5 to calculate the correlation coefficients and then calculated the GSAT-regressed tasmin for all scenarios using these coefficients. This correction method is applied to multiple other hazards that rely on tasmin input data.

Note that at the time of writing, NASA has issued a corrected data set which has now been fully downloaded and processed by S&P Global CCOE. The corrected data will be used in all subsequent new hazards and hazard updates.

Data Availability

Tn5p data are used as part of the Physical Risk dataset.

Extreme Heat

Motivation

The increasing frequency and severity of extreme heat events due to climate change pose significant challenges to businesses and infrastructure. Elevated temperatures strain HVAC systems and power grids as demand for air conditioning surges, leading to higher energy costs and potential grid failures. The strain on healthcare systems intensifies as heat-related illnesses and deaths rise, particularly affecting vulnerable populations such as the elderly and children. Economically, reduced worker productivity and increased healthcare burdens threaten social stability and economic growth. Additionally, extreme heat worsens environmental issues like droughts and wildfires, damaging crops and threatening food security and biodiversity.

Metrics

- Tx90pAbs: The 90th percentile daily maximum temperature in degrees Celsius.

- Tx50pAbs: The 50th percentile (median) daily maximum temperature in degrees Celsius.
- Tx90p: The frequency of days above the historical 90th percentile daily maximum temperature. This metric is dimensionless and bound between 0 and 1.
- Tx50pAbsChg: The absolute change in median maximum temperature relative to the historical median maximum temperature. This metric has units of degrees Celsius.
- Tx90pAbsChg: The absolute change in the 90th percentile maximum temperature relative to the historical 90th percentile maximum temperature. This metric has units of degrees Celsius.

Methods

Tx90pAbs is calculated by finding the 90th percentile daily maximum temperature for every year in every model. Tx50pAbs is calculated by finding the median (50th percentile) daily maximum temperature for every year in every model. For the remaining three metrics, the 90th and 50th percentile metrics are compared to the historical period. We calculate the baseline 90th percentile and median daily maximum temperature over the historical period from 1950 to the end of 2014. For each model, Tx90pAbsChg (Tx50pAbsChg) is calculated by subtracting the baseline 90th percentile (50th percentile) from the annual 90th percentile (50th percentile). Finally, Tx90p is calculated as the percent of days annually where the 90th percentile daily maximum temperature exceeds the baseline 90th percentile temperature. Each of these metrics is calculated per model, per year. These values are GSAT regressed following the method outlined above to create a new annual time series for each model. We calculate the ensemble mean of the models to create an annual time series of each metric. Finally, the decadal average is taken for each grid cell from the annual time series. It is worth nothing that while the CMIP6 modelled daily maximum temperature (tasmax) and GSAT include influences of the El Niño Southern Oscillation (ENSO), there is variability across the models that results in the ENSO signal being reduced in the ensemble mean. Then, taking the decadal average of the ensemble mean further suppresses ENSO impacts on global temperature and extreme heat.

Validation

Similar to the downscaled tasmin data, we identified erroneous tasmax values through internal quality control affecting all NEX-GDDP CMIP-6 models for scenarios SSP1-2.6 and SSP3-7.0. We confirmed this error was spatially concentrated along parts of the continental coastline. To protect metric reliability, we apply the same targeted mitigation technique outlined for the tasmin data rather than discarding scenarios for all grid cells. For the previously flagged grid cells only, we excluded SSP1-2.6 and SSP3-7.0 from the GSAT regression so- the known, erroneous tasmax values could not contaminate the fitted forced response. We instead fit GSAT regression coefficients using SSP2-4.5 and SSP5-8.5 for those grid cells and then apply those coefficients to generate SSP1-2.6 and SSP3-7.0 tasmax- hazard metrics.

As stated in the previous section, we acknowledge that the data provider (NASA) has issued a correction to these problematic locations. We have compared the final metrics in problematic locations to metrics calculated with the updated datasets and found no significant difference in the results from our amended method using only two scenarios for the GSAT-regression, thus validating our method.

The most recent version (V2) of the Extreme Heat hazard now features regression on global surface air temperature to isolate the forced hazard metric. As such, we perform a qualitative consistency check against the prior Extreme Heat metrics (Tx90p, Tx50pAbsChg, Tx90pAbsChg) under SSP5-8.5, confirming that the GSAT regressed outputs preserved expected large scale patterns (e.g., elevated Tx90p in equatorial regions, strong warming in North America/Russia/Brazil, amplified high latitude warming) while appearing smoother, reflecting the removal of uncancelled variability, and avoiding non-physical mid-century scenario crossovers. Further, we confirmed that these results were consistent with current findings in scientific literature.

Data Availability

Tx90p data are available on Climanomics. Tx90p and Tx50pAbsChg are used in the Physical Risk Dataset.

Fluvial Flooding

Motivation

Understanding fluvial (river) flood events is crucial because they cause significant physical damage to commercial infrastructure, disrupt supply chains, and impair transportation networks. These disruptions lead to substantial financial losses for businesses and can slow economic growth in affected regions. Additionally, frequent flooding increases insurance costs and necessitates costly mitigation efforts, impacting overall economic stability. Addressing river flood risks is therefore essential for safeguarding business continuity and maintaining a resilient economy.

