Hazard Explorer: Technical Methodology

Hazard Data Methodology — Abbreviated • v1.0 • 2026-03-12

Prepared by D.J. Rasmussen, PhD • Degree Day, LLC
dj.rasmussen@degreeday.org • www.degreeday.org

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1 Overview

The Hazard Explorer provides a consistent framework for assessing the exposure of assets worldwide to both climate-related and geological hazards. Included perils span flooding, extreme heat, drought, wildfire, extreme winds, hail, earthquakes, landslides, and land subsidence. Rather than developing all datasets from scratch, the methodology curates and integrates dozens of peer-reviewed, globally recognized datasets to ensure that information is scientifically credible and transparently documented. These data sources include historical weather observations, reanalysis datasets, land cover and elevation data, and specialized models for hazards such as flooding and drought. Data are typically represented on global grids, in some cases down to 90 m resolution for flood inundation.

The **Hazard Explorer** presents these data through an interactive mapping interface for global hazard screening. Each hazard layer is scored on a 1–10 scale with accompanying hazard categories. The application is designed for exposure screening only; it does not model vulnerability, loss, or resilience.

Table 1 summarizes the hazard metrics presented in the Hazard Explorer, including the physical quantity, statistical basis, units, spatial resolution, and data source for each layer.

Table 1: Summary of hazard metrics in the Hazard Explorer.

Hazard Layer	Metric	Units	Resolution	Source
Wildfire	Annual burn probability	%/yr	30″ (∼1 km)	Multi-source; Proprietary
Extreme Heat	Annual max. temperature, 10-yr return level	°C	30″ (∼1 km)	Multi-source; Proprietary
Human Heat Stress	Annual max. wet-bulb temperature, 10-yr return level	°C	30″ (∼1 km)	Multi-source; Proprietary
Human Cold Stress	Annual min. temperature, 10-yr return level	°C	30″ (∼1 km)	Multi-source; Proprietary
Snowfall Intensity	Mean annual max. 1-day snowfall	m SWE	∼10 km	Reanalysis
Drought	Composite drought hazard score	Index	Basin	Proprietary
River & Coastal Flood	Flood depth	m	1″ (∼30 m)	Multi-source
Coastal Exposure	Coastal Exposure Index	Index	1–30 m	Multi-source; Proprietary
Surface Water Flooding	Annual max. hourly precip., 50-yr return level	mm	30″ (∼1 km)	Proprietary
Extreme Wind	3-s wind gust, 1,000-yr return level	km/h	30″ (∼1 km)	Multi-source; Proprietary
Lightning	Annual thunder hours	hrs/yr	∼5 km	Satellite-based
Large Hail	Annual prob. of large hail day (>5 cm)	%/yr	∼31 km	Reanalysis-based
Tornado (U.S.)	Annual prob. of EF2+ tornado	%/yr	∼40 km	Observational
Derecho (U.S.)	Annualized derecho-footprint frequency	yr^{-1}	∼4 km	Observational
Earthquake	PGA, 475-yr return period (rock site)	g	∼11 km	Multi-source mosaic
Land Subsidence	Land subsidence rate	mm/yr	30″ (∼1 km)	ML-based global model
Landslide (U.S.)	Susceptibility score	Index	3″ (∼90 m)	USGS
Landslide (Global)	Susceptibility score	Index	3″ (∼90 m)	Published global model
Heating Demand	Annual HDD (base 18.3 °C)	°C-day	30″ (∼1 km)	Multi-source; Proprietary
Cooling Demand	Annual CDD (base 18.3 °C)	°C-day	30″ (∼1 km)	Multi-source; Proprietary

Table 2 describes the practical relevance of each metric and the rationale for the statistical basis or return period chosen.

Table 2: Metric relevance and rationale.

