Integrating Sea Level Rise into CAT Bond Pricing: Monte Carlo Analysis of Hurricane Risk in Miami

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1. Abstract

Florida's coastal insurance market faces escalating stress as reinsurance capacity contracts and flood risk intensifies. This paper develops a Monte Carlo catastrophe (CAT) bond pricing framework calibrated to Miami-Dade hurricane risk and augmented with an explicit sea level rise (SLR) adjustment. Using storm-surge data from NOAA HURDAT2 records and damage thresholds informed by the Florida Public Hurricane Loss Model, the model simulates 100,000 draws per scenario across three consecutive 3-year bond issuances, spanning a 9-year rolling horizon. Four SLR scenarios are evaluated — No SLR, Low (0.02 m/yr), Medium (0.03 m/yr), and High (0.07 m/yr) — to assess how rising baseline sea levels compound flood damage and erode investor returns over time. Results indicate that SLR has a negligible effect on pricing within any single bond cycle, as storm-surge variability dominates the short-run signal. Over the full 9-year horizon, however, cumulative SLR produces a 27–42% increase in expected principal losses under the High SLR scenario relative to the no-climate-change baseline. Trigger frequency remains relatively stable across scenarios (~16.9–17.1%), while full-loss probability rises from 0.61% to 0.83% by the third issuance under High SLR — a 34% increase in tail risk. These findings suggest that static historical calibration methods systematically underestimate climate-exposed CAT bond risk at long planning horizons, and that a rolling, SLR-augmented framework offers a more accurate tool for issuers and investors operating in high-risk coastal markets.

2. Introduction

Florida's coastal insurance market is under mounting stress. Insurance premiums in high-risk coastal counties have risen sharply over recent years, and the pool of available reinsurance capacity has contracted precisely when it is needed most (Carrillo et al., 2022). The exposure driving this pressure is not hypothetical: a repeat of the 1926 Great Miami Hurricane under current conditions is estimated to generate roughly $125 billion in losses (Clark, 2015). At the same time, Miami's tidal water levels are rising at approximately one inch per year, roughly ten times the global average, meaning that even moderate storm surges increasingly penetrate further inland and cause damage at lower wind intensities than historical records would suggest (Kolbert, 2015).

Catastrophe (CAT) bonds offer one of the few scalable mechanisms for transferring this risk away from primary insurers and onto capital markets. In the standard structure, a special purpose vehicle (SPV) issues bonds to investors and holds the proceeds in a collateral account. If a qualifying event occurs and a trigger threshold is breached, some or all the principal is redirected to the issuer to cover losses; otherwise, investors receive their principal back at maturity along with a premium coupon that compensates them for bearing the catastrophe risk (Polacek, 2018). The instrument is therefore priced on the probability and severity of the underlying event, making accurate hazard modeling central to fair valuation.

A critical gap in many existing CAT bond frameworks is the static treatment of physical hazard. Conventional models calibrate storm-surge distributions from historical observations and hold them fixed over the bond's life. This approach ignores the compounding effect of sea level rise (SLR): as the baseline water level increases, any given surge height translates into a greater flood depth and, consequently, a higher damage outcome. Failing to account for this dynamic systematically underprices climate-exposed bonds and misallocates risk between issuers and investors.

This project addresses that gap by developing a Monte Carlo CAT bond pricing framework specifically calibrated to Miami hurricane risk and augmented with a linear SLR adjustment. The model is designed around three objectives:

- Construct a parametric pricing model grounded in historical storm-surge data from NOAA HURDAT2 records.
- Incorporate sea level rise projections into the flood-damage function so that bond pricing evolves with the underlying climate trajectory.
- Evaluate how pricing and risk metrics change across SLR scenarios and across consecutive 3-year bond issuances, providing a forward-looking view of how the instrument would perform over a 9-year rolling horizon.

