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Counterfactual Analytics

This document answers some of the key outstanding questions asked at the Oasis Insight Conference in London on 24th April 2024 during the counterfactual panel discussion.

# Background

**How does counterfactual loss modelling differ from stochastic event loss modelling in catastrophe insurance?**

Counterfactual loss modelling and stochastic event loss modelling are two distinct approaches used in catastrophe (re)insurance modelling that are designed to test potential loss impacts from given scenarios.

Counterfactual Loss Modelling

Counterfactual loss modelling explores "what if" scenarios by modifying the parameters of historical losses to analyse the potential consequences if certain risk mitigation measures were absent or in place or if the event itself had manifest itself differently (such as an altered landfall track[[1]](#footnote-1)). It aims to quantify the benefits of implemented risk reduction interventions by simulating a worse outcome without those interventions and/or if the event itself had played out differently.

The key features of this approach include:

* Analysing a specific historical event by altering parameters such as hazard intensity or track path to impact increased insured exposure values, or vulnerability to create harsher consequences that generate higher losses[[2]](#footnote-2).
* Highlighting the effectiveness of existing risk mitigation efforts by comparing the actual losses to the resulting simulated worse outcome.

Stochastic Event Loss Modelling

Stochastic event loss modelling generates hypothetical catastrophe scenarios based on probabilistic distributions to estimate potential losses[[3]](#footnote-3). It does not modify historical events but creates synthetic event catalogues that represent the frequency and severity of these events, while attempting to replicate the randomness and uncertainty of losses using statistical techniques.

The key features of this approach include:

* Using probabilistic models to simulate a large number of catastrophe events to replicate both historical and future potential losses their characteristics, capturing frequency, severity and likely geographic location of events.
* Capturing the full range of possible future event scenarios and associated losses.

In summary, counterfactual models can alter specific historical events by worsening parameters (size, intensity, path, etc) to show credible outcomes, which could then be used to demonstrate risk reduction benefits. Stochastic models generate synthetic catastrophe scenarios from probabilistic models to estimate future potential losses.

The counterfactual approach might be especially useful for quantifying and communicating the often-invisible benefits of disaster risk reduction programs or internal extreme disaster scenario analysis. Using known historical events, parameters could be altered to show how these events could have had even worse outcomes, which in turn could assist with identifying previously unknown or overlooked risks.

**Does a big difference between a counterfactual model result and a standard model result mean that a model is not doing a good job?**

Differences between the results of a counterfactual model and a standard [stochastic event loss] model does not necessarily imply that either model is performing poorly. Counterfactual models and standard predictive models have different goals and make different assumptions, so their results can diverge substantially, even when both are accurate within their respective frameworks.

Counterfactual models aim to estimate the causal effect of an intervention by modelling the potential outcomes under different scenarios (factual through historical data and counterfactual with more extreme consequences). They may make tougher assumptions to identify causal effects from observational data resulting in the counterfactual predictions differing from those of standard models that have not made such assumptions.

Standard predictive models simply aim to make accurate predictions without explicitly modelling the causal relationships.

If the results are divergent, it does not necessarily mean one model is wrong; it’s more a reflection of the different purposes and assumptions of the two modelling approaches. Evaluating their performance requires checking whether their respective assumptions hold for the given data. Ultimately, users should consider the appropriate metrics for evaluating the performance of each, not least whether standard models are designed to answer the specific scenarios that are being asked of a counterfactual model.

**Do these model gaps (for US) just show over-calibration/reliance on Hurdat? Real long-term frequencies by category should be much smoother.**

The model gaps and limitations mentioned in these sources do not seem to be primarily due to over-calibration or reliance on the HURDAT2 hurricane database. The sources, referenced below, discuss several other factors contributing to the uncertainties and gaps in hurricane risk modelling for the United States Windstorm risk.

