A Probabilistic Catastrophe Risk Model for Site-Specific Tropical Cyclone Loss Quantification

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Abstract

Quantifying the financial risk posed by landfalling tropical cyclones requires statistical methods that extend beyond the limits of a short and non-stationary historical observational record. This paper presents the mathematical formulation of an open, modular probabilistic catastrophe risk model for site-specific tropical cyclone loss estimation, structured around the four components used throughout the catastrophe modeling industry: hazard, exposure, vulnerability, and financial loss. Storm intensities drawn from NOAA's HURDAT2 database over the satellite era (1970–2025) are fit to a continuous Weibull distribution via maximum likelihood estimation, from which a 10,000-year synthetic event catalog is generated and propagated to individual properties using a Holland-type wind-field decay model. The hazard catalog is evaluated against a synthetic Industry Exposure Database of 10,000 properties (total insured value of $39.01 billion) distributed across six high-hazard U.S. Gulf and Atlantic coast counties, allocated using NOAA Office for Coastal Management county-level economic indices. Physical damage is estimated via construction-class-specific log-normal vulnerability functions, and resulting ground-up losses are passed through standard insurance contract terms (deductibles and policy limits) to obtain net insured liabilities. The resulting annualized loss distribution yields insured loss thresholds of $124,968, $138.3 million, $381.7 million, and $1.87 billion at the 1-in-10, 1-in-50, 1-in-100, and 1-in-500 year return periods, respectively. We discuss the model's relationship to existing open-source and commercial catastrophe modeling platforms, the limitations introduced by its stationarity assumptions and synthetic exposure base, and the implications of a non-stationary, warming climate for long-tail insured loss estimation.

1 Introduction

Landfalling tropical cyclones are the single largest source of insured catastrophe losses in the United States, and the property and casualty (P&C) insurance and reinsurance sectors have relied on probabilistic catastrophe models to price and reserve against this risk for nearly four decades. The central statistical challenge has not changed since the field's founding: the historical record of North Atlantic hurricanes spans roughly 170 years, but reliable, instrument-based intensity estimates are confined to the geostationary satellite era beginning around 1970. A record of this length is far too short to characterize the tail of the loss distribution that determines insurer and reinsurer solvency: a 1-in-100 or 1-in-500 year event, by construction, may not appear even once in 50–75 years of usable observations.

Early actuarial practice addressed this gap with simple historical-average loss ratios, an approach that implicitly assumes the future will resemble the recent past in both hazard and exposure. Friedman (1984) was among the first to argue formally that natural hazard insurance pricing required an explicit probabilistic treatment rather than raw historical averaging [4]. Clark (1986) operationalized this argument for hurricanes, introducing computer-simulated event sets and establishing the four-component architecture (hazard, exposure, vulnerability, financial loss) that remains the structural backbone of catastrophe models used across the industry today [2].

Subsequent work refined each of these components individually. On the hazard side, Holland (1980) provided the parametric pressure-and-wind-field profile that underlies most modern wind field models [5], while Vickery et al. (2000) and Emanuel et al. (2006) developed full track-based stochastic simulation techniques, generating synthetic storm tracks from genesis to landfall rather than anchoring intensity to fixed regional points, that substantially improved the spatial realism of simulated hazard [3, 11]. On the statistical side, Strupczewski et al. (2001) demonstrated, in the context of flood frequency analysis, the value of fitting continuous extreme value distributions rather than relying on the empirical, discretized tails of short historical samples [10], a principle directly applicable to tropical cyclone intensity modeling. Woo (2011) gives a comprehensive treatment of how these components are combined in operational catastrophe modeling practice [12].

Despite this long methodological history, most operational catastrophe models remain proprietary, vendor-controlled platforms (e.g., Verisk/AIR, Moody's RMS), which limits independent scrutiny of their assumptions. A smaller body of open-source work, most notably the CLIMADA platform [1], has begun to make the full hazard-exposure-vulnerability-loss pipeline transparent and reproducible. This paper contributes to that effort.

