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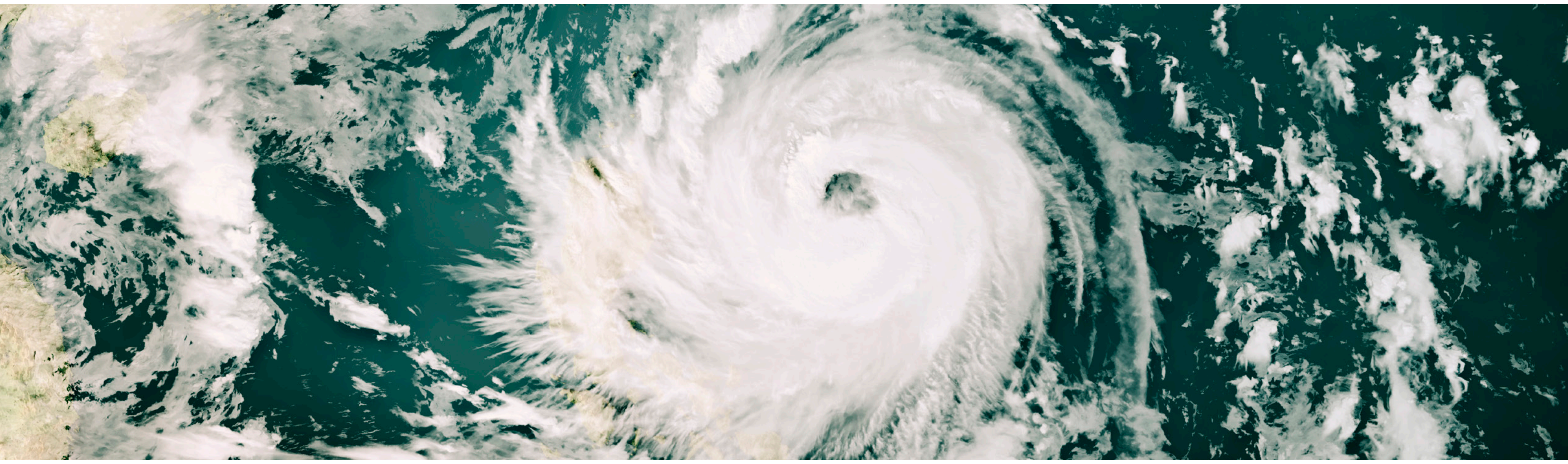

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Catastrophe Modeling 101

Catastrophe models have become indispensable to understanding and quantifying the risks posed by natural and man-made disasters. This white paper provides a foundational understanding of such models, delves into their core components, and examines the outputs they produce. It also looks toward the future of catastrophe modeling, which we believe will be affected by advances in artificial intelligence and machine learning.

Introduction

In an increasingly uncertain world, understanding and quantifying the risks posed by natural and man-made disasters is critical for effective decision-making. Catastrophe models, or "cat models," have become indispensable tools in this effort, providing a structured framework to assess the potential impact of catastrophic events. Widely used in (re)insurance, as well as by governments and other stakeholders, these models help evaluate exposures, price coverage, manage portfolios and plan for extreme events.

This white paper provides a foundational understanding of catastrophe models, beginning with their purpose and the motivations behind their development: Why were they created? What problems do they solve?

Next, the paper delves into the core components of a catastrophe model: hazard, vulnerability and financial. Following this, we examine the outputs of catastrophe models, explore commonly used techniques and calculations, and address their "frequently asked questions."

Finally, the paper looks toward the future of catastrophe modeling: Can advances in technology, particularly artificial intelligence (AI) and machine learning, lead to improvements?

Whether you are new to catastrophe modeling or seeking deeper insights, this paper offers a clear and comprehensive introduction to this critical field.

Why Do Catastrophe Models Exist?

It's incredibly challenging to predict where the next Category 5 hurricane or magnitude 9 earthquake will occur. With fewer than 100 U.S. landfalling major hurricanes over the last 170 years, compared to a wealth of datapoints in other industries such as health and auto, traditional actuarial methods of risk assessment are not sufficient in analyzing the occurrence of low-probability, high-severity natural catastrophes. This became horribly evident in the 1990s, when major events such as southern Florida's Hurricane Andrew and Los Angeles's Northridge earthquake caused unprecedented amounts of economic and insured damages. After decades of benign losses, many insurers became insolvent due to a lack of preparedness for events of such severity.[1] Regulators quickly responded by detailing solvency requirements based on the risks held by insurers. The previous approach of estimating losses via historical claims data did not consider the full range of possible natural catastrophe events, underestimating the potential for severe losses outside what had already been observed.[2]

IS CATASTROPHE PREDICTABLE?

Hurricane Andrew produced unprecedented damage.

Source: https://www.nytimes.com/2016/10/07/us/hurricane-matthew-andrew-florida.html.

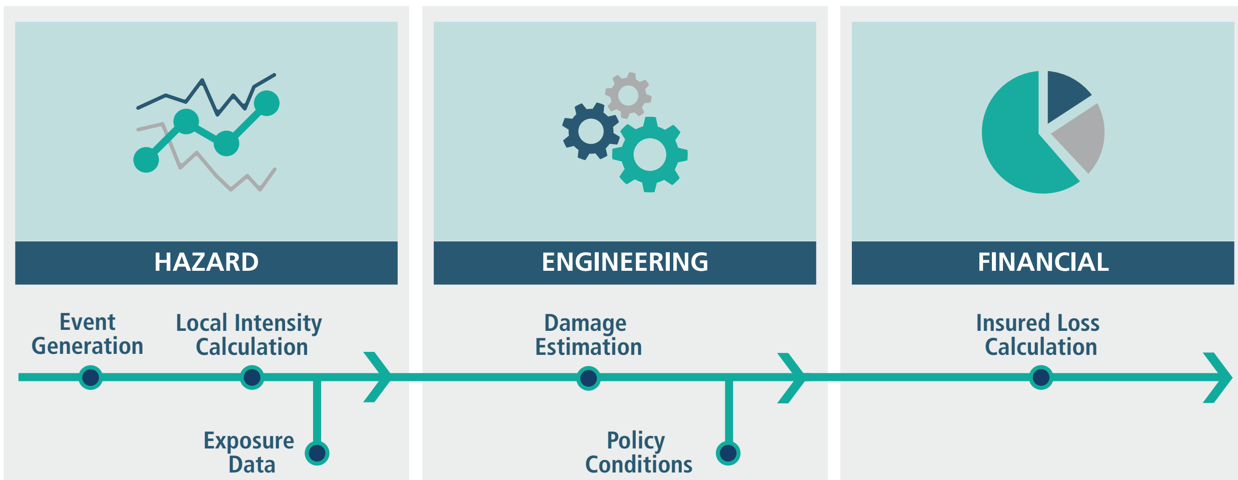
In addition to sparse historical data on the physical events themselves, the underlying assets at risk (the "exposure") changed with time: Miami today is not the same city that existed during the Category 5 Great Miami Hurricane of 1926. Therefore, any solution needed to account for an up-to-date view of exposure to accurately assess catastrophic risk in real time. Contemporaneously, the development of larger computing power set the stage for the emergence of third-party catastrophe-modeling firms such as Risk Management Solutions (RMS, now part of Moody's), and AIR Worldwide (now part of Verisk). These startups combined meteorological, seismic, engineering and industry claims data to create sophisticated, probabilistic models to address this problem. At the time of Hurricane Andrew, the magnitude of Verisk's $13 billion estimate of insured losses was considered implausible by the industry. With actual estimates reaching $15.5 billion,[3] more in line with Verisk than industry expectations, these third-party catastrophe models, once seen as an academic or supplementary exercise, became a necessary currency of the (re)insurance industry.[4]

