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RESEARCH

Ranking, Not Point Estimates: Risk Tiering and the Case for AI-Assisted Loss Data in Caribbean SIDS Credit

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ABSTRACT

PURPOSE: To examine what physical risk information remains identifiable for credit in Caribbean Small Island Developing States (SIDS), where hazard data are rich but loss records scarce.

DESIGN/METHODOLOGY/APPROACH: Using storm tracks and four damage-function calibrations, we assess Caribbean risk rankings through Monte Carlo simulation, stochastic dominance and independent records, and compare Caribbean and United States wind-loss relationships using wild cluster bootstrap inference.

FINDINGS: Territory tiering is identifiable and broadly stable across damage-function choice, whereas point magnitudes remain imprecise under sparse Caribbean loss records.

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ORIGINALITY/VALUE: We identify an ordinal-cardinal boundary in Caribbean SIDS: risk tiering supports screening today, while precise loss estimates for pricing require better records that artificial intelligence (AI)-assisted methods may help develop.

RESEARCH LIMITATIONS/IMPLICATIONS: Territory tiering can support risk screening, while data limitations motivate further research on AI-assisted loss-data generation for finer pricing.

KEYWORDS: *Credit Risk Management; SIDS; Climate Finance; Climate Risk; Data Scarcity; Economic Losses; Caribbean.*

INTRODUCTION AND LITERATURE REVIEW

Caribbean states face relatively high financing costs. Official lending rates across the region range from 5% to 15%, and effective borrowing costs are often higher. These costs partly reflect severe climate hazard exposure and public debt burdens that exceed 100% of gross domestic product (GDP) in several states (World Bank, n.d.). The underlying hazard burden is severe and rising for Caribbean Small Island Developing States (SIDS). Evidence from the International Monetary Fund (IMF) (Ötker and Loyola, 2017) shows that small states are highly disaster-prone, with an average loss of approximately 13% of GDP. This impacts 10% of the population, compared with roughly 1% for both metrics in larger economies. Compounding this, Capodagli *et al.* (2025) report that the region loses an estimated 2% of its aggregate capital stock each year to chronic climate impacts and biodiversity loss. This comes with disproportionate harm to tourism, agriculture, and coastal infrastructure, which form the backbone of regional economies.

Against this background, regional stakeholders, including development finance institutions such as the Caribbean Development Bank (CDB) and private sector firms, have increasingly adopted Enterprise Risk Management (ERM) frameworks informed by Environmental, Social and Governance (ESG) principles. Capodagli *et al.* (2025), in a conceptual framework published in the *World Journal of Management, Entrepreneurship and Sustainable Development*, also outlined this direction for the Caribbean, providing a pathway for regional ESG-ERM integration. The study also highlighted a persistent implementation gap: insufficient quantitative tools and "information-related barriers" hinder the implementation of ESG risk taxonomy, making it challenging to forecast and monetise the financial impacts of ESG risks. As a result, climate risk has often remained a qualitative, secondary issue rather than a core component of financial and strategic decision-making.

The key bridge from climate risk to financial decision-making is credit pricing that depends on quantifying climate-related losses. Physical risk is, in principle, easier to localise and quantify case

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by case than transition risk because its drivers are observable hazards acting on identifiable assets. It is also disproportionately severe for SIDS that face large hazard exposures but possess few of the data layers needed to price them.

The Network for Greening the Financial System (NGFS, 2025) documents the standard decomposition for such assessments. Physical climate risk is a function of climate hazards, exposure and vulnerability, and each element carries specific data requirements. In practice, the NGFS identifies some binding constraints: asset-level exposure data are scarce, especially in developing economies; damage functions lack coverage of perils and regions; and harmonised historical loss records are uneven across countries. Where these data layers exist, markets respond quickly. Correa *et al.* (2026) draw on the Spatial Hazard Events and Losses Database (SHELDUS) to show that United States (US) loan spreads rise for borrowers with operations in disaster-prone areas even when the event does not hit them directly. At the firm level, Sautner *et al.* (2023) measure climate change exposure from earnings calls, using machine learning to capture how much attention firms and analysts devote to climate topics. Both approaches require data that are scarce in Caribbean SIDS.

In the Caribbean, the hazard layer is comparatively well developed, including more than four decades of storm tracks and daily rainfall records, whereas exposure, vulnerability and loss data remain less complete. Historical loss records cover only a minority of territories, asset-level exposure data are largely absent, and the damage functions available for the region rely largely on external calibrations. The question, therefore, is what level of risk information remains identifiable under these constraints, and whether it is useful for credit decisions.

