nuveen
A TIAA Company

Coping with change and uncertainty in your life:

An analysis of thirteen physical climate risk model vendors

14 May 2025

Mckenzie Mandich
Senior Climate Risk Associate

nuveen
A TIAA Company

Contents

Abstract

- Physical climate risk (PCR) model vendors vary widely in their methodology and scope.
- This is reflected in the variation of results they provide, even for the same asset.
- Both asset managers and model vendors should move towards a risk quantification methodology that considers both central tendency and tail risks.
- PCR models are one of many tools to understand climate risk. Combining quantitative and qualitative analyses from multiple sources will produce the most robust risk assessments.
- There is no one size fits all solution. Effectively addressing the impacts of climate change on real assets demands a holistic approach.

The Importance of Physical Climate Risk Models for Financial Institutions

Climate change is no longer an emerging risk. We are already experiencing its impacts: anthropogenic greenhouse gases have warmed the earth by ~1.2˚C since 1880, and 2023 was 1.48˚C above baseline. Analyses of global extreme weather events from 2011 to 2022 found that 402 of the 504 events analyzed were affected by climate change (55 no influence, 47 inconclusive; from Carbon Brief). Climate change is defined in the modern context as long-term shifts in temperature and weather patterns from human-induced increase in atmospheric greenhouse gases. Its impacts are typically divided into two categories: chronic shifts, such as sea level rise and rising temperature averages; and acute shifts, such as changes to flood or wildfire frequency, severity, and geographic range. Chronic climate change impacts can diminish the reliability of infrastructure, accelerate disease transmission, decrease worker productivity, shift agricultural patterns, make species extinct, and sink countries. Acute climate change impacts can lead to loss of life, supply chain disruptions, and destruction of our built environment. Combined, these changes have the potential to make areas of the world uninhabitable; diminish the length and quality of human life; induce major climate migration, human and otherwise; decimate biodiversity; and exacerbate global inequality.

As awareness of the potentially devastating impacts of climate change grows, businesses and governments are incorporating climate considerations into their decision-making process. One means of incorporation is risk management. We define risk as a possibility of harm or damage. We therefore define physical climate risk (PCR) as the possibility of harm or damage due to long term shifts in temperature and weather patterns from a human-induced increase in atmospheric greenhouse gases. The most important word in this definition is possibility: it is the uncertainty of how exactly climate changes will manifest that creates risk. We know heat stress and wildfires will increase, for example, but where? By how much? And when?

Discussions of how to assess PCRs often focus on this overwhelming uncertainty. There is uncertainty on multiple fronts: the uncertainty of how quickly humanity will reduce greenhouse gas emissions, the uncertainty of how well models predict climate changes, the uncertainty of how climate change may damage a specific asset, and the uncertainty of how that will translate to financial impacts. There is no better field to address uncertainty than risk management. Risk management exists because uncertainty exists. Its role is to detect and manage possibilities of loss or gain. Assessing PCR does not require eliminating uncertainty (then there would be no risk), but it does require taking an informed view of the degree of uncertainty.

To understand how risk management can address climate change, we can look to the similar but more mature field of natural catastrophe risk management. Natural catastrophe ('cat') models are now ubiquitous in the insurance industry, but it took Hurricane Andrew and eleven insurer bankruptcies in 1992 for the industry to begin rigorously assessing cat risk (cat models were developed in the 1980s, but take-up was low until after Andrew). Cat models use historical data enhanced with random statistical techniques to estimate losses from natural hazards such as hurricanes and earthquakes. The uncertainty in these models is enormous: the standard deviation of portfolio average annual loss (AAL) estimates is often larger than the average. Nonetheless, their take-up by the industry effectively halted catastrophe-driven insurer bankruptcies until recently. Cat models have been successful not because they are precise, but because they capture uncertainty by measuring both central tendency and variability. This allows insurers to match how much risk they take on to their risk appetite.

Unfortunately, traditional cat models are not sufficient to address the risks of climate change. Their foundation in historical data assumes a steady-state climate. In response to the demand for models to assess PCR and the inability of cat models to meet it, a market for PCR models has exploded in recent years.

The rise of PCR models has coincided with an increasing awareness of the potential impacts of climate change throughout the economy. Estimates of this impact vary widely. A study published in Nature Climate Change found that US properties exposed to flood risk are overvalued by US$121-237B. A study from S&P puts the cost of physical climate impacts on global real assets at 3.3% on average by 2050 but up to 28% in the tail. Another study, published by researchers at LSE in 2016, estimated climate value at risk as 1.8% of all financial assets globally. Like the S&P study, they calculate long tails – the 99th percentile estimate is 16.9%. Furthermore, some researchers have suggested that many climate models substantially underestimate the impacts of climate change on asset values (Pitman 2022, Schewe 2019). Results vary substantially between PCR models (ULI 2022). Despite extensive disagreement on the 'true' price tag of physical climate risks, we can assume that the number is substantial.

Asset managers and owners, especially those with significant real asset holdings, face pressure to address PCR from multiple fronts – investor demand, government regulation, and risk management. Most asset managers lack the internal expertise to build climate risk models from scratch. Vendor PCR models allow clients to assess the risk to individual assets in specific locations with specific characteristics, for specific perils, at specific timescales. By using models effectively, asset managers can quantify risk concentration, prioritize effective mitigation at their highest risk assets, and enhance due diligence for new acquisitions. PCR models enable asset managers and owners to make risk-informed financial decisions. However, given the uncertainty and model disagreement highlighted above, effective use of PCR vendor models requires extensive research and a deep understanding of model methodologies.

Motivation & Background

This project is inspired by the Urban Land Institute (ULI) and LaSalle 2022 paper 'How to choose, use, and better understand climate-risk analytics' and its 2024 sequel, 'Physical Climate Risks and Underwriting Practices in Assets and Portfolios'. The ULI reports describe the state of the PCR model vendor universe, explore how real estate (RE) investment firms measure their risk, and suggest improvements. We expand on their work by extending the scope to multiple real asset classes and quantitatively comparing model vendors' results for identical inputs. Furthermore, we conduct interviews with model vendors themselves rather than RE investment professionals.

Our decision to focus on all real assets is rooted in several factors. First, most published research on PCR has focused on RE. As Nuveen is a major global manager of multiple real assets classes, we chose to expand our view to include agriculture, timber, and infrastructure assets. However, we chose not to expand any further – for example, to include public equities – because PCR models for other asset classes use a different type of model called an integrated assessment model. Comparison between the different model types is not straightforward.

Through interviews with vendors and comparison of trial analyses, we address three questions –

How do PCR model vendors assess risk?

How do PCR model vendors' choices and assumptions impact their results?

How can asset managers use PCR models most effectively?

Part 1: How do PCR model vendors assess risk?

Apples and Oranges: vendor basics vary widely

Scientific disagreement is a good thing. When researchers develop different conclusions, we learn more. In recent months, several news articles have explored what those in climate risk analytics know very well – models don't agree. An analysis in Bloomberg News compared results from PCR vendors First Street and CoreLogic with a UC Irvine model in San Francisco, finding limited agreement in their 1-in-100-year flood depth predictions. Another, by Carbon Plan, compared flood risk estimates from Jupiter and XDI. In both cases, the researchers' ability to draw conclusions was limited by the difficulty of comparing fundamentally un-alike models (a limitation noted in their respective analyses). For example, Jupiter provides AAL estimates based on the impact a peril is expected to have for a certain building type, while XDI assesses exposure to a peril based on geography. ULI's 2022 and 2024 papers include a figure shared with them by an asset manager highlighting the extent of vendor disagreement (Figure 1).

Variations across Providers among Overall Physical Risk

Asset	State	Vendor A	Vendor B	Vendor C
A	CA	High	Very low	Low
B	DC	Medium	Very low	Low
C	FL	Low	Medium	Very low
D	IL	Medium	Very low	High
E	NY	Very high	Low	Medium
F	TX	Medium	Very low	Low
G	VA	Medium	Very low	None

Figure 1. From ULI: "This figure was shared by one institutional RE manager. It depicts a set of aggregate risk scores generated by three different providers (vendors A, B, and C) for assets (A to G)." Details were not provided on whether vendors are measuring risk exposure or financial impact.

We reached out to vendors offering location-based physical climate risk models for real assets. All vendors agreed to complete our methodology questionnaire, with many providing additional methodology documentation. A summary table of the vendors is provided below

(Table 1). Because of the speed with which this field is evolving, our list of vendors is not comprehensive. All vendor data and descriptions are as of 12/10/2024.

Vendor	Analysis Type	Asset Type Coverage
Vendor 1	Exposure	Other real assets
Vendor 2	Exposure+Financial Impact	RE + other real assets
Vendor 3	Exposure+Financial Impact	RE only
Vendor 4	Exposure+Financial Impact	RE + other real assets
Vendor 5	Exposure+Financial Impact	RE only
Vendor 6	Financial Impact	RE only
Vendor 7	Exposure or Financial Impact	RE only
Vendor 8	Exposure	N/A
Vendor 9	Financial Impact	RE only
vendor 10	Exposure+Financial Impact	RE + other real assets
Vendor 11	Financial Impact	RE + other real assets
Vendor 12	Exposure	N/A
Vendor 13	Exposure	N/A

Table 1. Key attributes of vendors included in this study.