Metrics

Two fluvial flood metrics are in use: 1. The future projected annual frequency of the baseline (1950-2000) 100-year return period flood depth. The baseline value is 0.01/year (1 in 100 years). The resolution is 0.25° (~25 km). This relative frequency metric is currently in use on delivery platforms. 2. The flood depth above ground (meters) at nine return periods (2, 5, 10, 20, 50, 100, 200, 500, 1000 years) at a resolution of 0.000225° (~25 m) in the US and several European countries and 1/3600° (~30 m) elsewhere.

Methods

We employ statistical relationships developed by AECOM (2013) between three climate variables and the 10-year and 100-year return period (RP) river flow rates developed by AECOM (2013). The climate variables used in this analysis are annual 5-day precipitation, longest annual stretch of consecutive dry days, and annual number of frost days. The river flow rate extremes are then related to 10-year and 100-year flood depths averaged over river drainage basins. These basin-averaged flood depths are computed for the baseline (1950-2000) period and future projected periods with a set of 19 CMIP6 models. (This is the model set from which the three climate variables can be derived for the baseline and all future scenarios.)

At drainage basin resolution (~tens of kilometers), flood depths are not useful directly as hazard metrics, because the effect of ground elevation at high spatial resolution (tens of meters) is not represented. Instead, we compute the change in the baseline frequency (0.01/year) of the 100-year flood depth by decade and scenario, without providing the baseline flood depth itself. To compute future frequencies, we use both the 10-year and 100-year results, log-interpolating to obtain intermediate values. The resulting frequency is a relative change metric; for example, the baseline frequency of 0.01/year might become 0.02/year in future, independent of the actual 100-year depth. The spatial resolution is 0.25° (~25 km), same as the resolution of the underlying NEX-GDDP CMIP6 climate variables.

The new fluvial hazard metric greatly improves upon the relative change metric by providing flood depth above ground at high resolution (0.000225°, or roughly 25m, in the US and some European countries and 1/3600°, or roughly 30m, elsewhere) at nine return periods: 2, 5, 10, 20, 50, 100, 200, 500, and 1000 years. We have partnered with the flood modeling firm JBA, who have provided global country-by-country current-climate flood depth data at up to six return periods. These flood depth data are projected forward to future decades and scenarios with the relative frequency change metrics described above. For most countries, JBA provides data at 1/3600° (~30m) resolution, and we pass this through our analysis. For the US and several European countries, we aggregate JBA's 4.5e-5° (~5m) resolution to 0.000225° (~25m), due to contractual obligations. Note that this 5m-to-25m resolution reduction is not done by averaging; instead, we select the most flood prone 5m pixel inside the 25m pixel and assign those return period flood depths to the 25m pixel. In this way, we maintain the flood impact of the 5m resolution without specifying its location within the larger 25m pixel.

At each pixel (25m or 30m) we use Generalized Extreme Value (GEV) distributions to fit JBA's flood depths return period data. Once fit, we select the nine return periods to evaluate the distribution. For future decades, the distributions are shifted, both intercept and slope, according to the 10-year and 100-year frequency shifts described above. (In some cases, a two-component GEV fit is necessary, to accommodate break points in the depth return period data driven by inferred topography barriers.) In this way, we maintain the high spatial resolution, driven by heterogeneous elevation and topography implicit in JBA's modeling, with the lower resolution change envelope derived from the CMIP6 data.

JBA also provides information on municipal flood defenses, such as levees, in terms of stated return periods of protection. For example, a town may be stated to be protected to the 100-year flood level. We convert this information to a flood depth of protection at each pixel inside the protected region. Undefended flood depths are provided in output files, along with the defense elevation, so that the user can choose to apply the defense or not. In applying defenses, if the undefended depth is less than the defense level, no flooding occurs. However, if it exceeds the defense level, then flooding occurs to the full undefended depth.

Validation

JBA conducts extensive validation of their flood modeling. In addition, we have performed comparisons of flood maps to flooded extent data from specific historical flood events, as derived from the MODIS satellite instrument and archived by the Global Flood Database. In all cases tested, the modeled flood maps at sufficiently long return periods encompass the observed flood extents. More information about these comparisons can be found in published case studied in Sacramento and Frankfurt. By performing the comparisons at different return periods, we not only validate the model, but we are also able to estimate the return period of the historical event. In addition, we have performed country-by-country QA for the absolute fluvial flood metrics, ensuring that projected flooding follows known river channels and flood prone areas.

Data Availability

Both the relative and absolute fluvial flooding hazard data are available on Climanomics. Relative fluvial flooding hazard data are used in the Physical Risk dataset.

Heat Stress

Motivation

Heat stress poses a significant occupational hazard that can lead to serious health issues such as heat exhaustion and heat stroke. For businesses, this hazard results in decreased worker productivity, increased absenteeism, and a higher risk of workplace accidents. On a broader economic scale, heat stress contributes to billions of dollars in lost labor output and increased healthcare costs annually.

Metrics

The Heat Stress hazard is currently quantified via different metrics derived from the Heat Index (HI). This index is a measure of perceived temperature and combines relative humidity and temperature information. It is an absolute index with units of degrees Celsius. We provide a set of relative and absolute metrics defined below.