[1] https://www.rmets.org/metmatters/extreme-weather-catastrophe-modelling-and-reinsurance-industry.
[2] https://www.businessinsurance.com/hurricane-andrew-impacted-how-industry-models-catastrophe-risks/.
[3] Ibid.
[4] Ibid.

How Are Catastrophe Models Built?

Catastrophe models are typically constructed with the following primary components: stochastic event generation and hazard, vulnerability and financial.[5] The models consider uncertainties in the specific characteristics of an event and, in aggregate, generate a probabilistic representation of the relationship between event frequency and severity in order to estimate potential insurance losses. The below figure illustrates how the Verisk model components cooperate to generate results; other vendor models operate similarly.

THE CATASTROPHE MODELING FRAMEWORK



Source: https://www.verisk.com/en-gb/resources/about-catastrophe-modeling/.

Below, we explain each module in detail. Although the framework can be utilized across different natural catastrophes (wildfire, severe convective storms etc.), here, we simply focus on North Atlantic hurricanes.

Event Generation

The goal of event generation is a comprehensive set of hypothetical events that represents the full range of possibilities, not just what has been observed historically. These events collectively form a stochastic event set, where each synthetic event is unique and has its own set of physical characteristics such as, in the case of North Atlantic hurricanes, position, Saffir-Simpson category and central pressure for the storm's duration. Each event will also have a corresponding frequency or rate of occurrence.

The first question one must ask is, "where will an event occur and at what severity?"; this is known as primary uncertainty.[6] Not all hurricane seasons are created equally, as some years are more active than others. Much of this fluctuation in activity is due to natural variability: atmospheric, oceanic and climatic processes that occur periodically. These processes include changes in sea surface temperatures, wind shear and large-scale weather phenomena like El Niño and La Niña.

Once a storm is formed, the track is further influenced by short-term factors, such as atmospheric steering patterns, which introduce a significant element of randomness. Consequently, the complex interconnections among these processes make it challenging to rely solely on the historical record for statistically robust risk assessments, especially for such low-probability, high-impact events. This challenge becomes even greater when considering smaller geographical areas; for example, while the historical record might suffice to estimate the annual probability of a Category 2 hurricane landfalling somewhere along the U.S. coastline, it is likely inadequate for predicting the probability of a commercial property on the North Carolina coast experiencing Category 5 wind speeds.

[5] https://forms2.rms.com/rs/729-DJX-565/images/rms_guide_catastrophe_modeling_2008.pdf.
[6] https://www.verisk.com/blog/Understanding-Uncertainty/.

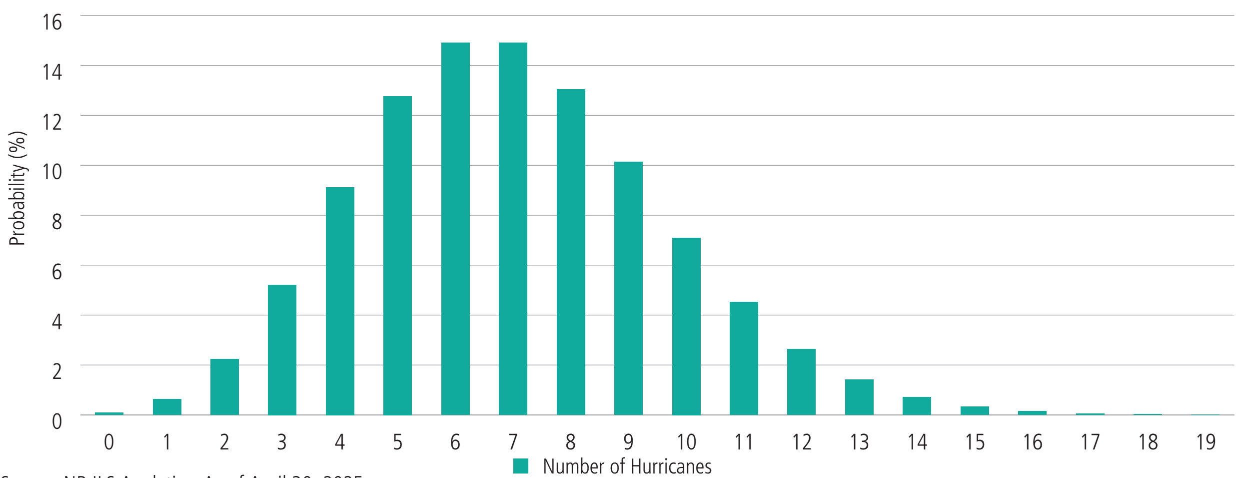
The traditional method of event generation adopted by catastrophe modelers is to use statistical techniques to simulate tens of thousands of synthetic years of catastrophe activity to extrapolate the historical record.[7] In the case of North Atlantic hurricanes, the hurricane database (HURDAT)[8] provided by the National Hurricane Center (NHC) is widely used as the historical basis for seeding stochastic models. The HURDAT database encompasses all known tropical and subtropical systems in the Atlantic Ocean, Gulf of Mexico and Caribbean Sea back to the year 1851, and comprises six-hourly estimates of position, intensity and size. Due to advances in aircraft reconnaissance, data after 1944 is considered more reliable.