When point estimates are unavailable, ordinal information is the usual currency of credit risk communication. For instance, sovereign ratings express risk in relative rank order rather than as a specific default frequency. Formally, the stochastic dominance criterion (Hadar and Russell, 1969) provides a partial order. If one territory's loss distribution lies above another's at every threshold, any monotone loss function preserves their ordering. Ordinal output must not, however, be mistaken for a complete decision rule. Cox (2008) shows that collapsing continuous risk into coarse categories can distort trade-offs and produce inconsistent priorities, and Manski (2003) demonstrates that ordinal information can, at best, bound the underlying continuous risk parameter, rather than pin it down. Using ordinal output well is therefore a question that needs answering, rather than a default.

Research Gap

The gap this paper addresses lies between what Caribbean credit decisions need and what Caribbean data can supply. Credit pricing requires loss magnitudes, yet loss records are sparse and uneven across the region. It remains unclear whether the available hazard and loss data support reliable territory-level risk rankings, how clearly they distinguish risk tiers, and how precisely they identify loss magnitudes for pricing.

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Contribution

The paper's contribution is to distinguish the physical risk information that can support credit decisions under current Caribbean data constraints from the loss information required for finer pricing. Our analyses show that broad risk tiering can support preliminary credit screening, while sparse and uneven loss records limit the precision of loss magnitudes for finer credit pricing. We also discuss how AI-assisted loss-data development could help address this limitation.

METHODOLOGY

Analytical Framework

To link climate information with credit-risk assessment, this paper draws on and extends two established strands of literature: Merton's (1974) structural credit-risk model and Monnin's (2018) physical-transition climate-risk distinction. The framework incorporates transition risk arising from the shift to a low-carbon economy $\alpha_{transition}$ as a one-off adjustment at loan origination, and annual physical risk arising from climate-related hazards $\alpha_{physical}$ as a drift adjustment in the asset-value process. Thus, the climate-adjusted default probability (PD) is defined as:

$$PD_{climate} = \Phi\left(-\frac{\ln\left(\frac{V_0\,(1-\alpha_{transition})}{D}\right) + \left(\mu + \ln\left(1-\alpha_{physical}\right) - 1/2\,\sigma^2\right)T}{\sigma\sqrt{T}}\right)$$

where V_0 is the initial asset value, D the debt, μ the expected annual return on the firm's assets, σ asset volatility, and T the debt maturity. The physical term is the expected annual loss rate,

$$\alpha_{physical} = \sum_{i=1}^{N} w_i \times \left(1 - \prod_{k=1}^{K}(1 - \lambda_{ik} \times \eta_{ik})\right)$$

where the hazard and exposure data are arranged on a grid of cells at a certain resolution; i indexes the grid cell; N is the number of grid cells within the project boundary, with asset-value weights w_i, K hazard types, annual hazard occurrence probabilities λ_{ik} , and loss ratio η_{ik} .

This is a final quantification goal and improves understanding of climate-related credit risk. In this paper, we focus on estimating $\alpha_{physical}$ under data-scarcity constraints.

Data

The Centre for Research on the Epidemiology of Disasters (CRED, 2021) documents substantial data gaps in the damage estimates of the Emergency Events Database (EM-DAT), its global disaster database. Over 2000-2020, 80.38% of disaster entries lack a damage estimate. Insured damage and reconstruction cost variables are even more deficient, with missing rates of 95.22% and 99.80%, respectively.

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This paper uses three data sources:

1. storm tracks come from the International Best Track Archive for Climate Stewardship (IBTrACS) (Gahtan *et al.*, 2024), are converted to gridded maximum wind speeds using CLIMADA, an open-source software framework for climate risk assessment and adaptation (Aznar-Siguan and Bresch, 2019; Aznar-Siguan *et al.*, 2025), and are mapped to damage ratios using the Emanuel (2011) function,
2. recorded losses come from the United Nations Office for Disaster Risk Reduction (UNDRR) open-source database DesInventar (UNDRR, n.d.) for the Caribbean, and
3. the National Oceanic and Atmospheric Administration (NOAA) Storm Events Database (NCEI, n.d.) for the US, which provides the county-level records used to compile SHELDUS.

In this study, we use data from 1980-2025, as IBTrACS defines the modern satellite era as beginning in 1980, and 2025 is the latest complete year available at the time of analysis.