- The Average Maximum Heat Index (AvgTop10MxHI): The average of the annual top ten maximum daily HI values, reported as the average over each projected decade. This metric reflects daytime conditions (usually mid to late afternoon) and is based on the daily maximum temperature and minimum relative humidity. The units are degrees Celsius.
- The Average Minimum Heat Index (AvgTop10MnHI): The average of the annual top ten minimum daily HI values on the days when the top ten maximum annual HI values occurred, reported as the average over each projected decade. This metric reflects nighttime conditions (usually around dawn) and is based on the daily minimum temperature and maximum relative humidity. The units are degrees Celsius.
- The average annual number of days on which the daily maximum HI exceeds 32.2°C (Extreme Caution category), reported as decadal averages over each projected decade.
- The average annual number of days on which the daily maximum HI exceeds 39.4°C (Danger category), reported as decadal averages over each projected decade.

Methods

The Heat Index is calculated from daily minimum and maximum relative humidity and temperature. Since the downscaled NEX-GDDP CMIP6 relative humidity data shows strong biases when compared to reanalysis data, we bias correct the input variables prior to calculating the Heat Index. This bias correction is done via Quantile Delta Mapping using ERA5 as a target data set. Both input variables are corrected using this method to ensure consistency. Additionally, since the downscaled NEX-GDDP CMIP6 data set only provides daily mean relative humidity, we derive daily minimum and maximum temperature from a regression analysis of ERA5 data that relates the mean to the extrema. We then compute the Heat Index following Steadman (1979) and Rothfusz (1990), which also serves as the operational algorithm used by the National Weather Service in the United States. All hazard metrics are subsequently derived from the Heat Index as described in their definitions. The hazard metrics are computed over land only and available at a spatial resolution of one-quarter degree.

Validation

In the development of the Heat Stress hazard metric, we used ERA5 reanalysis as our primary historical reference to support bias correction, the derivation of daily humidity–temperature relationships, and the evaluation of baseline metrics. Since ERA5 does not output relative humidity directly, we computed hourly relative humidity in-house from hourly temperature and dew point data using the August–Roche–Magnus relationship. The Heat Stress hazard is based on the Heat Index which requires daily temperature and daily relative humidity to be calculated. Preliminary quality control revealed unphysical values when deriving the Heat Index from raw NEX-GDDP data. As such, we opt to bias-correct the NEX-GDDP input data using ERA5 reanalysis data using Quantile Delta Mapping. Note that this step is necessary in particular when constructing absolute hazards, as biases in the magnitude of the hazard metrics are concealed when using relative metrics.

To ensure that the Heat Index values are physically meaningful, since NEX-GDDP provides only daily mean relative humidity, we statistically estimated daily minimum relative humidity (which generally co-occurs with daily maximum temperature) and maximum relative humidity (which generally co-occurs with daily minimum temperature) by fitting a monthly, location-specific quadratic regression trained on hourly ERA5 over 1995–2014. This step helps preserve the co-occurrence of temperature and humidity extremes rather than pairing temperature extremes with same day mean humidity, thereby preventing over or underestimates of the Heat Index.

We validated the Heat Index by comparing the bias-corrected NEX-GDDP based version to that computed from ERA5. Note that consistency is expected since ERA5 was used to bias-correct the Heat Index input variables. Spatial patterns and the Heat Index magnitude are in strong agreement globally with regional discrepancies largely attributable to differences in the relative humidities in both data sets. The non-linearity of the Heat Index translates small differences in humidity to larger differences in the Heat Index. A detailed discussion is found in the technical report.

As outlined in the Extreme Heat and Extreme Cold hazards, previous internal quality control uncovered erroneous NEX-GDDP data at several grid cells for two scenarios (SSP1-2.6 and SSP3-7.0) in the daily minimum temperature (tasmin) and daily maximum temperature (tasmax) data. Since both variables are used for the Heat Index, at those grid cells, the GSAT regression is applied only to scenarios SSP2-4.5 and SSP5-8.5. Subsequently, the linear regression model is used to derive the forced daily mean temperature response at all four scenarios. This means that even at the affected grid cells, a hazard value is provided for all four scenarios. We applied additional QA controls during GSAT regression of annual threshold counts by capping regressed values to physically meaningful bounds (0–365 days).

Data Availability

AvgTop10MxHI data are available on Climanomics.

Landslides

Motivation

In complex terrain, rainfall-induced landslides are among the most widespread and destructive natural hazards, responsible for thousands of fatalities and billions of dollars in economic losses each year. As climate change intensifies the hydrological cycle, the frequency and severity of extreme precipitation events — the primary trigger for shallow landslides — are projected to increase across many regions. Yet most existing landslide inventories are backward-looking, offering limited insight into how hazard exposure will evolve under future climate scenarios.

Metrics

The landslide hazard has both a relative and absolute metric. The relative metric used to quantify landslide risk is the change in the number of days exceeding the 95th percentile of the 7-day Antecedent Rainfall Index (ARI). This metric has been shown to provide excellent landslide predictive power when combined with susceptibility maps that define how vulnerable a given area is to rainfall induced landslides (Kirschbaum et al. 2018). The absolute metric quantifies annual expected events, characterized using a hazard matrix that converts daily standardized precipitation and landslide susceptibility to event probability. The metric defines significant landslides and does not characterize small-scale landslides that can occur under equivalent rainfall.