3. Methodology

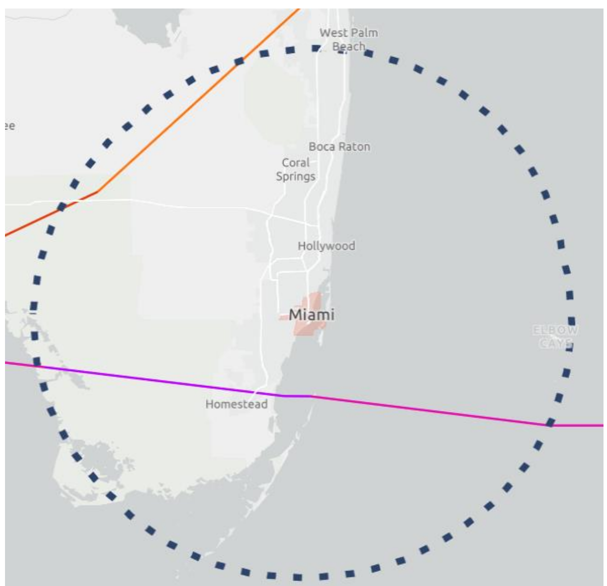
The model is implemented as a Monte Carlo simulation with 100,000 draws per scenario. Each simulation traces a single 3-year bond from issuance to maturity, stepping through the bond's annual periods and recording hurricane events, flood damage, and the resulting principal loss. The sections below describe each component of the framework.

3.1 Data Sources

- **Storm-surge distribution.** Historical water level observations are derived from NOAA HURDAT2 hurricane records during Wilma (2005) and Andrew (1992) (Landsea & Franklin, 2013). Using surge values, converted from feet to meters.
- **Hurricane occurrence probability.** The HURDAT2 record is also used to estimate the annual probability of a Category 3 or stronger hurricane passing through a 50 mi radius around Miami-Dade (Figure 1), set at 6% per year.

- **Damage and principal exposure.** The Florida Public Hurricane Loss Model (FPHLM) informs the damage thresholds (Tao et al., 2022). The worst-case catastrophe loss is set at $123.629 billion, consistent with Clark (2015) adjusted by Miami-Dade's infrastructure budget - $1.37 billion (Miami-Dade County, 2025) to determine the principal cost.
- **Discount rate.** A 6% annual discount rate, sourced from Federal Reserve data, is used to discount the bond's expected cash flows. This rate was selected as a level that would have materially outperformed inflation over the prior decade.

Figure 1. Hurricanes category 3 or more since 1990 (Landsea & Franklin, 2013)



3.2 Storm-Surge Calibration

Surge heights are assumed to follow a lognormal distribution, a standard choice in hydrological modeling that prevents the heavy right tail associated with extreme events (*Stedinger,* 1980). The parameters μ and σ of the underlying normal distribution are estimated directly from the HURDAT2-derived observations:

$$ln(surge_i) \sim lognormal(\mu, \sigma^2)$$

where $surge_i$ is the observed surge in metres for event i. Fitted values are $\mu = -0.5179$ and $\sigma = 0.9912$. Each Monte Carlo draw samples a new surge from this distribution conditional on an event occurring in that year.

3.3 Sea Level Rise Adjustment

Sea level rise is incorporated as a linear additive term applied to the sampled surge before computing flood depth. For a hurricane occurring in simulation year y, the effective flood depth is:

$$flood\_depth = surge + (y\_offset + y) \times SLR\_rate$$

where y_offset is the cumulative number of years elapsed before the current bond issuance (0 for the first bond, 3 for the second, 6 for the third) and y is the year within the current bond period (0, 1, or 2). This formulation ensures that SLR accumulates continuously across consecutive re-issuances rather than resetting to zero at each new bond. Four SLR scenarios are evaluated: No SLR (0.00 m/yr), Low (0.02 m/yr), Medium (0.03 m/yr), and High (0.07 m/yr).

3.4 Damage Function and Loss Tranches

South Florida's mean elevation of approximately 1.8 metres above sea level serves as the damage threshold: flood depths below this level are assumed to produce negligible structural damage (Kolbert, 2015). Excess depth above the threshold is transformed into a modelled damage index through a nonlinear power function:

$$damage = max(flood\_depth - 1.8, 0)^{1.5}$$

The exponent of 1.5 reflects the empirical observation that damage scales superlinearly with inundation depth. The damage index is then mapped to one of three principal loss tranches:

- **Minor loss (10% of principal):** damage index below 0.30 m.
- **Moderate loss (40% of principal):** damage index between 0.30 m and 2.50 m.

- **Full loss (100% of principal):** damage index at or above 2.50 m, corresponding to the catastrophic scenario consistent with Clark (2015). Total losses per simulation are capped at the face value M = $123.629 billion.