Empirical Strategy

The empirical analysis asks how much risk information the available data can support. It proceeds in three steps: constructing hazard-based expected loss ranking measures and testing their sensitivity to damage calibration, validating ranking and tier stability, and testing how precisely event-level loss records capture hazard-loss magnitudes.

Ethical Statement

This study uses publicly available data from established third-party sources. As the analysis does not involve human participants, personally identifiable information or primary data collection, institutional ethical approval was not required.

Use of AI

AI tools were used solely to assist with language polishing and coding for routine data formatting and cleaning. The authors reviewed and verified AI-assisted outputs.

EMPIRICAL ANALYSIS AND RESULTS

Construction of Ranking

We use tropical cyclone tracks from IBTrACS and CLIMADA's wind-field model to derive maximum wind speeds within a 0.1° grid (approximately 11km spacing). Following the common convention, we classify grid cells with wind speeds ≥17.5m/s (63km/h) as affected by tropical storms and ≥33m/s (119km/h) as affected by hurricanes.

A substantial share of Caribbean grid cells records no hurricane events over 1980-2025 (e.g., Trinidad), but the absence of observed events does not imply the absence of risk. We therefore

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model the annual occurrence rate λ, measured in expected events per year. With a Gamma(1,2) prior and n events over $N=46$ years, tthe posterior is Gamma(n+1, 48), with mean $\lambda=(n+1)/(N+2)$.

Because Caribbean economic loss data are largely missing, we use Emanuel's damage function; this maps wind speed to a mean damage ratio (MDR) η through $MDR=v^3/(1+v^3)$, where $v=max\{0,(V-v_{thresh})/(v_{half}-v_{thresh})\}$, with V is the wind speed, v_{thresh}= 25.7 m/s and v_{half} the wind speed at which the damage ratio reaches 50%. For cells with no events, we borrow the regional median damage ratio for η.

The parameter v_{half} has been calibrated for different regions and objective functions. For the Caribbean, we retain the CLIMADA default (v_{half}= 74.7 m/s, the mean of the values estimated by Sealy and Strobl (2017), who applied Emanuel's damage function to coastal properties in the Bahamas) and three regional calibrations from the CLIMADA impact-function dataset for the North Atlantic region, covering the Caribbean, Mexico and Central America (Eberenz *et al.*, 2021): total damage ratio (TDR: 66.3m/s), root-mean-squared fraction (RMSF: 59.6m/s), and event damage ratio (EDR: 59.6m/s).

Annual expected loss rate for every 0.1° cell:

$$E_{cell} = \lambda_{hurricane} \times \eta_{hurricane} + \lambda_{storm\ only} \times \eta_{storm\ only}$$

$\alpha_{physical}$ is the asset-weighted, multi-hazard version of E_{cell}, and equals E_{cell} when one hazard and one cell are assumed.

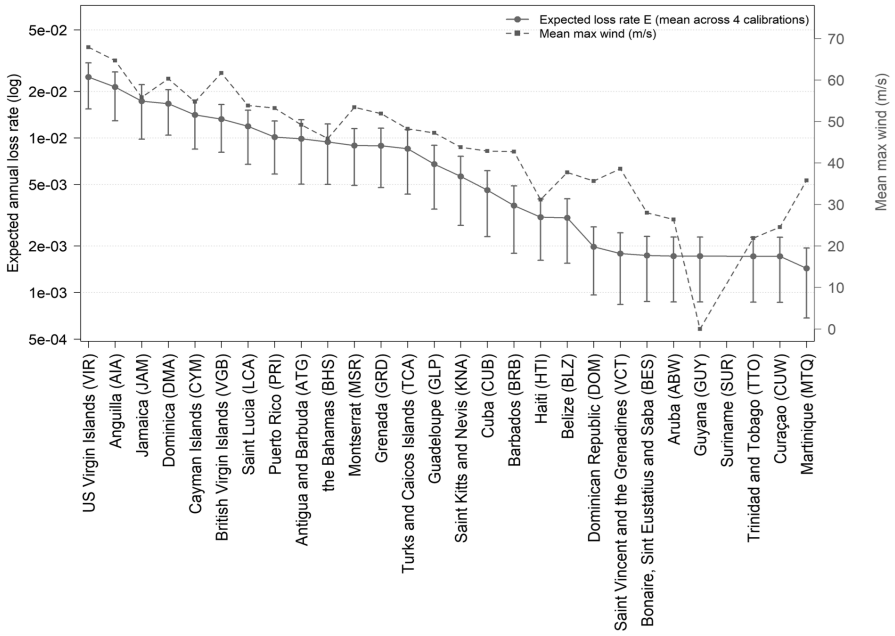


Figure 1: Territory ranking: expected loss interval vs wind speed

Source: Constructed by the authors using R

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For each of the 4 damage calibrations, we compute E_{cell} over the 46 years, aggregate the cells to territories using unweighted means, and report the ensemble mean alongside its minimum-maximum range across the 4 calibrations.