The following sources provide some more context:

1. The AIR hurricane model (see[[4]](#footnote-4) and [[5]](#footnote-5)) relies on stochastic simulations of hurricane seasons calibrated to historical observations. While HURDAT2 provides the historical data, the key limitation discussed is the need to sample these simulations to create catalogues representing future climate scenarios. This sampling process introduces uncertainties in capturing the full range of potential changes in hurricane frequency and intensity under climate change.

2. The study[[6]](#footnote-6) highlights the uncertainties in physics-based projections of future hurricane activity under climate change scenarios. It notes that current risk models do not fully account for these uncertainties from climate models due to computational complexity. Instead, they use simple probabilistic assumptions which may not capture the full range of potential changes.

3. The review paper[[7]](#footnote-7) suggests that general circulation models (GCMs) provide a more direct approach to assessing climate change impacts on hurricane risk compared to methods relying solely on historical hurricane data.

Overall, while HURDAT2 provides the baseline historical data, the key challenge seems to be adequately modelling the complex physical processes involved, capturing the full range of potential changes projected by climate models, and addressing computational limitations in combining all these factors within risk models.

Over-calibration or over-reliance on HURDAT2 itself is not highlighted as a major gap across these sources.

**What's the difference between looking at counterfactual losses and selected tail stochastic events with similar characteristics?**

The main difference between counterfactual losses and selected tail stochastic events with similar characteristics lies in their underlying assumptions, modelling approaches and their purpose.

Counterfactual losses are derived by modelling the potential outcomes under different assumptions from historical events scenarios (the factual scenarios). For US Hurricane risk, this would imply estimating the losses that might have occurred had a specific hurricane taken a different track or if it’s intensity or other characteristics had become more severe. This requires expert judgement to ensure that the counterfactual assumptions made are both plausible and preserve physical consistency and realism. The goal is to understand how the outcome would change if certain factors were different, providing insights into causal relationships.

On the other hand, selected tail stochastic events refer to extreme or rare events sampled from stochastic simulations or models that do not explicitly account for causal relationships. These simulations may incorporate probabilistic assumptions about tail risks but do not necessarily satisfy the assumptions required for causal inference.

While both approaches deal with adverse scenarios, counterfactual losses specifically estimate what the losses would have been if the adverse scenario had not occurred (the counterfactual), by explicitly modelling the causal effect of that scenario. In contrast, selected tail events simply represent extreme realizations from the underlying stochastic model, without explicitly disentangling the causal impact.

The difference arises from the causal modelling framework and assumptions behind counterfactuals, which aim to isolate the causal effect of the scenario rather than just characterizing tail losses from a stochastic process. This distinction is important for applications like stress testing that aim to quantify the causal impact of specific scenarios.

In summary, counterfactual analysis focuses on understanding causal relationships by modelling alternative scenarios, while selecting tail stochastic events is a risk modelling technique to assess the potential for extreme losses by simulating events with similar characteristics to historical data. The former is more concerned with causality, while the latter is focused on quantifying risk exposure.

**Should we be using counterfactual event sets in model validation?**

Counterfactual event sets can be beneficial for model validation. However, it requires careful consideration of the underlying assumptions and appropriate methodologies.

Catastrophe models are built using historical events together with assumptions, such as the maximum potential intensity of tropical cyclones and earthquakes at a specific location. These may not capture the potential for extreme or unprecedented events[[8]](#footnote-8). Counterfactual analysis allows risk modellers to explore “what-if” scenarios by modifying the characteristics of past events, which in turn allows users to stress-test existing models.

Further, in the absence of limited loss history, a counterfactual model analysis could allow for the analysis of emerging risks where data is lacking.