1.1 Contribution

We present a fully specified, end-to-end probabilistic catastrophe risk model for tropical cyclones, implemented as open-source software, and apply it to a synthetic but realistically structured U.S. Gulf and Atlantic coast property portfolio. Our specific contributions are: (i) a continuous Weibull hazard model fit to satellite-era HURDAT2 intensities, combined with a Holland-type spatial wind field decay model evaluated at the level of individual properties rather than aggregated geographic zones; (ii) an exposure database seeded from publicly available NOAA economic indices rather than arbitrary or hardcoded asset allocations; (iii) construction-class-specific log-normal vulnerability functions; and (iv) a financial loss layer that reproduces standard deductible and policy-limit contract mechanics to produce annualized loss and exceedance probability metrics. The remainder of this paper describes the methodology (Section 2), reports results from the synthetic case study (Section 3), discusses the model's positioning relative to existing frameworks and its current limitations (Section 4), and concludes with directions for future work (Section 5). Implementation and computational-performance details are reported separately in Appendix A, as they are not central to the model's scientific contribution.

2 Data and Methods

The model is organized around four sequential components, each described below: the hazard module, which generates a synthetic catalog of storm events; the exposure module, which constructs the property portfolio at risk; the vulnerability module, which converts physical hazard intensity into structural damage; and the financial loss module, which converts physical damage into insured liability.

2.1 Hazard Module: Continuous Intensity Fitting and Wind Field Attenuation

Historical storm intensities are drawn from NOAA's HURDAT2 database, restricted to the 1970–2025 satellite era to avoid the detection and intensity biases known to affect pre-satellite records. Rather than resampling directly from this limited historical set (which by definition cannot contain unobserved tail events), maximum wind speeds are modeled as a continuous random variable via a two-parameter Weibull distribution, fit by maximum likelihood estimation (MLE):

$$f(v; k, \lambda_w) = \frac{k}{\lambda_w}\left(\frac{v}{\lambda_w}\right)^{k-1} e^{-(v/\lambda_w)^k}, \quad v \geq 0, \tag{1}$$

where v is the storm's peak sustained wind speed (knots), $k > 0$ is the shape parameter governing the heaviness of the upper tail, and $\lambda_w > 0$ is the scale parameter. Fitting a continuous distribution allows the model to generate physically plausible intensities, including storms more intense than any in the 1970–2025 record, while remaining anchored to the empirical distribution of observed storms.

The annual frequency of storm formation is modeled as a discrete Poisson process with rate λ equal to the historical mean annual storm count over the same period:

$$P(N_y = n) = \frac{\lambda^n e^{-\lambda}}{n!}, \quad n = 0, 1, 2, \ldots, \tag{2}$$

where N_y is the number of storms simulated in year y. Each simulated storm year therefore draws a storm count from Equation (2), and an independent peak intensity for each storm from Equation (1).

To translate a storm's peak intensity into the wind speed actually experienced at a given property, each simulated storm is assigned a landfall point (Lat_0, Lon_0) and a translation heading θ, defining a track line. For a property located at perpendicular distance d from this track (computed via the Haversine great-circle distance formula), the local wind speed is attenuated using a Holland-type radial decay profile [5]:

$$v_{\text{local}} = v_{\max} \times \min\left[1.0, \left(\frac{R_{\max}}{d + \epsilon}\right)^{\alpha}\right], \tag{3}$$

where $v_{\max}$ is the storm's simulated peak wind speed from Equation (1), $R_{\max}$ is the radius of maximum winds (km), $\alpha \in (0, 1)$ is an empirical decay coefficient controlling how quickly wind speed falls off with distance from the storm core, and $\epsilon = 10^{-5}$ is a small constant added to prevent a division singularity for properties located directly on the track line ($d \to 0$).

2.2 Exposure Module: A NOAA-Anchored Synthetic Industry Exposure Database

A realistic Industry Exposure Database (IED) requires a defensible basis for distributing property value across a region, rather than an arbitrary or uniform allocation. We use county-level Gross Domestic Product (GDP) data from NOAA's Office for Coastal Management Economics: National Ocean Watch (ENOW) dataset to construct normalized wealth weights for each county c in the set of target high-hazard counties C:

$$w_c = \frac{\text{GDP}_c}{\sum_{i \in C} \text{GDP}_i}. \tag{4}$$

These weights are used to probabilistically allocate 10,000 synthetic properties across six U.S. Gulf and Atlantic coast counties (Miami-Dade, FL; Hillsborough, FL; Harris, TX; Orleans, LA; Charleston, SC; and New Hanover, NC), with each property's coordinates jittered around its county's economic centroid to emulate realistic suburban dispersion. Each property is assigned an occupancy type (residential or commercial), a construction class (Wood Frame, Masonry, Steel Frame, or Reinforced Concrete), and a Total Insured Value (TIV) drawn from a log-normal distribution,

$$V_{\text{asset}} \sim \text{Lognormal}(\mu_v, \sigma_v), \tag{5}$$

with distribution parameters μ_v, σ_v set separately for residential and commercial occupancy to reflect the markedly right-skewed value distribution of real-world property portfolios, in which a small number of high-value commercial assets coexist with a much larger number of lower-value residential structures.

2.3 Vulnerability Module: Construction-Class Fragility Curves

The vulnerability module converts the local wind speed experienced by a property, v_{local}, into a Mean Damage Ratio, MDR $\in [0, 1]$, representing the expected fraction of total building value lost. Fragility is modeled as a log-normal cumulative distribution function (CDF), following standard engineering practice for wind damage curves:

$$\text{MDR}(v_{\text{local}}) = \Phi\left(\frac{\ln(v_{\text{local}}) - \ln(\text{scale})}{s}\right), \quad v_{\text{local}} \geq 34\ \text{kt}, \tag{6}$$

where $\Phi(\cdot)$ is the standard normal CDF, scale is the median wind speed at which 50% damage is expected for a given construction class, and s is the log-standard deviation governing the steepness of the failure curve. MDR is set to zero below the 34-knot tropical storm threshold, below which structural wind damage is assumed negligible. Curve parameters (scale, s) are specified independently for each construction class, so that, for example, a Wood Frame structure reaches 50% expected damage at a substantially lower wind speed than a Reinforced Concrete structure. Ground-up monetary loss is then

$$L_{\text{gu}} = V_{\text{asset}} \times \text{MDR}(v_{\text{local}}). \tag{7}$$

2.4 Financial Loss Module: Contractual Liability Reshaping

The financial module converts ground-up physical loss into the net liability actually retained by an insurer, by applying a fixed-dollar policy deductible D_f and an absolute policy limit L_p:

$$L_{\text{insured}} = \min\left(\max\left(L_{\text{gu}} - D_f,\ 0\right),\ L_p\right). \tag{8}$$

Insured losses are aggregated across the full $Y = 10{,}000$-year simulated catalog to compute the Average Annual Loss (AAL), the standard long-run pure premium benchmark in catastrophe risk pricing:

$$\text{AAL} = \frac{1}{Y}\sum_{y=1}^{Y}\sum_{e\in E_y} L_{\text{insured}}(e), \tag{9}$$

where E_y is the set of simulated events occurring in year y. We additionally report the portfolio's Occurrence Exceedance Probability (OEP) curve, defined as the probability that the largest single-event annual loss exceeds a given threshold ℓ,

$$\text{OEP}(\ell) = P\left(\max_{e\in E_y} L_{\text{insured}}(e) > \ell\right), \tag{10}$$

from which return-period loss thresholds (e.g., the 1-in-100-year loss) are read directly as ℓ such that $\text{OEP}(\ell) = 1/100$. To characterize risk beyond a single percentile, we also compute the Tail Value at Risk (TVaR) at probability level p,

$$\text{TVaR}_p = \mathbb{E}\left[L \mid L > \text{VaR}_p\right], \qquad \text{VaR}_p = \inf\{\ell : \text{OEP}(\ell) \leq p\}, \tag{11}$$

which captures the expected severity of losses conditional on exceeding a given return-period threshold, and is the more conservative metric typically required for reinsurance capital adequacy assessment.

Table 1: Insured loss thresholds by return period.

Return Period	Insured Loss Threshold
1-in-10 years	$124,968
1-in-50 years	$138,329,736
1-in-100 years	$381,740,812
1-in-500 years	$1,874,541,679

3 Results

Applying the four-stage model described above to the synthetic $39.01 billion property portfolio yields a smooth, non-linear annualized loss distribution. Table 1 reports insured loss thresholds at standard return periods.