Hazard Layer	Relevance
Wildfire	Annual burn probability quantifies the likelihood that a location experiences wildfire in any given year, informing land-use planning, insurance underwriting, and defensible-space requirements.
Extreme Heat	The 10-year return level of annual maximum temperature captures rare but realistic hot extremes that stress infrastructure (pavement buckling, transformer failures, power-grid strain) and affect outdoor worker safety and productivity.
Human Heat Stress	Wet-bulb temperature integrates heat and humidity, reflecting physiological heat-stress limits more accurately than air temperature alone. A 10-year return level identifies locations where dangerous heat-stress episodes affect outdoor worker safety and productivity.
Human Cold Stress	The 10-year return level of annual minimum temperature captures cold extremes that drive pipe bursting, heating-demand spikes, and hypothermia risk. This return period is relevant for outdoor worker safety and mechanical-system design.
Snowfall Intensity	Mean annual maximum 1-day snowfall captures the magnitude of the heaviest single-day snow accumulation in a typical year, relevant for structural roof loading, transportation disruption, and emergency planning.
Drought	A composite drought hazard score integrates meteorological, hydrological, and agricultural drought dimensions into a single index, supporting water-supply planning and supply-chain resilience analysis.
River & Coastal Flood	Flooded land area directly quantifies the spatial extent of potential inundation at a location, making it well suited for screening property exposure and prioritizing sites for detailed hydraulic study.
Coastal Exposure	Identifies land areas whose elevation falls below hypothetical extreme coastal water level elevations, supporting screening of long-term tidal and sea-level-rise exposure for coastal portfolios, infrastructure planning, and site prioritization.
Surface Water Flooding	The 50-year hourly rainfall depth captures the short-duration, high-intensity precipitation events most likely to overwhelm urban drainage systems and cause surface water flooding.
Extreme Wind	The 3-second gust is the standard metric for structural wind loading in building codes worldwide. The 1 000-year return period aligns with design standards for critical and essential facilities.
Lightning	Annual thunder hours indicate the frequency of thunderstorm activity, relevant for designing electrical-system protection, assessing outdoor-activity safety, and evaluating wildfire ignition risk from lightning strikes.
Large Hail	Hailstones exceeding 5 cm can cause significant damage to roofs, facades, vehicles, solar panels, and crops. The annual probability of a large-hail day informs material selection, insurance pricing, and maintenance planning.
Tornado (U.S.)	EF2+ tornadoes generate winds exceeding 180 km/h, capable of significant structural damage. The annual probability informs safe-room requirements, shelter planning, and insurance risk. Coverage is limited to the contiguous United States.

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Table 2 continued

Hazard Layer	**Relevance**
Derecho (U.S.)	Derechos are long-lived, widespread windstorms produced by organized convective systems. The annualized footprint frequency quantifies how often a location is affected by derecho-force winds, informing infrastructure resilience, utility planning, and insurance risk. Coverage is limited to the United States east of the Rocky Mountains.
Earthquake	Peak ground acceleration on rock is the standard seismic-hazard metric used in building codes worldwide. The 475-year return period corresponds to a 10 % probability of exceedance in 50 years, the most widely adopted seismic design level.
Land Subsidence	Gradual ground subsidence damages foundations, buried pipelines, roads, aviation runways, and rail infrastructure over time. The annual rate indicates long-term structural and maintenance risk.
Landslide (U.S.)	A susceptibility score reflects terrain vulnerability to landslides based on slope, geology, soil properties, and land cover, supporting development siting and slope-stability screening.
Landslide (Global)	Provides the same landslide susceptibility information as the U.S. layer but with global coverage, enabling consistent screening of international portfolios.
Heating Demand	Heating degree days quantify cumulative cold exposure that drives space-heating energy consumption. Higher values indicate greater heating costs, fuel demand, and mechanical-system sizing requirements.
Cooling Demand	Cooling degree days quantify cumulative warm exposure that drives space-cooling energy consumption. Higher values indicate greater cooling costs, peak electricity demand, and refrigeration infrastructure needs.

For each hazard, notable advantages and limitations are summarized. Because appropriate use cases vary widely, expert judgment is required to interpret results in the context of a specific application. General considerations and limitations are provided at the end of this document.

2 Hazards

2.1 Flooding

Flood hazard is assessed from both inland and coastal sources. Inland flooding encompasses riverine (fluvial) and stormwater (pluvial) mechanisms, while coastal flooding captures sea-level rise, tides, and storm surge. Each is evaluated separately due to distinct causal drivers, physical mechanisms, and modeling approaches.

A Note on Elevation Data. Accurate elevation data is fundamental to flood hazard modeling. The quality of any flood depth or inundation extent estimate is strongly dependent on the underlying digital elevation model. Airborne lidar and ground-based surveys provide the most reliable terrain data, with sub-metre vertical accuracy, but such datasets are available only in a limited number of countries and regions. Where high-quality survey data are unavailable, satellite-derived elevation products are used instead. These datasets vary considerably in accuracy from place to place, depending on land cover, terrain complexity, and sensor characteristics. Users should be aware that flood hazard estimates in regions relying on satellite-derived elevation data carry greater vertical uncertainty, and results in those areas should be interpreted as screening-level assessments rather than engineering-grade predictions.