Methods

To calculate the relative metric, the methodology estimates how climate change may alter rainfall conditions associated with landslide risk by combining a calibrated antecedent rainfall index (ARI) with global climate model (CMIP6) projections. ARI is calculated as a weighted average of daily precipitation over the previous 7 days, with stronger weight given to more recent rainfall, following Kirschbaum et al. (2018), and low-rainfall cases are excluded. Because landslide response also depends on terrain sensitivity, the analysis is interpreted alongside an existing global susceptibility classification based on factors such as slope and land cover. The susceptibility is defined on a 1 km grid (0.00833 degrees). The ARI threshold metrics calculated at 0.25 degrees are mapped to the 1 km susceptibility cells using a nearest neighbors algorithm. This means that the 1km cells take on the rainfall patterns estimated at a lower resolution but could experience more intense or less intense rainfall based on local factors including elevation changes and land cover. Future annual ARI distributions from 23 CMIP6 models under SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 are then used to compute the fraction of days each year exceeding that historical threshold, producing a global time series of future "days above threshold." Finally, because these annual results contain both climate-change signal and year-to-year variability, they are regressed against each model's GSAT trajectory to isolate the forced response, enabling scenario-consistent projections and multi-model ensemble averages by decade.

To calculate the absolute metric, the methodology combines hourly ERA5-Land precipitation and temperature at 0.1 degrees with a high-resolution susceptibility grid at 0.0083 degrees (Kirschbaum et al 2018). Daily triggering rainfall is standardized as z-scores relative to local climatology and fed into a hazard matrix parameterized by susceptibility class and standardized rainfall intensity to compute daily event probabilities. Annual expected event density is obtained by summing daily probabilities within susceptible pixels, and for future scenarios, daily precipitation from 22 NEX-GDDP climate models is linked to the grid using bias correction to align with ERA5-Land historical values. Daily triggering rainfall is standardized as z-scores relative to local climatology and fed into a hazard matrix parameterized by susceptibility class and standardized rainfall intensity to compute daily event probabilities. Annual expected event density is obtained by summing daily probabilities across susceptible pixels, and for future scenarios, daily precipitation from 22 NEX-GDDP climate models is linked to the grid using bias correction to align with ERA5-Land historical values.

The approach is calibrated and harmonized through two factors: a global multiplicative calibration that scales results to match the World Bank target of 400,000 annual events, and a pixel-level bias-correction factor that ensures each climate model-scenario combination reproduces the ERA5-Land baseline over 2015–2024. Annual trajectories are then regressed against standardized Global Surface Air Temperature (GSAT) to isolate climate change signals from interannual variability, with pixel-specific linear coefficients fitted per model. Results are aggregated to decadal scales with ensemble statistics (mean, 5th, 95th percentiles) and output separately by scenario.

Validation

We grounded the relative landslide hazard metric in observed events by calibrating the definition of the Antecedent Rainfall Index (ARI) (i.e. 7-day weighted rainfall window with a −2 weighting exponent) against an inventory of 949 historical landslides (2007–2013). Additionally, the 95th percentile historical ARI is an established way to parameterize landslide-risk thresholds in prior work. We then performed a qualitative, event-based check by confirming that most inventoried landslides occur at ARI < ~300 mm and within high susceptibility classes (4–5), while documenting that some events fall in lower classes because the inventory includes non-rainfall triggers. This cross-check helps validate that the combined ARI and susceptibility framework behaves as expected relative to the event record. We also used pre-existing landslide susceptibility maps that are described as consistent with ARI observations and apply a defined 1–5 susceptibility rating (driven primarily by slope and land cover).

To ensure a resolution consistent baseline, we compute the historical ARI 95th percentile threshold at 0.25° for each grid cell using the CMIP6 historical period (1950–2014) and used that for future exceedance calculations. We screened for model completeness by including only climate models with precipitation for the historical and all four projected scenarios. This avoids spurious cross-scenario comparisons. To remove unforced and uncancelled variability, we regress annual exceedance frequencies on GSAT to extract the forced climate-change signal and produce smoother scenario separation consistent with GSAT trajectories. After this regression, we applied post-processing QC to cap any negative exceedance frequencies to remove nonphysical values.

For the absolute metric, baseline expected event counts for the 2010s were evaluated at the locations of documented historical landslide disasters. A set of 36 large rainfall-triggered landslide events was compiled from public databases and published studies containing event location and timing information. Together, these events represent almost 400,000 mapped landslides. Event locations were aggregated to the resolution of the susceptibility grid (1 km^2), and the corresponding susceptibility classes and 2010s expected event counts were extracted. The results were then compared to determine which events occurred in locations that are flagged as highly susceptible and exposed to extreme event frequencies, relative to other locations.

Data Availability

Relative and absolute landslide data are available on Climanomics. Relative landslide data are used in the Physical Risk dataset.

Pluvial Flooding

Motivation

Pluvial flooding, also known as surface water flooding, occurs when heavy rainfall overwhelms the capacity of the ground and drainage systems to absorb or channel water away, leading to flooding in urban and rural areas independent of rivers or coastal surges. This type of flooding is particularly common in cities where extensive concrete and asphalt surfaces prevent water infiltration, causing runoff to accumulate rapidly. Pluvial flooding can damage infrastructure, homes and businesses, as well as cause disruption to transportation and emergency services.