3.5 Bond Pricing

The bond price at any point in time is the present value of the expected residual principal, discounted at the risk-free rate over the remaining maturity $\hat{T}$:

$$P = e^{-rT} \times (M - E[L])$$

where r = 0.06 is the discount rate, T is the time remaining to maturity, M is the face value, and E[L] is the simulated expected principal loss. At issuance (T = 3), the price is approximately $102B under the baseline scenario, reflecting the discount and the small expected loss. As the bond approaches maturity, the discount factor shrinks toward one, and the price converges to M − E[L] ≈ $122B. This glide path is computed continuously across all 50 interpolated time points within each 3-year period.

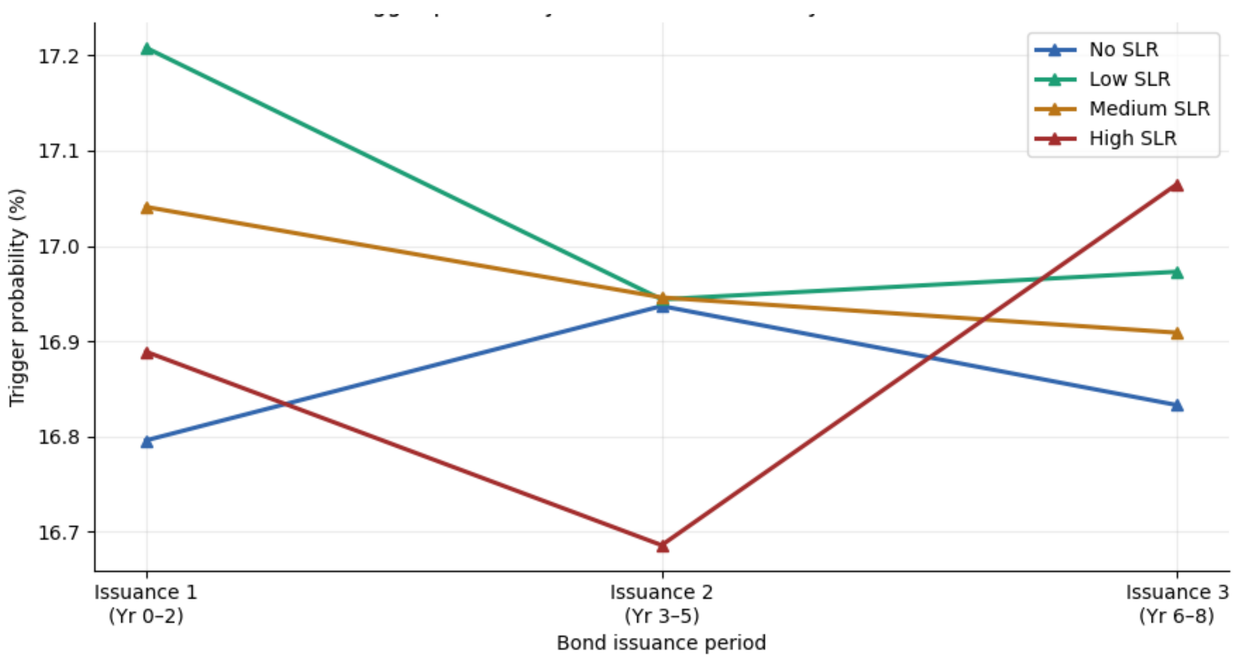
3.6 Rolling Issuance Framework

To assess how the instrument performs over a longer climate horizon, the bond is modelled as three consecutive 3-year issuances covering real-world years 0–2, 3–5, and 6–8. Each issuance is re-priced independently using fresh Monte Carlo draws, but the SLR offset is carried forward so that investors in the second and third bonds face a higher baseline sea level than those in the first. This rolling structure allows the model to show how expected losses, trigger probabilities, and investor net returns evolve as a function of the assumed SLR trajectory, without requiring the bond to have a single long maturity that would compound convergence issues in the discount factor.

4. Results

The model was run across four sea level rise (SLR) scenarios — No SLR, Low (0.02 m/yr), Medium (0.03 m/yr), and High (0.07 m/yr) — and three consecutive 3-year bond issuances spanning years 0–8. SLR rates do not affect the frequency of events on this model, as seen on Figure 2.

Figure 2. Trigger probability across 3 issuances by SLR scenario



4.1 Rolling Issuance Results

Table 1 presents the full set of simulation outputs — expected principal loss, bond price, trigger probability, and full-loss probability — for each combination of SLR scenario and bond issuance. Within the No SLR scenario, all three metrics remain stable across issuances, confirming that the model's stochastic components are well-calibrated and that drift in the no-climate-change baseline is attributable to Monte Carlo sampling variance rather than structural effects.

