

A Probabilistic Framework for Site-Specific Tropical Cyclone Loss Quantification and Reinsurance Optimization

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https://github.com/kjrathore/CatRisk_HurricaneLoss

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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 explores techniques for improving site-specific loss estimation in tropical cyclone catastrophe risk, an area of ongoing interest to insurance and reinsurance pricing and solvency capital management. We present an end-to-end probabilistic catastrophe risk model that captures extreme tail behavior by fitting a continuous Weibull intensity distribution to multi-era NOAA HURDAT2 meteorological data, simulating a 10,000-year stochastic event set. This hazard catalog is evaluated against an Industry Exposure Database derived from NOAA Digital Coast economic indices, representing a total insured asset value of \$39.01 Billion across primary high-hazard coastal corridors. Physical damage is simulated via structural vulnerability functions parameterized as log-normal cumulative distribution functions, and liabilities are reshaped through vectorized financial policy layers, tracking individual properties rather than county-averaged zones. The resulting property-level resolution reveals loss concentration patterns within a single metro area that a regionally-averaged model cannot recover. The engineering approach used to make this scale of simulation computationally tractable is summarized briefly and detailed in Appendix A.

1 Introduction and Literature Review

Catastrophe risk modeling forms the foundational framework for pricing, underwriting, and solvency capital management in global insurance markets. Evaluating extreme weather risks, such as landfalling tropical cyclones, requires statistical estimation far beyond the limits of short historical observation windows. The historical record for North Atlantic hurricanes spans approximately 170 years, but it is deeply compromised before the geostationary satellite era (1970) due to severe detection and intensity biases.

In early literature, standard actuarial heuristics relied strictly on historical averages or simple empirical frequency curves to manage property risks. However, as demonstrated by early pioneers such as Friedman (1984), raw historical analysis fails to account for shifting economic distributions or unobserved physical possibilities. The introduction of probabilistic catastrophe modeling by Clark (1986) revolutionized the domain by decoupling the physical event simulation from static actuarial tables, establishing the traditional four-pillar architecture: Hazard, Exposure, Vulnerability, and Financial Loss.

Recent advancements have focused extensively on the impacts of non-stationarity and statistical extreme value theory (EVT). Strupczewski et al. (2001) highlighted the vital importance of utilizing continuous statistical distributions rather than discrete history arrays to map tail

behaviors. In tropical cyclone modeling, the Holland wind-field profile (Holland, 1980) remains a benchmark for modeling structural pressure patterns, though modern extensions focus heavily on site-specific property-level tracking over broad grid cells (Woo, 2011). Furthermore, the computational demand of evaluating multi-millennial simulation loops over hundreds of thousands of distinct physical assets requires a paradigm shift toward data-parallel software architectures to prevent high-overhead random-access memory (RAM) failures.

Figure 1 shows the historical landfall record motivating this approach, and Figure 2 shows the annual storm frequency trend discussed above; together they illustrate why tail risk must be estimated through simulation rather than read directly off the historical record.