We asked all participating vendors for information on their methodology and products. Vendors offer a wide variety of time intervals, decades, perils, and scenarios (Tables 2 & 3). As can be seen in Table 3, most vendors cover three types of floods (coastal, fluvial, and pluvial), extreme heat, tropical cyclone, and wildfire. Most vendors also include the SSP2-4.5 (middle of the road) and 5-8.5 (business as usual) scenarios (Table 2). SSP1-1.9, which limits warming to 1.5C by 2100 with an aggressive decarbonization path, is not provided by many vendors. While this scenario is the most closely aligned with the Paris Agreement goals, it is usually not required for reporting. Furthermore, for risk managers focused on potential losses, the 'best case' scenario is likely not very interesting.

Vendor	**SSP1-1.9 ('Net Zero 2050')**	**SSP 1-2.6**	**SSP 2-4.5 (Middle of the Road)**	**SSP3-7.0**	**SSP5-8.5 ('Hot House')**
Vendor 1					
Vendor 2					
Vendor 3		N			
Vendor 4					
Vendor 5		n			
Vendor 6*					
Vendor 7	N				
Vendor 9**					
Vendor 10					
Vendor 8					
Vendor 11					

Table 2. Scenario coverage across vendors. Red=not covered, green=covered, orange=in development.

*In addition to SSP scenarios, Vendor 6 provides several REMIND scenarios.

** Vendor 9 uses an ensemble approach that is scenario-agnostic.

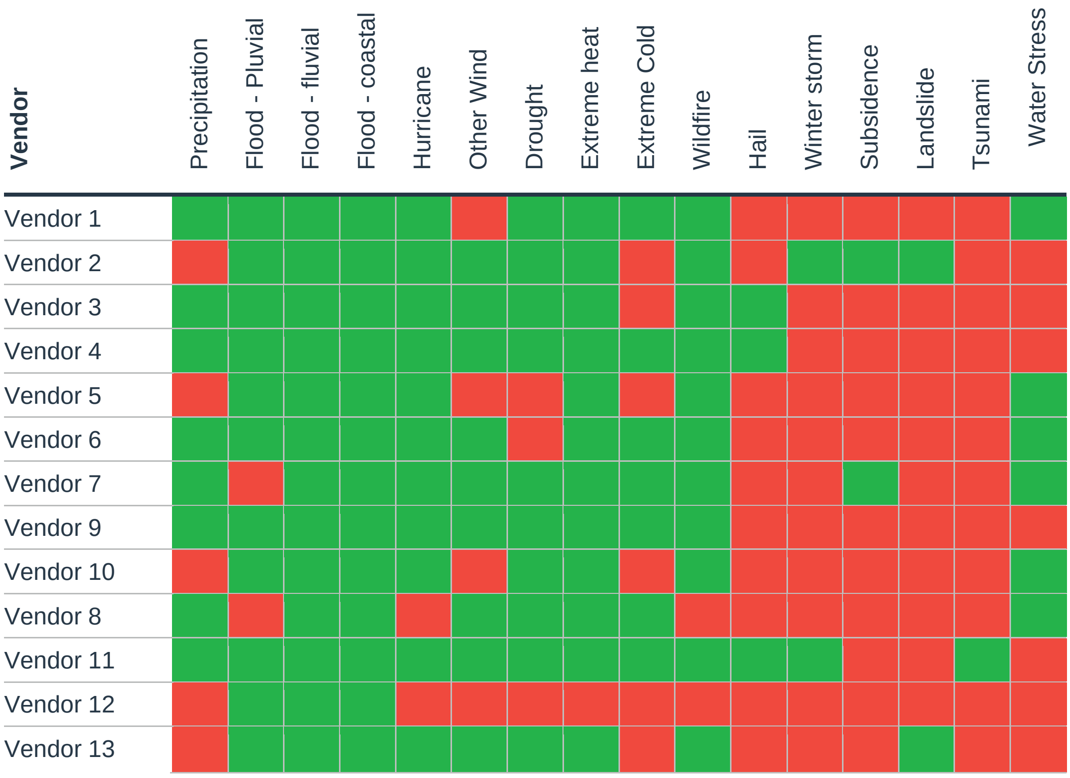

Table 3. Vendor climate projection capabilities by peril. Red=not covered, green=covered. Tropical cyclone includes wind and/or storm surge from hurricanes, while extreme wind refers to non-hurricane windstorms. Coastal flood includes storm surge, coastal flood, and/or sea level rise. Vendors 5, 7, and 11 also model current catastrophe risk for hail, non-hurricane wind, winter storm, subsidence, landslide, tsunami, and earthquake.

The foundation of everything: Global Climate Models

CMIP, the Coupled Model Intercomparison Project, is an initiative that coordinates global climate models from universities, governments, and institutions and sets experimental parameters. These parameters are described by SSP or RCP scenarios. Data from CMIP models forms the foundation of each new IPCC report. For CMIP6, which underlies the most recent IPCC report, over 100 models from 49 different research groups were published. Each model may be run dozens of times for different scenarios.

All PCR model vendors use an ensemble of either CMIP5 or CMIP6 global climate models as the foundation of their product. Those still using CMIP5, an earlier version, were updating to CMIP6 at the time of writing. Most vendors use an ensemble approach by combining output from several models to account for model disagreement. While the universal use of CMIP models implies a level of scientific consensus, CMIP models themselves exhibit a high degree of variability within each SSP or RCP scenario (Figure 4). Because every CMIP model is run with the same scenario inputs and grid size, we know that this variability is a result of how different research groups model the extremely complex physics of our earth.

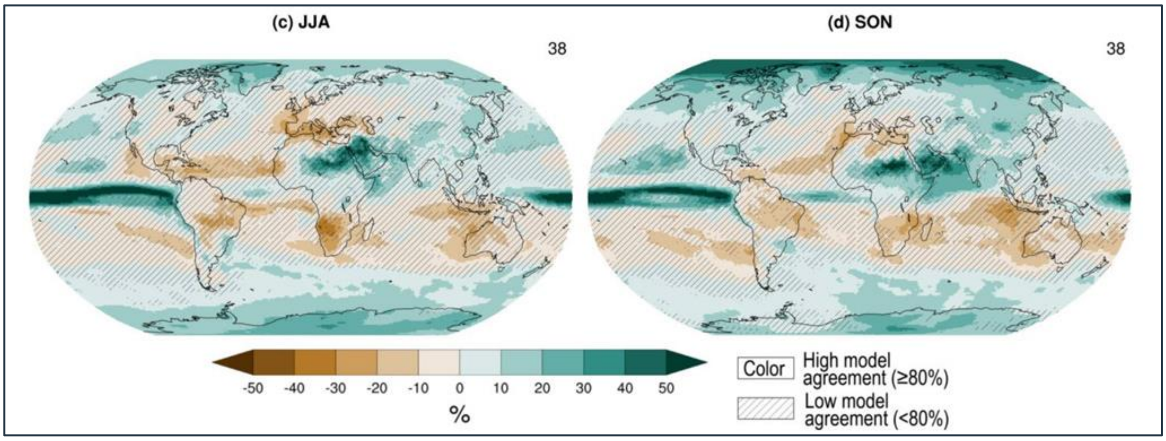

Figure 4. Mean precipitation percent change by season between now and 2100 from an ensemble of CMIP6 models for the SSP2-4.5 scenario. Note the areas of 'low model agreement' cover most of the globe between 80 N and S. Source: IPCC AR6

Global climate models are run at too coarse a resolution to model granular extreme weather events such as floods. One major function performed by PCR model vendors is to increase grid resolution through downscaling. Downscaling, the process of increasing model resolution, can be performed statistically or dynamically. Statistical downscaling exploits the relationship between local climatological data and global climate model output to produce more granular data. Dynamic downscaling is much more resource intensive and involves building smaller regional models that can run at a higher resolution and that use global climate model results as inputs. Most vendors use statistical downscaling; a few use dynamical downscaling for some or all perils.

Different approaches to building a PCR model: exposure versus financial impact

PCR models can include up to three modules (Figure 2): exposure, where client-provided locations are layered over global climate model output to assess inherent risk exposure to various perils; vulnerability, where damage is estimated based on how a particular asset type is impacted by peril exposure; and a financial module, where damage is translated to dollars.

Vendors can choose to build only the first module, providing asset exposure to climate perils using downscaled global climate models and other environmental and climate data. The result is an exposure score – usually a normalized value from 0-10 or 0-100 – that allows users to compare the risk exposure of assets in their portfolio. The advantage of this type of model is that it is agnostic to asset type. Users can measure climate risk exposure for any asset with a physical location and are not constrained by the lack of availability of impact functions for less common asset types.

Asset managers utilizing exposure scores for climate risk assessments can choose between adopting the predetermined vendor thresholds for high/medium/low risk or setting their own. Comparison of what a vendor describes as 'high risk' to local investment team knowledge can help determine whether custom thresholds are necessary. Customizing thresholds can also allow asset managers to incorporate their knowledge of the vulnerability of different asset types to different perils. For example, an office building would be vulnerable to wildfire but less vulnerable to drought. Setting a less stringent threshold for drought is a straightforward way to integrate this knowledge into a climate risk assessment without relying on vendor impact functions.