The pronounced jump in loss severity between the 1-in-10 and 1-in-50 year thresholds reflects the heavy-tailed nature of the fitted Weibull intensity distribution combined with the nonlinearity of the log-normal vulnerability curves: below roughly Category 2 intensity, losses are concentrated in a small number of properties near the storm track and are frequently absorbed by policy deductibles, whereas higher-intensity events produce damage across a much larger fraction of the portfolio simultaneously.

Figure 1 shows the spatial distribution of accumulated insured loss across the portfolio. Loss concentration closely tracks the underlying property value density established by the NOAA ENOW-derived exposure weights (Equation 4), with the largest accumulations occurring in the highest-GDP coastal counties.

Figure 2 presents the full Occurrence Exceedance Probability curve underlying Table 1, plotted on a logarithmic return-period axis as is standard in catastrophe modeling practice.

Finally, Figure 3 decomposes total simulated loss by construction class. Wood Frame residential structures account for a disproportionate share of ground-up loss relative to their share of total insured value, consistent with their lower fragility-curve damage thresholds (Equation 6) relative to Reinforced Concrete and Steel Frame commercial structures.

4 Discussion

4.1 The Renewed Case for Catastrophe Modeling

Interest in transparent, independently verifiable catastrophe models has grown substantially over the past decade, driven by three converging trends. First, the volume and quality of publicly available hazard and exposure data has expanded considerably: multi-decade satellite reanalysis products, NOAA's freely accessible HURDAT2 and Digital Coast economic datasets, and similar open repositories now provide much of the raw material that was once available only through expensive proprietary licenses. Second, the computational cost of running large stochastic event catalogs has fallen sharply, making it practical for individual researchers and smaller institutions to build and run full-resolution catastrophe models that would have required dedicated computing clusters a decade ago. Third, the reinsurance and P&C sectors have faced a sequence of loss years (e.g., the 2017, 2021, and 2022 Atlantic hurricane seasons) that has intensified scrutiny of vendor model assumptions and accelerated demand for model diversification and independent validation. Together, these trends have created space for open frameworks to complement, and in some respects challenge, the small number of proprietary platforms (Verisk/AIR, Moody's RMS) that have historically dominated catastrophe risk pricing.