All of this information can be used to parameterize a statistical track model where, for each hurricane season simulation, the number of storms is initially sampled from a distribution, for example a Poisson, of seasonal frequencies constructed from the historical record.[9] For reasons already discussed, the number of hurricanes in a season varies, so a distribution is appropriate to capture that uncertainty. Two seasons highlight this: 2024 was a hyperactive season (as forecast), with 11 hurricanes, whereas 2013 was well below average, with only two storms reaching hurricane status.[10]

We can see how this looks in practice by plotting our own Poisson distribution using the 30-year average (1990 – 2020) frequency of North Atlantic hurricanes as the λ parameter (in this instance equal to seven[11]) to describe the probability of X hurricanes within a season. According to this distribution, the probability of a 2013 season in terms of hurricane occurrences is less than 2.5%.

POISSON DISTRIBUTION OF NORTH ATLANTIC HURRICANE FREQUENCY BASED ON 30-YEAR AVERAGE (1990 – 2020)

Poisson Distribution: $\lambda = 7$



Source: NB ILS Analytics. As of April 30, 2025.

For each storm within a simulated season, genesis location and severity (i.e., central pressure and maximum windspeed, or Vmax),[12] can be initially sampled according to observed distributions, with each storm's subsequent track, severity and other physical characteristics simulated forward in time at a specified increment for the life cycle of the storm.[13] Note that vendors can differ in the statistical methods they use to generate stochastic tracks; for example, Verisk uses a Markov process to describe track directional changes.[14] To validate these simulated hurricane tracks, it is typical for model vendors to ensure that simulated landfall frequencies across a set of predefined landfall gates or regions across North America are consistent with the historical record.[15] Since catastrophe models are designed for low-frequency, high-severity events, most North Atlantic hurricane models restrict their stochastic set to events that landfall or bypass at intensities of Saffir-Simpson Category 1 or above (hurricane wind speeds).

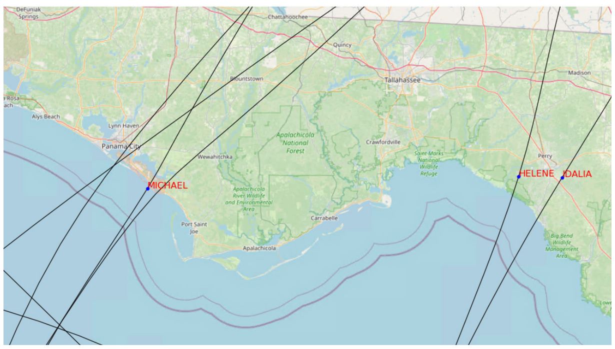
[7] https://www.verisk.com/en-gb/resources/about-catastrophe-modeling/.
[8] https://www.aoml.noaa.gov/hrd/hurdat/Data_Storm.html.
[9] https://fchlpm.sbafla.com/media/4fdg1eyk/rms21standardsdisclosures_05192023.pdf.
[10] https://tropical.atmos.colostate.edu/Realtime/index.php?arch&loc=northatlantic.
[11] https://www.nhc.noaa.gov/climo/.
[12] Defined as the highest one-minute average or sustained wind speed observed at 10 meters above the surface.
[13] https://fchlpm.sbafla.com/media/4fdg1eyk/rms21standardsdisclosures_05192023.pdf.
[14] https://fchlpm.sbafla.com/media/bq0ivq2m/vsk2021_submission_notrackedchanges_20231117.pdf.
[15] Ibid.

The plots below underscore the importance of stochastic event generation by focusing on a portion of the Florida coast near Tallahassee. The first plot shows all hurricanes in the HURDAT database that were at major hurricane (Category 3 or above) status within the plot boundary. Interestingly, three of these events, Helene (2024), Idalia (2023) and Michael (2018), have occurred in the past decade, while the other three storms highlighted occurred before 1900. The noticeable gap in landfalling major hurricanes between the landfall locations of Michael and Helene highlights the limitation of the historical record: Despite over a century of data, the observed dataset is not large enough to capture the full range of possible events at such low frequencies. Although the historical record shows no major hurricane landfalls in this stretch of coastline, we know from physical principles that a landfalling major hurricane is entirely possible there; the absence in the record is a reflection of the low probability and limited sample size.

The second plot displays all hurricanes at major status within the specified boundary, as generated by an open-source stochastic event set[16] that employs methodologies consistent with those previously outlined. The stochastic set greatly improves geographical coverage, capturing even rare, low-frequency major hurricanes. This is immediately evident in the plot, which now shows hypothetical landfalls in areas of the coast with no recorded historical events.

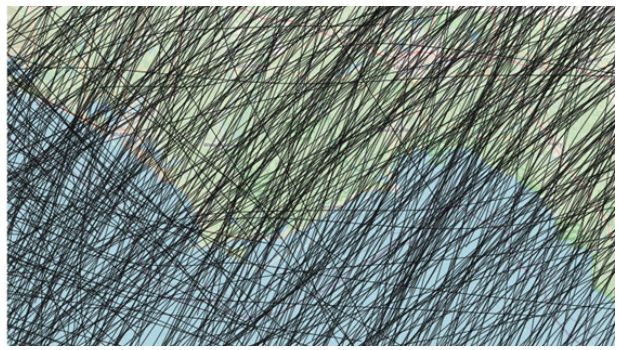
SIMULATIONS BROADEN THE PAST

Historical Major Hurricane Tracks, Coast in Tallahassee Vicinity



Source: OpenStreetMap contributors, NHC Hurdat. As of April 30, 2025.

Stochastic Major Hurricane Tracks, Coast in Tallahassee Vicinity



Source: https://doi.org/10.6084/m9.figshare.c.6724251.v1.

Hazard

Once the set of simulated hurricane tracks is developed, the next step is determining each track's wind field, which is ultimately used to assess the hazard level at the granularity of an individual building. The output of this process is a high-resolution grid, typically of the three-second peak gust, as it is highly correlated with damage.[17] This grid is termed the "hazard footprint" and represents the maximum hazard over the lifetime of the modeled stochastic event within each grid cell. Of course, other types of natural catastrophes may require different measures of hazard.

Well-publicized methods[18] (Willoughby 2005) exist to describe the one-minute sustained windspeed over water for any point based on distance to storm center, as well as other macro parameters such as the Vmax, the forward speed (how fast the hurricane is moving), and the radius of maximum wind speeds, Rmax.[19] The Willoughby wind profile employs exponential functions to describe how wind speeds decrease radially from the Rmax, effectively capturing the intense winds within the eyewall region, which diminish rapidly as one moves toward the eye and more gradually as one moves outward from the eyewall.[20]

Local intensities are further influenced by the asymmetric nature of a hurricane wind field (see figure below) and local land-surface topography.[21] In the Northern Hemisphere, the right side of a hurricane (relative to its direction of movement) experiences stronger winds because the storm's rotational winds combine with its forward motion, whereas the left side experiences weaker winds. This asymmetry in wind strength is caused by the combined effects of the hurricane's movement and the Coriolis effect, which together create an uneven wind field around the eye of the storm. With respect to topography, rougher land surface will slow a storm and weaken its wind speeds.