Metrics

Two pluvial flood metrics are in use: 1. The future projected annual frequency of the baseline (1950-2000) 100-year return period flood depth. The baseline value is everywhere 0.01/year (1 in 100 years). The resolution is 0.25° (~25 km). This relative frequency metric is currently in use on delivery platforms. 2. The flood depth above ground (meters) at nine return periods (2, 5, 10, 20, 50, 100, 200, 500, 1000 years) at a resolution of 0.000225° (~25 m) in the US and several European countries and 1/3600° (~30m) elsewhere. This absolute flood hazard metric has been prepared for platform implementation in 2026.

Methods

The pluvial analysis starts with daily precipitation time series from 26 NEX-GDDP downscaled (0.25°) and debiased CMIP6 models. Note that the relative frequency change metric avoids the need for high resolution land elevation-based water channel modeling. The absolute flood depth is never specified, only the change in frequency of an unspecified baseline-period flood depth. (But see below for new high-resolution flood-depth hazard metrics.) A key additional approximation allows us to equate the change in frequency of extreme precipitation to the change in frequency of extreme pluvial flooding: topographic properties such as elevation, impervious surface fraction, soil absorption rate, and urban drainage capabilities are held fixed. With this assumption, the remaining variable factor causing change in pluvial flooding is the change in precipitation itself, and therefore it is sufficient to model precipitation change.

To model changes in extreme precipitation, at each 0.25° grid cell for each CMIP6 model we decompose the 151-year CMIP6 simulation period (1950-2014 historical and 2015-2100 projected) into seven 30-year windows and apply stationary Generalized Extreme Value (GEV) modeling to each window's sequence of annual maxima precipitation. Testing indicates that a 30-year duration is not sufficiently long to obtain reliable GEV estimates of the 100-year return period precipitation. We group the 8 adjacent 0.25° grid cells with the center grid cell, effectively extending the 30-year series to 270-year series. In the GEV fitting, we use a fixed shape parameter, as determined from the ERA5 analysis of Courty et al. (2019), but the location and scale parameters vary with the data. The series of GEV location and shape parameter window values are then regressed on the model's GSAT from all four SSP scenarios to obtain the climate-forced component, which is re-expressed for each decade and scenario.

Using the decadal values of GEV coefficients, we can derive the projected frequency of any selected baseline (1950-2000) return period. The projected frequency of the 100-year baseline return period (0.01/year by definition) is selected for the relative change metric. However, both the 10-year and 100-year are used for the high-resolution absolute flood depths.

The new pluvial hazard metric greatly improves upon the relative change metric by providing flood depth above ground at high resolution (0.000225°, or roughly 25m, in the US and some European countries and 1/3600°, or roughly 30m, elsewhere) at nine return periods, 2, 5, 10, 20, 50, 100, 200, 500, and 1000 years. We have partnered with the flood modeling firm JBA, who have provided global country-by-country current-climate flood depth data at up to six return periods. These pluvial flood depth data are projected forward to future decades and scenarios with the relative frequency change metrics described above. For most countries, JBA provides data at 1/3600° (~30m) resolution, and we pass this through our analysis. For the US and several European countries, JBA's resolution is 4.5e-5° (~5m), and we are contractually obliged to reduce the resolution to 0.000225° (~25m). Note that this 5m-to-25m resolution reduction is not done by averaging; instead, we select the most flood prone 5m pixel inside the 25m pixel and assign those RP flood depths to the 25m pixel. In this way, we maintain the flood impact of the 5m resolution without specifying its location within the larger 25m pixel.

At each pixel (25m or 30m) we use Generalized Extreme Value (GEV) distributions to fit JBA's pluvial flood depths return period data. Once fit, we select the nine return periods to evaluate the distribution. For future decades, the distributions are shifted, both intercept and slope, according to the 10-year and 100-year pluvial frequency shifts described above. (In some cases, a two-component GEV fit is necessary, to accommodate break points in the depth return period data driven by inferred topography barriers.) In this way, we maintain the high spatial resolution, driven by heterogeneous elevation and topography implicit in JBA's modeling, with the lower resolution change envelope derived from the CMIP6 data.

Validation

JBA conducts extensive validation of their flood modeling which is relevant to the new pluvial flood depth metric. In addition, we have performed comparisons of flood maps to flooded extent data from specific historical flood events that include fluvial and pluvial, as derived from the MODIS satellite instrument and archived by the Global Flood Database. In all cases tested, the modeled flood maps at sufficiently long return periods encompass the observed flood extents. By performing the comparisons at different return periods, we not only validate the model, but we are also able to estimate the return period of the historical event. In addition, we have performed country-by-country QA for the absolute pluvial flood metrics, ensuring that projected flooding follows patterns in the local topography.

Data Availability

Relative pluvial flooding hazard data are available on Climanomics. Relative pluvial flooding hazard data are used in the Physical Hazard dataset. Absolute pluvial flooding hazard data will be released towards the end of 2026.