The second approach includes all three modules. Vendors taking the second approach generally provide a loss value such as AAL. In the vulnerability module, impact functions form an added layer of analysis after peril exposure is modeled based on location. For acute perils, most vendors assess physical damage to assets, and possibly business interruption. For chronic perils, impact pathways are more complex and there is less scientific consensus. For example, an office building might be exposed to extreme heat and wildfire. Extreme heat (chronic) might increase operating expenses through cooling costs, faster HVAC degradation, and/or decreased worker productivity. It might also decrease operating expenses in cold climates. Meanwhile, wildfire (acute) would result in physical damage to the building and contents, plus downtime for repairs. The latter is much more easily translated into financial loss.

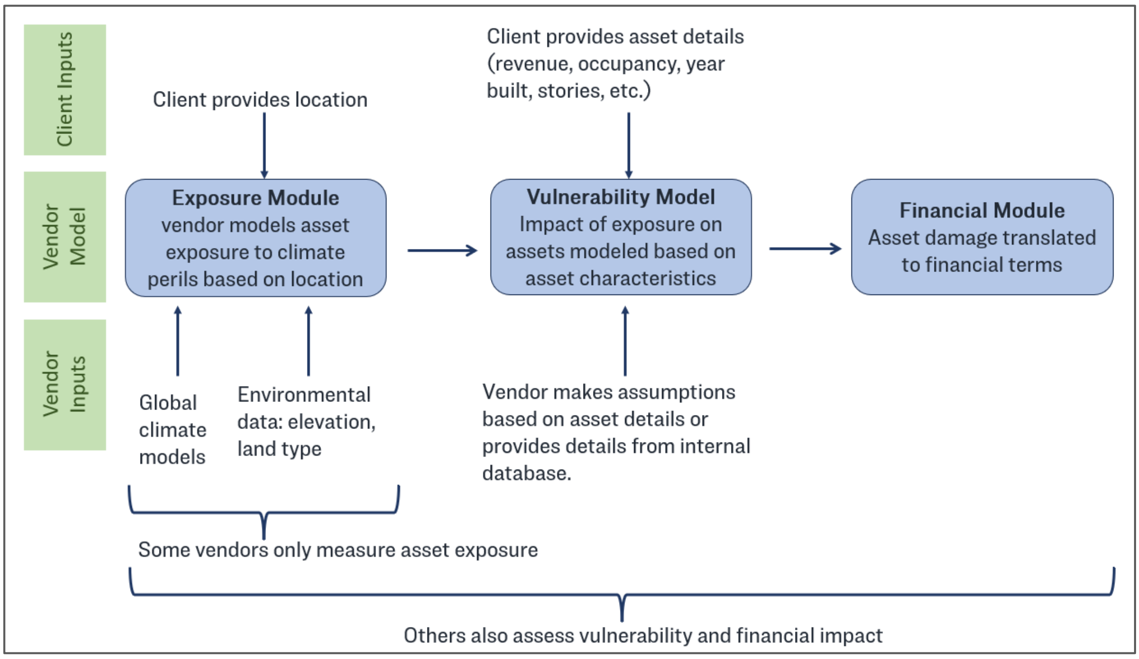

Figure 2. How PCR models work – a diagram.

Impact functions are built based on scientific literature, engineering models and experiments, and/or AI. A vendor might build dozens or hundreds of different impact functions based on building factors such as asset type, construction type, year built, and first floor height. Most vendors who take the second modeling approach have impact functions for RE. Fewer branch out into ‘atypical’ asset types like hospitals, roads, wind farms, or cornfields. In practice, the limiting factor for the second type of model is often the client’s ability to provide the above information for all their assets. Some vendors provide asset information from an internal database, while others make broad assumptions (ex. assuming all single-family homes are two stories).

Different approaches to building a PCR model: Indexing versus Modeling

PCR model vendors face another fundamental choice in deciding whether to build exposure models for each peril, or to use an exposure index based on climate variables. The index approach is computationally less demanding, but also less able to capture the range of possible climate events. In this approach, exposure is based on climate metrics related to a given peril – for example, temperature, humidity, wind speed, and land cover for wildfire – which are used to construct an index that correlates to the likelihood of that peril occurring. Data may be sourced from downscaled global climate models and other open-source climatological data, such as land cover and elevation maps. Vendors using an index approach rarely provide uncertainty ranges. There is basis risk in this approach because the index may not perfectly correlate to the occurrence of the event itself. We found that vendors use indices more frequently for chronic perils.

The second approach involves building an exposure model that takes the outputs of global climate models as inputs. Models may be deterministic, probabilistic, or stochastic.

Deterministic models use a set of inputs to produce one output. Probabilistic models use a range of inputs to produce a range of outputs with varying likelihoods. Stochastic models randomly vary input parameters across a distribution to produce the widest range of possible outcomes. Many vendors use probabilistic models for all perils except hurricane, where stochastic models are more common. Some vendors have also built stochastic models for other acute perils including wildfire and flood.

Catastrophe models use a stochastic modeling approach, so we refer to the stochastic models as climate-conditioned catastrophe models. These are the most computationally expensive option, and the best at describing tail risks. We describe climate conditioned catastrophe modeling using the example of hurricane. The first step is gathering historical event information, such as the location, wind speed, sea surface temperature, atmospheric pressure, and wind shear of past hurricanes. Historical data forms the basis of the model's empirical boundary conditions. Boundary conditions limit what event could theoretically occur. For example, lower sea surface temperatures in Maine compared to Florida lower the possible intensity of hurricanes there. This process is the same as traditional catastrophe models.

In a climate conditioned catastrophe model, boundary conditions are modified based on output from global climate models. This shifts the theoretically possible likelihood and intensity of a peril. For example, we expect sea surface temperatures will increase in the future due to climate change. A warmer range of sea surface temperatures may make hurricanes more frequent or stronger. The new climate-conditioned boundary conditions then form the parameters for a Monte Carlo simulation, which stochastically generates tens or hundreds of thousands of theoretically possible years in which hurricanes occur. Each year may have hurricanes occurring one or more times. This is referred to as the event set.

Client asset locations are layered over each of the thousands of possible years in the event set, and damage and financial impacts are computed based on wind speed, duration, and location characteristics. For storm surge damage, there is an added flood model layer to determine where water will flow based on surface characteristics.

Climate-conditioned catastrophe models can provide AALs and expected losses at different probabilities, which can be used to construct an exceedance-probability (EP) curve (Figure 3). In our opinion, stochastic models are the most methodologically rigorous option and have the most potential for integration into financial risk management and risk appetite calculations. However, climate-conditioned catastrophe models require large amounts of data, which are not available for all regions/perils. Furthermore, their complexity may be unnecessary for perils with a narrower range of possible outcomes or less severe consequences. We recommend a proportional approach where model complexity is commensurate to peril volatility and damage potential. Where multiple models with different approaches are available to the user, comparison can inform interpretation of the simpler index or deterministic approaches.

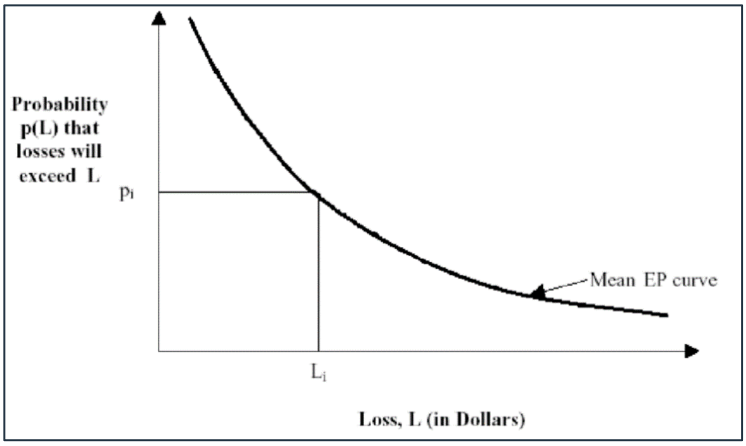

Figure 3. Example of an EP curve. From Application of Wildfire Mitigation to Insured Property Exposure 10.13140/RG.2.2.13898.39366.

Peril Parameters

We highlight two model parameters that vary substantially between vendors. The first is peril definition. For example, while PCR model vendors generally define flood similarly, they might predict defended or undefended flood, or both (‘defended’ means including flood defense infrastructure, like levees. Both measures can be useful – some regions of the world lack good data on flood defenses, and vendors don’t always model the probability of levees overtopping, so comparing defended to undefended flood can give users an idea of the range of possible outcomes). Some vendors define ‘hurricane’ as wind only, while others include storm surge. Sometimes storm surge from hurricanes is included in coastal flooding risk rather than hurricane. Flood might be broken into fluvial/pluvial/coastal types or combined into a single flood metric. Metrics labeled wind might include hurricane wind only, or severe storm and tornado too. There is a daunting level of variation if one does not know the right questions to ask. Nonetheless, knowing what is being modeled is critical to understanding model output.

The second parameter is peril resolution, which ranges from 30m^2 to 50km^2 depending on vendor and peril. This parameter is critical for acute perils like flood, where averaging data over a wide geographic range can mask significant variability. To understand why resolution is so important for flood, consider an apartment at the top of a hill in the Riverdale area of the Bronx. The elevation is 50m above sea level. The main commercial street in the neighbourhood, about ½ km away, sits at an elevation of 10m. Too coarse an elevation map will average out the elevation differences, masking distinctly different risk exposures. Furthermore, any hydrodynamic model will then ignore water flowing downhill to the commercial area and exacerbating exposure there. Most vendors modeled flood at under 100m^2 resolution (see Appendix A for details on peril resolution and definition for each vendor).