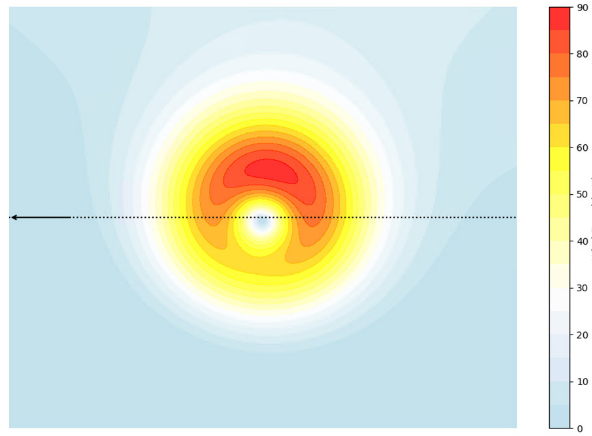
[16] Sparks, Nathan; Toumi, Ralf; "IRIS: The Imperial College Storm Model;" figshare, 2024. https://doi.org/10.6084/m9.figshare.c.6724251.v1.
[17] https://fchlpm.sbafla.com/media/fwkpwgwg/fchlpm_corelogic2021_24april2023.pdf.
[18] https://journals.ametsoc.org/view/journals/mwre/134/4/mwr3106.1.pdf.
[19] Defined as the distance from the center of a tropical cyclone to the location where the maximum sustained wind speed (Vmax) occurs.
[20] https://www.air-worldwide.com/SiteAssets/Publications/AIR-Currents/attachments/AIRCurrents--Wind-Profiles-in-Parametric-Hurricane-Models.
[21] https://fchlpm.sbafla.com/media/bq0ivq2m/vsk2021_submission_notrackedchanges_20231117.pdf.

The plot to the right is a hypothetical one-minute sustained wind speed footprint using the method devised by Willoughby[22] for a Category 5 hurricane with an Rmax of 50 kilometers moving west at 10 meters per second. Note that a three-second peak gust can be translated from a one-minute sustained wind using a simple multiplicative rule.[23]

By generating wind hazard footprints for each event in the stochastic set, we extrapolate wind speeds at specific locations beyond what has been historically observed. This ensures that, even if a site has never recorded Category 5 winds, the model accounts for that possibility by leveraging the full distribution of modeled events and their footprints which interact with that location.

The plot below from Karen Clark & Company (KCC),[24] another catastrophe model vendor, illustrates this comparison by showing modeled maximum one-minute sustained wind speeds for historical hurricanes (left figure) for 1900 – 2020 alongside KCC's own stochastic model output at the 1-in-250-year return period (right figure). Focusing on our section of the Florida coast near Tallahassee, the historical plot reveals that most of the area, apart from the swath marking 2018 Hurricane Michael's landfall, had not experienced major hurricane-force winds. In contrast, the 1-in-250-year return period plot in that region displays a continuous band of wind speeds exceeding major hurricane-force wind speeds along the coastline. The incompleteness of the historical plot, showing no modeled major hurricane-force winds in the Big Bend region up to 2020, is underscored by the subsequent landfalls of Idalia (2023) and Helene (2024), both of which made landfall there as major hurricanes.

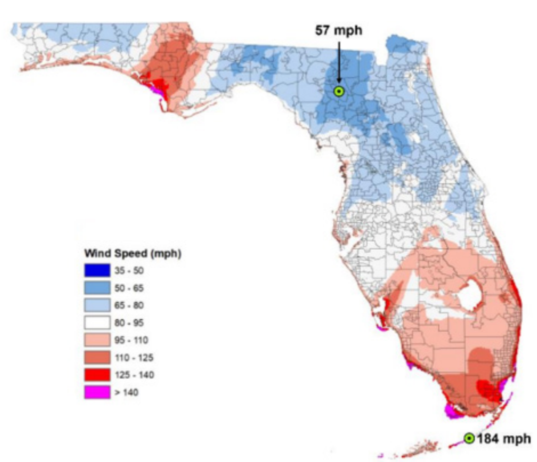
HYPOTHETICAL WIND FIELD FOR A CAT 5 HURRICANE



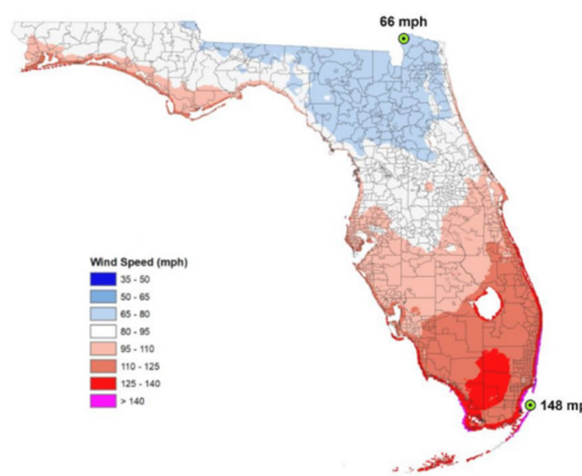
Source: NB ILS Analytics. As of April 30, 2025.

MODELED WIND SPEEDS FOR FLORIDA

Modeled Maximum One-Minute Sustained Wind Speed for Historical Hurricanes,1900 - 2020



1-in-250 Year Modeled Maximum One-Minute Sustained Wind Speed for Stochastic Model



Source: Karen Clark & Company.

[22] https://journals.ametsoc.org/view/journals/mwre/134/4/mwr3106.1.pdf.
[23] https://journals.ametsoc.org/view/journals/mwre/149/12/MWR-D-21-0059.1.xml.
[24] https://fchlpm.sbafla.com/media/zicplqcr/kcc22_submission_document_draft_p20230627_ntc.pdf.

Winds are not the only source of hurricane damage. Storm surge, whose hazard is usually measured in feet, also needs to be translated into a high-resolution grid for each simulated hurricane. Storm surge has its own set of considerations in creating this grid that include timing of the tide and regional bathymetry data.[25] For instance, the Gulf Coast is highly vulnerable to storm surge due to its shallow and gently sloping continental shelf.[26]

Exposure

Following the hazard module, models require accurate exposure data to represent the assets at risk. During the underwriting process, primary insurers collect comprehensive information about each property they insure. This includes details such as location, year built, construction type (e.g., wood, concrete, masonry), occupancy (e.g., single-family home, apartment, mobile home), building characteristics, contents and the financial value of the assets, along with specifics of the underlying insurance policy.[27] These are input into the model and are the basis for calculating the subsequent vulnerability and overall replacement cost to hazards such as the wind speeds and storm surge just discussed.