Subsidence

Motivation

Land subsidence is a gradual but consequential hazard driven in many regions by long-term groundwater depletion. When groundwater is withdrawn faster than aquifers can recharge, pore pressures decline and compressible sediments compact, causing the land surface to sink. This downward motion can damage buildings, roads, pipelines, and other infrastructure, reduce drainage capacity, increase flood exposure, and permanently diminish groundwater storage. Because subsidence often accumulates slowly over time and may not be visible until impacts are substantial, a quantitative indicator is needed to track where groundwater stress is most likely to translate into material surface deformation.

Metrics

The absolute annual subsidence rate in mm/year is reported as the subsidence metric and defines the rate attributable to groundwater depletion.

Methods

The methodology defines groundwater-depletion-driven subsidence hazard at each 1 km location as the product of two modeled components: the probability that subsidence occurs, based on geologic susceptibility, and the rate of subsidence expected under groundwater depletion, yielding an absolute hazard metric in mm/year. The probability component is derived from the Herrera-Garcia et al. groundwater subsidence susceptibility index (GSS), a global 1 km dataset ranked from 1 to 6, by fitting a global logistic regression between GSS and observed subsidence occurrence using InSAR-based vertical land motion data from California, Iran, and several European countries; subsidence presence was defined where mean vertical displacement exceeded 1 mm/year downward, and model skill was evaluated with a 70/30 train-test split, producing an AUC of 0.73 before final coefficients were fit using all data. The rate component relates subsidence magnitude to groundwater depletion estimated from ISIMIP hydrological outputs, where depletion is calculated as total potential groundwater withdrawals minus recharge, negative values are set to zero, extreme values are capped for quality control, and five CMIP6-WaterGAP model combinations are averaged, then interpolated from 0.5° to 1 km for baseline and future decades under SSP1-2.6, SSP3-7.0, and SSP5-8.5. A constrained linear model, fit to compiled global observations of subsidence and depletion, is then used to estimate subsidence rate from depletion, with the median quantile relationship adopted as the central estimate.

Validation

We applied a number of preprocessing QA steps to ensure the subsidence model is trained on physically credible signals. We calibrated InSAR satellite vertical-displacement measurements against high resolution ground GPS observations and noted that the work is backed by extensometer measurements in some areas. We prioritized cross-region consistency by selecting European and California InSAR products processed by the same contractor (TRE Altamira) using similar procedures. Our model was trained only on regions with reliable high-resolution gridded displacement data (California, Iran, and selected European countries), regions with conflicting or inconsistent uplift signals (e.g. from glacial isostatic adjustment) were removed.

We defined subsidence occurrence labels in a controlled way using the 1 km mean displacement rate, marking a pixel as subsiding only if mean displacement is > 1 mm/year, and we curated the displacement compilation by modifying the Davydzenka et al. (2024) dataset—replacing California with more recent regional datasets from the California Department of Water Resources and adding data compiled for Iran from Haghighi & Motagh (2024)—while explicitly documenting that compiled surveys vary by satellite generation, period, and processing pedigree (treating expert-processed products as higher reliability). We also documented a known interpretability limitation in susceptibility inputs by noting that step changes along political boundaries in the GSS layer likely reflect reporting/assembly artifacts rather than true geologic discontinuities. These discontinuities across political boundaries impact the subsidence model's results, and the model could be improved in the future with improved consistency in reporting across political boundaries.

We validated and constrained model components and final outputs to maintain physical plausibility and reduce noise. Groundwater depletion scenarios are used to estimate subsidence rates using a predictive model. The depletion scenarios are calculated from water withdrawal and groundwater recharge components obtained from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) for the WaterGAP global hydrological model. We enforced physically constrained preprocessing by setting negative depletion to zero and capping extreme depletion at the 99.5th percentile for quality assurance. We included five GCM realizations of the WaterGAP ensemble and computed an ensemble-mean depletion field. The transformation involves spatial processing by bilinearly interpolating 0.5° depletion to the 1 km grid. For the probability component, we performed out of sample validation by splitting data 70%/30% into training/evaluation, assessing skill with ROC curves, summarizing performance with AUC = 0.73, and only then refitting on all data to finalize coefficients between depletion and subsidence rate (b = −3.847, m = 0.693). For the rate component, we calibrated the subsidence–depletion relationship using linear least squares constrained through (0,0) (zero depletion implies zero subsidence), fit multiple quantiles (50th, 75th, 90th, 95th, 99th) to characterize scatter and support uncertainty-aware use, and restricted fitting to positive depletion and downward motion to avoid contamination from uplift or recharge-dominant processes. At the whole-metric level, we checked system behavior by tracking globally aggregated "volume subsided through time" to confirm scenario ordering and diagnose variability. We then reduced incoherent decadal variability by fitting grid-cell linear time trends (constrained to start at the baseline value) as a smoothing step because GSAT regression is not applicable to depletion-driven signals. Finally, to avoid false precision given compounding uncertainties, we released an additional six-bin categorical hazard (low to extreme) alongside continuous mm/year values as a results QA/communication control.

Data Availability

Subsidence hazard data are available for export on Climanomics.

Surface Wind

Motivation

Surface wind is important because it poses risks to public safety, including injuries and fatalities from flying debris and structural damage. High winds can damage infrastructure such as power lines, buildings, and transportation networks, leading to costly repairs and disruptions. They also affect transportation safety, especially for aviation and road travel, by causing turbulence and accidents. Surface winds influence environmental conditions by spreading wildfires, dispersing pollutants, and impacting local weather patterns. Finally, wind hazards can disrupt economic activities, including energy production, agriculture, and commerce, making it essential to monitor and manage these risks.