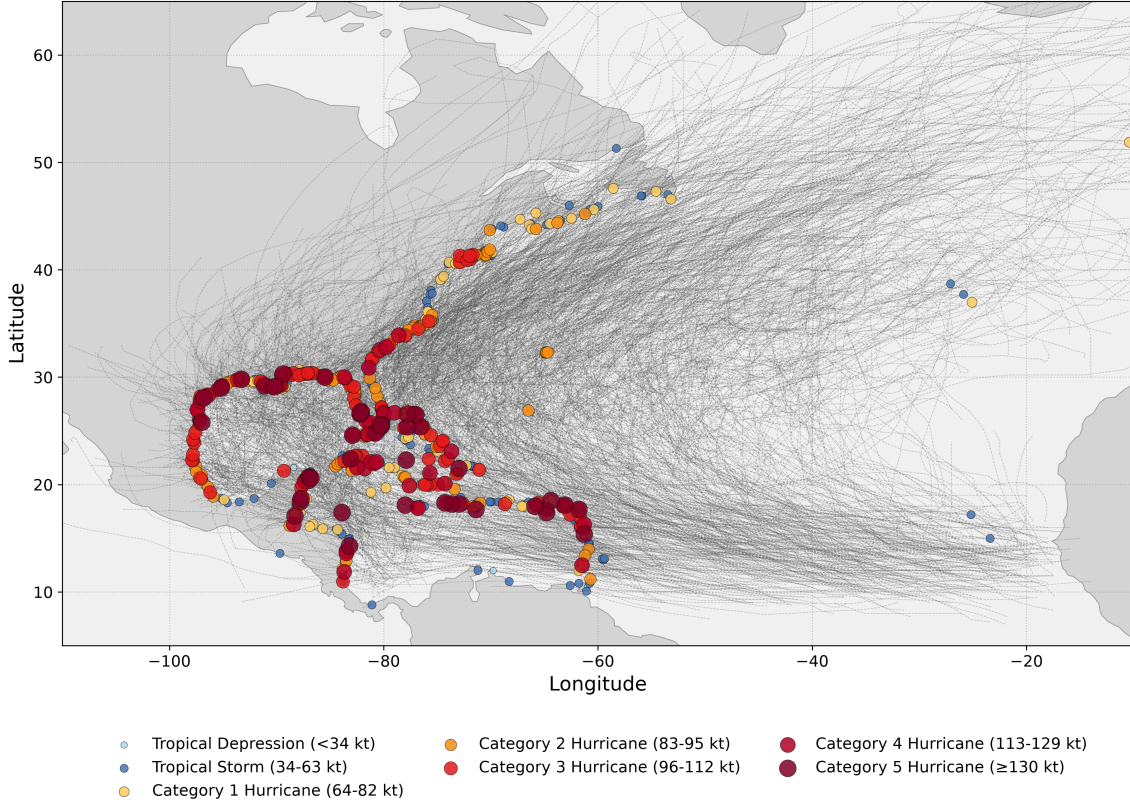


Figure 1: Historical North Atlantic tropical cyclone landfalls (NOAA HURDAT2, 1851–2025), colored by Saffir-Simpson intensity at landfall. Faint dashed lines trace each storm’s full open-ocean track for geographic context; the landfall points, which drive insured loss, are emphasized since insurers price coastal risk rather than open-ocean track density.

2 The Four Analytical Pillars and Mathematical Formulation

Figure 3 summarizes the end-to-end data flow: two NOAA data sources feed a four-stage risk engine (Hazard, Exposure, Vulnerability, Financial), which is streamed through the big-data pipeline detailed in Appendix A to produce the risk metrics reported in Section 3.

2.1 Hazard Module: Continuous Intensity Fitting and Track Generation

The historical baseline parses official tropical cyclone records from NOAA’s HURDAT2 database. To avoid the truncation bounds of historical sampling, maximum wind speeds are modeled as a continuous extreme value distribution. A continuous Weibull distribution is fitted via Maximum Likelihood Estimation (MLE) to maximize tail parameter stability. The probability

