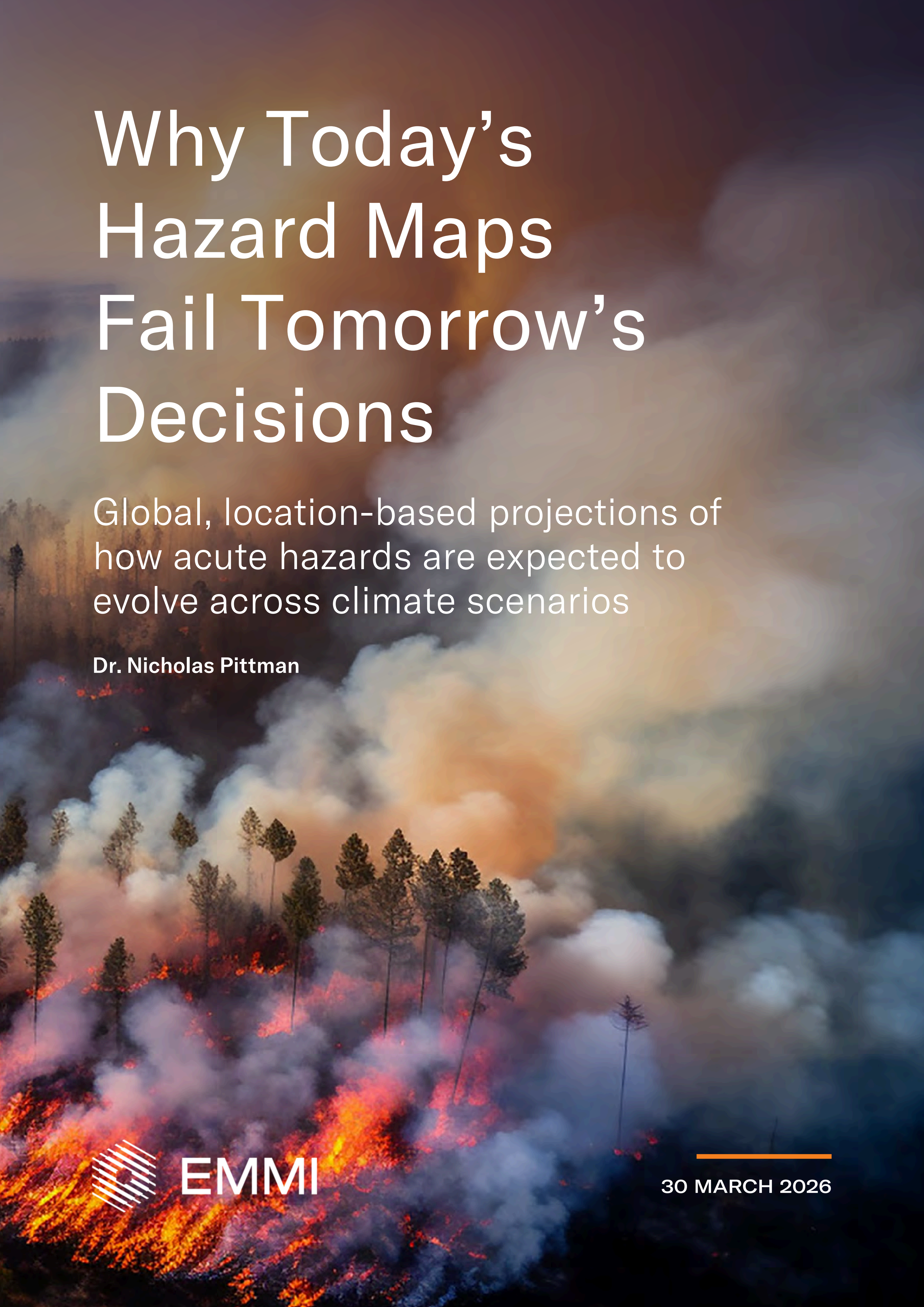

Why Today's Hazard Maps Fail Tomorrow's Decisions

Global, location-based projections of how acute hazards are expected to evolve across climate scenarios

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Executive Summary

Climate change is fundamentally altering the frequency and severity of acute physical hazards worldwide. The central challenge is no longer simply understanding which hazards exist today, but quantifying how hazard conditions at specific locations are expected to change under different future warming pathways, and how those changes may become financially material over long time horizons (Average Annual Loss). Approaches that rely on static hazard maps or absolute risk thresholds implicitly assume the future resembles the past, an assumption that does not hold under continued warming.

Emmi's Climate Hazard Diagnostics (CHD) provides global, location-based projections of how acute hazards, including wildfire, tropical cyclones, and coastal and fluvial flooding, are expected to evolve across multiple climate scenarios and time horizons. Built on established, peer-reviewed datasets, including CMIP6 fire-weather projections (Quilcaille et al., 2023), STORM synthetic cyclone simulations (Bloemendaal et al., 2020), and WRI Aqueduct flood models (Ward et al., 2020), the product delivers standardised hazard metrics at 1 km and 11 km resolutions for a historical baseline and future periods spanning 2030 to 2080 under RCP2.6 to RCP8.5 scenarios.

Each hazard is represented by four complementary dimensions for assessing the potential financial implications of physical risk: a normalised intensity index, which captures maximum potential severity, and an annual exceedance probability, which captures how often damage-relevant conditions are expected to occur. These metrics are combined and calibrated into Average Annual Loss (AAL), representing expected annual economic damage as a fraction of asset value, enabling direct interpretation of physical hazard change in financial terms. Rather than focusing on absolute hazard levels, the methodology emphasises changes relative to a historical baseline, isolating the climate-driven signal from local infrastructure, land use, and defence features that global models cannot reliably resolve.

To preserve meaningful differentiation across climate pathways, hazard intensities are normalised using scenario-consistent global reference maxima, rather than local or historical scaling. This ensures that higher-emissions pathways register proportionally higher hazard levels and enables robust comparison across scenarios, supporting consistent interpretation of hazard escalation over time.

In addition to hazard metrics, CHD provides a calibrated Average Annual Loss (AAL) layer, translating physical hazard conditions into long run expected annual economic damage as a fraction of asset value. This enables direct integration into financial risk assessment frameworks, including expected loss and Value-at-Risk (VaR).

Climate Hazard Diagnostics maps provide a transparent, standardised foundation for assessing how acute physical climate hazards may evolve at asset-relevant locations, particularly where exposure is long-lived and difficult to relocate. The datasets are designed to support comparative analysis, scenario-based assessment, and prioritisation workflows, and to integrate with broader physical climate risk and financial impact frameworks where further asset-specific modelling or interpretation may be applied.