Metrics

The surface wind hazard is made up of a set of relative metrics as well as change factor ratios. The relative metrics are calculated annually and for the four seasons and are defined as follows.

- Strong winds: Frequency of days above the historical 90th percentile baseline surface wind speed.
- Light winds: Frequency of days below the historical 10th percentile baseline surface wind speed.

The change factor metric is defined as the ratio between the mean annual projected surface wind and the historical baseline surface wind.

Methods

The Surface Wind hazard is computed from daily surface wind variable of the downscaled NEX-GDDP CMIP6 models. We compute the historical thresholds from the historical scenario and subsequently count threshold exceedances to arrive at the hazard metrics as defined above. The hazard metrics are computed over land only and available at a spatial resolution of one-quarter degree.

Validation

The NEX-GDDP surface wind variable is subject to a number of documented inconsistencies, all of which were addressed prior to the construction of the metric. First, similar to other hazards, we made use of only those climate models that provide the surface wind variable for the historical period and all four projected scenarios.

We excluded model KACE1-0-G after detecting major historical-to-projection discontinuities. We retained model CMCC-ESM2 regardless of the known missing year 2014 values by redefining the historical baseline for that model to 1950–2013. We also screened for a known SSP3-7.0 regional anomaly (where SSP3-7.0 had distinct regional differences from the other scenarios) consistent with prior analysis and published findings (Shen et al., 2022). We prevented that pattern from biasing our forced-signal estimation by excluding SSP3-7.0 when fitting regression coefficients and later reconstructing SSP3-7.0 using the GSAT-regressed forced-response coefficients. We ensured all surface wind values were physically meaningful by flagging negative values and setting an upper cap of 135 meters per second. Values outside of that range were deemed unrealistic, set to NA, and subsequently interpolated in time.

Post GSAT regression of the frequency metric, we explicitly checked whether regressed frequencies fell outside the physically meaningful 0 to 1 range and confirmed that no out-of-bounds values occurred, so no post-hoc capping was required. To validate our GSAT regression approach, we computed the standard error of the regression slope. The ratio of the slope to its error provides a measure of the slope's significance. If the slope is near zero, we conclude that changes in the wind speed at that location for that model is not a "forced" signal, that is, it is not driven by global climate change. Hence, in our application, a statistically insignificant result has value and tells us that climate forcing does not play a role. Finally, we also qualitatively validated the spatial pattern of our metric against published results in the peer-reviewed literature and found good agreement.

Data Availability

Both strong and light surface wind data are available on Climanomics.

Tropical Cyclone

Motivation

Tropical cyclones pose significant physical hazards, including destructive winds, which can cause extensive damage to infrastructure and property. These events often lead to immediate business disruptions, such as supply chain interruptions, operational shutdowns, and damage to facilities. The economic impact extends beyond direct damages, encompassing recovery costs, lost revenue, and increased insurance premiums. Overall, tropical cyclones can have profound and lasting effects on regional economies and business resilience.

Metrics

Two metrics from the TC model are currently in use: 1. The annual frequency of Category 3 and higher ("Cat3+") TCs passing within 50 km of locations on a 25 km grid. 2. Surface TC wind speed (km/hour) at nine return periods (2, 5, 10, 20, 50, 100, 200, 500, and 1000 years) on a 25 km grid. Note that wind speeds are "marine equivalent exposure" wind speeds. That is, they represent wind speeds 10m above the surface as if over open water. Neither frictional topographic nor other obstructions are included currently.

Methods

The tropical cyclone (TC) model is a globalized version of the North American Stochastic Hurricane Model (NASHM), which has been extensively published in the peer-reviewed literature (e.g., Hall and Jewson, 2007; Hall and Yonekura, 2013; Hall et al, 2021). The model generates large ensembles of stochastic TC tracks (6-hourly TC-center location, date, time, central pressure, maximum sustained windspeed, and radial extent) trained on TC observations recorded by various national meteorological agencies, as archived and quality controlled in the Joint Typhoon Warning Center (JTWC) repository (Howell et al. 2025). To capture the effects of climate variability and change, model training data also includes seasonal and regional averaged sea-surface temperature (SST) metrics. SST is a key influence on TC behavior. We capture this influence in the historical record, then project the relationships to future decades and scenarios using the SST metrics from CMIP6 models. However, because the SST-TC relationships are indirect and imperfectly captured in the training, it is not appropriate to extrapolate the relationships to SST well outside the range in the training period. Thus, we only project TC changes to the 2040s, flatlining activity at the 2040s values for future decades. Global climate models, to the extent they can directly simulate TCs, predict a wide range of projected activity.

The basic TC model consists of four components: formation (how many, where and when in the year a TC forms), propagation (where does a TC propagate), intensity (the evolution along the TC track of the maximum sustained near-surface wind speed), and termination (where does the TC track terminate). Each of the components is stochastic, and each depends on the SST metrics with different sensitivities. The methodological approaches to simulating these components and their statistical relations to SST are described in the papers referenced above.

Once large (50,000 years) stochastic TC sets are simulated for SST metric values of the baseline and future decades, various gridded diagnostics are computed over the tracks.