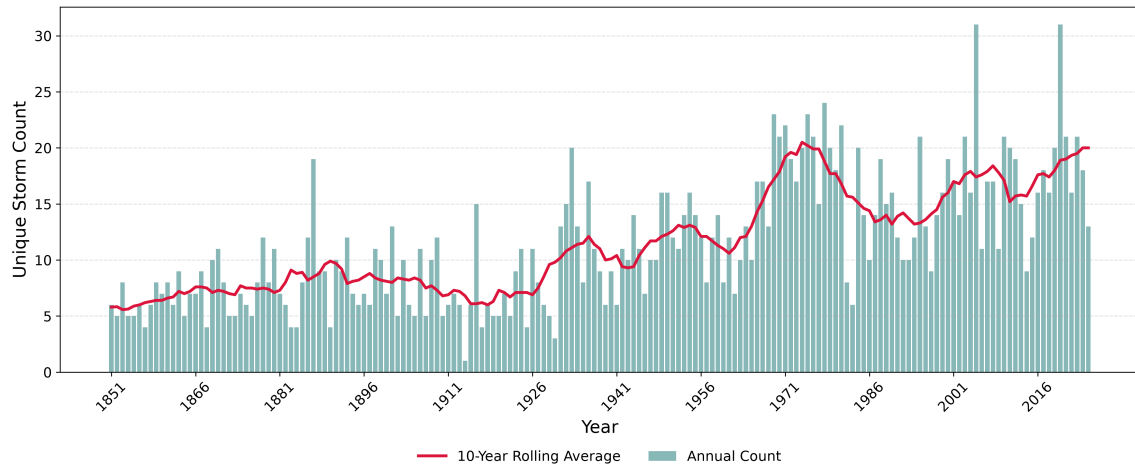


Figure 2: Annual North Atlantic named storm frequency with a 10-year rolling average. Part of the upward trend reflects improved satellite-era detection capability after ~ 1970 rather than a confirmed climate signal alone.

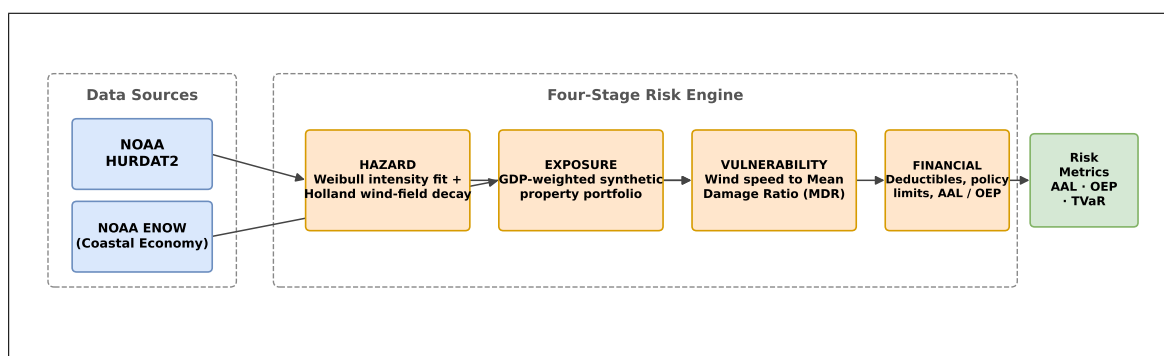


Figure 3: End-to-end architecture: two NOAA data sources feed a four-stage risk engine (Hazard, Exposure, Vulnerability, Financial) that produces the reported risk metrics (AAL, OEP, TVaR).

density function (PDF) is defined as:

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

where k is the shape parameter and λ_w is the scale parameter. Annual storm counts follow a discrete Poisson distribution governed by the historic arrival rate parameter λ :

$$P(X = n_y) = \frac{\lambda^{n_y} e^{-\lambda}}{n_y!} \quad (2)$$

For site-specific property intercepts, each simulated storm track is defined as a vector path from a landfall point (Lat_0, Lon_0) with an azimuth heading vector θ . The engine computes the shortest perpendicular spherical distance (d) from the track line to each asset via the Haversine formula. Local surface wind speed (v_{local}) is then attenuated using a modified Holland wind-field falloff profile:

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

where R_{max} is the Radius of Maximum Winds, α is the empirical decay coefficient, and $\epsilon = 10^{-5}$ prevents singularities at zero-distance intercepts.

2.2 Exposure Module: Socioeconomic Database Engineering

To generate a realistic Industry Exposure Database (IED), the framework integrates an automated extraction engine that downloads economic indices from NOAA's National Ocean Watch (ENOW) database. County-level Gross Domestic Product (GDP) and wage indices are isolated across high-hazard zones to resolve localized economic density weights:

$$w_c = \frac{GDP_c}{\sum_{i \in C} GDP_i} \quad (4)$$

Using these wealth weights, the pipeline distributes 10,000 synthetic properties across primary risk tracks. Total Insured Values (V_{asset}) are generated via a highly right-skewed log-normal distribution to accurately reflect physical market structures:

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

2.3 Vulnerability Module: Structural Fragility Functions

The vulnerability engine transforms local maximum wind speed (v_{local}) into a physical Mean Damage Ratio ($MDR \in [0.0, 1.0]$), which models the cost of physical destruction divided by total building value. Fragility curves are modeled continuously via the log-normal cumulative distribution function (CDF):