Reinsurance coverage based on indemnity or ultimate net loss (UNL) derives from actual losses incurred by the counterparty (typically an insurer) and are modeled using the counterparty's actual portfolio of insured assets. An insurer will collect the aforementioned detailed information about each of its policies, which then informs the model of what is at risk. Conversely, protection based on losses incurred by the entire industry, such as Industry Loss Warranties or industry-index trigger catastrophe bonds, are modeled using a reconstruction of the entire insurance industry's exposure, referred to as the Industry Exposure Database (IED).

Each third-party modeling agency has its own proprietary procedure for creating its internal IED. Like a primary insurer underwriting its own portfolio, the modeling agency will take a bottom-up, data-driven approach to cataloging insured assets across insurance companies, collecting information like the above on property characteristics and associated policies. The vendor will then separate this data among various lines of business (e.g., residential, mobile home, auto and commercial). This process is repeated across modeled peril regions, each with unique challenges such as sparse or outdated data, which is common among countries with emerging insurance markets. The model vendor's exposure team comprises experts across engineering, economics, insurance and GIS to overcome such challenges.

Once created, these IEDs are validated against insurance company data, macroeconomic data, regional news and post-event damage surveys. It is critical that IEDs are continuously updated to capture real-time values, as populations, wealth, built environment and infrastructure in hazard-prone regions can meaningfully change over relatively short timescales.

To update this data, IEDs can be indexed or inflated annually until the next complete, comprehensive rebuild, which will occur more frequently for developed insurance markets like the U.S. The methods for building and maintaining IEDs continue to develop and increase in sophistication. For example, machine learning on satellite imagery can be used to supplement sparse datasets in emerging insurance markets or for the purpose of validation in more developed regions such as the U.S.[28] These advances strengthen our understanding of the assets at risk and provide opportunity to introduce risk transfer solutions to new regions.

Vulnerability

The vulnerability module quantifies the relationship between a given hazard and the resulting damage of an exposed asset. This relationship is defined by the vulnerability function, in which the mean damage ratio (MDR), the proportion of the expected or average repair cost to the total building (or contents) replacement value, increases as a function of the hazard intensity. Similarly, "time element" vulnerability functions consider the cost of additional living expenses or business interruption and relate the extent of building damages to the amount paid to the policyholder while the structure is being repaired.[29]

[25] https://forms2.rms.com/rs/729-DJX-565/images/RMS-North-Atlantic-Hurricane-Models.pdf.
[26] https://www.nhc.noaa.gov/surge/.
[27] https://www.marsh.com/en/services/property-risk-management/insights/catastrophe-modeling.html.
[28] https://www.verisk.com/blog/modeling-fundamentals-air-industry-exposure-databases/.
[29] https://fchlpm.sbafla.com/media/4fdg1eyk/rms21standardsdisclosures_05192023.pdf.

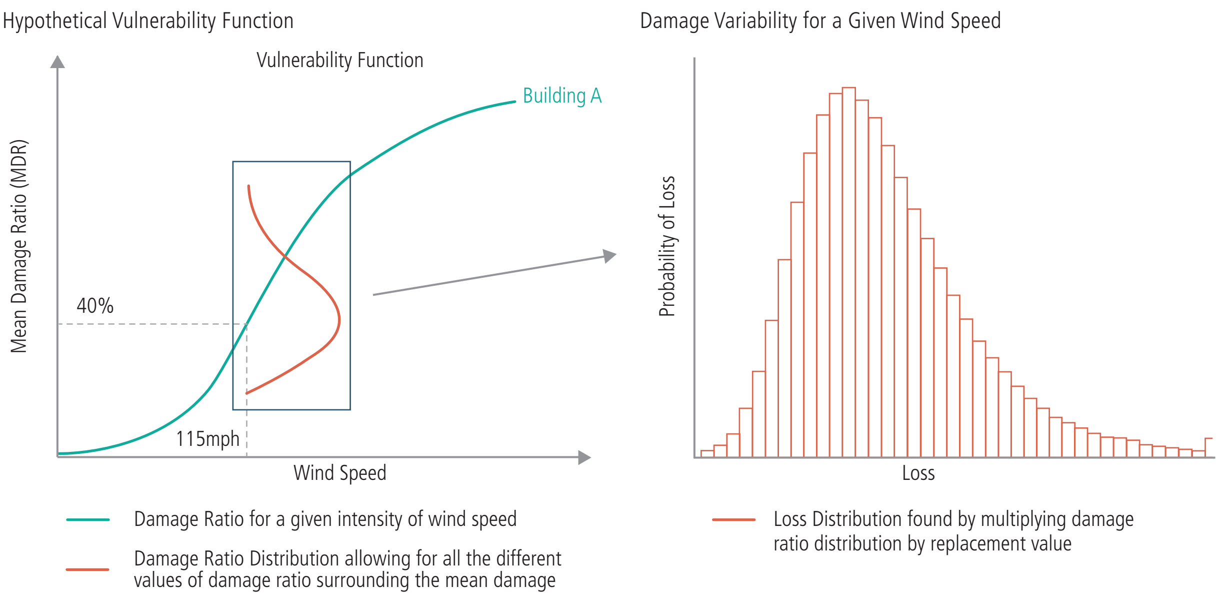
These functions are created using a combination of historical hazard data, engineering analysis and theory, and claims data. Vulnerability functions are greatly influenced by peril, region, building characteristics and building code. In the case of Japan, which is vulnerable to both earthquakes and typhoons, heavy roof tiles are commonly seen as effective in resisting the uplift of strong winds, but magnify damage when experiencing a strong earthquake.[30] The hazard will also inform the shape of the vulnerability function. Comparing wind speeds and storm surge, flood damage increases rapidly up to one foot of water depth before slowing between three and five feet. In contrast, wind speed damage is slow to accumulate up to 100mph and increases rapidly thereafter. Regional building codes, and their enforcement, also make a meaningful difference. Florida's rigorous building codes will likely reduce vulnerability relative to a state such as Mississippi, which has no such codes.[31]

The primary building characteristics considered in generating vulnerability functions include construction material, year built, building height, building occupancy, floor area, and region or state. Commercial buildings utilize similar primary classes.[32]

Given the lack of empirical damage data, MDR values are not deterministic. As we have already discussed, uncertainty in catastrophe modeling can be split into primary and secondary, with primary uncertainty reflected in the event-generation component of the model. Secondary uncertainty captures all remaining sources of uncertainty in predicting the ultimate damage caused by an event, and includes the uncertainty in local hazard levels experienced. Using wind speed hazard as our example, while a vulnerability function will only show a point estimate MDR for a given wind speed, that value corresponds to a full distribution of potential damage ratios of 0 – 100%.[33] Another way to think about it is that a given wind speed has an expected level of damage, but there is a chance that the wind speed will cause anywhere from no or minimal damage to full damage.