Across the climate scenarios, two patterns emerge. First, expected losses and full-loss probabilities increase with both SLR rate and issuance number, reflecting the compounding effect of cumulative sea level rise on flood depth. Second, the High SLR scenario exhibits the steepest progression: by Issuance 3, E[Loss] reaches $2.04B — a 42% increase relative to the No SLR baseline — and the full-loss probability rises from 0.66% to 0.83%.

Figure 3. Expected principal loss across 3 issuance by SLR scenario

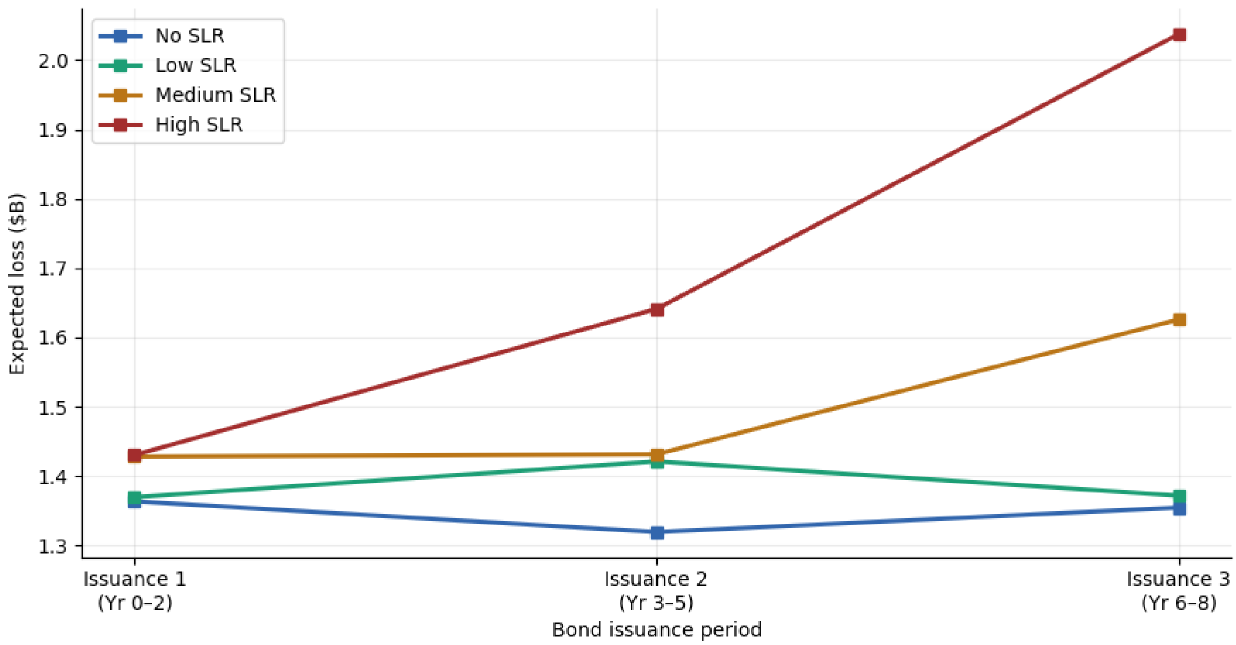


Table 1. Rolling Issuance Summary — All Scenarios

Scenario	Issuance	Period	E[Loss] ($B)	Bond Price ($B)	P(Trigger)	P(Full Loss)
No SLR	1	Yr 0–2	$1.3636B	$102.1246B	16.80%	0.62%
No SLR	2	Yr 3–5	$1.3194B	$102.1616B	16.94%	0.58%
No SLR	3	Yr 6–8	$1.3546B	$102.1322B	16.83%	0.62%
Low SLR	1	Yr 0–2	$1.3697B	$102.1196B	17.21%	0.61%
Low SLR	2	Yr 3–5	$1.4211B	$102.0766B	16.94%	0.63%
Low SLR	3	Yr 6–8	$1.3719B	$102.1177B	16.97%	0.60%
Med. SLR	1	Yr 0–2	$1.4282B	$102.0707B	17.04%	0.67%