> "The most important climate risk question is not where hazards are today, but how rapidly and unevenly they escalate under different warming pathways.

Contents

Introduction

Quantifying climate-driven hazard change

Climate change amplifies acute physical hazards through warmer temperatures, rising sea levels, and more intense precipitation. The IPCC Sixth Assessment Report confirms with high confidence that human influence has already intensified extreme weather events globally (IPCC, 2021). The key analytical question is how rapidly, and how unevenly, hazard conditions are expected to evolve across locations under different warming pathways.

Historical hazard maps describe past conditions but do not capture how risk profiles may change over time. Conversely, generic climate projections describe changes in global temperature or precipitation, but these do not translate into spatially explicit, damage-relevant hazard metrics. Climate disclosure frameworks such as CSRD and TCFD require physical risk to be assessed under multiple emissions pathways because future hazard escalation depends on warming from emissions. A location with moderate flood exposure today, for example, may experience limited intensification under lower-emissions pathways but substantial escalation under higher-warming scenarios.

When physical risk is assessed without accounting for trajectory, locations with similar present-day exposure can appear equivalent even as their future hazard paths diverge. This obscures the influence of emissions pathways on physical outcomes and limits the interpretive value of scenario analysis.

Existing approaches to physical risk assessment tend to fall along two extremes. At one end, engineering-grade models provide site-specific failure probabilities and damage estimates, but require detailed local inputs and are not scalable across large geographies or asset portfolios. At the other end, high-level climate indicators describe regional climate trends but lack the spatial resolution and hazard specificity needed to assess location-level exposure or compare scenarios in a financially interpretable way.

Climate Hazard Diagnostics (CHD) addresses this gap. The framework focuses on relative hazard change ('delta risk') rather than absolute hazard levels, leveraging the strength of global climate models in projecting how hazard conditions shift under warming while avoiding false precision around local infrastructure, protection standards, or asset-specific vulnerability. By quantifying how hazard intensity and frequency evolve relative to a historical baseline, the approach isolates the climate-driven signal that is most relevant for long-term exposure assessment. This structure also supports the derivation of Average Annual Loss (AAL), linking changes in physical hazard directly to expected annual economic damage.

> "Historical hazard maps describe past conditions; decision-relevant risk depends on how those conditions change."

A further design objective is scenario consistency. Hazard metrics are constructed to preserve proportional differences across emissions pathways, ensuring that higher-warming scenarios systematically register higher hazard levels where climate science indicates escalation. This enables meaningful comparison across scenarios and time horizons, supporting evaluation of how mitigation pathways influence future physical hazard conditions.

Taken together, this approach provides a coherent, scalable foundation for assessing how acute physical climate hazards are expected to change across locations, particularly where assets are long-lived, immobile, and sensitive to cumulative hazard escalation.

When physical hazard assessment relies on static representations or locally normalized risk scores, changes driven by climate warming can be difficult to detect. Conditions may worsen in absolute terms while relative risk appears unchanged. Locations that look similar today can diverge materially over time, and differences between climate scenarios may be flattened or obscured. In these cases, the issue is not a failure of the underlying science, but of analytical frameworks that are not designed to make change visible.

Designing a Framework for Comparing Hazard Change

Why comparing change matters

Climate change alters physical hazards unevenly across locations and over time. A framework designed to compare hazard change must therefore do more than describe present-day conditions. It must make visible how hazard intensity and frequency evolve under different warming pathways, and do so in a way that supports consistent comparison across locations and scenarios.

Focusing on change rather than absolute conditions

Global climate models are best suited to this task when they are used to analyse change relative to a historical baseline, rather than to estimate absolute local conditions. While global models may not resolve fine-scale features such as local drainage, flood defences, or land management, they reliably capture how extreme conditions intensify as the climate warms. By anchoring hazard metrics to changes from baseline conditions, the framework isolates the climate-driven signal while minimising sensitivity to local factors that affect both present and future conditions in similar ways.

Separating severity from frequency

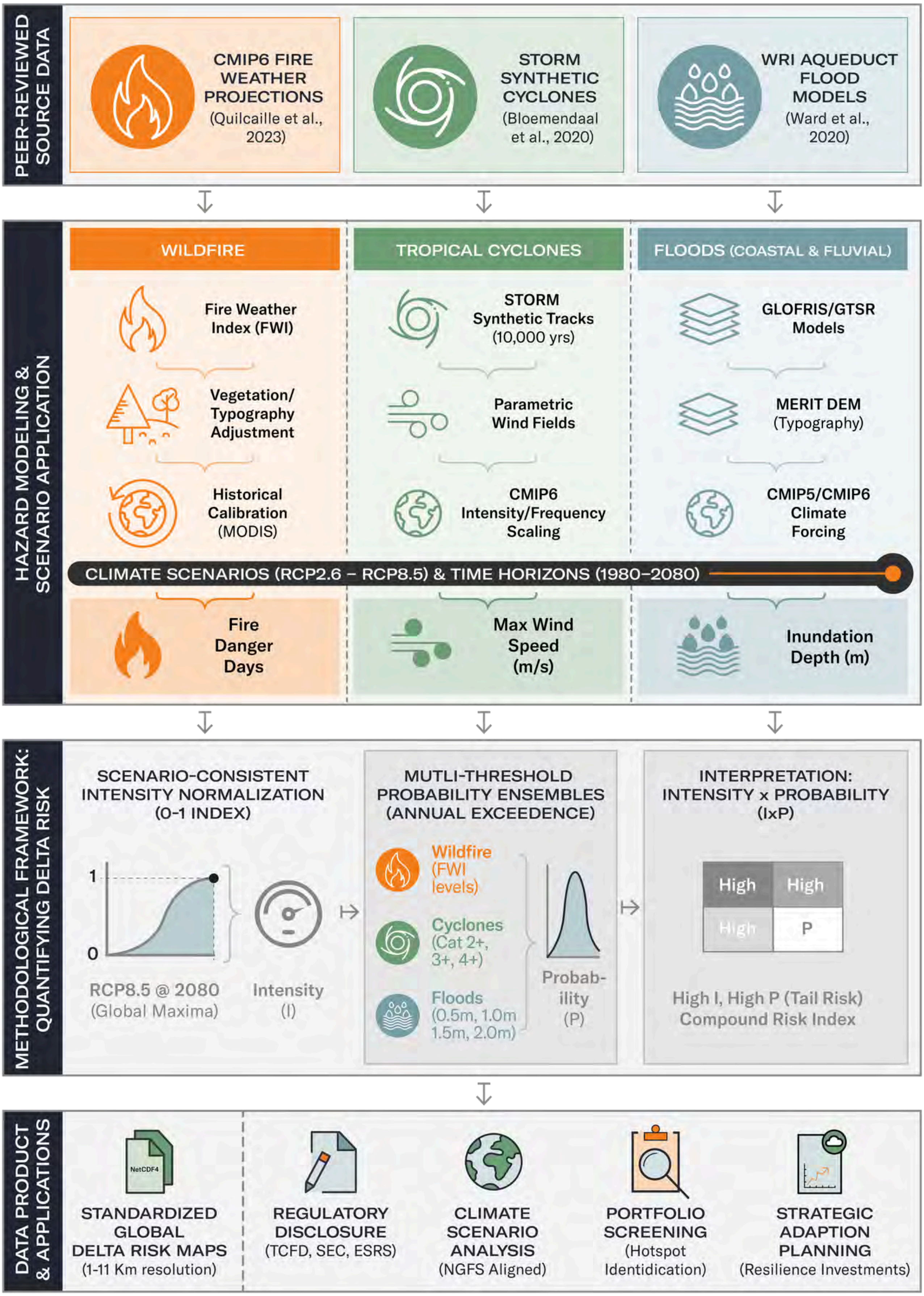
To support interpretable comparison, each hazard is described along two independent dimensions: severity and frequency. Severity reflects how extreme conditions can become, while frequency captures how often damage-relevant thresholds are exceeded. Both dimensions matter for understanding risk escalation. High severity may indicate potential for catastrophic loss, while increasing frequency reflects growing disruption over time. Treating these dimensions separately avoids conflating fundamentally different types of hazard change.