2.1.1 Inland Flooding

Inland flooding is assessed by analyzing its two primary drivers: riverine and stormwater flood hazards.

Riverine Flood. Riverine flooding occurs when rivers, streams, or other natural channels overflow their banks due to excessive water input. The riverine flood hazard layers provide flood inundation depths for multiple return periods at $\sim$90 m resolution, developed using a chain of hydrological and 2D hydraulic models forced by reanalysis meteorology. Flood defenses are not represented; inundation extents represent undefended flood hazard.

Limitations: Flood defenses are not incorporated; the model is not locally calibrated at the hydraulic level; smaller headwater streams below a minimum upstream area threshold are excluded.

Surface Water Flooding. Surface water (pluvial) flooding occurs when rainfall exceeds local drainage capacity and water ponds on developed surfaces. Because it is not feasible to simulate drainage systems and local ponding processes at global scale, this hazard is screened using the frequency and magnitude of extreme hourly rainfall as a proxy for the meteorological conditions that can lead to surface water flooding.

Extreme hourly precipitation statistics are derived using a rainfall-specific extreme value framework applied to quality-controlled hourly gauge observations and dynamically downscaled reanalysis using high-resolution convection-permitting numerical weather simulations. The resulting statistics are regionalized to a 30″ ($\sim$1 km) grid using machine learning and environmental predictors.

Limitations: Results represent extreme rainfall hazard as a proxy; they do not simulate runoff, drainage performance, or flood depth directly. Areas with similar rainfall hazard may experience different flood outcomes depending on imperviousness, terrain, and drainage infrastructure.

2.1.2 Coastal Flooding

The coastal flood hazard layer provides probabilistic flood depth estimates for the 100-year return period at 1″ ($\sim$30 m) resolution globally. Coastal flood forcing combines extratropical cyclone surges driven by reanalysis data, synthetic tropical cyclone surges, and astronomical tidal levels to produce storm tide return levels along the global coastline. These water levels are spatially interpolated and used as inputs to a connectivity-based inundation screening model.

Surface elevations are derived from a high-resolution ($\sim$30 m) global coastal digital terrain model corrected using spaceborne lidar. Vertical datum alignment between the geoid and local mean sea level is applied globally.

The inundation model propagates water inland from coastal seed pixels using a connectivity-based bathtub approach with distance-based energy attenuation. Attenuation rates vary as a function of surface water occurrence, with lower attenuation in permanent waterways and higher attenuation over dry land. Flood depth is computed as the difference between the propagated effective water level and the local DEM elevation.

Advantages: Globally consistent; explicitly accounts for tropical cyclone surge via synthetic TC tracks; high-resolution coastal DEM with sub-metre vertical accuracy.
Limitations: The model is not mass, momentum, or energy conserving; inundation extents may be overestimated. Does not account for wave setup, wave runup, or dynamic flow routing. Coastal flood protection infrastructure is not represented. Compound flooding is not captured. Coastal DEM vertical accuracy ($\sim$0.45 m MAE globally) introduces uncertainty in low-lying terrain.

2.1.3 Flood Defense Data

Both the riverine and coastal flood hazard layers represent *undefended* flood hazard: levees, floodwalls, storm surge barriers, and other engineered defenses are not incorporated into the hydraulic or inundation models. To provide context on where flood defenses may reduce actual risk, a global levee inventory has been compiled from official government sources and open-source levee databases covering over 20 countries. The inventory is used as a spatial overlay to flag locations where engineered flood defenses are present. Where design heights are available, levees are assumed to provide protection up to their design capacity; elsewhere, only the presence of a defense structure is flagged. The inventory is not exhaustive, particularly in South and Southeast Asia, Sub-Saharan Africa, and Latin America.

2.2 Coastal Exposure

The Coastal Exposure Index identifies land areas whose elevation falls below hypothetical extreme coastal water level elevations, providing a screening tool for long-term tidal and sea-level-rise exposure. The baseline water level is referenced to the mean higher high water (MHHW) tidal datum, derived from published tidal benchmarks within the United States and from a global tidal model elsewhere. Global mean dynamic topography corrections are applied to ensure vertical datum consistency.