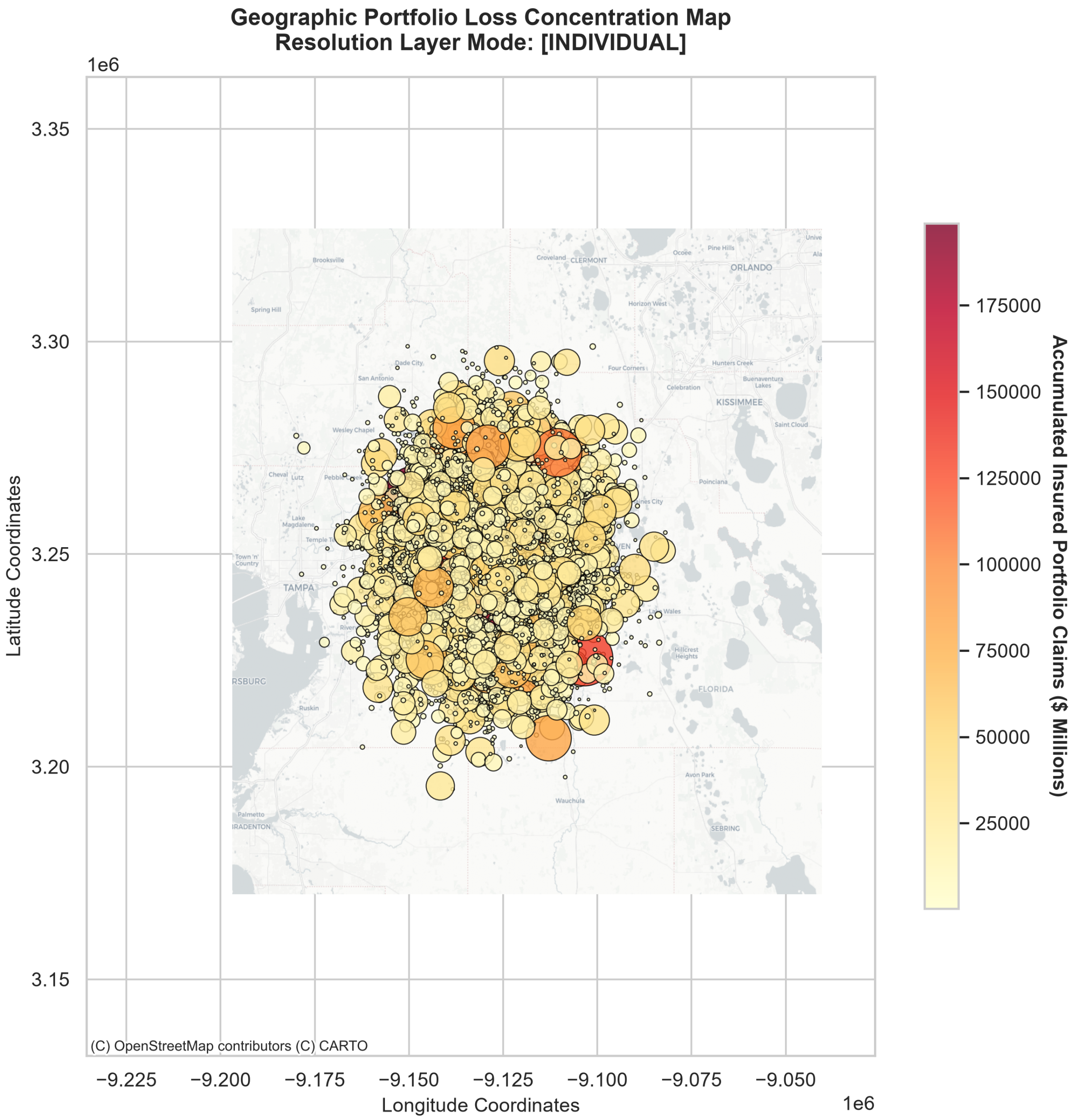

Figure 1: Geographic accumulation of simulated insured loss across the synthetic property portfolio. Marker size reflects property total insured value; color reflects accumulated lifetime insured loss.