The following two figures are both representations of secondary uncertainty. The charts illustrate a hypothetical vulnerability function relating the mean damage ratio to peak wind speed gusts (green line). Damage slowly accumulates and then increases rapidly before finally leveling off as the building approaches complete destruction. At the 115mph mark, the mean damage ratio level is 40%, and we see a rotated red curve that serves as a graphical representation of the corresponding secondary uncertainty. This red curve represents the range of potential damage values for that wind speed; so, while the mean centers around 40%, 115mph winds could cause much more or much less damage in practice. The red chart is then translated to a loss distribution by multiplying each damage ratio by the replacement value.

CAPTURING SECONDARY UNCERTAINTY



Source: http://understandinguncertainty.org/node/622.

[30] https://www.air-worldwide.com/SiteAssets/Publications/AIR-Currents/attachments/AIR-Currents--Anatomy-of-a-Damage-Function.
[31] Ibid.
[32] https://fchlpm.sbafla.com/media/4fdg1eyk/rms21standardsdisclosures_05192023.pdf.
[33] https://www.verisk.com/blog/Modeling-Fundamentals--Understanding-Uncertainty/.

The aerial imagery exemplifies secondary uncertainty in practice: The house apparently remains fully intact amid the destruction of similarly built buildings surrounding it.

UNCERTAINTY IN THE REAL WORLD

Source: https://www.theguardian.com/world/article/2024/jul/12/solitary-wooden-house-on-union-island-escapes-fury-of-hurricane-beryl.

Financial

The financial module converts location-level ground-up losses into policy-level outcomes by applying input contractual terms such as deductibles, coinsurance and coverage limits. Deductibles and coverage limits may vary by site and are typically divided into buildings, contents and "time element" for business interruption. An insurer's total gross loss is calculated by aggregating location-level losses within each policy, accounting for further applicable limits and deductibles, and then summing these policy-level gross losses across the entire portfolio.

The module also incorporates reinsurance to provide a "net" perspective where losses are redistributed between the reinsured and reinsurers. Reinsurance programs can be divided into two main types:

- *Facultative:* Coverage of singular, often high-value risks.
- *Treaty:* Coverage of many similar risks based on type or geographic location.

Facultative and Treaty reinsurance can be categorized as follows:

- *Proportional:* Losses shared in a fixed proportion between the reinsured and reinsurer.
- *Non-proportional:* Reinsured retains losses below a predetermined threshold (attachment point); reinsurer covers losses above the threshold.

These categories may then be subdivided again, which presents further modeling complexities. Thus, detailed modeling is required to accurately reflect how losses flow from the ground up.

Most financial modules allow interrogation of losses from different financial perspectives, for instance, at the ground-up level before any financial conditions are applied or at the gross level after policy conditions, but before any reinsurance applications. Knowing the pertinent financial perspective is critical for accurate calculations. For instance, an insurer's head of exposure management will be interested in the ultimate net exposure after application of all policy and reinsurance conditions, whereas a catastrophe modeler validating industry-insured losses will need the gross loss perspective after the application of insurance policy terms only.

Exceptionally large events typically experience economic and social conditions that inflate losses, known in catastrophe models as Post-event Loss Amplification (PLA). For example, to capture PLA, Moody's includes mechanisms such as Economic Demand Surge, which captures an increase in the cost of building materials and labor due to a supply-demand imbalance; Claims Inflation due to the difficulties in fully adjusting claims; and Super Catastrophe Scenarios, which consider exacerbated losses due to containment failures, evacuation impacts and localized recessions in some urban regions.[34] Other meaningful considerations, such as inflation caused by real-time macroeconomic conditions or overly litigious/fraudulent behavior, remain unmodeled and thus must be accounted for by the end user.

All the modules together represent a complete catastrophe model, and we are now able to explain the output and applications.

Using the Models

Output

Use of a catastrophe model allows the user to answer questions like "What is the probability of a Florida hurricane causing an insurance industry loss of $50 billion or more?"

Before we get to that point, let's look at the data structure from the ground up; the typical output looks like a Monte Carlo simulation with a variation of the following columns:

- *Period:* The independent simulation period for a specific timeframe, usually a year. Typically, a large number of simulations (e.g., 10,000 iterations of one year of risk) are needed to ensure statistically robust risk metrics.
- *Event ID:* The identification of a sampled unique event from the stochastic set.
- *Date:* The date of the event in question; it is critical to capture the seasonality of perils (where appropriate), especially when considering the risk over a short time period such as June 1 to July 31 (before the climatological peak of North Atlantic hurricane season).
- *Loss:* Denotes the loss for various financial perspectives, including the policy losses to an individual insurance company or to an investor in a catastrophe bond.

Risk Metrics

A common way of distilling the output of a specific catastrophe model is known as the Exceedance Probability (EP) curve.[35] The curve enables a visualization of the frequency-severity relationship with the probability of exceedance decreasing as loss increases. EP curves can be constructed on an occurrence or aggregate basis and are typically expressed using annual probabilities:

- *Occurrence EP (OEP)* is defined as the probability that at least one event will occur which causes individual losses greater than or equal to a given loss threshold L.
- *Aggregate EP (AEP) is* defined as the probability that a combination of one or more events will occur where the sum of their individual losses is greater than or equal to a given loss threshold L.

It is simple to construct an EP curve from a simulated (Monte Carlo) catastrophe model output: Assuming 10,000 simulation years, each loss threshold L would either be the maximum or the sum of Loss within the simulated year, and each EP point would be the corresponding rank (descending) divided by 10,000. In other words, one is performing a count of modeled years that are greater than or equal to the loss threshold L in question. Return period is a common way to express EP values; for instance, a 1-in-100-year event corresponds to an OEP value of 1%. In terms familiar to traditional financial markets, this can also be described as the Value at Risk (VaR) at the 99th percentile. Another commonly used risk metric is Tail Value at Risk (TVaR). While VaR represents the minimum loss expected at a given probability threshold, TVaR indicates the average severity of losses that exceed that threshold.