Scenario	Issuance	Period	E[Loss] ($B)	Bond Price ($B)	P(Trigger)	P(Full Loss)
Med. SLR	2	Yr 3–5	$1.4315B	$102.0679B	16.95%	0.63%
Med. SLR	3	Yr 6–8	$1.6260B	$101.9055B	16.91%	0.72%
High SLR	1	Yr 0–2	$1.4304B	$102.0689B	16.89%	0.66%
High SLR	2	Yr 3–5	$1.6412B	$101.8928B	16.69%	0.70%
High SLR	3	Yr 6–8	$2.0375B	$101.5617B	17.06%	0.83%

4.2 Scenario-Level Aggregation

Table 2 aggregates results across the three issuances within each SLR scenario, providing a higher-level view of how total expected losses and average risk metrics scale with the assumed climate trajectory. Total expected losses rise monotonically from $4.04B under No SLR to $5.11B under High SLR — an increase of approximately 27% over the 9-year horizon. Average trigger probabilities remain relatively stable across scenarios (~16.9–17.0%), indicating that the trigger threshold is crossed at similar frequencies regardless of SLR intensity; the primary effect of higher SLR is to increase the magnitude of losses conditional on a trigger event, not the frequency of triggering.

Table 2. Scenario Aggregation Across Three Issuances

Scenario	SLR Rate (m/yr)	Total E[Loss] ($B)	Cumul. Investor Return ($B)	Avg P(Trigger)	Avg P(Full Loss)
No SLR	0.000	$4.0376B	~$62.74B	~16.86%	~0.61%
Low SLR	0.020	$4.1627B	~$62.63B	~17.04%	~0.62%
Med. SLR	0.030	$4.4857B	~$62.35B	~16.97%	~0.67%

Scenario	SLR Rate (m/yr)	Total E[Loss] ($B)	Cumul. Investor Return ($B)	Avg P(Trigger)	Avg P(Full Loss)
High SLR	0.070	$5.1091B	~$61.77B	~16.88%	~0.73%

4.3 Investor Net Returns

Table 3 reports the investor net return for each issuance as the gross coupon less the expected principal loss. With a gross coupon of $22.25B per issuance, net returns remain positive across all scenarios but erode as SLR intensifies and losses accumulate, as seen in Figure 4, where plot lines begin to distinguish from each other upon the third issuance of the bond. The High SLR Issuance 3 net return of $20.22B represents the most adverse outcome — a reduction of roughly $0.67B relative to the No SLR baseline for the same issuance period. From the issuer's perspective, higher SLR increases the effective cost of risk transfer, as larger expected payments to investors do not offset the growing expected loss absorption.