Peril definition and resolution are key criterion for model selection. However, we caution against the generalization that more granular perils or higher resolutions are universally better. For example, while resolution is critical for flood, there may be diminishing returns for less geographically variable perils such as drought and extreme heat. Similarly, breaking down flood into multiple sub-types does not necessarily enhance understanding of risk because mitigation measures are the same regardless.

Part 2: How do PCR model vendors' choices and assumptions impact their results?

Qualitative comparison of vendor results

In part one, we described how PCR model vendors' approaches vary. We now use a sample of 20 global real assets modeled by vendors to assess how methodological variations between vendors impact their results. Vendors with US-only coverage modeled nine of the 20 assets.

First, let us examine a visual representation of expected losses at one location (Figure 5). The figure depicts the AAL for 730 3rd Avenue in midtown Manhattan from wildfire only. The total asset value provided to the vendors was ~$350M. Three vendors provided AALs of zero. All vendors provided a flat trend over time (i.e., no increase in risk due to climate change). Vendor 4 provided an AAL of ~$11,000 from physical damage to the building. While Vendor 4's AAL is the outlier in this group, it is very small relative to asset value. Two of the vendors use a climate index to measure wildfire risk, the Fire Weather Index. Vendor 4 uses a probabilistic model and Vendor 5 uses a stochastic model. For urban areas, vendors may mask out small exposures in their model due to the lack of available fuel.

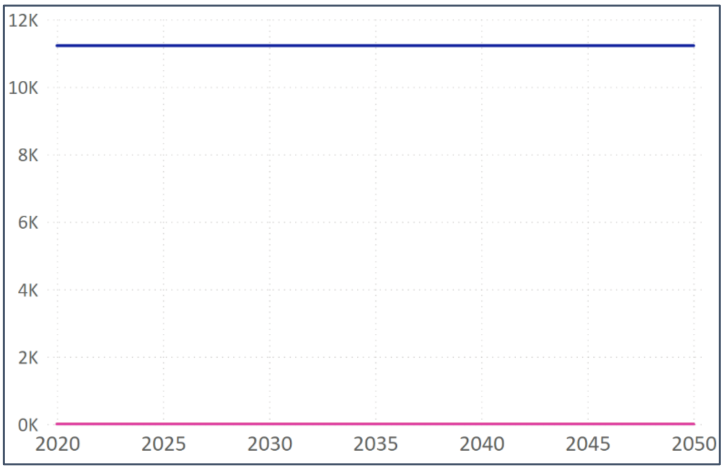

Figure 5. AAL from wildfire at 730 3rd Avenue in NYC according to four vendors.

Figure 6 compares vendor results for other perils at the same location in Manhattan. Vendor 10 provided the highest AALs for extreme heat and flood. Vendors agree that drought losses will be near zero. The largest outlier is Vendor 4's estimate of hurricane losses. At less than 0.3% of asset value, their estimate is low. However, other vendors' estimates are nearly an order of magnitude lower. The loss measured by Vendor 4 is solely due to wind. While Vendor 4 estimated a higher exposure score for hurricane than other vendors, their exposure score was similar to Vendor 3's score. Vendor 4 provides multiple return periods for their loss calculation. They calculate a long tail for losses at this location, indicating that the AAL is driven by low frequency, high damage events.

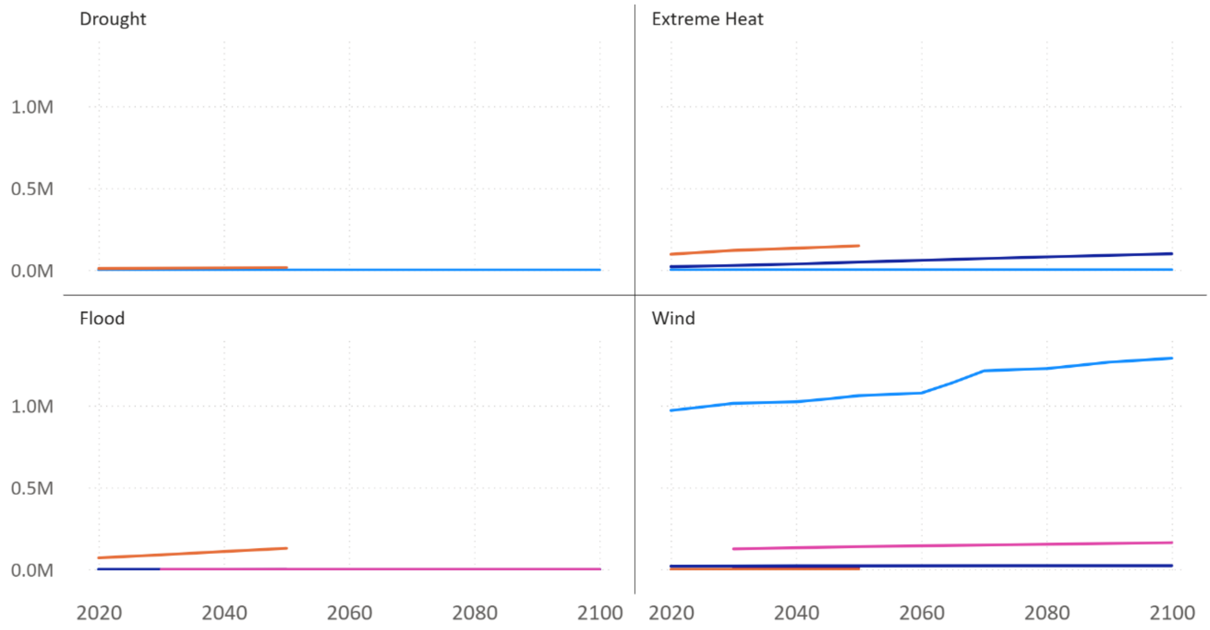

Figure 6. AAL from various perils at 730 3rd Avenue.

This is just one location: how do vendors' AAL estimates compare across other trial locations? We focus on the US because vendor coverage is highest. Figure 7 illustrates AALs for wildfire across eight US locations. Several locations with low losses have high agreement between vendors (USCMF SFR Atlanta, Randall Commercial, Phoenix – West Peoria, and 730 3rd Ave). Variability increases as vendors try to put a price on higher levels of risk.

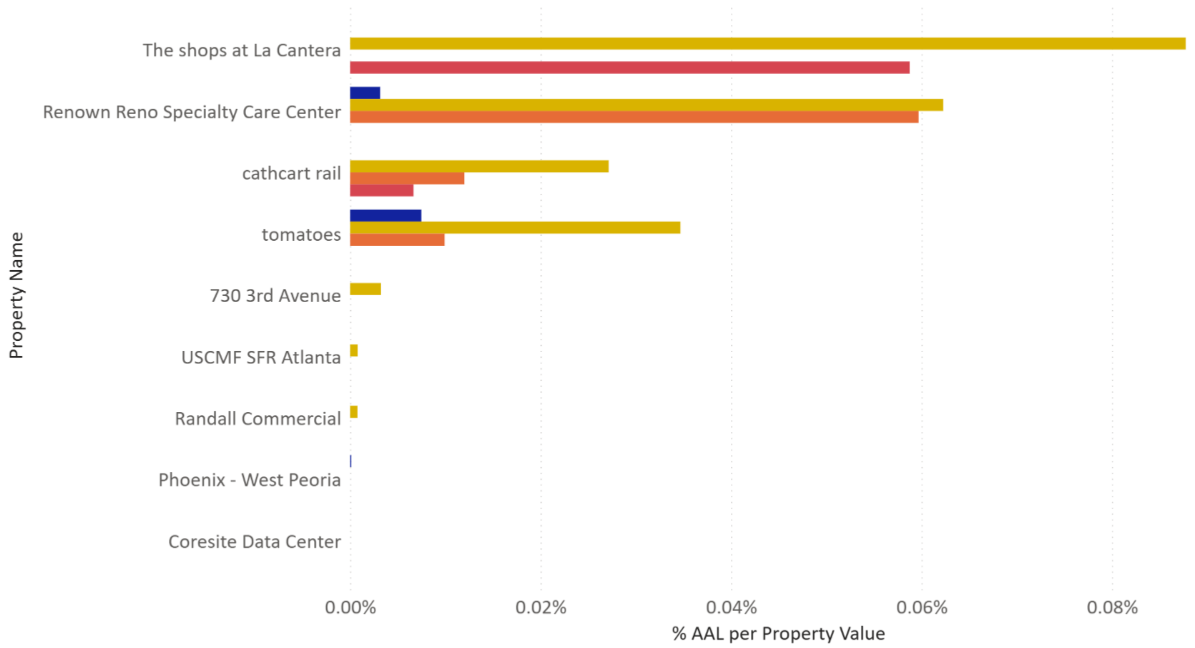

Figure 7. Comparison of average financial losses from wildfire across vendors for nine US assets in 2050, averaged across available scenarios. Results are expressed as a percent of total asset value.

Variation between AALs at high-risk locations may be due to differences in the exposure module, vulnerability module, or both. We can disentangle the underlying cause by comparing

AALs to exposure scores. Figure 8 displays wildfire exposure scores for two of the above vendors (others do not provide exposure scores). Variation in exposure scores appears just as high as in AALs.