The model predicts large regional variation in TC climate change signals, with some regions experiencing decreasing hazard and other increasing hazard. This variation is due to the often-competing SST sensitivities of the different TC components. For example, while strong TCs are generally forecast to become stronger (greater wind speed), the paths they take on average also change. Even if TC intensity is increasing overall, if its less likely to landfall on a particular region, that region's hazard may be reduced.

Validation

The TC model has undergone extensive validation of its predicted regional landfall statistics, including out of sample tests against regional observations (Hall and Jewson, 2008). In addition, Hall et al (2021) demonstrated that the model's climate sensitivity provides a demonstrable increase in regional forecast skill in out of sample tests. The TC model has also been used for seasonal forecasting the North American sector, and its seasonal forecast skill has been evaluated. In addition, we have used the model to calculate the climate change component of specific historical TCs, such as Hurricane Melissa in 2025, and the estimates compare favorably to other studies.

Data Availability

Both the relative and absolute tropical cyclone data are available on Climanomics. The frequency of Cat3+ storms is used in the Physical Risk dataset.

Wildfires

Motivation

Wildfires pose a significant physical hazard to businesses by threatening infrastructure, assets, and operational continuity. The immediate impacts include property damage, operational shutdowns, supply chain disruptions, loss of life, and health effects. Beyond the direct effects, wildfires can lead to substantial economic losses through increased insurance costs, recovery expenses, and reduced economic activity in affected regions.

Metrics

The Wildfire hazard is currently quantified by a relative and absolute metric, both of which are based on the Fire Weather Index (FWI) and quantify wildfire conditions. The relative metric is defined as the number of days on which the FWI exceeds the historical 90th percentile baseline. The absolute metric is defined as the number of days on which the FWI exceeds high wildfire conditions (FWI > 23.1).

Methods

The FWI is computed from input variables of the downscaled NEX-GDDP CMIP6 data set. Specifically, we make use of temperature, relative humidity, surface winds, and precipitation. The FWI was developed for the Canadian Forest Fire Danger System, a methodology which we follow here. Since the calculation requires all variables to be at local noon, we use a regression on ERA5 data to derive local noon conditions from the daily mean variables available to us. As part of the FWI calculation, we compute the length of the fire season from daily temperature data. To allow for the most realistic representation of wildfire conditions, we overwinter the drought code involved in the computation of the FWI. This means that we accumulate precipitation during the off-fire season, which allows us to take into account past weather conditions in the projections of wildfire conditions for the next season.

Validation

The input variables of the Fire Weather Index (FWI) underwent extensive quality control prior to calculation. We restricted the CMIP6 ensemble to models that provide all four required variables (temperature, relative humidity, precipitation, and surface winds) across all scenarios to avoid partial-input calculations and inconsistent coverage. We computed the FWI over land-only grid cells using a landmask created by downscaling ETOPO v2 topography to the NEX-GDDP 0.25° grid. We standardized time to the Gregorian calendar with leap years, filled missing daily values by time interpolation per model and grid cell to prevent gaps from propagating through the recursive moisture codes. We enforced physical plausibility via range checks on each input variable (precipitation < 0 → 0; surface winds < 0 → 0; surface winds > 500 km/hour → NA then interpolated).

Since FWI requires input variables at local noon but the climate models only output daily averages or extremes, we apply a regression based on ERA5 variables to derive conditions at local noon. We evaluate the approach by mapping root mean square error between “actual” ERA5 local-noon values and regression-estimated local-noon values for temperature, relative humidity, and surface wind, documenting that errors are generally low for wind and temperature and larger for relative humidity (8–10% in some regions) but acceptable given the absence of other proxies.

To reduce artificial discontinuities, we defined fire-season start and end dates using sustained temperature thresholds (start: daily maximum temperature > 12°C for 3 consecutive days; end: daily maximum temperature < 5°C for 3 consecutive days) rather than calendar boundaries. We also standardized initialization values of the moisture code and implemented overwintering for the drought code to avoid underestimating risk after dry winters or falls.

We assessed robustness and validation through both sensitivity testing and benchmarking against independent ERA5-based FWI products. We ran targeted sensitivity simulations at two test locations (California and Texas) by varying one meteorological driver at a time (holding the others at local means) and by varying pairs of drivers to generate joint-response contour plots. This confirmed that FWI is most sensitive to precipitation, that the canonical high-danger pattern (low precipitation, high temperature, low relative humidity, high wind) yields elevated FWI, and that responses to temperature, relative humidity, and wind are nonlinear (approximately exponential over tested ranges), with precipitation often dominating but interacting with warming. We then validated our method by computing FWI from historical ERA5 with our workflow and comparing it to two published ERA5-based datasets—McElhinny et al. (2020) and Copernicus CEMS EFFIS FWI—using five-point locations for 2005 (Australia, California, Texas, Ecuador, Algeria). We quantified agreement via time-series correlations (strong for 4 of the 5 sites with $r > 0.9$; lower for Ecuador where FWI is very low), compared mean ± standard deviation across methods, and contextualized residual differences by documenting expected drivers (grid differences between native ERA5 and the NEX-GDDP grid, and differing fire-season definitions across products).

Data Availability

Both the relative and absolute wildfire hazard data are available on Climanomics. FWI is used in the Physical Risk dataset.

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