Figure 4. Bond price glide path – 3 consecutive 3-yr issuances by SLR scenario

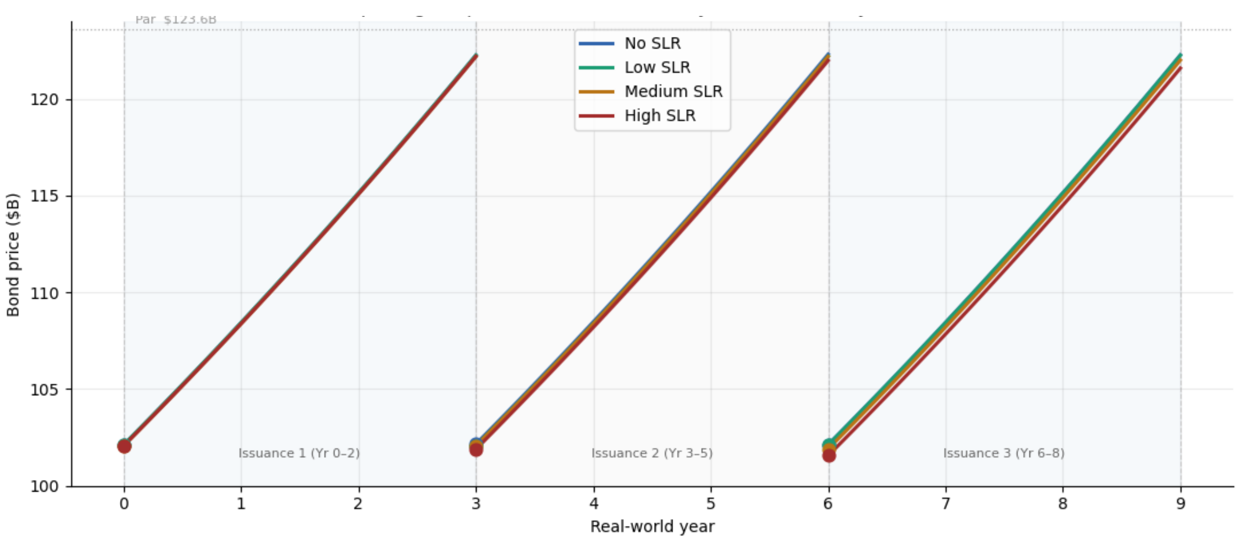


Table 3. Investor Net Returns by Scenario and Issuance

Scenario	Issuance	E[Loss] ($B)	Gross Coupon ($B)	Investor Net Return ($B)
No SLR	1	$1.3636B	$22.2532B	$20.8896B
No SLR	2	$1.3194B	$22.2532B	$20.9339B
No SLR	3	$1.3546B	$22.2532B	$20.8986B
Low SLR	1	$1.3697B	$22.2532B	$20.8835B
Low SLR	2	$1.4211B	$22.2532B	$20.8321B
Low SLR	3	$1.3719B	$22.2532B	$20.8813B
Med. SLR	1	$1.4282B	$22.2532B	$20.8251B
Med. SLR	2	$1.4315B	$22.2532B	$20.8217B
Med. SLR	3	$1.6260B	$22.2532B	$20.6273B
High SLR	1	$1.4304B	$22.2532B	$20.8228B
High SLR	2	$1.6412B	$22.2532B	$20.6120B
High SLR	3	$2.0375B	$22.2532B	$20.2157B

4.4 Key Findings

- SLR systematically increases expected losses. Even the Low SLR scenario (0.02 m/yr) produces a cumulative loss increase of approximately 3% relative to No SLR; the High SLR scenario produces a 27% increase over the same 9-year window.
- Loss escalation is back-loaded. The most pronounced increases occur in Issuance 3, when cumulative SLR is largest. This has implications for bond investors and issuers pricing risk at the start of each issuance: static historical calibration will increasingly underestimate tail exposure in later periods.

- Trigger frequency is relatively inelastic to SLR. Average trigger probabilities cluster around 16.9–17.1% across all four scenarios. The damage function's power-law structure means that moderate increases in flood depth translate into higher conditional losses rather than more frequent crossings of the trigger threshold.
- Full-loss probability is the most sensitive tail metric. The full-loss probability rises from 0.61% (No SLR) to 0.73% (High SLR) in cumulative average terms, and reaches 0.83% in the High SLR Issuance 3 — a 34% increase relative to the no-climate baseline. For investors holding the third issuance under a high-SLR trajectory, the expected value of the instrument deteriorates meaningfully.

5. Discussion

The simulation results reveal that over a single 3-year bond issuance, sea level rise has a negligible effect on pricing. Across all four SLR scenarios, from No SLR to High (0.07 m/yr), bond prices at issuance differ by less than $1 billion, a rounding error relative to the $102 billion face value. This is not a failure of the model; it is a structural property of the problem. Storm surge variability is far larger than any SLR increment that can accumulate over three years. A Miami hurricane can generate a surge anywhere along the full distribution of historical observations, and that stochastic variability swamps the deterministic SLR offset in the short run.

Where SLR does exert material influence is over the rolling 9-year horizon. By the third issuance under the High SLR scenario, expected losses rise to $2.04 billion — a 42% increase relative to the No SLR baseline for the same period — and the full-loss probability climbs to 0.83%. This escalation is the key insight of the framework: the financial consequences of sea level rise are not felt in any single bond cycle, but they accumulate steadily across consecutive issuances. An investor or issuer pricing only the current bond with a static historical calibration would not detect this drift. It would, however, compound silently in the background, surfacing as a systematic underpricing of risk by the time it becomes large enough to notice in market data.

This finding has direct implications for long-term financial planning. Institutions holding multi-issuance exposure to Miami coastal hurricane risk — whether as CAT bond investors, reinsurers, or municipal financiers — should treat SLR not as a negligible perturbation but as a slow-moving tail risk that warrants explicit scenario analysis at planning horizons of 10 years or more. The rolling issuance structure developed here offers a straightforward mechanism for incorporating that analysis: by carrying the SLR offset forward across bond generations rather than resetting it at each issuance, the framework allows long-horizon investors to observe how cumulative sea level rise reshapes the expected loss distribution over time.