Within the United States, the Index uses lidar-derived digital elevation models. Outside the United States, a satellite-corrected global coastal digital terrain model provides elevations at 1′′ (∼30 m) resolution. Areas are identified as exposed when land elevation falls below the selected water level threshold and is hydraulically connected to the coast. Topographically isolated low-lying areas are excluded by default. Levee and coastal defense data are incorporated within the United States.

Advantages: Uses peer-reviewed elevation data and published tidal benchmarks; connectivity-based delineation excludes topographically isolated areas; integrates coastal defense data within the United States; globally consistent screening at 1–30 m resolution.
Limitations: Not based on physical storm or flood simulation. Does not account for erosion, changes in storm frequency, inland flooding, or rainfall. Satellite-derived elevation accuracy (∼0.45 m MAE globally) introduces uncertainty. Best suited for long-term tidal exposure screening; site-level decisions should be supported by local surveys.

2.3 Temperature and Energy Demand

This section describes methods for assessing extreme temperature hazards and their implications for building energy demand.

2.3.1 Human Cold and Heat Stress

Extreme temperature hazards are assessed using a regionalization framework that combines station-level extreme value modeling with machine-learning-based spatial prediction. The analysis focuses on two metrics: (1) extreme cold temperature and (2) extreme wet-bulb temperature.

Quality-controlled weather station observations from global archives are used to fit extreme value distributions at each station. Wet-bulb temperature is calculated from air temperature and humidity observations. Annual block maxima (or minima for cold extremes) are modeled using an extreme value distribution within a non-stationary Bayesian framework that accounts for temporal trends. Return levels are estimated for specified recurrence intervals (e.g., 10-year, 50-year).

To produce spatially continuous global fields at 30′′ (∼1 km) resolution, station-derived distribution parameters are regionalized using a machine learning model with high-resolution climate, elevation, and terrain predictors.

Advantages: Grounded in observed station data; non-stationary Bayesian framework quantifies uncertainty; high-resolution (1 km) global estimates; explicitly models wet-bulb temperature for combined heat and humidity stress.
Limitations: Results depend on station density and record length. Wet-bulb calculations rely on humidity observation accuracy. The analysis characterizes meteorological extremes only and does not model vulnerability or infrastructure response.

2.3.2 Energy Demand

Building-related energy demand is assessed using Heating Degree Days (HDD) and Cooling Degree Days (CDD), calculated from daily temperature fields derived from a high-resolution (30′′; ∼1 km) global climate dataset for the period 2004–2023. The underlying climate data are produced using a statistical downscaling approach that accounts for topographic influences on temperature and precipitation.

HDD and CDD are computed relative to a standard 18.3 °C (65 °F) balance-point temperature and aggregated to annual totals.

Advantages: High spatial resolution (1 km) with terrain-informed temperature fields; standardized methodology ensures cross-regional comparability.
Limitations: Degree-day metrics approximate temperature-driven demand only and do not account for humidity, solar gains, building efficiency, or behavioral adaptation. The fixed balance point may not represent all building types.

2.4 Snowfall Intensity

Snowfall intensity is assessed using a proxy derived from a global land-surface reanalysis product at ∼10 km resolution. Snowfall is estimated from positive day-to-day changes in snow depth (snow water equivalent, SWE) computed from daily mean snow depth fields spanning several decades of reanalysis record. For each year, the annual maximum 1-day snowfall is extracted, and the intensity metric is the long-term mean of these annual maxima, expressed in meters of SWE. **Advantages:** Multi-decadal record provides stable climatological estimates; global land coverage at ∼10 km resolution; consistent reanalysis-based methodology avoids reliance on sparse gauge networks for snowfall measurement.
Limitations: Snowfall is inferred from changes in snow depth rather than measured directly; the proxy underestimates true snowfall when within-day melt or compaction offsets accumulation. Conversion from SWE to physical snow depth requires an assumed snow density ratio. Reanalysis-based values in data-sparse regions carry greater uncertainty.

2.5 Wildfire

Estimating wildfire hazard is inherently complex due to the many interacting drivers of fire behavior, including atmospheric conditions, ignition sources, fuel availability, and fire suppression. Modeling fire spread introduces further complexity, and limited observations of large, high-intensity wildfires constrain calibration and validation efforts. All estimates should be carefully scrutinized.