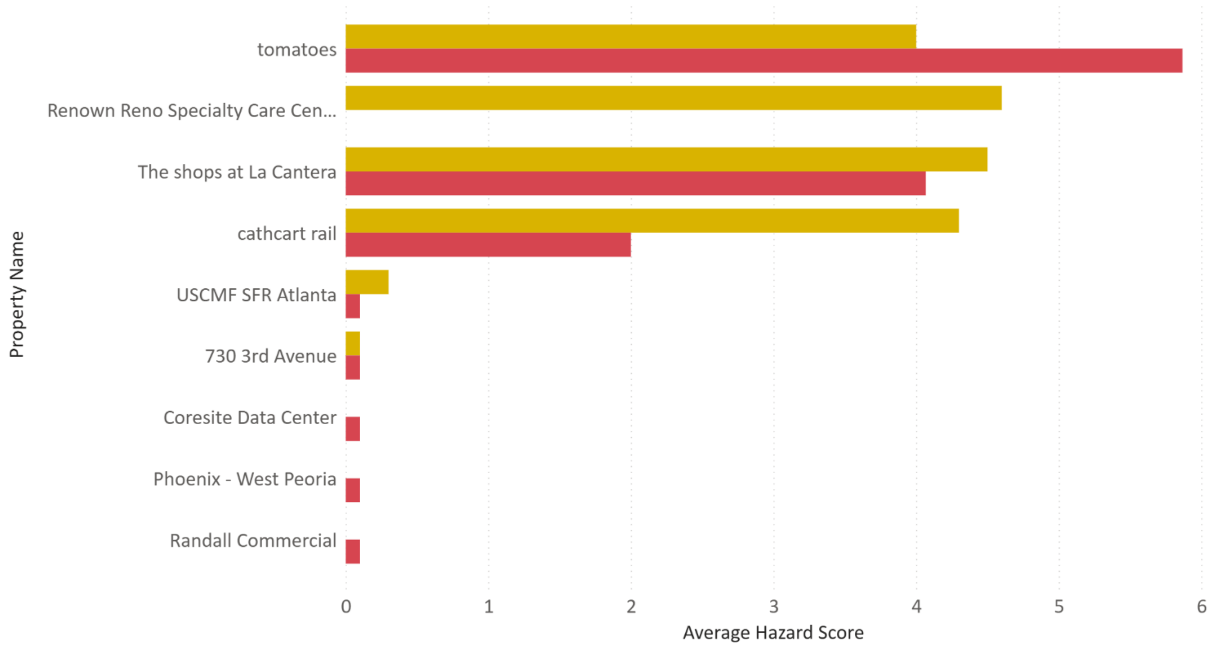

Figure 8. Comparison of exposure scores from wildfire across vendors for nine US assets in 2050, averaged across available scenarios.

Vendor Correlations: a quantitative comparison of vendor results

We hypothesized that impact functions, being mostly proprietary and substantially different between vendors, were the primary explanatory variable for differences between model vendor results. However, our brief analysis of wildfire risk indicates that differences in exposure estimates may also contribute substantially. To explore this trend more rigorously, we calculated correlations between vendor results. For the tables below, individual location results from each vendor were ranked from 1 to 20, with ties receiving the same rank. Exposure scores and AALs of zero were removed. Correlation was calculated between ranks rather than the underlying values (spearman's rank correlation). This method is used because the data is not normally distributed. Any scenario and/or decade for which both vendors provided results was included in the correlation, meaning the number of data points varied for each computation.

	Vendor 13	Vendor 11	Vendor 3	Vendor 4	Vendor 8	Vendor 5	Vendor 7	Vendor 6	Vendor 10
Vendor 13	1.00		0.01				0.81		0.89
Vendor 11		1.00							
Vendor 3	0.01		1.00				0.04		0.25
Vendor 4				1.00				0.73	
Vendor 8					1.00				
Vendor 5						1.00			
Vendor 7	0.81		0.04	0.44			1.00	0.29	0.63
Vendor 6				0.73			0.29	1.00	0.72
Vendor 10	0.89		0.25	0.80			0.63	0.72	1.00

Table 5. Spearman's rank correlation coefficients between exposure results for vendors for wildfire.

While correlations are generally low, consistent with findings from others, some correlations between vendor results are unexpectedly high. We examine two of these in more detail – between vendor 10 and Vendor 13 exposure scores (0.89, Table 5) and between Vendor 11 and Vendor 5 AALs (0.81, table 6).

First, we note that Vendor 13 only provides exposure scores based on the SSP2-4.5 scenario in 2050 for US properties, so the correlation between vendor 10 and Vendor 13 is based on nine data points. Vendor 10 and Vendor 13 both use the fire weather index to measure wildfire exposure, providing a methodological basis for their similar scores. Nonetheless, their similarity is somewhat surprising given the differences in resolution – $100m^2$ for Vendor 13 compared to $25km^2$ for vendor 10. These results add credence to our speculation in Part One that peril resolution is less important for perils with wide geographic footprints. While floods or tornadoes may destroy one house while leaving its neighbour intact, thus requiring very high granularity to model accurately, large-scale event like wildfires may not require as much granularity.

Vendor 11 and Vendor 5 both provide AALs for wildfire risk. Both vendors provide results across multiple decades and scenarios. However, only four locations are included in the calculation because locations with zero risk were excluded from the analysis. This left a total of 24 data points for comparison. Both vendors use climate conditioned catastrophe models for wildfire. Vendor 11's resolution is higher, at $30m^2$ compared to $\leq 250m^2$ for Vendor 5. Vendor 11 also provides individual asset characteristics from an internal database to feed into the impact function, while Vendor 5 relies on asset type assumptions. Despite their differences, estimates were highly similar for three of the four locations. At the fourth location, in Nevada, Vendor 5 estimated a ~20x higher average losses than Vendor 11 (but comparable to Vendor 4's AAL). The scale of this difference did not impact the rank-order correlation.

	Vendor 13	Vendor 11	Vendor 3	Vendor 4	Vendor 8	Vendor 5	Vendor 7	Vendor 6	Vendor 10
Vendor 13	1.00								
Vendor 11		1.00		0.17		0.81			-0.47
Vendor 3			1.00						
Vendor 4		0.17		1.00		0.59		0.78	0.36
Vendor 8					1.00				
Vendor 5		0.81		0.59		1.00		0.28	0.00
Vendor 7							1.00		
Vendor 6				0.78		0.28		1.00	
Vendor 10		-0.47		0.36		0.00			1.00

Table 6. Spearman's rank correlations between financial loss results for vendors for wildfire.

Tables 5 and 6 show that agreement between vendors is higher for exposure scores than AALs, which is consistent with our initial hypothesis. Vendor 10 demonstrated the largest decrease in correlation for exposure score versus financial loss. Vendor 10 is the only vendor included in our correlation calculations that provides AALs for agricultural and timberland crops. (Vendor 1 provides highly sophisticated loss estimates for agricultural and timber crops, but they are not included in this comparison due to the unique nature of their product). Because these asset types behave very differently from the built environment, vendor 10's AALs for those assets differ substantially from other vendors and contribute to the lower AAL correlation (Figure 9).

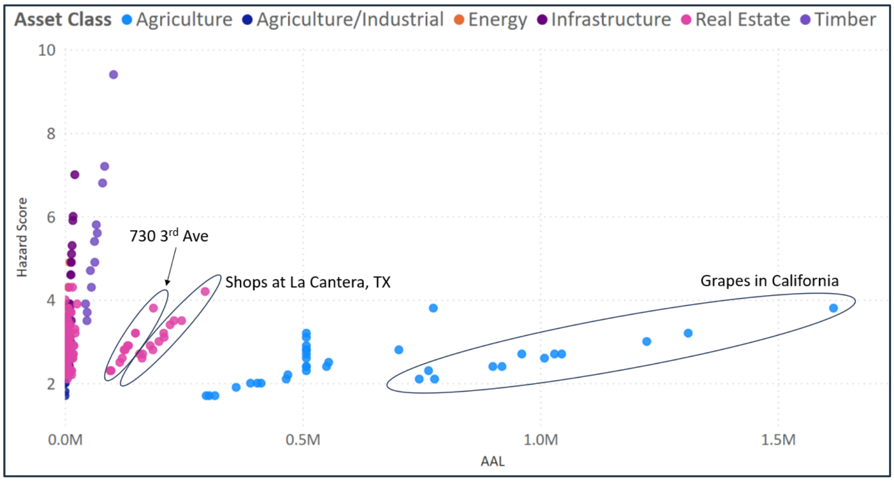

Figure 9. Plot of vendor 10 peril scores vs AALs for extreme heat. Individual data points show the property's score in different decades. Values were averaged across the four scenarios vendor 10 provides (SSP1-2.5, SSP2-4.5, SSP3-7.0, and SSP5-8.5).

Performing similar correlation calculations for other perils yielded similar results (Appendix B). For perils where we received both exposure scores and AALs from vendors – wildfire, wind, flood, and extreme heat – correlations between vendors were higher for exposure scores than for AALs. Across perils, correlations were highest for wind and precipitation and lowest for flood and water stress. Estimating flood requires complex models with components such as digital elevation models, land type, hydrodynamics, flood barriers, soil absorption, and water usage. Water stress modeling requires projecting water supply and demand, thus considering socioeconomic as well as physical effects. Furthermore, global climate model uncertainty is generally higher for precipitation than temperature changes. Combined, these factors mean flood and water stress are a) more uncertain and b) present more opportunities for vendors to make different choices in their data sourcing and model development.