The model's expected loss rate of approximately 1.1% (E[Loss] ≈ $1.38B relative to a bond price of ~$102B) aligns reasonably with the historical market-wide CAT bond default rate of approximately 2.0% (Artemis, 2026), lending some face validity to the calibration. That said, the alignment should be interpreted cautiously given the several limitations described below.

5.1 Limitations

Several important shortcomings constrain the conclusions that can be drawn from this analysis:

- The storm surge distribution is calibrated from only two Category 3 or stronger hurricanes affecting the Miami area since 1990: Andrew (1992) and Wilma (2005). This is a thin empirical basis for fitting a lognormal distribution, and the tails of that distribution — which drive the full-loss probability and the highest-consequence outcomes — are therefore poorly constrained. Additional hurricane observations would reduce this uncertainty, but such data were not readily available for this geography at this intensity for two reasons: the Virginia Key tide gauge, which provides the most locally relevant water level measurements for Miami-Dade, was not installed until 1994, and major hurricane tracks through the area have occurred less frequently over the past 30 years, limiting the observational record at the intensities most relevant to this model.

- Perhaps the most significant limitation is that the framework relies entirely on a statistical surge distribution. A physics-based model such as Deltares FloodAdapt (Aellen et al., 2025) would allow the flood depth to respond dynamically to storm track, forward speed, coastal bathymetry, and barrier island morphology in ways that a fitted lognormal cannot capture. Critically, a physical model could also incorporate the direct interaction between sea level rise and surge inundation, rather than treating SLR as a simple additive offset.
- The model holds hurricane frequency fixed at a 6% annual probability throughout all scenarios. This ignores a growing body of evidence suggesting that a warming climate may intensify Atlantic hurricane activity and alter storm tracks in ways that affect landfall probabilities (Balaguru et al., 2023). Incorporating a climate-adjusted hurricane occurrence and intensity distribution — rather than a stationary historical one — would be a meaningful extension of the framework, particularly for the third issuance of the rolling horizon where climate forcing is largest.
- The analysis focuses exclusively on hurricane storm surge, but Miami's flood risk also includes king tides, which are already causing regular inundation of low-lying neighborhoods independent of any storm event, and wind damage, which contributes

substantially to insured losses in major hurricanes and is not captured in the damage function. A more complete risk model would integrate surge, tide, and wind damage into a unified loss estimate.

6. Conclusion

This project developed a Monte Carlo CAT bond pricing framework calibrated to Miami's hurricane and flood risk, with sea level rise explicitly incorporated into the damage function across a rolling three-issuance horizon. The model demonstrates that investors currently pay approximately $102 billion for a $123.6 billion face-value bond, earning roughly 6% annually as compensation for bearing the low-probability but high-consequence risk of a major hurricane landfall in Miami-Dade.

The primary result — that SLR has negligible pricing effects over a single 3-year bond but produces a 27–42% increase in expected losses across a 9-year horizon — underscores why standard static calibration methods are insufficient for climate-exposed instruments. Sea level rise is not a risk that shows up in any individual pricing cycle; it is a slow-moving, compounding hazard that reshapes the tail of the loss distribution across bond generations. For issuers and investors making long-term commitments to this market, ignoring SLR is not a conservative assumption — it is a systematic underestimation of future exposure.

The framework is deliberately modular. Hurricane probability, SLR rate, damage thresholds, and bond maturity can all be updated as new observational data and climate projections become available, making it a living tool rather than a one-time analysis. Future work should address the identified limitations — particularly by replacing the statistical surge distribution with a physically-based hydrodynamic model that can respond dynamically to both storm characteristics and rising baseline sea levels, and by incorporating climate-adjusted storm frequency and intensity projections. Extending the model to include king tides and wind damage would bring the estimated risk envelope closer to the true economic exposure faced by coastal property holders in South Florida.

Ultimately, the value of this framework is not precision — a data-sparse, statistically calibrated model applied to a rapidly changing physical environment cannot claim that. Its value is structure: a reproducible, transparent, and extensible architecture for asking how climate variables propagate through CAT bond risk metrics over multi-decade planning horizons. As Florida's reinsurance market continues to contract and coastal flood risk continues to rise, tools of this kind will become increasingly important for pricing risk accurately and distributing it efficiently.

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