The wildfire hazard model is a machine learning framework trained on detailed wildfire modeling outputs from the U.S. Forest Service and high-resolution (30′′; ∼1 km) global environmental predictors. The methodology integrates multiple spatially explicit variables characterizing climatic forcing, fuel aridity, surface conditions, and ecological context. Predictor categories include bioclimatic variables, moisture indices, wind speed, snow metrics, terrain, and biome classifications.

The model is trained on spatial samples across the United States using a spatial block cross-validation strategy to ensure geographic robustness. Topographic–moisture interaction terms are used to reduce biases in humid high-elevation regions by conditioning predictions on fuel aridity. Global inference is performed at 30′′ (∼1 km) resolution, with predictions masked to burnable land classes using satellite-derived land cover data.

Advantages: High-resolution (1 km) global coverage; terrain-informed climate inputs; spatial cross-validation for robustness; explicit masking of non-burnable land classes.
Limitations: The model is trained exclusively on U.S. burn probability data. Global application assumes that relationships learned in U.S. ecosystems transfer to other continents; transferability has not been formally validated outside the training domain. The framework does not explicitly simulate ignition frequency, human suppression, or dynamic fire spread.

2.6 Drought

Meteorological drought is assessed using basin-scale precipitation deficits derived from observation-constrained reanalysis data. Precipitation drought metrics are computed at two complementary spatial scales: hydrologically defined watersheds and first-order administrative regions for complete global coverage.

Long-term daily precipitation from a global reanalysis product is aggregated to multi-year accumulations to capture persistence relevant to water supply systems and reservoir storage. Extreme value analysis is applied to annual minima of rolling multi-year precipitation accumulations to estimate return levels for rare drought events (e.g., 25-year, 50-year, 100-year).

The composite drought hazard score (0–100) emphasizes absolute hydrological scarcity rather than relative departures from local climatology. For each spatial unit, remaining water is estimated as the climatological mean precipitation minus the rare drought deficit. This quantity is then transformed into a globally comparable score using a percentile-based ranking, where regions with the least remaining water receive the highest scores.

The score is relative but physically grounded: although it represents a global rank, it is anchored in the precipitation buffer against severe drought—the margin between a region's climatological mean precipitation and the precipitation deficit expected during a rare drought event. A score of 80 indicates that a region has less remaining water than approximately 80% of all regions evaluated worldwide.

Advantages: Emphasizes physical water availability rather than statistical anomaly magnitude; enables consistent comparison across wet and dry climates; aligns with infrastructure planning horizons through use of rare drought.
Limitations: Reflects meteorological water availability only; does not incorporate groundwater storage, reservoir

operations, interbasin transfers, or water demand. Spatial aggregation smooths local variability. Reanalysis-based precipitation carries uncertainty in data-sparse regions.

2.7 Wind and Convective Storms

This section describes methods for assessing hazards related to extreme wind and convective storm activity, including tropical cyclone winds, thunderstorm frequency, severe thunderstorm environments, large hail, and tornadoes.

2.7.1 Extreme Wind

Annual maximum 3-second wind gust estimates are produced at 30″ ($\sim$1 km) over land and nearshore regions. Gusts capture both tropical-cyclone (TC) and non-TC drivers. TC wind fields are derived from synthetic tropical cyclone track datasets, converted to 3-second gusts via a gust factor, and adjusted for surface roughness using satellite-derived land cover data.

Non-TC gusts are estimated from reanalysis data using a parametric gust profile methodology calibrated against in situ observations. The approach provides smooth fields in flat terrain and resolves fine-scale variability in mountainous regions.

Advantages: Downscaling procedure improves local reanalysis gust estimates; combines TC and non-TC wind hazard in a single layer.
Limitations: Highly localized phenomena (downbursts, derechos, tornadic winds) are not captured. The non-TC gust regression is calibrated against European observations only; transferability to other regions has not been independently validated.

2.7.2 Thunderstorm Frequency

Global thunderstorm frequency is assessed using a satellite-calibrated lightning detection dataset. Thunderstorm occurrence is represented using the *thunder hour* metric: any one-hour period with at least two lightning strokes detected within a specified radius of a location is counted as a thunder hour. These data are aggregated to annual totals on a uniform global grid at $\sim$5 km resolution.

Advantages: Near-global coverage and consistent thresholds enable cross-region comparability; multi-year records emphasize robust spatial patterns.
Limitations: Detection efficiency varies by region and stroke intensity; using lightning as a proxy for thunder audibility introduces uncertainty.