Preserving comparability across scenarios

A further design objective is scenario consistency. Hazard metrics are constructed to preserve proportional differences across emissions pathways, ensuring that higher-warming scenarios systematically register higher hazard levels where climate science indicates escalation. Intensity metrics are therefore normalised using common global reference conditions rather than local or historical maxima. Local normalisation can obscure climate-driven amplification by construction, making locations appear stable even as absolute conditions deteriorate. Scenario-consistent normalisation ensures that differences across warming pathways remain visible and comparable.

Together, these design choices establish a coherent framework for comparing how acute physical hazards are expected to change across space, time horizons, and climate scenarios. By focusing on relative change, separating severity from frequency, and preserving the climate signal across scenarios, the framework is designed to reveal where and under which pathways hazard escalation is most pronounced, particularly for long-lived, immobile exposures that are sensitive to cumulative change rather than short-term variability.

Emmi Climate Hazard Diagnostics pipeline: From source data to actionable climate insights



Scope and coverage of hazard projections

Climate Hazard Diagnostics (CHD) provides spatially explicit hazard datasets for multiple acute physical hazards, with consistent temporal horizons and scenario alignment across hazards where source data permits. Data availability varies by hazard type due to differences in the underlying climate models, spatial resolution, and scenario coverage.

The dataset includes four hazard categories: wildfire, tropical cyclones, coastal flooding, and fluvial (riverine) flooding. For each hazard, outputs are provided for a historical baseline and future time horizons of 2030, 2050, and 2080. These horizons align with common medium- and long-term planning and assessment intervals, while avoiding near-term periods where climate signal differentiation across scenarios is limited by climate system inertia.

Scenario coverage reflects the constraints of the underlying source models. Wildfire and tropical cyclone hazards are available across the full suite of Representative Concentration Pathways (RCP2.6, RCP4.5, RCP6.0, and RCP8.5), drawing on CMIP6-era datasets. Flood hazards are limited to RCP4.5 and RCP8.5, reflecting the availability of the WRI Aqueduct flood models, which are based on CMIP5-era climate forcing.

Spatial resolution also varies by hazard. Wildfire and tropical cyclone datasets are provided at 0.1° resolution (~11 km), consistent with the resolution of the underlying global climate and hazard models. Coastal and fluvial flood hazards are provided at a finer 0.0083° resolution (~1 km at the equator), reflecting the higher spatial detail required to represent floodplain and coastal inundation processes.

Across all hazards, outputs include both normalized intensity metrics and associated annual exceedance probabilities, along with the underlying raw physical variables (e.g. flood depth in metres, wind speed in metres per second, fire danger days). This structure enables consistent comparison of hazard escalation across locations and scenarios, while preserving access to physical units for downstream analysis where more detailed modeling is applied.

A summary of hazard coverage, scenarios, spatial resolution, and temporal availability is provided in Table 1.

Table 1: CHD data availability

Hazard	Years	Scenarios	Metrics	Resolu-tion	Climate Basis	Notes
Wildfire	Baseline, 2030, 2050, 2080	Baseline, RCP2p6, RCP4p5, RCP6p0, RCP8p5	Intensity, fire_danger_days, probability	0.1°	CMIP6	Global land surfaces
Tropical Cyclones	Baseline, 2030, 2050, 2080	Baseline, RCP2p6, RCP4p5, RCP6p0, RCP8p5	Intensity, wind_speed_mps, probability	0.1°	CMIP6	Global land surfaces
Coastal Floods	Baseline, 2030, 2050, 2080	Baseline, RCP4p5, RCP8p5	Intensity, depth_meters, probability	0.0083°	CMIP5	RCP2.6, RCP6.0 unavailable; no-subsidence variant
Fluvial (Riverine) Floods	Baseline, 2030, 2050, 2080	Baseline, RCP4p5, RCP8p5	Intensity, depth_meters, probability	0.0083°	CMIP5	RCP2.6, RCP6.0 unavailable

Scenario and baseline reference frames

Scenario alignment across RCP and SSP frameworks

For consistency across hazards, all Climate Hazard Diagnostics (CHD) outputs are labeled using Representative Concentration Pathway (RCP) nomenclature. This choice reflects practical data lineage considerations rather than a preference for one scenario framework over another.

Flood hazard projections are derived from WRI Aqueduct v2.0, which uses CMIP5-era climate forcing with native RCP scenarios (RCP4.5 and RCP8.5). In contrast, wildfire and tropical cyclone hazards are derived from CMIP6-era datasets that use Shared Socioeconomic Pathways (SSPs). To maintain cross-hazard consistency, SSP-based projections are mapped to equivalent RCP radiative forcing levels following IPCC conventions.

While SSPs incorporate socioeconomic narratives in addition to emissions trajectories, it is the radiative forcing pathway that governs the physical climate response driving hazard outcomes. For the purpose of physical hazard projection and comparison, the radiative forcing component is therefore the relevant dimension, making RCP labeling appropriate and internally consistent across hazards.