Impact versus exposure: comparing vendors to themselves

We calculate the correlation between financial and exposure metrics for two vendors that provide both metrics. If AAL is perfectly correlated to the exposure score, the correlation coefficient will be one. Because AAL ≈ exposure * impact, high correlation between AAL and exposure implies that the impact function explains very little of the variation in AAL.

	Vendor 4	Vendor 10
Flood	0.822	0.305
Wildfire	0.326	0.161
Heat	0.313	-0.125
Wind	0.471	0.886
Drought		0.256

Table 7. Correlation between financial and exposure metrics for two vendors.

While the sample is too small to draw any major conclusions, we can note some trends in the results. Correlation clearly varies by both peril and vendor. In other words, there appears to be as much inter-peril difference as there is inter-vendor difference. Correlations were lowest for extreme heat for both vendor 10 and Vendor 4, indicating that the impact function explained more of the AAL for this peril. Generally speaking, methodology for quantifying impacts of chronic perils such as heat is less mature and varies more between vendors. This could explain the low (sometimes negative!) correlation scores.

Correlations for Vendor 4 and vendor 10 varied widely by peril with no discernible pattern. We noted earlier that vendor 10 is the only vendor with impact functions for crops and timber, which lowers the correlation between exposure score and AAL. High correlation indicates that the impact functions clients may be paying a premium for add little information.

Part 3: How can asset managers use PCR models most effectively?

Six Recommendations for a Healthy Mindset

Analysis of vendor results in Part Two confirms that model vendors provide highly variable results. By digging deeper, we can see that many of these variations are explainable by the vendor's choices, including model resolution, peril definition, and impact functions. Some of these choices may be driven by resource constraints, but many are based on the scientific conviction that a certain way to model, data source to use, or impact function to build is the best way to measure the risk. Several vendors we spoke to emphasized that they had decided not to develop models for a certain peril or timeframe because they were not convinced that it was possible to do so given current scientific uncertainty. The most compelling vendor is not necessarily the most in-depth or the broadest, but rather the one where vendor methodology aligns with client use case.

Whatever the cause, the variation between vendor products makes a challenging landscape for asset managers to navigate. In addition to the extant variety, models are also developing rapidly; the products we describe here will look vastly different in a year or two. Between when we requested data from vendors and the time of publication (about eight months), five of the vendors rolled out major updates including introducing new perils, new timesteps, new models, and/or significantly increasing resolution. So, given this current state, how can asset managers use PCR models most effectively? We provide a series of recommendations here:

Stay true to you: vendor alignment

There are two main areas of consideration when selecting a vendor for a business use case. The first is pragmatic: does the vendor provide data in the right format, do they have impact functions for the right asset types, is there an existing contract or relationship, how much does the model cost, how easy is the vendor to work with? The last question is critical when internal subject matter expertise is limited. For example, Vendor 11's estimation of flood risk to one asset was very high compared to other vendors. When asked how they calculated their AAL, they responded quickly with a thorough explanation of the model's unexpected result for that location. No model is perfect, and often the only people who can understand why a certain result is produced are the vendor's own specialists. Good client services enhance the model's usability.

The second category is methodological. On the one hand, usage of the model will be limited if there is no conviction in the vendor's methodology. On the other hand, usage of the model will also be limited if there is high confidence in the vendor's methodology but limited ability to use and interpret model results. For example, some of the vendors in this study provide very rigorous, in-depth PCR models. However, both require skill on behalf of the client and support from the vendor to use.

Candidly assessing confidence in vendor methodology and internal capability will lead to better usage of the model. Considering the fast rate of model development mentioned earlier, we recommend considering internal and vendor roadmaps for the next few years in addition to the current state. Ideally, internal upskilling will complement increasingly sophisticated tools. Larger asset managers such as Nuveen may also be able to exert influence on product development to improve vendor methodological weaknesses or coverage gaps.

Don't resist discomfort: managing uncertainty

There is a saying, "what gets measured gets managed", that is often misunderstood to exalt the importance of measurement. By the same logic we can say, what gets mismeasured gets mismanaged. One recurring motif we observed in the results provided by vendors was false certainty. Most vendors provide AALs to several decimal points, implying an impossible level of precision, and some do not provide any measure of uncertainty.

Model results are not precise. It is impossible for them to be precise. While we can be confident the planet is warming, there is still significant disagreement between global climate models that run at much coarser resolutions on regional trends and global climate sensitivity (see again Fig 4). PCR model vendors layer upon this the uncertainty of their impact functions, peril-specific models, and downscaling process. Without quantification or even indication of uncertainty, we risk falling into the 'low accuracy/high precision' trap, leading to an unjustified level of confidence (Figure 12). Standard deviations, confidence intervals, and/or multiple return periods are acceptable methods of uncertainty quantification.

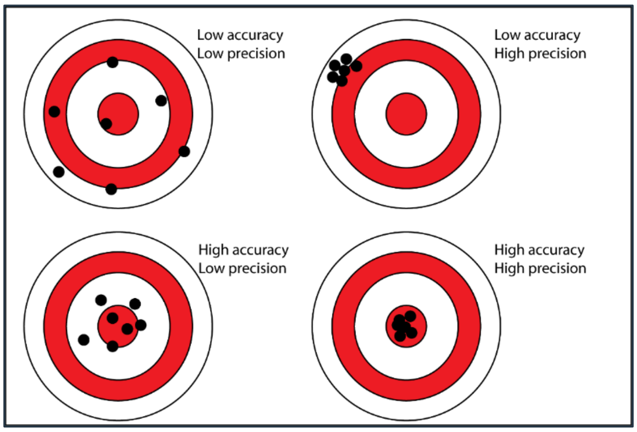

Figure 12. Alas, the bottom right is not an option.

Reporting use cases do not require tail risk quantification. However, if asset managers wish to integrate PCRs into their investment process, tail risks are important. PCR models that quantify uncertainty enable asset managers to set risk limits, incorporate model results into financial forecasts, build climate-optimal portfolios, and perform climate sensitivity analysis.

Seek support from those you trust: the role of consultants

In the catastrophe modeling industry, it's common practice for large brokers to license multiple vendor models and perform in-depth analyses of their methodology. In addition to modeling catastrophes for smaller insurers, they provide recommendations for insurers that model in-house on how to interpret the results; for example, by applying a correction factor if they believe risk is understated for a certain peril, region, or asset type. Brokers also validate catastrophe models against historical claims, meteorological data, and/or each other.

We believe consultants could fill a similar role for asset managers. By licensing multiple vendor models and comparing them as above, consultants could support asset managers in a) selecting the best model and b) using their chosen model effectively. The ability to compare model results to recent historical events, using weather records and insurance claims data, and construct narratives on why model results differ from history, would be incredibly useful for understanding how and why vendors differ. These practices are unlikely to be performed by asset managers due to the cost of licensing multiple models. To date, we are not aware of consultants offering this service.

Focus on the short term: model time horizons

Many vendor models provide AALs or exposure scores up to 2100. We question how much information can be gained from looking so far into the future. 2100 is 76 years away. 76 years ago, in 1948, computers barely existed, let alone the internet. Polio and smallpox were leading diseases worldwide, the Soviet Union would not fall for another 40 years, and most global climate models consisted of about three equations. While modeling decades into the future can be useful for broad strategic or economic decisions, the idea that we can estimate the value a single building will lose over that time from climate change is unjustified. Beyond 2050, the range of possible temperature impacts increases massively between and within climate scenarios (Figure 13).

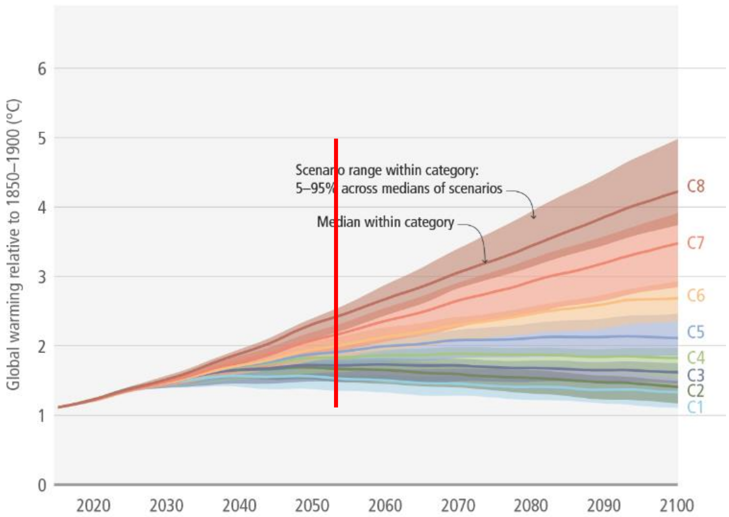

Figure 13. Median global warming across 8 scenarios. The horizontal red line at 2050 is the same height as the range of possible temperature increase at 2100. IPCC AR6.

We suggest that the maximum period asset managers need to consider is double their own investment horizon to answer the question of how much the asset might be worth to potential buyers, assuming they have the same investment horizon. For assets with very long investment horizons of 20 to 30 years, the need to look at double one's investment horizon should be balanced by how much one trusts the model results as uncertainty increases.