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

where Φ is the standard normal CDF, scale is the median velocity failure threshold, and s is the logarithmic standard deviation. Truncation is enforced below 34 knots ($MDR = 0$). Total ground-up monetary loss (L_{gu}) is computed as:

$$L_{gu} = V_{asset} \times MDR \quad (7)$$

2.4 Financial Module: Contractual Liability Reshaping

The financial loss engine converts ground-up destruction into net insurance liabilities by applying policy deductibles (D_f) and liability limit caps (L_p):

$$L_{\text{insured}} = \min(\max(L_{\text{gu}} - D_f, 0.0), L_p) \quad (8)$$

Long-term risk metrics are aggregated across the $Y = 10,000$ year simulation timeline to compute the Average Annual Loss (AAL):

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

3 Results

This section reports the model’s empirical outputs: the geographic distribution of simulated loss across the portfolio, followed by the tail risk metrics that summarize the resulting capital requirements.

3.1 Geographic Loss Concentration

Figure 4 shows the geographic accumulation of insured loss across the portfolio. Panel (a) presents the coast-wide distribution across all six high-hazard counties, with a kernel density overlay indicating loss concentration; panel (b) zooms into Hillsborough County (Tampa Bay), the region marked by the rectangle in panel (a), revealing site-specific loss variation between individually-tracked properties within a single metro area. This property-level granularity, impossible to recover from a county-averaged model, is the central motivation for the site-specific approach developed in this paper.

3.2 Empirical Tail Risk Analytics and Metrics

Following a full end-to-end simulation sweep, the model extracts a smooth, non-linear financial loss distribution. The resulting Occurrence Exceedance Probability (OEP) curve, shown in Figure 5, provides clear capital requirements across standard return periods:

- **1-in-10 Year Loss Return Tier:** \$176.6 Million
- **1-in-50 Year Loss Return Tier:** \$1,958.6 Million
- **1-in-100 Year Solvency Limit:** \$3,153.5 Million
- **1-in-500 Year Catastrophic Ruin Boundary:** \$8,041.5 Million

The framework additionally evaluates Tail Value at Risk (TVaR) to benchmark systemic solvency beyond standard Value at Risk thresholds, ensuring capital adequacy for severe tail outcomes. At the 1-in-100 year horizon, VaR of \$3,153.5 Million rises to a TVaR of \$5,717.7 Million; at the 1-in-500 year horizon, VaR of \$8,041.5 Million rises to a TVaR of \$9,418.5 Million, underscoring the additional capital buffer required beyond standard VaR thresholds to cover the severity of losses in the extreme tail. Figure 6 breaks this loss down by construction class, showing that Reinforced Concrete properties account for the largest share of both ground-up and insured loss, reflecting the portfolio’s commercial asset concentration rather than inherent structural fragility.