A summary of the SSP–RCP mapping conventions used in CHD is provided in the table below.

Defining the historical reference state

All hazards in CHD are expressed relative to a nominal '1980' baseline, representing late 20th-century climate conditions prior to the period of rapid anthropogenic warming acceleration. This baseline serves as a reference state against which future changes are measured, rather than a literal snapshot of conditions in the year 1980.

The underlying reference periods vary by hazard and data source, reflecting the validated climatological baselines used in each contributing model. These reference periods are summarized in Table 3.

The use of a pre-acceleration baseline serves three purposes. First, it maximises the observable climate signal between baseline and future scenarios; using a contemporary baseline would compress scenario differentiation, as approximately 1.1°C of warming has already occurred. Second, it respects source data constraints, as underlying datasets are anchored to specific historical periods that cannot be arbitrarily shifted without reprocessing. Third, it maintains methodological consistency with standard climatological reference periods used in IPCC assessments and peer-reviewed climate science.

Table 2: RCP-SSP mapping conventions

CHD Label	Floods (CMIP5)	Fire/ Cyclones (CMIP6)	Radiative Forcing	Approx. Warming by 2100
RCP2p6	RCP 2.6	SSP1-2.6	2.6 W/m²	~1.8°C
RCP4p5	RCP 4.5	SSP2-4.5	4.5 W/m²	~2.7°C
RCP6p0	RCP 6.0	SSP3-7.0	6.0 W/m²	~3.6°C
RCP8p5	RCP 8.5	SSP5-8.5	8.5 W/m²	~4.4°C

Table 3: Hazards baseline year regerence periods

Hazard	Climate Reference Period	Source
Wildfire	1950-1980	CMIP6 historical climatology (Quilcaille et al., 2023).
Tropical Cyclones	1980–2017	IBTrACS observations (Bloemendaal et al., 2020)
Coastal & Fluvial Floods	1960–1999	EUWATCH reanalysis (Ward et al., 2020)

Positioning the framework within risk analysis

Climate Hazard Diagnostics (CHD) is designed as a scenario-aligned hazard diagnostics layer that enables consistent comparison of how acute physical hazards evolve across locations, time horizons, and warming pathways. The framework focuses on relative hazard escalation, rather than absolute risk levels or asset-specific damage outcomes.

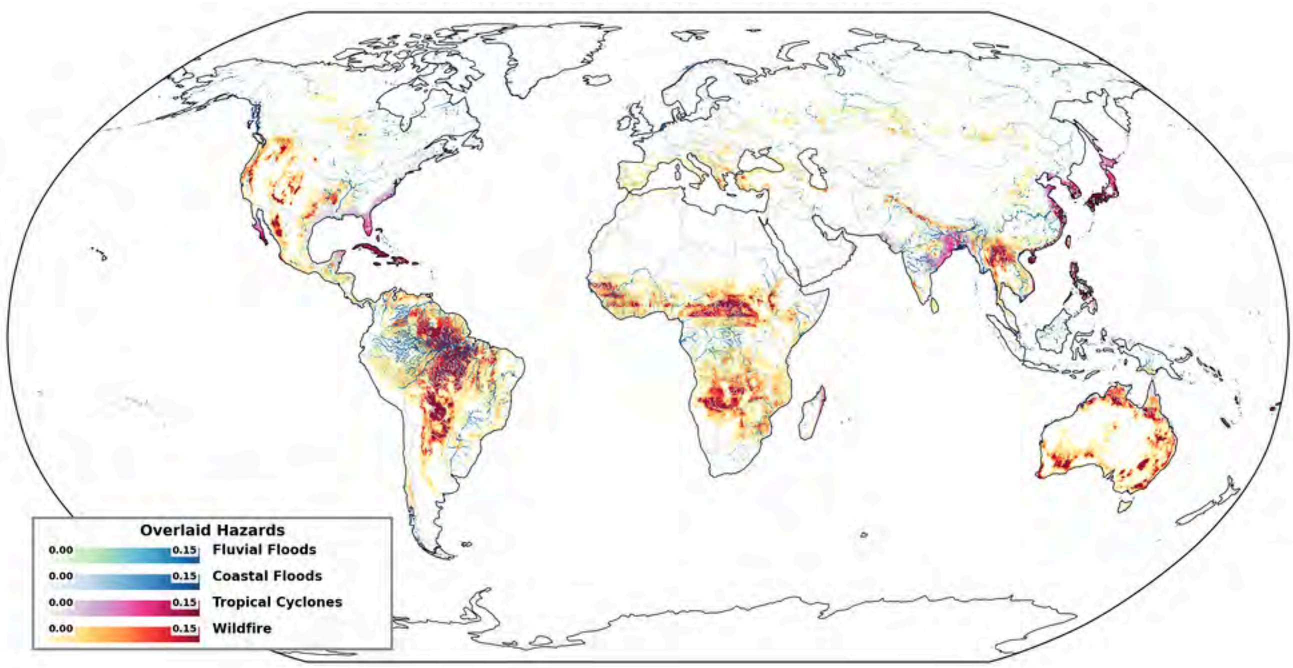
By providing standardised metrics across multiple hazards and scenarios, the dataset supports high-level comparison and prioritisation and includes a calibrated Average Annual Loss (AAL) layer, enabling direct integration into financial risk assessment workflows, where more detailed modelling is applied.

> “The value of hazard diagnostics lies in prioritisation, not prediction.

Translating Climate Signals into Hazard Metrics

This section describes how large-scale climate signals are translated into spatially explicit hazard metrics for key acute physical risks. For each hazard, projections are constructed to capture both the severity and frequency of damage-relevant events, and to do so consistently across locations, time horizons, and warming pathways. The resulting maps provide a common basis for comparing how different hazards are expected to evolve under climate change, while preserving the relative differences that underpin scenario-based analysis.

Figure 2: Global RCP4.5 2050 Hazard AAL (Expected Damage Fraction; Intensity x Probability)



Wildfire: Climate-driven escalation of fire weather

Climate drivers and observed trends

Wildfire activity is governed by the interaction of temperature, precipitation, humidity, and wind, which together determine fuel dryness and fire spread potential. Rising temperatures increase evapotranspiration and reduce fuel moisture, earlier snowmelt extends the fire season in many regions, and compounding drought conditions increase the availability of combustible fuels (Abatzoglou et al., 2019).

Climate model projections consistently indicate widespread increases in fire weather severity under warming scenarios, with particularly strong increases projected in Mediterranean regions, western North America, the Amazon basin, southern Africa, and boreal zones (Quilcaille et al., 2023). These projections are consistent with observed historical trends, with global fire weather seasons lengthening by approximately 18.7% between 1979 and 2013 (Jolly et al., 2015).