Figure 1 shows that, holding wind fields and occurrence rate λ fixed, the choice among the 4 defensible damage-function calibrations changes the annual expected loss rate by a factor of 1.97-2.90 (median 2.61) across all 28 territories.

Robustness and External Comparison of the Ranking

We first test whether the ordering depends on the choice of damage calibration by ranking the 28 territories under each of the 4, with occurrence rates held at their posterior means. Table 1 shows that the pairwise Spearman correlations *(ρ)* are close to one, indicating robust territory rankings across the available calibrations, even without more locally specific Caribbean calibrations.

Table 1: Pairwise Spearman Correlations Between Rankings

Calibration pair	*ρ*
Emanuel_default vs TDR	0.9918
Emanuel_default vs RMSF	0.9863
Emanuel_default vs EDR	0.9863
TDR vs RMSF	0.9973
TDR vs EDR	0.9973
RMSF vs EDR	1.0000

Source: Authors' calculations

For validation, we use DesInventar; this is compiled independently of the damage-function calibration and captures small, local events rather than only major disasters. We correlate the model ordering with affected population. Across the twelve territories with data in DesInventar, the two agree broadly (Spearman $\rho = 0.804$), with four of the five highest-risk and four of the five lowest-risk territories matching the record.

How clearly can we Distinguish Higher- and Lower-Risk Territories?

To quantify the distribution of the ordering, we run 2,000 Monte Carlo draws, sampling annual occurrence rate λ from its Gamma posterior (per grid cell, given 46-year event counts) and drawing 1 of the 4 damage calibrations with equal probability. Each draw yields a complete territory ranking, providing a rank distribution and pairwise win probabilities.

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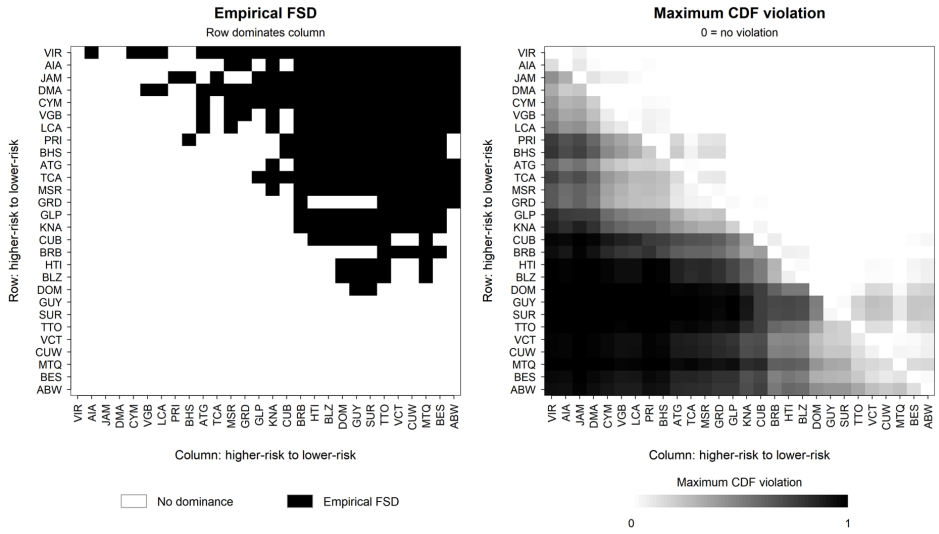