2.7.3 Severe Thunderstorm Potential

Severe thunderstorms are associated with large hail, intense rainfall, downbursts, and tornadoes. Severe thunderstorm potential is estimated using a composite parameter combining atmospheric instability and vertical wind shear, calculated from reanalysis vertical profiles at $\sim$31 km resolution. The 95th percentile of this parameter provides a globally consistent measure of severe thunderstorm potential, conditioned on observed lightning activity to ensure values reflect actual storm occurrence.

Advantages: The composite parameter has been extensively evaluated and is more geographically universal than U.S.-specific severe weather parameters.
Limitations: Performance outside the U.S. and Europe is less established; coarse reanalysis resolution requires convective parameterization, affecting vertical profile accuracy.

2.7.4 Large Hail

The large hail layer is based on a global climatology of very large hail (VLH; ≥ 5 cm / 2 in), derived from a statistical convective hazard model applied to atmospheric reanalysis data at $\sim$31 km resolution over a multi-decadal period. The model estimates the probability of VLH occurrence at each grid point by combining the probability of thunderstorm occurrence with the conditional probability of VLH given a thunderstorm. Atmospheric predictors include measures of instability, vertical wind shear, moisture, and other convective parameters.

The model was trained and evaluated using lightning observations and hail reports from multiple continents and subsequently applied globally, providing spatially consistent estimates of mean annual VLH frequency.

Advantages: Multi-decadal globally consistent climatology derived from physically interpretable environmental predictors; reproduces known regional hotspots and seasonal cycles.
Limitations: Reanalysis data do not explicitly simulate hail; VLH occurrence is inferred from environmental conditions via a statistical model. Model skill may vary in regions with sparse observational records.

2.7.5 Tornadoes

The tornado layer provides a U.S. climatology of significant tornado activity (EF2+), derived from historical tornado records. The metric represents the annual probability of an EF2+ tornado occurring within a specified radius of a given location, calculated over a multi-decadal baseline period. EF2+ tornadoes are the focus because they are associated with substantial structural damage and are more consistently reported over time. Spatial aggregation accounts for track uncertainty and provides a location-relevant exposure metric.

Advantages: Observationally based with standardized EF-scale ratings; spatial aggregation produces a stable screening metric.
Limitations: Tornado records are influenced by reporting practices, radar deployment, and population density. The dataset reflects historical frequency only and does not account for future climate change.

2.7.6 Derechos

Derechos are long-lived, widespread convective windstorms produced by organized mesoscale convective systems, typically associated with bow echoes. They are characterized by persistent swaths of damaging straight-line winds extending over hundreds of kilometres and pose significant threats to utility infrastructure, forestry, agriculture, and the built environment.

The derecho hazard layer is derived from a peer-reviewed observational derecho climatology covering the United States east of the Rocky Mountains over an 18-year period. The dataset was constructed using an automated detection framework that integrates satellite-based storm tracking, machine-learning bow-echo identification, and physically based derecho classification criteria, at 4 km spatial resolution.

Event footprints are converted to binary masks and summed across all events, then divided by the number of years to produce an annualized derecho-footprint frequency field (yr^{-1}). The raw field is spatially smoothed using a moving-window mean to produce a generalized climatological hazard surface suitable for regional screening.

Advantages: Based on a peer-reviewed observational dataset with physically based event-identification criteria; high spatial resolution (4 km); annualized frequency metric is intuitive and directly comparable across locations.
Limitations: Coverage is limited to the United States east of the Rocky Mountains. The 18-year record may not fully capture long-term frequency of rare events. Spatial smoothing generalizes native-resolution footprint edges.

2.8 Geohazards

2.8.1 Seismic Hazard

The seismic hazard layer represents peak ground acceleration (PGA) with a 10% probability of exceedance in 50 years (return period of 475 years), expressed in units of g. It is compiled as a global approximately 1 km resolution raster by merging the best available regional probabilistic seismic hazard models with a global background layer. Over 20 regional models are incorporated, covering the United States, Canada, Europe, the Middle East, South America, Southeast Asia, Australia, New Zealand, and other regions. Where regional models exist, they take precedence over the global background. All models assume rock or firm-rock site conditions.

Source grids are resampled to a common approximately 1 km global grid. Where models overlap, the maximum PGA value is retained. The global background provides uniform worldwide coverage for areas not covered by a regional model, though it may not reflect the most current seismological understanding in all regions.