Data sources and modeling framework

The wildfire hazard component is based on CMIP6-derived Fire Weather Index (FWI) projections compiled by Quilcaille et al. (2023). The FWI is a widely used meteorological fire danger metric developed by the Canadian Forest Service that integrates temperature, relative humidity, wind speed, and precipitation into a single indicator of fire potential (Van Wagner, 1987).

FWI projections are further refined through a series of spatial adjustments, including vegetation and land-cover weighting using Copernicus Global Land Cover data (Buchhorn et al., 2020), topographic adjustment to account for slope and elevation effects, and historical calibration against MODIS satellite-derived burned area observations (Giglio et al., 2018) over the period 2001–2020. These steps ensure that spatial patterns in modeled fire danger align with observed fire occurrence while preserving the underlying climate-driven signal.

Representing severity and frequency

Wildfire intensity is derived from the annual number of days on which the Fire Weather Index exceeds a threshold associated with significant fire potential. This count is transformed into a normalized intensity index (0–1) using a power-law function calibrated to the global distribution under RCP8.5 conditions in 2080. The transformation emphasises locations where extreme fire weather becomes persistent while compressing the upper tail of the distribution.

The raw variable, fire_danger_days (integer count from 0 to 365), is retained in the dataset for users who wish to apply alternative thresholds or transformation functions.

The annual fire occurrence probability is estimated by combining the frequency of high-fire-danger days with ignition likelihood and regional fire-regime characteristics. Probabilities are weighted using observed fire occurrence patterns from MODIS data to reflect regional differences in ignition sources, land management, and suppression effectiveness.

Spatial and temporal coverage

Wildfire hazard maps cover the global land surface excluding Antarctica at a spatial resolution of 0.1° (approximately 11 km). Outputs are provided for a historical baseline and for future time horizons of 2030, 2050, and 2080 under all available climate pathways (baseline, RCP2.6, RCP4.5, RCP6.0, and RCP8.5).

Further details on the methodology, including an example calculation, are available in CHD: Wildfire. Please email info@emmi.io to request a copy.

Tropical cyclones: Intensification and shifting risk profiles

Climate drivers and observed trends

Tropical cyclones derive their energy from warm ocean waters, where sea surface temperatures exceeding approximately 26.5°C enable evaporation and latent heat release. Climate change influences tropical cyclone behavior through multiple interacting mechanisms. Warmer ocean temperatures increase the energy available for storm intensification, potentially raising maximum wind speeds and rainfall rates. Changes in vertical wind shear and atmospheric stability influence storm formation and development, while poleward expansion of warm ocean regions allows storms to maintain intensity at higher latitudes (Knutson et al., 2020; Kossin et al., 2014).

Observational evidence from recent decades indicates an increase in the proportion of the most intense storms (Category 4–5), a poleward migration of cyclone tracks of approximately 50 km per decade, and a reduction in storm translation speed (Kossin et al., 2014; 2018). Climate model projections suggest that while global tropical cyclone frequency may remain stable or decrease slightly under warming, the intensity of the strongest storms is expected to increase substantially, on the order of 13% per 1°C of global warming for the most extreme events (Knutson et al., 2020).

Data sources and modeling framework

Tropical cyclone hazard projections are based on the STORM (Synthetic Tropical cyclOne geneRation Model) database, which generates 10,000-year synthetic storm tracks across all six major cyclone basins using a statistical–deterministic framework (Bloemendaal et al., 2020). This approach overcomes the limitation of the observational record, which spans only approximately 40 years of reliable satellite data and is insufficient to robustly estimate low-frequency, high-intensity events.

For each synthetic storm, wind fields are computed using the Holland (1980) parametric wind profile, which relates maximum wind speed, central pressure deficit, and radius of maximum winds to generate spatial wind speed fields. As storms move over land, wind speeds decay following the Kaplan and DeMaria (1995) empirical model, calibrated to observed landfalling cyclones. Future climate effects are incorporated through basin-specific intensity and frequency scaling factors derived from CMIP6 ensemble projections summarized by Knutson et al. (2020). Intensity scaling ranges from approximately +1.5% to +5.5% per 1°C of warming, depending on basin, while frequency adjustments vary by region, reflecting shifts in sea surface temperature gradients and large-scale circulation patterns.

Representing severity and frequency

Cyclone intensity is defined using maximum sustained wind speed, expressed in meters per second. Wind speed values are transformed into a normalized intensity index (0–1) using a quadratic function, reflecting empirical wind–damage relationships where losses increase non-linearly with wind speed (Emanuel, 2011). The raw physical variable, wind_speed_mps, is retained in the dataset for users requiring direct physical values. Annual exceedance probability is calculated from the frequency of synthetic cyclone events exceeding a defined wind speed threshold (50 m/s, corresponding approximately to Category 3 and above). Probabilities are derived empirically from the synthetic event catalogue and adjusted consistently across scenarios using basin-specific frequency scaling.

Spatial and temporal coverage

Tropical cyclone hazard maps cover global ocean-adjacent regions between 40° S and 60° N at a spatial resolution of 0.1° (approximately 11 km). Outputs are provided for a historical baseline and for future horizons of 2030, 2050, and 2080 under all available climate pathways (baseline, RCP2.6, RCP4.5, RCP6.0, and RCP8.5).

Further details on the methodology, including an example calculation, are available in CHD: Cyclones. Please email info@emmi.io to request a copy.

Flooding: Non-Linear Responses to Warming (Coastal and Fluvial)

Climate drivers and observed trends

Flood hazard arises from different physical drivers in coastal and fluvial settings, but both are strongly influenced by climate change through shifts in precipitation extremes, sea level, and hydrological variability.

Fluvial (riverine) flooding is primarily driven by extreme precipitation events and upstream hydrological responses. Warming increases the atmosphere's moisture-holding capacity, intensifying heavy rainfall events and increasing peak river discharge in many regions. Changes in snowmelt timing and soil moisture further modify runoff dynamics, particularly in snow-dominated and temperate basins (Winsemius et al., 2016; Dottori et al., 2018).

Coastal flooding results from the interaction of mean sea-level rise, storm surge, and extreme sea levels associated with tropical and extratropical storms. Rising mean sea levels elevate baseline coastal water levels, increasing the frequency and severity of inundation for a given storm surge height. Even modest sea-level rise can therefore lead to large increases in flood frequency in low-lying coastal zones (Fox-Kemper et al., 2021; Jevrejeva et al., 2018).