Figure 2: Stochastic Dominance of Expected Annual Loss Rates

Source: Constructed by the authors using R

First-order stochastic dominance (FSD) comparisons provide further evidence of separation between higher- and lower-risk territories in Figure 2. The left panel shows whether the row territory's expected annual loss rate distribution first-order stochastically dominates the column territory's (black indicates dominance); the right panel shows the maximum cumulative distribution function (CDF) violation, with darker shading indicating larger violations. Tiers are defined by median Monte Carlo ranks: top (1-5), mid (6-23) and bottom (24-28). Strict dominance holds for all top-tier versus bottom-tier pairs (100%), for 70.7% of top-versus-mid and 77.5% of mid-versus-bottom pairs, but for only 20.6% of within-tier pairs. Pairwise comparisons are decisive across tiers (for example, P (Jamaica > Barbados) = 1.00, P (Jamaica > Trinidad and Tobago) = 1.00 and P (Barbados > Trinidad and Tobago) = 0.97) while some within-tier comparisons remain ambiguous. These results support clear separation between higher- and lower-risk territories, while leaving the ordering of many territories within tiers unresolved.

How do Recorded Losses Relate to Storm Intensity?

Table 2 compares DesInventar records for the Caribbean sample with US records from NOAA Storm Events. The US database contains substantially more records and a higher share reporting positive monetary losses, providing richer data for the subsequent regression analysis.

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Table 2: Record and Loss Coverage in the Two Databases

	Territories / States	*Records*	*Records with a loss value*	*Share with a loss value*	*What one record is*
DesInventar	12	1,427	151	10.6%	one event entry for a parish, dated
NOAA Storm Events	69 (reporting units; areas)	716,890	268,382	37.4%	one event report for a county, dated (multiple wind hazards)

Source: Authors' calculations

We ask two questions about both databases. The first is whether a database records the storm, and whether it records a loss for it. The second is whether it supports estimating the marginal loss a storm causes.

We build the sample from the hazard record first, independently of any loss data. For every territory and every tropical cyclone in IBTrACS from 1980 to 2025, the storm enters that territory's sample when its centre passes within 100km of the territory. This frame contains 1,242 territory-storm observations for the US and 373 for the Caribbean.

We then match loss records to the frame by date, so a record counts for an observation only if its date falls within that storm's passage window. We keep only cyclone-related event types, where the NOAA wind family also includes thunderstorms and high-wind reports.

Within this frame, 362 of the 1,242 US observations have a matched cyclone-related record, and 255 have a positive recorded monetary loss. The corresponding counts for the 373 Caribbean observations are 78 and 38. Panel A and the *ln(1 + loss)* regressions in Panel B use the full frame, while the *ln(loss)* regressions use only positive-loss observations.

Writing y for the recorded outcome, the specification is

$$y_{ist} = \beta W_{ist} + \gamma_i + \delta_t + u_{ist}$$

The regressor W_{ist} is the strongest 10-metre wind within 100km, in knots, recorded while the storm was within that radius, where i indexes the territory/state, s the storm and t the year; and y is, in turn, an indicator for whether the storm appears in the record or whether a monetary value was entered. Country/state fixed effects (FE) γ_i control for time-invariant differences across countries or states. Year/decade FE δ_t control for common annual factors, while decade FE provide a coarser control for common changes over time. The specifications use either year or decade FE, as indicated in Table 3. Standard errors are clustered by territory. Results are shown in Table 3.

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Table 3: Wind Speed and Recorded Tropical Cyclone Losses

Panel A: Record layer

	US any TC record	*Caribbean 12 any TC record*	*US positive amount*	*Caribbean 12 positive amount*
Max storm wind (knots)	**0.0065*** **	**0.0042*** **	**0.0074*** **	**0.0042*** **
	(0.0007)	(0.0009)	(0.0005)	(0.0007)
Events (sample / used)	1,242 / 1,240	373 / 371	1,242 / 1,240	373 / 371
Countries/states (sample / used)	41 / 39	12 / 12	41 / 39	12 / 12
p (cluster-robust)	<0.001	<0.001	<0.001	<0.001
p wild restricted	**0/999**	**0.015**	**0/999**	**0.001**
p wild unrestricted	**0/999**	**0.003**	**0/999**	**0/999**