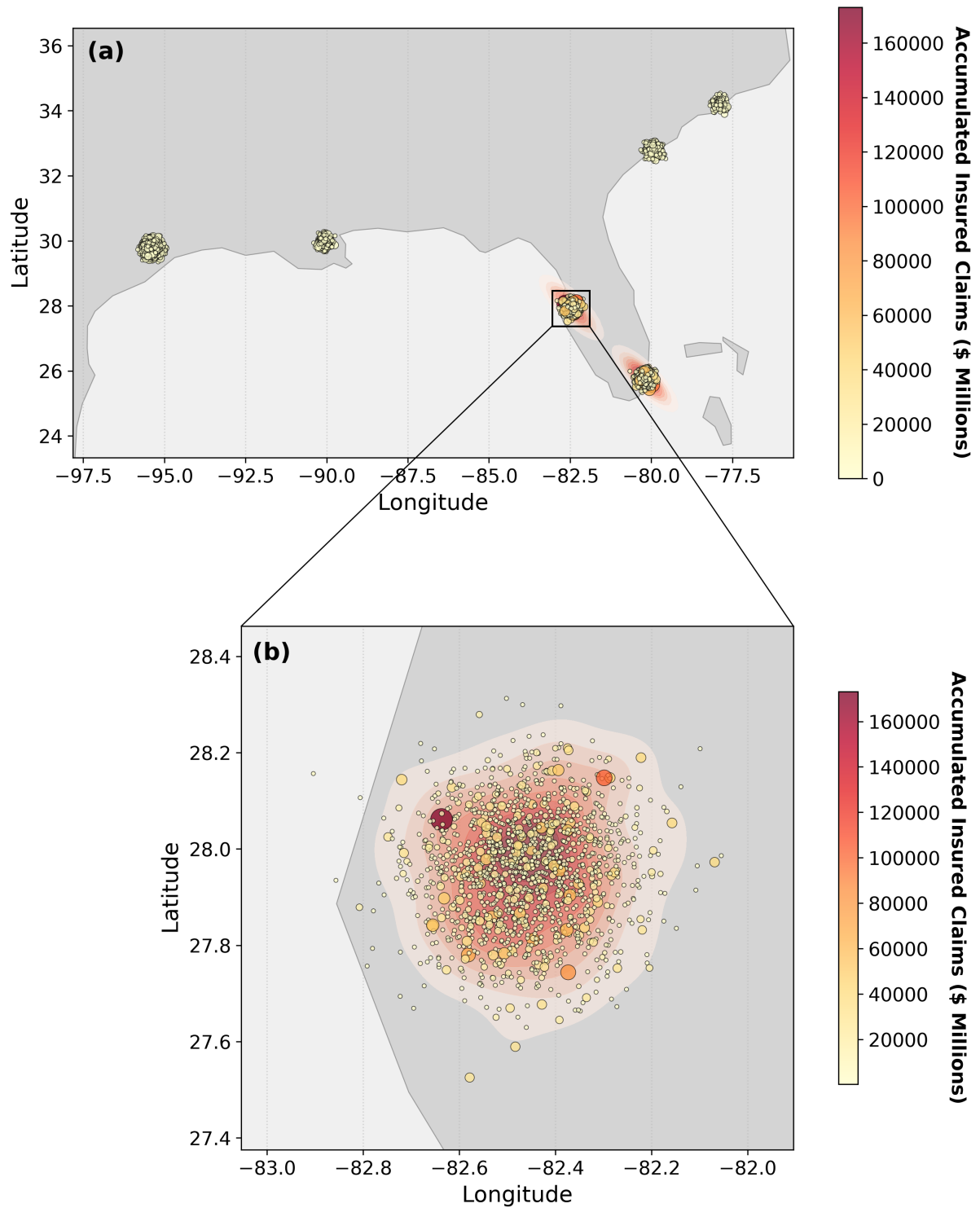


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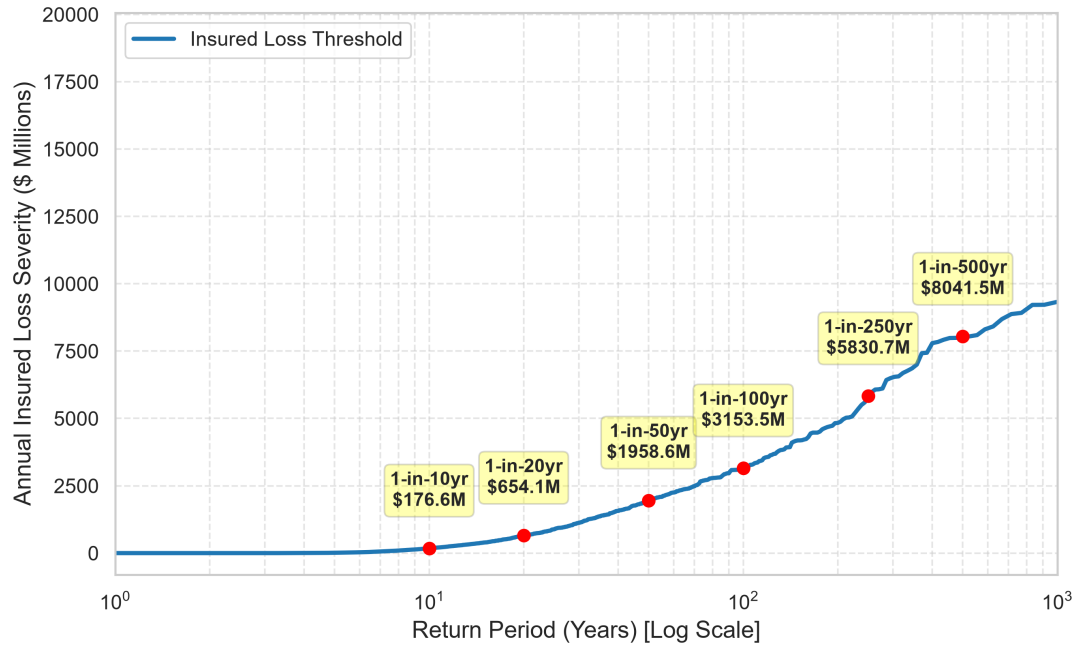