Both flood types exhibit strong non-linear responses to warming, where incremental increases in climate forcing can produce disproportionate increases in inundation extent and depth. These dynamics make flood hazards particularly sensitive to emissions pathways and long-term warming trajectories.

Data sources and modeling framework

Coastal and fluvial flood hazards are derived from the WRI Aqueduct Floods v2.0 dataset, which provides globally consistent flood hazard projections based on hydrological and hydraulic modeling frameworks (Ward et al., 2020; Winsemius et al., 2013).

Fluvial flood modeling combines global hydrological simulations with river routing models to estimate peak discharge and associated inundation extents across river basins. Coastal flood modeling integrates storm surge, extreme sea levels, and mean sea-level rise to estimate coastal inundation depth. Both components are driven by CMIP5-era climate forcing and are available for a subset of emissions scenarios reflecting Aqueduct data availability.

The Aqueduct framework is designed for global-scale comparability rather than site-specific precision. As such, it does not explicitly model local flood defences, drainage infrastructure, or land subsidence unless these effects are incorporated in the underlying global datasets.

Representing severity and frequency

For both coastal and fluvial floods, intensity is defined using inundation depth associated with the 100-year return period event, a widely used benchmark in flood risk assessment and infrastructure design. Raw flood depth, expressed in meters, is transformed into a normalised intensity index (0–1) using a square-root function informed by global depth–damage relationships compiled by the Joint Research Centre (Huizinga et al., 2017). This transformation reflects empirical evidence that damage increases steeply at shallow depths, where most structural losses occur.

The raw physical variable, depth_meters, is retained in the dataset for users requiring direct depth values or alternative damage functions.

Annual exceedance probability is computed relative to a single flood depth threshold of 1.0 m, representing severe structural damage and evacuation-level flooding. Probabilities are derived by interpolating Aqueduct return-period layers to estimate the annual likelihood of exceeding this threshold.

Spatial and temporal coverage

Flood hazard maps cover global coastlines and major river basins at a spatial resolution of 0.0083° (~1 km at the equator), excluding Antarctica and Greenland. Outputs are provided for a historical baseline and future horizons of 2030, 2050, and 2080 under the available emissions pathways (baseline, RCP4.5, and RCP8.5).

Flood projections are limited to RCP4.5 and RCP8.5 scenarios due to constraints in the underlying Aqueduct source data. Near-term scenario differentiation prior to 2040 is limited by climate system inertia; as a result, only a single near-term horizon (2030) is provided.

In subsidence-prone coastal regions (e.g. major deltaic cities), relative sea-level rise driven by local subsidence may exceed climate-driven sea-level rise. Users requiring total flood exposure in such locations should supplement CHD outputs with local subsidence data.

Further details on the methodology, including an example calculation, are available in CHD: Floods. Please email info@emmi.io to request a copy.

> The purpose of these hazard maps is not to predict individual events, but to make differences in hazard escalation visible across locations, scenarios, and time horizons."

Interpreting Scenario-Driven Hazard Change

Preserving the climate signal through normalisation

Intensity metrics are normalized using global reference maxima derived from high-end climate conditions (RCP8.5 at 2080) rather than local or historical maxima. This approach ensures that intensity scores preserve proportional differences across emissions pathways and time horizons.

Normalising intensity locally, by scaling each location to its own maximum, would obscure the climate change signal by construction. For example, a location experiencing a substantial increase in flood depth would show no change in normalized intensity if both historical and future values were scaled to a local maximum of 1.0. Scenario-consistent normalisation avoids this artefact by anchoring all locations to the same global reference, allowing changes in intensity to be interpreted as climate-driven escalation rather than rescaling effects.

This design choice is essential for meaningful comparison across scenarios, locations, and hazards, and underpins the ability to evaluate how different warming pathways alter relative hazard severity.

Defining damage-relevant event thresholds

For each hazard, probability is calculated relative to a single, damage-relevant threshold. This approach balances interpretability with comparability across locations and scenarios.

Thresholds are defined as follows:

- **Floods:** 1.0 m inundation depth, representing severe structural damage and evacuation-level flooding
- **Tropical cyclones:** 50 m/s sustained wind speed (approximately Category 3 and above)
- **Wildfire:** a single fire-weather threshold calibrated to observed burned area

Using a single threshold avoids the complexity and opacity introduced by multi-threshold probability curves, while still capturing meaningful changes in the frequency of damaging conditions.

Combining severity and frequency for comparative analysis

Intensity and probability capture complementary dimensions of hazard. These dimensions are combined and calibrated to derive Average Annual Loss (AAL), representing expected annual economic damage as a fraction of asset value, and are designed for relative comparison and screening rather than precise asset-level loss estimation.

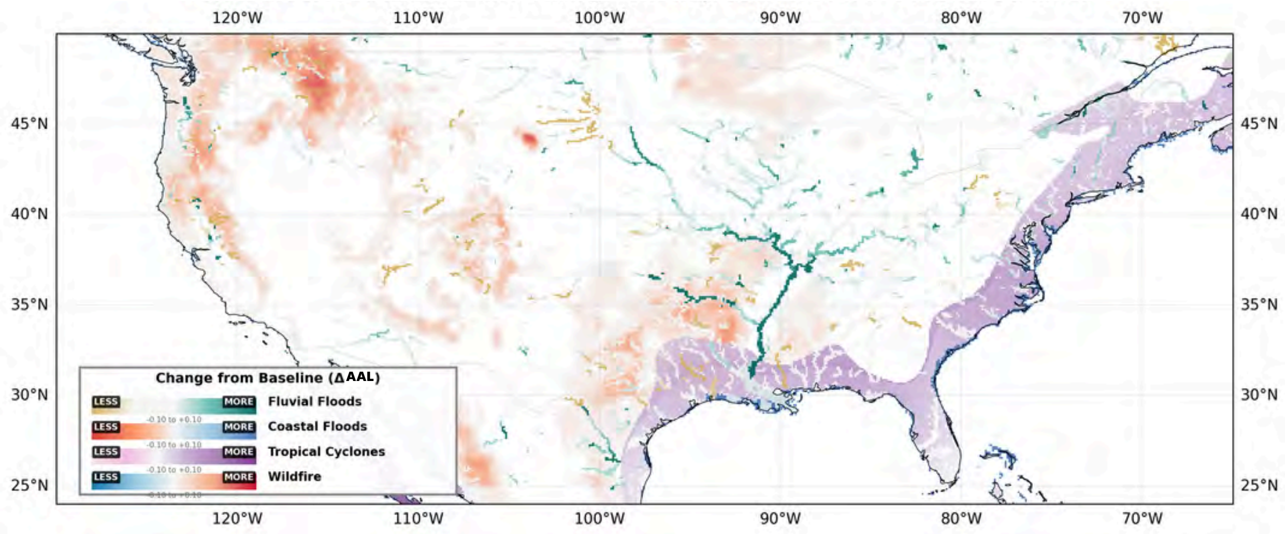
The intensity transformations applied, square-root for floods, quadratic for cyclones, and power-law for wildfire, are calibrated to approximate empirical damage relationships observed in historical data. However, the AAL formulation reflects standardised assumptions and does not incorporate asset-specific vulnerability.