**Can you see a future where Model Vendors provide counterfactual scenarios as part of their event response?**

Catastrophe model vendors could potentially provide counterfactual scenarios as part of their event response services in the future. There are several potential benefits and use cases that make this a plausible development:

Benefits of Counterfactual Scenarios

1. Stress Testing: Counterfactual scenarios representing more severe or impactful event outcomes can be used by insurers and reinsurers to stress test their risk management frameworks and assess their resilience to extreme events.
2. Cognitive Debiasing: Counterfactual analysis can help overcome cognitive biases and recency effects by considering plausible alternative scenarios beyond just the observed event.
3. Real-Time Decision Support: Counterfactual storylines can inform risk mitigation strategies and decision-making by illustrating the potential consequences of different event outcomes.
4. Emerging Risk Analysis: For risks with limited historical data, like cyber[[9]](#footnote-9) or liability clash, counterfactual scenarios can augment traditional probabilistic loss modelling approaches.
5. Regulatory Compliance: Regulators are increasingly interested in using downward counterfactual scenarios as a tool to validate catastrophe models and communicate uncertainty. Providing these scenarios as part of an event response would enable model vendors to demonstrate regulatory compliance.

Potential Use Cases

1. Real-Time Event Response: As part of their real-time event response solutions, vendors could generate counterfactual scenarios exploring alternative storm tracks, intensities or other parameters to quantify the "near-miss" risk.
2. Model Validation: Counterfactual scenarios can be used to validate and benchmark catastrophe models by assessing their ability to capture a wider range of potential outcomes.
3. Risk Communication: Vivid counterfactual examples based on actual events can make it easier to communicate risks and model uncertainties to stakeholders.

While generating robust counterfactual scenarios requires additional effort, the sources suggest this capability could provide significant value to model users by enhancing risk awareness, model validation, and decision support under uncertainty. As catastrophe modelling continues evolving, offering counterfactual analysis may become an important competitive advantage for vendors.

**Following up, what event attributes are required to be the same/ similar to make an event counterfactual? I.e. how similar does an event need to be?**

There are no strict rules or thresholds defined for how similar an event needs to be to the factual event in order to be considered a valid counterfactual scenario. However, some key considerations and desirable properties for constructing meaningful counterfactual events or instances would include:

1. Plausibility/Realism: Counterfactual events should be plausible and realistic representations of how the world could have unfolded differently under the counterfactual conditions. This often requires preserving certain key attributes of the factual event / instance, such as maintaining windspeed whilst altering landfall path of a tropical cyclone.
2. Minimal Intervention: Good counterfactual instances should differ from the factual instance by making only the minimal changes necessary to the features / attributes to achieve the counterfactual outcome. Changing too many attributes can make the counterfactual implausible or uninterpretable.
3. Actionability: The changes made in the counterfactual event should correspond to actionable variables that are under the decision-maker's control. Changing immutable attributes provides no actionable recourse.
4. Causality: Ideally, the changes made in the counterfactual should correspond to features/attributes that have a causal influence on the outcome, rather than just correlations.

Counterfactual events need to be sufficiently similar to the factual event in terms of preserving key plausible attributes and background context. But they should make minimal, actionable and causal, changes to the attributes relevant to the counterfactual outcome being explored.

**What about hurricane events that do not make landfall or their genesis means they were not recognised as events? How does counterfactual deal with this?**

Based on the principles and methodologies discussed above, we can infer some potential approaches:

1. For hurricanes that did not make landfall:
	1. These could still be considered as factual events for counterfactual analysis, even if they did not cause significant damage or losses.
	2. Downward counterfactuals could explore scenarios where the storm track shifted towards landfall or intensified, potentially causing impacts.
	3. This allows assessing the "near-miss" risk and consequences that were narrowly avoided due to the actual favourable storm evolution.
2. For hurricane genesis events that were not initially recognized:
	1. Once the event is identified retrospectively (e.g. through post-storm analysis), it can still be used as the factual baseline for counterfactual analysis.
	2. Downward counterfactuals could consider what if the system had been identified earlier and monitored more closely.
	3. This allows exploring how delayed recognition may have impacted preparedness, response, evacuation decisions and other risk mitigation strategies
3. General principles:
	1. Counterfactual analysis is not inherently limited to only events that caused damage or were immediately recognized.
	2. Any observed hazard event can serve as the factual baseline to construct plausible counterfactual scenarios exploring worse outcomes.
	3. The value of counterfactuals for lower probability / higher severity impact tail events that may be under-sampled in historical data.