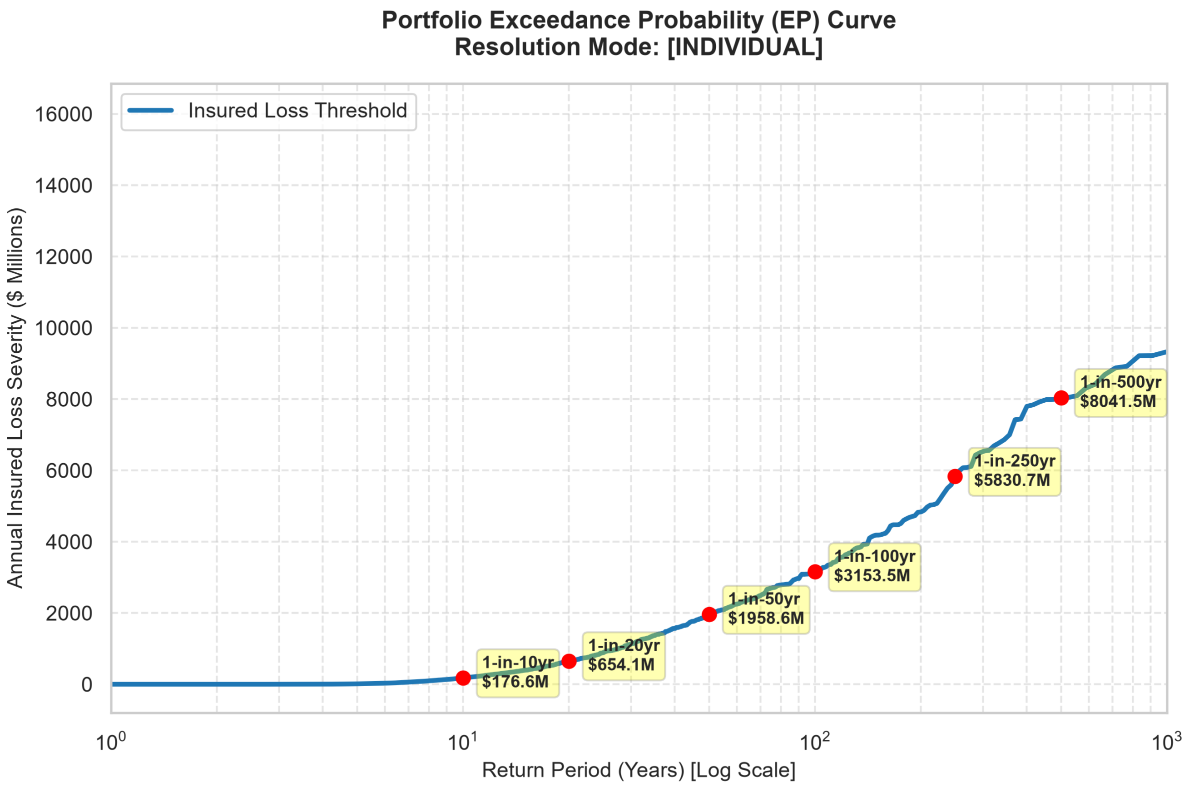

Figure 2: Occurrence Exceedance Probability (OEP) curve for the synthetic portfolio, with standard return-period benchmarks annotated.

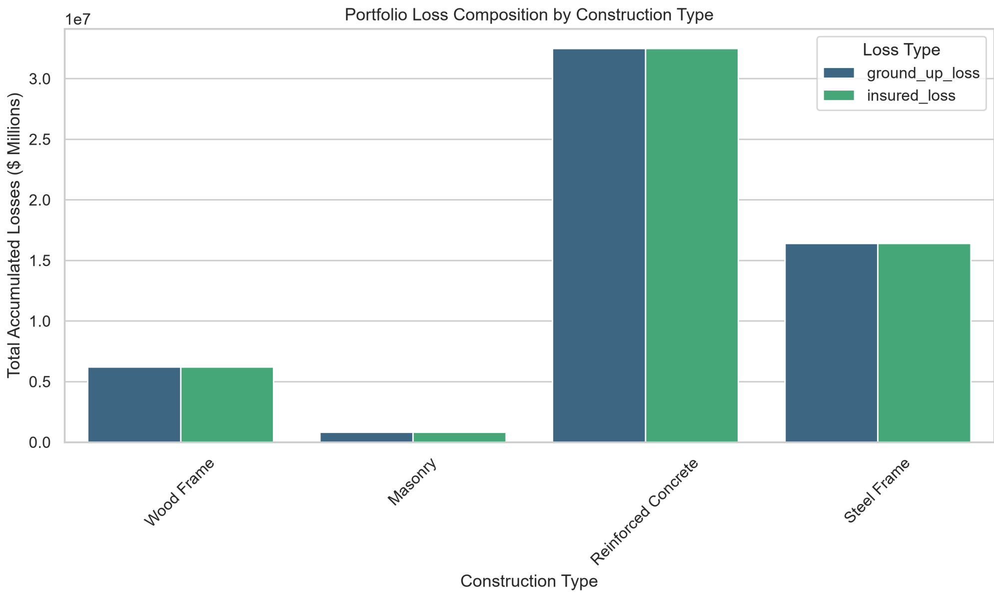

Figure 3: Ground-up versus insured loss aggregated by construction class.

4.2 Relationship to Existing Frameworks

The model presented here follows the same four-component architecture established by Clark (1986) [2] and used across both commercial platforms and open-source efforts such as CLIMADA [1]. It differs from full track-based stochastic models such as those of Vickery et al. (2000) and Emanuel et al. (2006) [3, 11] in that storm tracks are generated as simplified straight-line paths from a single landfall point and heading, rather than simulated continuously from genesis through dissipation. This simplification substantially reduces computational and implementation complexity, at the cost of omitting realistic track curvature, recurvature, and intensity evolution along the storm's lifetime, features that materially affect the spatial distribution of landfall risk in more complete models.

4.3 Limitations

Several limitations should be considered when interpreting the results in Section 3. First, the Weibull hazard distribution is fit under a stationarity assumption: a single set of shape and scale parameters is assumed to hold throughout the simulated 10,000-year catalog, even though the underlying climate system is not stationary (Section 4.4). Second, the exposure database is synthetic; while it is anchored to real NOAA economic indices rather than arbitrary weights, it is not a substitute for a real industry exposure book, and absolute loss figures should be interpreted as illustrative of the methodology rather than as estimates of actual market risk. Third, the straight-line track approximation described above omits storm curvature and the post-landfall weakening dynamics captured in full track models. Fourth, the model considers wind damage only; storm surge and inland flooding, which frequently account for a majority of total hurricane losses (e.g., Hurricane Katrina, Hurricane Harvey), are not represented. Finally, the model has not been validated against observed historical industry loss data (e.g., PCS catastrophe loss estimates), which would be required before any operational use.