Different combinations of intensity and probability convey distinct risk characteristics:

- High intensity, high probability: frequent severe impacts (compound risk)
- High intensity, low probability: infrequent catastrophic events (tail risk)
- Low intensity, high probability: chronic, manageable disruption

This dual representation enables flexible downstream interpretation while maintaining a consistent comparative framework.

Figure 3: USA RCP4.5 2050 Hazard minus Baseline
(Average Annual Loss; Intensity x Probability)



Interpreting multi-hazard exposure

Many locations are exposed to multiple acute hazards, requiring consideration of how risks interact at the portfolio or geographic level. Climate Hazard Diagnostics (CHD) supports multi-hazard analysis through consistent metric definitions, aligned scenarios, and temporal coverage across all hazards.

Probability metrics are not directly comparable across hazards because they are derived using different physical and statistical approaches. Cross-hazard probability comparisons should therefore be interpreted as indicative rankings rather than precise relative frequencies.

Hazard dependence varies by mechanism and location. Tropical cyclones and coastal flooding are often physically correlated because the same storm systems drive both wind and surge impacts. In contrast, wildfire and fluvial flooding are generally independent at event timescales, though seasonal interactions may exist. A simple sum of probabilities across correlated hazards can therefore overstate risk and should be avoided.

For aggregation, AAL values may be combined across hazards using weighted averages or conservative approaches, such as taking the maximum AAL as the dominant risk driver at each location. Compound events, such as post-fire flooding or cascading infrastructure failures, are not explicitly modelled and should be treated as additional sources of risk beyond individual hazard assessments.

"Hazard dependence varies by mechanism and location

What the framework produces

Climate Hazard Diagnostics (CHD) produces a set of scenario-aligned hazard datasets designed to make changes in physical hazard conditions observable and comparable over time. Each output represents a spatial snapshot of hazard intensity and frequency for a defined hazard, scenario, and time horizon, constructed consistently to support comparison across locations and warming pathways.

For each hazard, outputs include two complementary metrics: a normalized intensity index, representing the severity of extreme conditions, and an annual exceedance probability, representing the frequency of damage-relevant events. These metrics are provided alongside the underlying physical variables (such as flood depth, wind speed, or fire weather days), allowing downstream analysis to apply alternative assumptions or damage relationships where required.

Crucially, all outputs are structured to preserve scenario consistency and temporal comparability. Metrics are aligned across hazards, scenarios, and time horizons, enabling direct comparison of how hazard conditions evolve relative to a historical baseline. This structure allows users to assess not only where hazards are projected to intensify, but how strongly outcomes diverge across warming pathways, which is central to evaluating climate-driven risk over long time horizons.

The purpose of these outputs is not to provide asset-level loss estimates or site-specific risk determinations, but to supply a consistent hazard diagnostics layer that can be integrated into broader physical risk and financial impact assessment workflows. In this way, the data serves as a foundation for understanding and prioritising climate-driven hazard escalation, rather than as a standalone risk model.

> The framework produces a consistent hazard diagnostics layer that makes climate-driven change comparable across locations, scenarios, and time horizons.

Confidence in Hazard Change Projections

Climate Hazard Diagnostics (CHD) integrates hazard projections from established, peer-reviewed models and datasets. Validation, therefore, focuses on two complementary dimensions:
(1) the ability of the underlying models to reproduce observed hazard patterns, and
(2) the robustness of relative changes across different climate scenarios.

For wildfires, Fire Weather Index projections have been evaluated against historical burned-area observations, showing that the spatial patterns of modeled fire danger align with observed fire occurrence across major fire-prone regions (Quilcaille et al., 2023; Giglio et al., 2018). Calibration steps applied within CHD further anchor modeled fire danger to observed fire regimes without altering the underlying climate-driven signal.

Tropical cyclone hazard projections are based on the STORM synthetic event framework, which has been extensively validated against historical cyclone statistics, including storm frequency, track density, and intensity distributions across basins (Bloemendaal et al., 2020). Using long synthetic catalogs reduces sampling uncertainty associated with the short observational record and improves representation of low-frequency, high-impact events.

Flood hazard projections derive from the WRI Aqueduct modeling framework, which has been benchmarked against observed discharge records, flood extents, and historical flood losses at regional and global scales (Winsemius et al., 2013; Ward et al., 2020). Comparative studies indicate that for scenario-relative changes at mid-century horizons, CMIP5- and CMIP6-forced projections show substantial overlap, supporting the use of CMIP5-based flood projections for relative hazard change analysis (Chen et al., 2021; Fox-Kemper et al., 2021).

Uncertainty in hazard projections arises from multiple sources. Climate model uncertainty reflects differences in model structure and climate sensitivity. Scenario uncertainty reflects divergence across emissions pathways, particularly beyond mid-century. Hazard model uncertainty arises from parameterisations, downscaling approaches, and the simplifications required for global-scale modeling. In addition, CHD does not explicitly represent local-scale processes such as engineered flood defences, drainage systems, or site-specific land management practices.

Importantly, the CHD framework is designed to be most robust for relative comparisons across scenarios, locations, and time horizons, rather than for absolute hazard estimation at individual sites. Uncertainty in absolute values is therefore less consequential than the consistency and direction of projected changes, which are the primary outputs of interest.

Making Sense of Hazard Change

Understanding multi-hazard interactions

Climate Hazard Diagnostics (CHD) outputs are intended to be interpreted primarily in terms of relative change rather than absolute hazard levels. Differences between future scenarios and the historical baseline represent the projected climate-driven signal at each location, independent of local infrastructure, protection standards, or asset characteristics.

Scenario comparison provides additional interpretive insight. The divergence between lower- and higher-emissions pathways reflects the sensitivity of hazard outcomes to future warming trajectories. When scenario differences are small, hazard escalation is relatively insensitive to emissions choices over the specified time horizon; when differences are large, mitigation pathways substantially influence future hazard conditions.