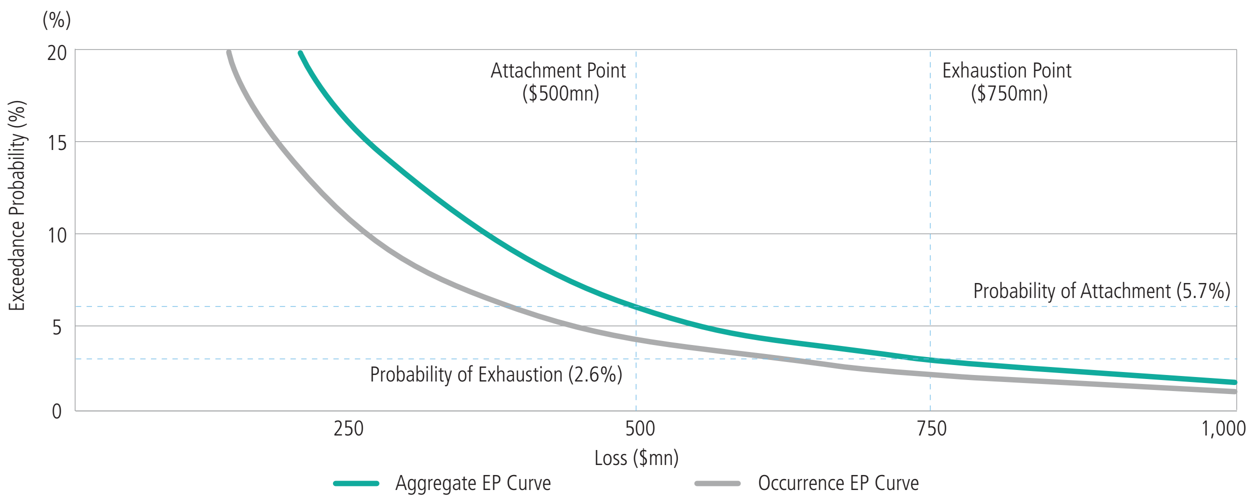
[34] https://fchlpm.sbafla.com/media/4fdg1eyk/rms21standardsdisclosures_05192023.pdf.
[35] https://forms2.rms.com/rs/729-DJX-565/images/rms_guide_catastrophe_modeling_2008.pdf.

Insurance-Linked Securities, specifically the catastrophe bond market, has its own related set of specific terms, which are defined below, assuming 10,000 simulated years of losses for a hypothetical catastrophe bond:

- *Probability of Attachment:* The probability that a transaction becomes impaired; a count of simulations where there is a modeled event or set of events that triggers the transaction divided by 10,000.
- *Expected Loss:* The long-term average annual loss to the transaction; the sum of all modeled loss payouts across the simulation set divided by 10,000.
- *Probability of Exhaustion:* The probability that a transaction is fully impaired; a count of simulations where the transaction is fully impaired divided by 10,000.

The figure below graphs EP curves of a hypothetical insurance portfolio. The portfolio's AEP curve has a VaR 90 of approximately $350 million, meaning that there is a 10% chance of experiencing an aggregate loss of $350 million or more. Another way of expressing this is that, over a long period of time, a loss of $350 million or more will occur every 10 years, on average. The OEP curve naturally sits below the aggregate, as it considers single-event losses rather than the aggregation of event losses.

EXCEEDANCE PROBABILITY (EP CURVE)



Source: NB ILS Analytics. As of April 30, 2025.

Now let's apply a catastrophe bond structure to this portfolio. The bond attaches (becomes impaired) at $500 million of aggregate losses and exhausts (full impairment) at $750 million. The vertical lines on the EP curves above illustrates where these attachment and exhaustion thresholds sit for this hypothetical portfolio. The probability of attachment and exhaustion, 5.7% and 2.6%, respectively, can be found by simply observing the exceedance probability at these thresholds.

Historical Analyses

Another useful feature of catastrophe models is the ability to assess the impact of a specific catastrophe as if it had happened today. These historical analyses are widely used in catastrophe modeling, with use cases such as a Northeast U.S.-focused insurer assessing its potential impact should an event like Hurricane Sandy (2012) happen in today's built and economic environment. Well-known events are a useful tool to communicate risk to interested parties, build intuition and evaluate the models themselves. Similarly, counterfactual analyses may provide valuable insight; what would the loss have been if Hurricane Dorian (2019) hadn't stayed off the coast of Florida and had made landfall there?

Hurricane Katrina, which caused catastrophic damage in Louisiana and Mississippi in 2005, serves as a useful reference point for understanding how losses from similar events could be materially different today. Accounting for inflation since 2005 only and using 2024 prices, Hurricane Katrina would cause $105 billion in insured losses; however, by also accounting for changes in population, the local economic environment and vulnerability, Swiss Re's internal model puts the number lower than the inflation-adjusted figure close to $100 billion.[36] This is primarily due to

[36] https://www.swissre.com/institute/research/topics-and-risk-dialogues/climate-and-natural-catastrophe-risk/hurricane-katrina-watershed-event-for-insurance.html.

the impact of the new flood defenses constructed in and around New Orleans to replace those destroyed in 2005 and the implementation of updated building codes. In addition, a decline in both population and economic activity in the broader region since 2005 has depressed insured exposure values. These historical reconstructions from modelers highlight the complex balance between vulnerability and exposure, as well as the importance of keeping up to date.

Event Response

Modeling agencies also provide analytical services during live events. As a storm is traveling across the Atlantic basin, modeling agencies will provide similar stochastic events (created in the event-generation module) that serve as analogs for potential landfall outcomes. Alternatively, a modeling agency may create a footprint or realization of the event in which the physical hazard characteristics are recreated and utilized to generate loss estimates.[37] There are also real-time forecasting tools, such as Moody's HWind,[38] which provides regular track updates for a given live event as it approaches landfall, distilling publicly available forecast data into probabilistic scenarios with corresponding loss estimates and EP curves.

Common Questions

What is the historical experience compared to model outputs?

Given the low probability nature of natural catastrophes and our limited dataset of event activity, it is challenging to rely solely on historical experience to assess model precision. Regardless, some analyses of the ILS market have concluded that actual losses lag modeled expectations, suggesting that models may be conservatively punitive.[39] Further, vendors validate their own catastrophe models at both the individual component level, for example, comparing stochastic event occurrence rates to actual observed data, and overall, using actual claims data and historical loss experience.[40] Finally, some states perform independent validation of models, such as the Florida Commission on Hurricane Loss Projection Methodology, to determine and approve which ones may be used for rate filings.[41]

What about seasonal forecasts and concerns around climate change?