Panel B: Loss layer

	United States					*Caribbean 12-country sample*				
Dependent variable	*ln(1+loss)*	*ln(loss), positive only*				*ln(1+loss)*	*ln(loss), positive only*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Max storm wind (knots)	**0.1424*** **	**0.1037*** **	**0.0991*** **	**0.1017*** **	**0.0992*** **	**0.0759*** **	**0.0566*** **	**0.0418*** **	**0.0454** **	**0.0502***
	(0.0088)	(0.0115)	(0.0120)	(0.0114)	(0.0120)	(0.0126)	(0.0164)	(0.0109)	(0.0135)	(0.0222)
Events (sample / used)	1,242 / 1,240	255 / 255	255 / 249	255 / 249	255 / 248	373 / 371	38 / 38	38 / 36	38 / 36	38 / 24
Countries/states (sample / used)	41 / 39	25 / 25	25 / 19	25 / 19	25 / 19	12 / 12	10 / 10	10 / 8	10 / 8	10 / 7
p (cluster-robust)	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.007	0.006	0.012	0.064
p wild restricted	**0/999**	**0/999**	**0/999**	**0.001**	**0.006**	**0.001**	**0.002**	**0.003**	**0.030**	**0.167**
p wild unrestricted	**0/999**	**0/999**	**0/999**	**0/999**	**0/999**	**0/999**	**0/999**	**0.018**	**0.026**	**0.153**

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	United States					*Caribbean 12-country sample*				
Dependent variable	*ln(1+loss)*		*ln(loss), positive only*			*ln(1+loss)*		*ln(loss), positive only*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Country/state fixed effects	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Decade fixed effects	No	No	No	Yes	No	No	No	No	Yes	No
Year fixed effects	Yes	No	No	No	Yes	Yes	No	No	No	Yes

Notes: Country/state refers to Caribbean countries and US states, respectively. Fixed effects (FE) are additive and marked Yes/No. The storm frame is 1980-2025, with a 100km passage rule and a +/-2-day match. Zeros describe recorded losses and do not establish absence of actual damage. Parentheses report standard errors clustered by country/state. Stars use conventional clustered p-values: *** p<0.01, ** p<0.05, * p<0.10. Both wild cluster bootstrap (WCB) rows are bold for visibility, irrespective of significance; coefficient stars do not indicate WCB significance. WCB uses 999 Rademacher draws, seed 7; 0/999 means no simulated exceedance, not a population p-value of zero. TC means tropical cyclone. Loss is recorded damage in US dollars; unmatched records enter as zero recorded loss, not verified zero damage. Panel B columns (1) and (6) include all events; other columns condition on positive recorded losses. Columns (5) and (10) are the primary positive-loss specifications. Other positive-loss columns are sensitivity checks. Sample / used reports the initial outcome-specific sample and the estimation sample. Sample retention differs across FE specifications.

Source: Authors' calculations

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Panel A asks whether stronger storms are more likely to leave a record (country/state and year FE). Both databases show a positive relationship between wind speed and the presence of disaster and monetary loss records. The Caribbean coefficients are smaller than the US coefficients for both recording indicators.

Panel B asks whether wind and loss records together support a usable magnitude relationship, as pricing would need. The *ln(1 + loss)* regressions retain zero recorded losses, capturing both whether a positive loss is reported and its magnitude. The *ln(loss)* regressions compare amounts only among positive-loss records. With country/state and year FE, the Caribbean coefficient (0.0502) is about half the US coefficient (0.0992). This describes a weaker relationship with recorded losses, rather than demonstrating that comparable storms cause half as much damage.

The US wind coefficient changes little across FE specifications, whereas the Caribbean estimate varies more noticeably. Differences in the number of US states and Caribbean countries and in their hurricane exposure seem insufficient to fully explain this contrast; incomplete country- and parish-level coverage in DesInventar may also contribute. Controlling for country differences and common annual influences further reduces the already limited Caribbean sample from 38 to 24 observations, compared with 255 to 248 in the US. Finer controls therefore leave less information for estimation in the Caribbean, potentially increasing sensitivity to the specification and limiting precision.

Because the number of country/state clusters is limited, particularly in the Caribbean, we also use the wild cluster bootstrap (WCB) to assess the reliability of statistical inference. The US result remains significant under both bootstrap versions, whereas the Caribbean result with country and year effects does not. The limitation is therefore not the absence of a positive association, but insufficient precision to confidently establish its magnitude.

The Caribbean estimate is also sensitive to a single record. A DesInventar entry citing The Daily Gleaner reports US$7 billion in island-wide losses from Hurricane Gilbert in Jamaica in 1988. This entry accounts for 64.8% of total recorded losses in the Caribbean regression sample. The currency and loss definition underlying this amount could not be independently verified, and the entry may contain a reporting or currency-conversion error. Excluding it lowers the wind coefficient from 0.0502 to 0.0376.