Avoid dwelling on things you can't control: impact functions

Impact functions are often a major component of vendor's IP, driven by their idiosyncratic choices and methodology. Vendor choices are especially important for impact functions built for chronic perils, which are understudied relative to acute perils. While we can all agree that a wildfire will burn a building, what about chronically higher temperatures? Productivity may decrease. Do we know how much productivity will decrease in an office building with AC versus a shipping warehouse? HVAC systems may also degrade faster, and cooling costs will increase, but by how much? Will this be offset by lower heating costs? In our opinion, vendors are not at a stage where they can answer all these questions confidently; indeed, the scientific community is not at a stage where they can answer all these questions confidently. We recommend that vendors with impact functions provide both exposure and loss metrics. This would make it more straightforward for clients to decompose results (is an AAL high because my asset in a high-risk location or is it a vulnerable structure type?).

By their own admission, one vendor we spoke to described impact functions as their weak point. Asset managers overseeing portfolios with atypical asset types may find that using an exposure model and performing an impact assessment in-house is preferable to using an oversimplified impact function. Even commercial RE asset managers may justifiably take the view that financial loss models available at their price point are too generalized to be decision useful, or that they can do a better job of holistically assessing financial impacts in-house. Alternately, asset managers may lack the data on asset attributes necessary to obtain the desired level of specificity from impact functions (ex. year built, square feet, first floor elevation).

Reframe your thoughts: building a holistic approach

“Monocausotaxophilia: a love of finding single causes to explain everything” – Ernst Poppel

Let us imagine a PCR model that does everything perfectly. Its impact functions are both accurate and precise, uncertainty is quantified, every peril is modeled to the highest level of scientific rigour. The asset manager has detailed information on all assets in their portfolio, which are input into the model to compute potential losses.

If the asset manager’s entire climate risk framework is based on that model’s outputs, it is still insufficient to fully capture their exposure to PCRs. There are risks that are outside the model scope. Broad social and economic impacts are not included. The risk to infrastructure that assets rely on is usually not included. Supply chain impacts are not included. A PCR model may – correctly – score an asset as low flood risk because it’s at the top of a hill. But if that asset is a retail store, how will customers get there? If the surrounding energy infrastructure is vulnerable to flood, how will it get power during a flood-induced outage? What if a critical supplier can’t ship their product? Will people to migrate away from the area due to increasingly damaging floods? Are there correlations between risks? How will insurance premiums, operational costs and rents be affected? Vendors are beginning to address some of these questions. For example, several vendors calculate correlation between some perils.

We recommend that asset managers assess perils individually, rather than adding or averaging results. All-peril metrics are often emphasized by vendors but have limited utility. For example, an asset may have a 5/5 exposure to flood, 2/5 to extreme heat, and 1/5 to wildfire according to the vendor. If the ‘high risk’ threshold for an asset is set at all-peril average of >3/5, the asset manager may overlook significant flood risks. Furthermore, mitigation actions are usually peril specific. Adding a defensible space around a property reduces wildfire losses but is useless against hurricanes. Insurance contracts often have peril-specific sub-limits. If an asset’s all-peril risk is high but there is no insight into what drives the risk, determining next steps beyond ‘invest or don’t invest’ is unfeasible.

We also recommend that asset managers develop a framework that complements what their model(s) do well & fills the gaps with expert knowledge and in-house research. Physical climate data – whether from a model vendor or public source - will always be the foundation of a climate risk framework. However, we strongly suggest moving beyond a ‘one vendor to rule them all’ approach. Most asset managers’ climate risk frameworks address three elements: reporting, enterprise/portfolio level risk assessment, and potential investment due diligence.

PCR models can be effective tools for all three, but one PCR model usually can't. And while PCR models are effective tools, they aren't the only tool. Asset managers can strengthen their climate risk framework by codifying expert knowledge from cross-functional groups of risk and investment experts or external consultants.

Conclusion: imagining the future of PCR modeling

As humans, we love neat little boxes and single numbers that describe everything. Monocausotaxophilia abounds in the PCR world, from clients who want a single vendor that does everything to vendors who offer a single number to quantify all climate risk. Unfortunately, climate change is complicated and the process of managing it is still nascent. Any robust framework for managing climate risks must face this reality head on. Temperature measures the energy of molecules. Faster moving molecules mean more – and more volatile – climate events. By increasing the volatility of the natural environment, the physical effects of climate change amplify financial uncertainty. Assets whose value is tied to a specific location, such as real assets, are at the forefront of this transformation. One day, we will have enough experience and data that managing climate risk will be boring. There is a lot to do before then.

What will boring climate risk management look like? It may be something like the 40-year-old field of catastrophe modeling now (please note that the author is a former cat modeler, and therefore biased). In an ideal future the two industries would be unified, with vendors providing models that analyze climate-impacted perils like hurricane and flood together with climate-agnostic ones like earthquake. Some vendors, particularly those offering climate-conditioned catastrophe models, are already doing this.

Broadly, we define PCR models as forward looking and cat models as backward looking. Current-day cat models are generally more robust than PCR models, though this is rapidly changing. Climate-conditioned catastrophe models – as built by some of the vendors in this project – are the 'gold standard' because they are mathematically rigorous, measure central tendency and tail risk, can calculate portfolio correlation, and can layer in complex insurance terms. Several vendors in this exercise have made significant strides towards fully cat-like climate models. Others have incorporated catastrophe risk modeling elements for some perils. Others yet primarily rely on indices.

Climate-conditioned cat models demand a high internal skill level and commitment from clients. Upskilling takes time. As we noted earlier, consultants in the cat modeling industry advise clients on how to use and understand their models: this arrangement could be leveraged to support asset managers as they learn how to incorporate climate-conditioned cat models. We end this thought exercise by emphasizing that the best climate risk management frameworks would include, but not rely on, models (ideally multiple models). It could look something like this:

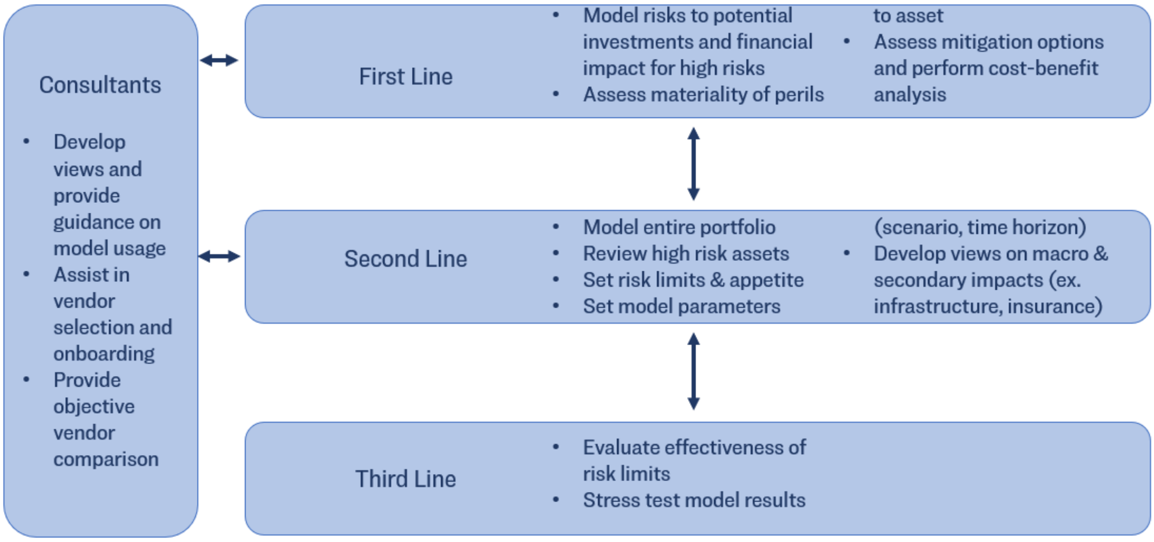

Figure 14. An enterprise-wide framework for climate and catastrophe risk analysis.

We conclude by reiterating the points emphasized in our abstract. PCR model vendors vary widely in their methodology and scope, which is reflected in the variety of results they provide for identical assets. No one vendor is 'right': each makes choices that reflect their convictions and constraints. One key area of improvement for PCR model vendors is the inclusion of uncertainty metrics and/or tail risks, rather than just central tendency. This is especially critical for acute climate risks that demonstrate skewedness and long tails. Lastly, we note that PCR models are one of many tools to understand climate risk. Secondary impacts such as flood-driven erosion, migration due to climate change, and rising insurance premiums are not included but are nonetheless highly relevant for risk management. A holistic approach is best suited to measuring the risks and opportunities from climate change. To paraphrase Teddy Roosevelt: let us focus on doing what we can, with what we have, where we are.

nuveen
A TIAA Company

Sources

1. AJ Pitman et al. Acute climate risks in the financial system: examining the utility of climate model projections. Environmental Research: Climate 2022.
2. Castoldi et al 2024. How Banks Can Transform Climate Risk into an Opportunity. Boston Consulting Group.
3. Chegwidden et al. Climate risk companies don't always agree. Carbon Plan.
4. J. Gourevitch, Kousky et al. Unpriced climate risk and the potential consequences of overvaluation in US housing markets. Nature Climate Change 2023.
5. J. Laidlaw et al. Quantifying the financial costs of climate change physical risks for companies. S&P 2023.
6. J. Schewe et al. State-of-the-art global models underestimate impacts from climate extremes. Nature communications 2019.
7. Newman R & Noy, I. The global costs of extreme weather that are attributable to climate change. Nature Communications 2023.
8. Roston et al. The Risky Business of Predicting Where Climate Disaster Will Hit. Bloomberg 2024.
9. Robinson et al. How to Choose, Use, and Better Understand Climate-Risk Analytics. ULI 2022.
10. Robinson et al. Physical Climate Risks and Underwriting Practices in Assets and Portfolios. ULI 2024.
11. S. Fuss. Substantial risk for financial assets. Nature Climate Change 2016.
12. CMIP6: The Next Generation of Climate Models Explained Carbon Brief 2019.