Advantages: Globally consistent estimates aligned with engineering standards; reference rock conditions ensure comparability; merges best available regional models with global coverage.
Limitations: Local site effects (soil amplification) are not captured; secondary hazards (liquefaction, surface rupture, tsunamis) are not represented; boundary discontinuities may exist between mosaicked regions.

2.8.2 Landslides

For regions outside the United States, landslide hazard is assessed using a global rainfall-driven model that combines terrain susceptibility (based on slope, lithology, vegetation, and soil moisture) with extreme rainfall data to estimate the conditional probability of landslide initiation at $3''$ ($\sim$90 m) resolution.

Within the United States, landslide susceptibility is assessed using terrain-based threshold models trained on a national compilation of documented landslides and high-resolution digital elevation data. Model outputs are provided at 90 m resolution.

Advantages: Global framework integrates rainfall forcing and terrain susceptibility at high resolution; U.S. models are empirically calibrated against a comprehensive landslide inventory.
Limitations: Global rainfall forcing data are coarse and may miss localized extremes. U.S. models are terrain-based and do not incorporate dynamic rainfall triggering; they represent relative susceptibility rather than event probability.

2.8.3 Land Subsidence

Land subsidence refers to the vertical sinking of the land surface. Subsidence estimates are derived from a global machine learning model trained on quality-controlled observation points, using predictors including groundwater abstraction, climate, geology, and topography. The resulting dataset is provided at 30″ (∼1 km) resolution.

Advantages: Globally consistent 1 km estimates; diverse predictors capture key physical drivers of subsidence.
Limitations: Local-scale subsidence can vary greatly due to factors not represented in global predictors. The model represents near-present-day conditions and does not project future changes.

3 Hazard Rating Scale

Each hazard layer in the Hazard Explorer is assigned an integer rating from 0 (negligible or below detection) to 10 (extreme). Ratings provide a standardized basis for comparing relative hazard severity across layers and locations. Two scoring approaches are used depending on the physical characteristics of each metric:

- **Percentile-based (decile) scoring:** All global land-area pixels are ranked and divided into ten equal-frequency bins (deciles). A score of 1 corresponds to the lowest decile and a score of 10 to the highest. This approach is applied to metrics whose distributions are continuous and span a wide range of values, ensuring that scores reflect relative global standing regardless of the underlying unit. Some layers exclude zero or near-zero values before ranking to avoid inflating the lowest bins (e.g., heating and cooling demand).
- **Custom-bin scoring:** For metrics with well-established engineering or scientific thresholds, or where the distribution is heavily zero-inflated or categorical, score boundaries are set at physically meaningful breakpoints rather than statistical percentiles. Examples include peak ground acceleration (aligned with seismic design categories), wildfire burn probability, lightning thunder hours, and land subsidence rate.

The choice between percentile and custom-bin scoring is driven by two considerations: (1) whether the metric has widely accepted engineering or regulatory thresholds that would be obscured by a purely statistical ranking, and (2) whether the global distribution is sufficiently continuous for decile binning to produce informative score gradations. Metrics that satisfy both conditions use percentile scoring; those with established absolute thresholds or highly non-continuous distributions use custom bins.

Human Cold Stress scores are inverted: lower (more extreme) temperatures correspond to higher scores. The global landslide layer uses a fixed categorical mapping from raw susceptibility classes to hazard scores (see table footnote).

Table 3 shows the minimum metric value required for each hazard rating. Values below the score 1 threshold receive a rating of 0.

Table 3: Hazard rating scale: minimum metric value for each score level.