4.4 Climate Change and Non-Stationary Tail Risk

The stationarity assumption in Section 4.3 is the most consequential simplification in this model, given the current scientific consensus on tropical cyclone behavior under anthropogenic warming. Knutson et al. (2020) assess, with at least medium confidence, that anthropogenic warming is altering the intensity distribution of tropical cyclones globally, including increases in the proportion of the most intense (Category 4–5) storms and in tropical cyclone-associated rainfall rates [6]. At the same time, Pielke et al. (2008) show that the historical growth in U.S. hurricane damage is overwhelmingly explained by growth in coastal wealth and population rather than by any detectable trend in storm climatology over the twentieth century [9], a reminder that exposure growth and hazard non-stationarity are distinct channels that must be modeled separately rather than conflated. A model that fits a single, time-invariant Weibull distribution to the full historical record, as done here, will therefore tend to understate tail risk under a warming climate to the extent that intensity distributions are genuinely shifting, while exposure growth must be addressed independently through the exposure module rather than the hazard module.

5 Conclusion and Future Work

This paper presented a fully specified, open probabilistic catastrophe risk model for tropical cyclone loss quantification, built around the hazard-exposure-vulnerability-financial loss architecture standard in the catastrophe modeling industry, and demonstrated its application to a NOAA-anchored synthetic property portfolio along the U.S. Gulf and Atlantic coast. The resulting loss distribution exhibits the heavy-tailed behavior expected of hurricane risk, with insured losses ranging from under \$150,000 at the 1-in-10-year return period to nearly \$1.9 billion at the 1-in-500-year level.

Several extensions would materially improve the model's realism and operational relevance. First, replacing the stationary Weibull hazard fit with a non-stationary or climate-conditioned formulation (for example, allowing the scale parameter λ_w to vary with sea surface temperature or a global warming level, following the projected response ranges in Knutson et al. (2020) [6]) would allow the model to produce climate-scenario-conditioned loss estimates rather than a single historical-baseline estimate. Second, replacing the simplified straight-line track model with a full genesis-to-lysis stochastic track simulation, following the approach of Vickery et al. (2000) or Emanuel et al. (2006) [3, 11], would improve the spatial fidelity of the hazard catalog. Third, extending the financial loss module to apply reinsurance contract structures directly to the simulated event loss table (e.g., per-occurrence excess-of-loss layers, aggregate deductibles, and reinstatement provisions) would convert the current single-policy financial layer into a genuine reinsurance structuring and optimization tool. Fourth, incorporating a storm surge or simplified inland flood peril alongside wind would address a substantial and currently unmodeled share of total hurricane loss. Finally, validating simulated losses against observed historical industry loss data, and replacing the synthetic exposure database with a real (anonymized) industry exposure book where available, would be a necessary step before any operational application of this methodology.

A Appendix: Computational Implementation

The methodology in Sections 2–3 was implemented in Python and evaluated over a full 10,000-year event catalog against the 10,000-property synthetic portfolio described in Section 2.2, producing approximately 500 million event-property interaction rows. Three engineering choices were used to keep this computation tractable on commodity hardware, none of which affect the statistical methodology described above:

1. **Disk-streamed columnar storage.** Event-property interactions were stored in Apache Parquet format and processed via PyArrow's `iter_batches()` interface in chunks of up to 5,000,000 rows, avoiding the need to hold the full interaction table in memory.

2. **Vectorized array operations.** Per-row Python loops were replaced with vectorized NumPy operations (`np.where`, `np.maximum`, `np.minimum`) for the vulnerability and financial loss calculations.

3. **Snappy block compression.** Columnar Parquet storage with Snappy compression reduced on-disk footprint by over 85% relative to an equivalent CSV representation, with no loss of 64-bit floating-point precision.

Together, these choices kept peak memory consumption under 50 megabytes throughout the full simulation, independent of total catalog size. Implementation code is available at `github.com/kjrathore/CatRisk_HurricaneLoss`.

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