Appendices

Appendix A: Questionnaire

Each vendor was contacted directly to answer the questions below.

Category	Subcategory	Question
Background		Year founded (of model, not company)
Background		Company type (+stage if company is startup)
Background		Primary location
Background		# employees working on PCR model
Background		Presence of outsourcing
Background		Currently licensed by Nuveen/TIAA?
Data and Modeling		What are the required & optional data inputs?
Data and Modeling		How often is the model updated?
Data and Modeling		How is the output provided?
Data and Modeling		Describe how the model is tested & what data is used in the testing process.
Data and Modeling	Hazard	Describe how global climate data is downscaled.
Data and Modeling	Hazard	What climate scenarios are available?
Data and Modeling	Hazard	What perils are available?
Data and Modeling	Hazard	What is the geographic resolution by peril?
Data and Modeling	Hazard	What is the geographic coverage by peril?
Data and Modeling	Hazard	What time range & interval is available?
Data and Modeling	Hazard	What years are used for the baseline?
Data and Modeling	Hazard	Describe the models/data used to build the hazard module
Data and Modeling	Hazard	Is hazard module uncertainty expressed in the final product?
Data and Modeling	Hazard	Describe any major assumptions.
Data and Modeling	Vulnerability	What asset types are covered?
Data and Modeling	Vulnerability	How are impact functions built for different asset types?
Data and Modeling	Vulnerability	Are building factors considered (ex. construction/occupancy, elevation)?
Data and Modeling	Vulnerability	Describe the models/data used to build the vulnerability module.
Data and Modeling	Vulnerability	Is vulnerability module uncertainty expressed in the final product?
Data and Modeling	Vulnerability	Describe any major assumptions.
Data and Modeling	Financial	Describe the models/data are used to build the financial module
Data and Modeling	Financial	How is damage translated to financial loss? Is it based only on physical damage to the asset or are other factors included?
Data and Modeling	Financial	Is financial module uncertainty expressed in the final product?
Data and Modeling	Financial	Describe any major assumptions.
Products & Services		Describe any specific products offered.
Products & Services		How well does the company communicate (ease, response time)?
Products & Services		How transparent are they about the model?
Products & Services		How customizable are their products?
Products & Services		How user friendly are their products?

Appendix B: Vendor Correlations

To calculate correlations, location-level results from each vendor were ranked from 1 to 20, with ties receiving the same rank. Exposure scores and AALs of zero were excluded from the analysis. Correlation was calculated between ranks rather than the underlying values (spearman's rank correlation). This method is used because the dataset is not normally distributed. Any scenario and/or decade for which both vendors provided results was included in the correlation, meaning the number of data points varied for each computation.

Table D1. Correlations between vendors for flood hazard results.

	Vendor 13	Vendor 11	Vendor 3	Vendor 4	Vendor 8	Vendor 5	Vendor 7	Vendor 6	Vendor 10
Vendor 13	1.00		0.81		-0.13				
Vendor 11		1.00							
Vendor 3	0.81		1.00		-0.15				
Vendor 4				1.00	0.36				
Vendor 8	-0.13		-0.15	0.36	1.00				
Vendor 5						1.00			
vendor 7							1.00		
vendor 6								1.00	
vendor 10									1.00
Average	0.34		0.33	0.36	0.02				

Table D2. Correlation between vendors for flood financial results (AALs)

	Vendor 13	Vendor 11	Vendor 3	Vendor 4	Vendor 8	Vendor 5	vendor 7	vendor 6	vendor 10
Vendor 13	1.00								
Vendor 11		1.00		-0.02		0.53	0.04		
Vendor 3			1.00						
Vendor 4		-0.02		1.00		0.01	0.68		
Vendor 8					1.00				
Vendor 5		0.53		0.01		1.00	-0.14		
vendor 7		0.04		0.68		-0.14	1.00		
vendor 6								1.00	
vendor 10									1.00
Average	0.18		0.22		0.13	0.19			

Table D3. Correlations between vendors for drought hazard results.

	Vendor 13	Vendor 11	Vendor 3	Vendor 4	Vendor 8	Vendor 5	vendor 7	vendor 6	vendor 10
Vendor 13	1.00						0.52		0.27
Vendor 11		1.00							
Vendor 3			1.00						
Vendor 4				1.00			0.40		0.48
Vendor 8					1.00				
Vendor 5						1.00			
vendor 7	0.52			0.40			1.00		0.88

nuveen
A TIAA Company

	Vendor 13	Vendor 11	Vendor 3	Vendor 4	Vendor 8	Vendor 5	vendor 7	vendor 6	vendor 10
vendor 6								1.00	
vendor 10	0.27			0.48			0.88		1.00
Average	0.40			0.44			0.60		0.54

Table D4. Correlations between vendors for precipitation hazard results.

	Vendor 13	Vendor 11	Vendor 3	Vendor 4	Vendor 8	Vendor 5	vendor 7	vendor 6	vendor 10
Vendor 13	1.00						0.87		
Vendor 11		1.00							
Vendor 3			1.00						
Vendor 4				1.00	0.81		0.90		
Vendor 8				0.81	1.00		0.84		
Vendor 5						1.00			
vendor 7	0.87			0.90	0.84		1.00		
vendor 6								1.00	
vendor 10									1.00
Average	0.90			0.85	0.82		0.86		

Table D5. Correlations between vendors for water stress hazard results

	Vendor 13	Vendor 11	Vendor 3	Vendor 4	Vendor 8	Vendor 5	vendor 7	vendor 6	vendor 10
Vendor 13	1.00								
Vendor 11		1.00							
Vendor 3			1.00						
Vendor 4				1.00			-0.44		-0.05
Vendor 8					1.00		0.38		0.62
Vendor 5						1.00			
vendor 7				-0.44	0.38		1.00		0.48
vendor 6								1.00	
vendor 10				-0.05	0.62		0.48		1.00
Average				-0.24	0.50		0.14		0.35

Table D6. Correlation between vendors for water stress financial results (AALs)

	Vendor 13	Vendor 11	Vendor 3	Vendor 4	Vendor 8	Vendor 5	vendor 7	vendor 6	vendor 10
Vendor 13	1.00								
Vendor 11		1.00							
Vendor 3			1.00						
Vendor 4				1.00					
Vendor 8					1.00				
Vendor 5						1.00			-0.08
vendor 7							1.00		
vendor 6								1.00	
vendor 10						-0.08			1.00
Average						-0.08			-0.08

Table D7. Correlations between vendors for wind hazard results

	Vendor 13	Vendor 11	Vendor 3	Vendor 4	Vendor 8	Vendor 5	vendor 7	vendor 6	vendor 10
Vendor 13	1.00								

Vendor 11		1.00							
Vendor 3			1.00						0.66
Vendor 4				1.00					
Vendor 8					1.00				
Vendor 5						1.00			
vendor 7							1.00		
vendor 6								1.00	0.79
vendor 10			0.66					0.79	1.00
Average			0.66					0.79	0.72

Table D8. Correlation between vendors for wind financial results (AALs)

	Vendor 13	Vendor 11	Vendor 3	Vendor 4	Vendor 8	Vendor 5	vendor 7	vendor 6	vendor 10
Vendor 13	1.00								
Vendor 11		1.00		0.94		0.75	0.97		0.63
Vendor 3			1.00						
Vendor 4		0.94		1.00		0.64	0.50	0.45	0.37
Vendor 8					1.00				
Vendor 5		0.75		0.64		1.00	0.82	0.48	0.51
vendor 7		0.97		0.50		0.82	1.00	0.66	0.53
vendor 6				0.45		0.48	0.66	1.00	
vendor 10		0.63		0.37		0.51	0.53		1.00
Average		0.84		0.62		0.67	0.72	0.53	0.56

Table D9. Correlations between vendors for heat stress hazard results

	Vendor 13	Vendor 11	Vendor 3	Vendor 4	Vendor 8	Vendor 5	vendor 7	vendor 6	vendor 10
Vendor 13	1.00		0.35				0.38		0.48
Vendor 11		1.00							
Vendor 3	0.35		1.00				0.95		0.18
Vendor 4				1.00	0.80		0.89		0.47
Vendor 8				0.80	1.00		0.83		
Vendor 5						1.00			
vendor 7	0.38		0.95	0.89	0.83		1.00		0.20
vendor 6								1.00	
vendor 10	0.48		0.18	0.47			0.20		1.00
Average	0.34		0.58	0.72	0.82		0.68		0.26

Table D10. Correlation between vendors for heat stress financial results (AALs)

	Vendor 13	Vendor 11	Vendor 3	Vendor 4	Vendor 8	Vendor 5	vendor 7	vendor 6	vendor 10
Vendor 13	1.00								
Vendor 11		1.00							
Vendor 3			1.00						
Vendor 4				1.00				0.36	-0.07
Vendor 8					1.00				
Vendor 5						1.00		0.88	0.63
vendor 7							1.00		
vendor 6				0.36		0.88		1.00	
vendor 10				-0.07		0.63			1.00
Average				0.15		0.75		0.62	0.28

4350208