Hazard Layer	Unit	1	2	3	4	5	6	7	8	9	10
Wildfire	%/yr	0.05	0.15	0.25	0.35	0.50	0.70	1.00	1.50	2.50	4.00
Extreme Heat	°C	25	31	34	36	38	40	42	44	47	51
Human Heat Stress	°C	16.0	21.0	23.0	25.0	27.0	28.5	29.5	30.5	31.5	33.0
Human Cold Stress[†]	°C	14.0	8.1	1.4	−3.3	−10.1	−24.7	−34.2	−42.2	−46.5	−49.9
Drought	score	0	27	37	44	51	60	62	71	83	91
Flood Depth (100-yr)	m	0.01	0.05	0.10	0.25	0.50	0.75	1.00	1.50	2.00	3.00
Surface Water Flooding	mm	0	15.2	18.0	21.8	28.3	40.5	53.7	74.7	104.6	121.7
Extreme Wind	km/h	68	85	100	115	130	145	165	185	210	250
Lightning	hr/yr	1	5	10	20	40	60	80	120	180	300
Severe Thunderstorm	m^2/s^2	100	200	300	400	500	600	700	850	1 000	1 200
Large Hail	%/yr	0.01	0.3	1.0	2.0	3.0	3.9	7.7	13.9	22.1	33.0
Tornado (EF2+)	%/yr	0.1	0.5	1.5	3.0	6.0	10.0	14.0	18.0	25.0	35.0
Derecho (U.S.)	events/yr	0.05	0.09	0.15	0.25	0.39	0.62	1.01	1.56	2.23	3.00
Earthquake	g	0.01	0.02	0.03	0.05	0.08	0.10	0.20	0.30	0.40	0.50
Land Subsidence	mm/yr	1.5	2	3	4	5	7	10	15	25	50
Landslide (U.S.)	index (0–81)	0	0	1	3	6	12	20	32	46	60
Landslide (Global)[‡]	class (0–5)	Fixed mapping: raw class 2 → 4; 3 → 7; 4 → 8; 5 → 10. Raw class $\leq$1 = no hazard.									
Heating Demand	°C-day	61	344	853	1 800	3 012	4 098	5 214	6 396	8 393	10 700
Cooling Demand	°C-day	18	84	280	658	1 156	1 771	2 349	2 749	3 010	3 267

[†] Inverted: lower temperatures correspond to higher scores.
[‡] Uses a fixed categorical mapping rather than threshold bins.

4 General Limitations and Considerations

1. **Interpretation and Intended Use:** The estimates herein provide indicative insights into the frequency and severity of natural hazards. They are intended to support high-level screening and strategic planning, not to replace site-specific engineering studies. Before applying results to planning or design, users should evaluate relevance in their local context and consult domain experts. Fitness for purpose is application- and assumption-dependent.
2. **Modeling Philosophy:** Methods aim to balance rigor and utility. While higher-resolution or specialized models may be more accurate for any single location, they often require substantial data, time, and cost. The methods used here are peer-reviewed and globally consistent, making them suitable for portfolio-scale screening where credible local data are unavailable or difficult to procure.
3. **Inherent Uncertainties:** All hazard models involve simplifying assumptions (e.g., limited resolution, imperfect observational records, parametric distributional choices). These limitations are especially relevant for localized or event-specific hazards such as convective storms, wildfires, and extreme rainfall. Users should incorporate multiple lines of evidence, including observed trends, accounts of past events, and alternative models.
4. **Relevance Over Time:** The data and methods reflect the best available understanding at publication. As observational records lengthen and methodologies improve, estimates should be revisited and updated accordingly.

5 Data Sources and Licensing

The hazard layers in this product draw on a wide range of third-party datasets, including global reanalysis products, satellite-derived climatologies, weather station observations, digital elevation models, tidal databases, land cover classifications, and published hazard models. All layers also incorporate proprietary methodologies developed by Degree Day, LLC. Table 4 summarises the relevant third-party data licences for each hazard layer.

Table 4: Third-party data licences by hazard layer.

Hazard Layer	Third-Party Data Licences
Wildfire	CC BY 4.0
Extreme Heat	Public domain; CC0
Human Heat Stress	Public domain; CC0
Human Cold Stress	Public domain; CC0
Snowfall Intensity	CC BY 4.0
Heating Demand	CC0
Cooling Demand	CC0
Drought	CC BY 4.0
River & Coastal Flood	CC BY 4.0; Copernicus licence
Coastal Exposure	CC BY 4.0; Public domain
Surface Water Flooding	CC BY 4.0; Public domain
Extreme Wind	CC BY 4.0
Lightning	CC BY-SA 4.0
Severe Thunderstorm	CC BY 4.0
Large Hail	CC BY 4.0
Tornado (U.S.)	Public domain
Derecho (U.S.)	CC BY 4.0
Earthquake	Public domain; CC BY-SA 4.0
Landslide (U.S.)	Public domain
Landslide (Global)	CC BY 4.0
Land Subsidence	CC BY 4.0

A detailed inventory of all datasets, providers, and licence terms is available in the full (unabbreviated) version of this methodology document.

Data

Degree Day

www.degreeday.org

info@degreeday.org