DISCUSSION

Key Findings

The Caribbean records that a storm happened; it rarely records what the storm cost. This paper examines that asymmetry, which shapes what the results can and cannot say. The hazard-based risk indicator provides an ordering of the region, supported by similar rankings across damage calibrations, stochastic dominance between higher- and lower-risk groups, and broad agreement with independent disaster-impact records where available. Caribbean records respond to storm

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intensity, although less strongly than US records. However, the relationship with recorded loss amounts is less precisely estimated in the Caribbean. The same specification yields a wind-loss coefficient of 0.0992 in the US and 0.0502 in the Caribbean, about half as large. The Caribbean estimate has limited precision, and its statistical significance is sensitive to the specification and inference method. So, the US figure is more precise, while the Caribbean figure is not precise enough to price a loan on.

For a lender, the distinction is not academic. A point estimate whose precision is not declared is worse than none, because it will be used, and whether the loss rate is 1% or 3% decides a loan contract. An ordering with clearly stated limitations provides a more defensible basis for preliminary risk screening. Where the evidence remains limited, the ordering can be used with judgement through broad risk categories, while uncertainty in loss magnitudes limits its use for precise loan pricing.

Limitations and AI-Assisted Measurement

Why is the loss record so much weaker than the hazard record? The two come from very different systems. Storm tracks come from global observing systems, satellites and meteorological services that every country shares. Loss records depend on national institutions, statistical offices, insurers and disaster-management agencies, whose capacity varies sharply across small states. In the Caribbean, recording is episodic, often assembled after major events rather than maintained continuously, and the DesInventar exports used in this paper end between 2000 and 2023, mostly around 2014. The gap is institutional rather than physical.

Three limitations constrain the interpretation and use of our results. Recorded losses are sparse and unevenly available over time, damage severity relies on external calibrations, and uniform grid weights do not capture asset exposure at loan locations. This is where AI has a role, and the role is closer to administration than prediction. Extracting loss records from existing reports, mapping exposure from satellite-derived building footprints, and estimating local building vulnerability from imagery are tasks that would compensate for limited official statistical capacity. AI could help perform these tasks more quickly and at lower cost, building the records needed to support lending decisions.

What AI can do in practice is concrete. After Hurricane Ian, Keen (2023) reported combining AI-derived damage maps with poverty data to route emergency cash transfers, cutting weeks of block-by-block assessment to hours (Keen, 2023). Satellite-based models classify building damage from pre- and post-disaster imagery, and crowdsourced platforms such as PetaBencana.id map floods in real time (Chandler *et al.*, 2026). Applied to the Caribbean, the same tools would translate into a specific workflow. Pre- and post-storm imagery would be scored building by building against footprint data, turning an event such as Hurricane Beryl into parish-level damage maps within days. Language models would pull loss records from existing post-disaster assessments. Damage maps would be overlaid on loan locations so that a lender could see which borrowers were affected and respond within days rather than months.

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CONCLUSIONS

This paper examines what existing hazard and loss data can support in assessing climate-related physical risk and inform credit risk management in Caribbean SIDS. The hazard-based indicator supports broad distinctions between higher- and lower-risk territories, although the ordering of several territories remains unresolved. Recorded losses respond positively to storm intensity, but the Caribbean magnitude estimates are less precise and more sensitive to the specification and inference method than those in the US.

The available evidence is therefore more useful for comparative risk screening than for precise loan pricing. Banks, development finance institutions and supervisors could use the ordering to guide preliminary screening and further investigation, while recognising its model assumptions and the limitations of recorded losses.

Improving the evidence requires more complete and comparable event-level loss records, locally validated damage relationships and information on asset exposure. AI-assisted extraction and mapping could help build these inputs. Future work should test their contribution and incorporate forward-looking hazard scenarios before extending the analysis towards project-level pricing.

Roles and Contributions

Xuehui led the development of the manuscript, including the design of the analytical framework, methodological development, and preparation of the original draft. She was responsible for data collection and processing, physical risk ranking and tiering, analysis of disaster and loss records, robustness analysis, data interpretation and visualisation, and the integration of the findings into credit-risk assessment. She also led the revision and refinement of the manuscript.

Stefano provided the initial research direction, conceptual guidance, and supervisory input throughout the development of the paper. He contributed critical comments, structural suggestions, and manuscript revisions, helping to refine the argument, strengthen the practical relevance of the framework, and improve the overall quality of the paper.

Conflicts of Interest

There were no conflicts of interest from the authors

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