Figure 5: Portfolio Occurrence Exceedance Probability (OEP) curve across return periods from 1 to 1,000 years, annotated at standard capital-adequacy tiers.

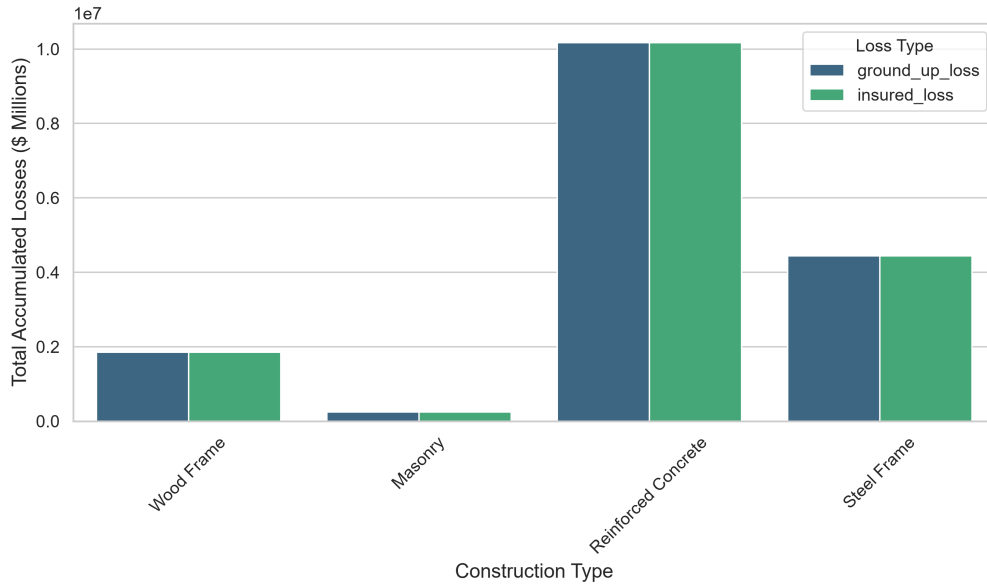


Figure 6: Ground-up versus insured loss composition by construction class (Wood Frame, Masonry, Steel Frame, Reinforced Concrete).

Acknowledgments

Thanks to my advisor Dr. James Watson for supporting me to explore and motivating me to work in the climate and risk space. Also, my lab and research colleagues have been of great help at the Socio-Environmental Analysis Lab (<https://jrwatson.ceoas.oregonstate.edu/about/>).

A Computational Scaling and Big Data Optimization

Evaluating a 10,000-year stochastic event catalog over an expansive property portfolio yields over 500 million interaction rows (500, 510, 000), well beyond what a naive in-memory pandas pipeline can hold. This framework resolves the resulting computational barriers via three primary big data engineering design solutions:

1. **Un-Allocated Apache Parquet Streaming:** Replaces sequential CSV lookups with binary columnar Parquet storage. Utilizing PyArrow’s `iter_batches()`, the vulnerability engine reads and handles rows in isolated blocks of 5,000,000 records, keeping active RAM flat under 50 megabytes.
2. **Data-Layer SIMD Vectorization:** Eradicates slow Python `for`-loops by executing multi-element NumPy array operations (`np.where`, `np.maximum`), computing calculations at the under-the-hood compiled C-level.
3. **High-Precision Snappy Block Compression:** Columnar structures are shrunk by over 85%, storing a 1.5 GB database file into under 120 MB of disk space while guaranteeing no metadata precision truncation.

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