Risk thresholds are inherently contextual rather than universal. There is no single intensity, probability, or ALL value that defines 'high risk' across all settings. Interpretation should therefore be calibrated to the specific exposure, vulnerability, and tolerance for disruption relevant to the analysis context. For users requiring alternative damage relationships or thresholds, the inclusion of raw physical variables enables custom interpretation beyond the standardized metrics.

Time horizons should be interpreted in relation to the persistence of exposure. Near-term horizons capture limited scenario differentiation because of climate inertia, whereas mid- and long-term horizons increasingly reflect divergence across emissions pathways. Uncertainty in absolute values does not negate the usefulness of relative change, provided comparisons are made consistently across scenarios and locations. Selection of appropriate horizons should therefore align with the expected duration of exposure.

> The divergence between lower- and higher-emissions pathways reflects the sensitivity of hazard outcomes to future warming trajectories.”

Where the framework is most applicable

The Climate Hazard Diagnostics (CHD) framework is suited to applications that require consistent, spatially resolved comparison of how acute physical hazards change over time and across scenarios. It is particularly appropriate where the objective is to identify relative differences, escalation patterns, or sensitivities rather than to produce site-specific damage estimates.

Appropriate applications include:

- Portfolio- or geography-scale screening, to identify locations where acute hazards are projected to intensify most strongly
- Scenario-based comparison, assessing how hazard outcomes differ under alternative warming pathways
- Relative prioritisation, supporting decisions about where further, more detailed analysis may be warranted
- Integration into broader physical risk or financial impact workflows, where hazard metrics serve as inputs to asset-specific vulnerability or valuation models

The framework is not designed to replace detailed engineering analysis, local floodplain mapping, insurance underwriting without local calibration, or real-time hazard forecasting. These applications require higher-resolution inputs and local context beyond the scope of global climate hazard projections.

Instead, CHD should be understood as a diagnostic and prioritisation layer, providing a consistent starting point for understanding where and under which scenarios acute physical hazards are likely to escalate.

Integration with Financial Risk Assessment

Climate Hazard Diagnostics (CHD) focuses on quantifying changes in physical hazards rather than directly estimating financial loss. The outputs are designed to integrate into broader physical risk and financial impact assessment frameworks by serving as hazard inputs that can be combined with exposure, vulnerability, and valuation data as appropriate.

The two core hazard dimensions, normalized intensity and annual exceedance probability, map naturally to common components of financial risk analysis. Intensity indicates the potential maximum disruption or damage severity, while probability captures the expected frequency of damage-relevant conditions. Together, these dimensions support the translation of physical hazard change into expected impact profiles when combined with asset-specific assumptions.

For workflows that estimate expected loss or Value-at-Risk–type metrics, hazard outputs can be applied in two ways. First, changes in intensity and probability relative to the baseline can be used to assess relative shifts in risk profiles across scenarios and time horizons, highlighting where future warming materially alters exposure. Second, the underlying raw physical variables retained in the dataset enable the direct application of custom vulnerability or damage functions, allowing financial metrics to be derived externally without altering the hazard framework.

'Physical hazard change becomes financially material only when combined with exposure and vulnerability.'

Average Annual Loss (AAL) provides a direct, scenario-aligned estimate of expected annual damage, combining hazard severity and frequency into a financially interpretable metric. Expressed as a fraction of asset value, AAL supports consistent comparison and prioritisation across locations, hazards, and scenarios. It is derived using standardised damage relationships and is intended for portfolio-scale analysis rather than precise asset-level loss estimation. Where higher-resolution analysis is required, users may apply asset-specific vulnerability functions to the underlying physical variables and integrate across the full hazard distribution.

By maintaining a clear separation between hazard quantification and financial modeling, CHD enables flexible integration across a range of analytical contexts. The framework supports escalation workflows, in which locations with high or rapidly increasing hazard metrics are flagged for deeper, asset-specific assessment rather than attempting to replace those downstream analyses.

Why Existing Approaches Fall Short

The availability of climate hazard data has expanded rapidly in recent years, driven by advances in climate modeling, increased computational capacity, and growing demand for forward-looking physical risk assessment. At the same time, expectations for the use of climate scenarios have evolved, with greater emphasis on comparing outcomes across emissions pathways and time horizons rather than relying on single-point estimates.

Much of the existing landscape remains fragmented. High-level climate indicators provide broad signals of change but lack spatial specificity and relevance to hazards. Conversely, highly detailed engineering or catastrophe models offer asset-level insight but are often constrained by data availability, cost, or scalability, particularly when applied across large geographies or diverse asset bases.

This has created demand for intermediate-scale hazard diagnostics that bridge global climate projections and downstream risk assessment workflows. Such diagnostics prioritise consistency, transparency, and scenario alignment, enabling relative comparison of hazard escalation while avoiding false precision where local data are unavailable or uncertain.

Within this context, Climate Hazard Diagnostics (CHD) reflects a broader shift towards scenario-consistent, change-focused hazard assessment, emphasising how physical conditions evolve under different warming pathways and where escalation is most pronounced. This approach aligns with emerging expectations for climate scenario analysis, stress testing, and long-horizon risk assessment, without prescribing specific decision frameworks or outcomes.

> "Highly detailed local models struggle to scale, while high-level indicators lack decision relevance, leaving a gap where scenario-driven hazard change should sit."

Conclusion

Climate change is reshaping the frequency and severity of acute physical hazards in ways that vary significantly across locations, time horizons, and warming pathways. Understanding these changes requires hazard assessments that move beyond static historical representations and provide consistent, forward-looking insight into how physical conditions are expected to evolve.

Climate Hazard Diagnostics (CHD) provides a global, scenario-aligned framework for quantifying relative changes in acute hazard intensity and frequency across wildfire, tropical cyclones, coastal flooding, and fluvial flooding. By focusing on delta-based metrics, scenario-consistent normalisation, and transparent hazard construction, the framework isolates the climate-driven signal while avoiding false precision around local conditions that global models cannot reliably resolve.

The datasets are designed to support comparative analysis, scenario evaluation, and prioritisation across geographies, particularly where exposure is long-lived, immobile, and sensitive to cumulative hazard escalation. By retaining both standardized metrics and the underlying physical variables, CHD enables flexible integration into broader physical risk and financial impact assessment workflows while maintaining clear boundaries for interpretation and use.

As climate-driven hazard patterns continue to evolve, consistent, reproducible, and scientifically grounded diagnostics will play an increasingly important role in understanding where and under which scenarios acute physical risks are likely to intensify. CHD provides a robust foundation for that assessment.

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To meet this need, we built Carbon Diagnostics - decision-useful climate insights, delivered at scale.

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