The default view provided by catastrophe model vendors provide a long-term average view of North Atlantic hurricane risk. Therefore, they do not explicitly consider annual forecasts or transient environmental conditions. However, most vendors include stochastic event catalogs that represent alternative views of risk relative to their default. Verisk offers a warm sea surface temperature catalog, which assesses hurricane landfall frequency conditioned more to "typical" warm sea surface temperature years.[42] Separately, Moody's offers a medium-term rate catalog that is calibrated to a five-year forward-looking view of hurricane activity, which aims to be more reflective of current environmental conditions.[43]

With their experience in building probabilistic forward-looking models to capture uncertainty, vendors are best placed to consider any climate change impacts to date and in the future. For example, in an analysis of hurricane activity since 1900, KCC concluded that insured losses to date are 11% higher due to the impact of climate change.[44] Although this impact to North Atlantic hurricane risk is relatively minor considering the long timescale, the immediacy and magnitude of climate change impacts varies across different perils. For example, there is high scientific confidence that the drier conditions associated with a warming world have already increased, and are projected to continue increasing, wildfire risk.[45]

While the impacts of climate change are important and must be considered, the general consensus is that the largest driver of increased insured losses from climate-related perils is the increasing value and concentration of assets in exposed regions.[46] A study by Aon found that over 80% of the 8.9% year-on-year increase in severe convective storm losses in the United States from 1990 to 2022 can be explained by exposure growth.[47]

[37] https://www.karenclarkandco.com/liveEvents.
[38] https://www.moodys.com/web/en/us/capabilities/catastrophe-modeling/hwind.html.
[39] Lane Financial, "The Natural Catastrophe ILS Market, 2001-2023 and Its Analysis," 2024.
[40] https://forms2.rms.com/rs/729-DJX-565/images/tc_2012_principles_model_validation_us.pdf.
[41] https://fchlpm.sbafla.com/media/532jql0c/2023-hurricane-roa.pdf.
[42] https://www.air-worldwide.com/SiteAssets/Publications/White-Papers/documents/Climatological-Influences-on-Hurricane-Activity--The-AIR-Warm-SST-Conditioned-Catalog.
[43] https://forms2.rms.com/rs/729-DJX-565/images/RMS-North-Atlantic-Hurricane-Models.pdf.
[44] Climate Change Impacts on Hurricanes and Insured Wind Losses https://www.karenclarkandco.com/news/publications/.
[45] https://www.karenclarkandco.com/climate.
[46] https://www.munichre.com/en/risks/natural-disasters.html.
[47] https://www.aon.com/en/insights/articles/rising-losses-from-severe-convection-storms-mostly-explained-by-exposure-growth.

It should be noted that catastrophe models provided by vendors are not static; they are updated as new scientific consensus emerges, including for observed climate change impacts. Once a critical mass of evidence is reached, vendors incorporate the latest research and data into their models. This dynamic process ensures that risk assessments remain aligned with our evolving understanding of the physical environment.

Which vendor has the best model?

No vendor catastrophe model is considered the "best." We believe that a multi-model approach provides the most robust consideration of risk and is best at mitigating primary and secondary uncertainties. In our view, models are more robust for catastrophic "peak peril" (i.e., hurricane and earthquake) risks, where most R&D resources are spent, than for "secondary" or "non-peak" perils. Furthermore, models for these perils tend to have a shorter track record of development, having emerged much more recently than the first hurricane and earthquake models. Additionally, some "non-peak" perils present unique challenges; for example, wildfire is inherently sensitive to dynamic environmental conditions and anthropogenic influences such as fire suppression, making it difficult to model using traditional techniques.

How is correlation captured?

Simulating from a physical representation of each stochastic event, with a corresponding hazard footprint, ensures that correlation between exposed risks is an emergent phenomenon and not simply based on any assumed relationship.

Do these models incorporate machine learning and AI?

While most vendor models remain statistical in their approach, vendors are leveraging machine learning to enhance model components. For example, Verisk is utilizing aerial satellite imagery to identify clusters of high-rise buildings in China where exposure data is not as readily available.[48] Another use case is event response. For example, Moody's is leveraging artificial intelligence and satellite imagery to enhance the speed and accuracy of damage estimates during post-event reconnaissance.[49]

Conclusion

Catastrophe models are deeply embedded in the insurance and reinsurance industries, serving as critical tools for underwriting, pricing and portfolio management. Their outputs have become the lingua franca for communicating risk, enabling stakeholders to evaluate exposures, set pricing and facilitate risk transfer mechanisms such as reinsurance treaties and catastrophe bonds. By translating complex concepts into actionable insights, catastrophe models are essential for managing uncertainty and allocating capital efficiently.

Although catastrophe models are widely used and valuable, they do have limitations. While their purpose is to account for events beyond those directly observed, they remain somewhat biased to events that have occurred and assume a certain stationarity. These models rely on historical data, probabilistic assumptions and simplified representations of highly complex systems, which can introduce and propagate uncertainty. For instance, such methodologies are not well suited for less stationary perils such as wildfires, where the risk is inherently sensitive to prevailing environmental conditions and can change rapidly. Furthermore, vulnerability components often generalize assumptions about building characteristics and geographic conditions. These limitations underscore the need for careful interpretation of model results by experienced practitioners.

That said, catastrophe models are a valuable tool and have come a long way since their inception. Models are dynamic, incorporating new information as it becomes available, such as post-event claims data, reconnaissance reports and advances in scientific literature. This adaptability ensures that models remain relevant and improve over time.

Additionally, the growing number of model vendors allows risk managers to access multiple views on the same risks, fostering a more comprehensive understanding of risk. Advances in technology and AI are also potential game-changers for the catastrophe modeling industry. For example, some newer model vendors are moving beyond traditional, backward-looking methodologies by leveraging AI and machine-learning algorithms to sift through environmental datasets, identify meaningful patterns ("signals in the noise") and derive stochastic event sets natively rather than overly relying on human judgment for model assumptions.[50]

These innovations could not only enhance accuracy and scalability but also open exciting possibilities for managing risks that were previously difficult to quantify. As the field continues to advance, catastrophe models are well positioned to remain indispensable tools for navigating uncertainty and building resilience against future challenges.

[48] https://www.verisk.com/blog/how-machine-learning-is-taking-catastrophe-modeling-to-a-new-level/.
[49] https://www.theinsurer.com/tv/reinsurancemonth/moodys-rms-steel-generative-ai-is-a-real-game-changer-for-the-industry/.
[50] https://reask.earth/2018/06/29/our-2018-hurricane-forecast-explained/.

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