Counterfactual analysis can still provide insights even for hurricane events that did not make landfall or whose genesis was delayed, by exploring the potential consequences if circumstances had unfolded differently. This aligns with using counterfactuals to quantify "near-miss" risks and identify areas to improve monitoring, forecasting and decision-making processes.

**What attributes of a hurricane event do you look at to create counterfactual events?**

When creating counterfactual hurricane events, some general principles and considerations should be followed:

1. Plausibility and Physical Consistency:

Counterfactual hurricane events should be physically plausible and the scenarios based on the underlying meteorological and climatological processes. Key attributes like storm genesis location, track, intensity, size, forward speed etc. need to be adjusted in a way that are physically robust.

1. Minimal Intervention:

Good counterfactual events should differ from the factual event by making only the minimal required changes to the relevant attributes.

Changing too many attributes can make the counterfactual implausible or uninterpretable.

1. Actionability:

The attributes changed in the counterfactual should correspond to actionable variables under the decision-maker's control, if the goal is to inform risk mitigation strategies. For hurricanes, this could include factors like forecast lead times, observational data availability, emergency preparedness decisions etc.

1. Diversity:

While individual counterfactuals aim for minimal edits, having a diverse set exploring different alternatives (e.g. varying track, intensity, rainfall, storm surge) is valuable.

1. Causal Relevance:
	1. Ideally, the changed attributes should have a causal influence on the outcome of interest (e.g. damage, losses), rather than just correlations.

Key hurricane attributes to potentially adjust include the storm track, intensity, size, forward speed, rainfall, storm surge to create plausible counterfactual scenarios. But this should be done judiciously - making minimal, diverse, causal, and actionable changes to construct meaningful counterfactual storylines aligned with the specific risk management goals. Domain expertise is required to determine precisely which attributes to modify for a given hurricane event.

**N.B.** There are more questions and answers in the accompanying doc: *Questions\_Oasis\_Insight\_London2024\_v3.xlsx*

1. Rye, C.J., Boyd, J.A. (2022). Downward Counterfactual Analysis in Insurance Tropical Cyclone Models: A Miami Case Study. In: Collins, J.M., Done, J.M. (eds) Hurricane Risk in a Changing Climate. Hurricane Risk, vol 2. Springer, Cham. https://doi.org/10.1007/978-3-031-08568-0\_9 [↑](#footnote-ref-1)
2. Learning From Success, Not Catastrophe: Using Counterfactual Analysis to Highlight Successful Disaster Risk Reduction Interventions

<https://www.frontiersin.org/articles/10.3389/feart.2022.847196/full> [↑](#footnote-ref-2)
3. A simulation of the insurance industry: the problem of risk model homogeneity

 <https://link.springer.com/article/10.1007/s11403-021-00319-4> [↑](#footnote-ref-3)
4. The AIR Hurricane Model for the U.S. v1.0.0 as implemented in Touchstone® <https://fchlpm.sbafla.com/media/41pll1yy/air_2019_fchlpm_submission_20210519.pdf> [↑](#footnote-ref-4)
5. Quantifying the Impact from Climate Change on U.S. Hurricane Risk <https://www.air-worldwide.com/siteassets/Publications/White-Papers/documents/air_climatechange_us_hurricane_whitepaper.pdf> [↑](#footnote-ref-5)
6. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7499252/> [↑](#footnote-ref-6)
7. <https://www.science.org/doi/10.1126/sciadv.adf0259> [↑](#footnote-ref-7)
8. Reimagining history Counterfactual risk analysis: <https://assets.lloyds.com/assets/reimagining-history-report/1/Reimagining-history-report.pdf> [↑](#footnote-ref-8)
9. Gallagher Re: A history of Near Misses <https://www.ajg.com/gallagherre/-/media/files/gallagher/gallagherre/2024/gallagherre-a-history-of-near-misses-counterfactual-analysis.pdf> [↑](#footnote-ref-9)