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Climate-Conditioned Catastrophe Modeling for Dynamic Risk Assessment

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Abstract

Seasonal climate variability strongly influences North Atlantic hurricane activity, yet catastrophe models used across risk transfer markets typically assume a stationary long-term climatology. This limits the ability of risk-transfer systems — spanning insurance, reinsurance, capital markets, and public risk financing — to anticipate predictable fluctuations in hazard and loss potential. We introduce a climate-conditioned catastrophe modeling framework that integrates probabilistic seasonal hurricane forecasts with stochastic event sets to generate dynamically updated loss distributions. The framework combines a climate-forced tropical cyclone generator with a statistical resampling engine that adjusts event frequency, intensity, and landfall patterns in catastrophe model output to reflect the expected climate state of each season. Applying this approach to a 40-year historical evaluation, we show that climate-conditioned loss distributions substantially improve the performance and resilience of insurance-linked securities portfolios. Dynamic portfolios informed by seasonal climate states achieve up to 30% higher mean returns and 50% smaller drawdowns compared with portfolios based on static climatology. These results demonstrate that seasonal climate information can be operationalized to improve risk assessment and capital-allocation decisions in sectors exposed to weather extremes. The methodology is hazard-agnostic and extensible to other climate-sensitive perils.

1 Introduction

Weather-related disasters impose growing economic and societal burdens as global warming alters hazard frequency and severity. Among these hazards, North Atlantic hurricanes remain one of the most

consequential for the insurance sector, responsible for over 30% of global insured losses since 1970 and eight of the ten costliest insurance events on record[1]. While long-term warming has increased the baseline risk of hurricane-related losses[2;3;4;5], year-to-year risk variability remains strongly modulated by predictable climate modes, including El Niño Southern Oscillation[6] (ENSO), the Atlantic Meridional Mode[7] (AMM), and Atlantic Multidecadal Variability[8] (AMV), that influence storm formation, intensification, and landfall probability.

Seasonal hurricane forecasts exploit these relationships to predict basin-wide activity months in advance. Although these forecasts have demonstrated skill in predicting storm counts and accumulated cyclone energy[9;10;11;12], their integration into catastrophe models and insurance pricing has remained limited. Although seasonal information is often used to support risk selection and secondary-market decisions[12], existing applications do not provide a widely adopted framework for translating probabilistic and spatially explicit seasonal hurricane ensembles into adjusted commercial catastrophe-model loss distributions.

Catastrophe models conventionally combine four principal components. The hazard component simulates the frequency, location, and physical intensity of potential events. The exposure component describes the geographic distribution and characteristics of the assets at risk. The vulnerability component relates event intensity to physical damage, while the financial component applies insurance and reinsurance contract terms to translate physical damage into insured losses. Together, these components generate stochastic loss distributions that support insurance pricing, capital allocation, and risk-transfer decisions.

The hazard component is generally calibrated to represent a long-term climatology[13] and is therefore not routinely updated to reflect predictable seasonal climate variability. Consequently, even when seasonal forecasts indicate an elevated or reduced probability of hurricane activity, the stochastic event sets used for catastrophe risk assessment generally continue to represent long-term average conditions. No widely adopted framework currently exists for conditioning catastrophe-model event sets on a forecast seasonal climate state[14].

This gap has significant implications. Insurance and reinsurance markets allocate billions of dollars annually to transfer hurricane risk, yet the catastrophe-model loss distributions supporting pricing and portfolio decisions generally represent long-term climatological conditions rather than forecast conditions for a specific season. As climate variability intensifies and capital markets become more sensitive to climate-related shocks, the need for dynamic, climate-aware risk assessment tools is increasingly urgent.

Here we introduce a climate-conditioned catastrophe modeling framework that bridges this structural limitation. The framework integrates a traditional catastrophe model, probabilistic hurricane simulations forced by seasonal climate forecasts, and a statistical engine that adjusts the frequency, intensity, and spatial distribution of events in the catastrophe model event sets to reflect seasonal hurricane risk (see Section 4.1). Importantly, the framework conditions the hazard representation while leaving the underlying exposure, vulnerability, and financial assumptions unchanged. We demonstrate its utility for an insurance-linked investment strategy in industry loss warranties (ILWs) over a 40-year investment period (see Section 4.2), showing that climate-conditioned loss distributions materially improve financial performance and resilience. More broadly, we show that seasonal climate predictability can be operationalized to enhance risk management across the insurance value chain.

2 Results

Before evaluating the investment strategies, we assess whether the long-term catastrophe model provides a suitable benchmark for the historical analysis (Figure 1b). The exceedance frequencies of annual industry losses generated by the long-term model (AIR North Atlantic Hurricane model v25.1.0[15]) are broadly consistent with those of historical insured hurricane losses (Property Claim Services[16]) normalized to 2024 exposure conditions. This comparison supports the use of the long-term catastrophe model as a baseline representation of hurricane loss risk, while recognizing the substantial sampling uncertainty associated with the limited number of observed extreme-loss years.

We additionally assess whether the probabilistic hurricane forecasts exhibit skill in predicting interannual variability in hurricane landfalls. The seasonally adjusted event sets underlying the climate-conditioned catastrophe model exhibit predictive skill across a range of landfall metrics, with likelihood ratios ranging from approximately 3 to approximately 800,000 depending on the intensity threshold and spatial aggregation (Supporting Information, Section S1).

The climate-conditioned catastrophe model produces seasonal loss distributions that differ from those generated by the long-term model, indicating higher or lower risk depending on the forecast climate state (Figure 1a). Two major drivers of interannual variability are the seasonal forecasts of the El Niño–Southern Oscillation and Atlantic Meridional Mode, represented here by the Relative Oceanic Niño Index[17] (RONI) and the Atlantic Meridional Mode sea-surface-temperature (AMM SST) Index[18]. Modeled losses tend to be higher during La Niña episodes than during El Niño (Figure 1c), due to below-average vertical wind shear over the North Atlantic. Modeled losses also tend to be higher during positive phases of the Atlantic Meridional Mode (Figure 1d), due to positive sea surface temperature

anomalies in the Tropical North Atlantic.

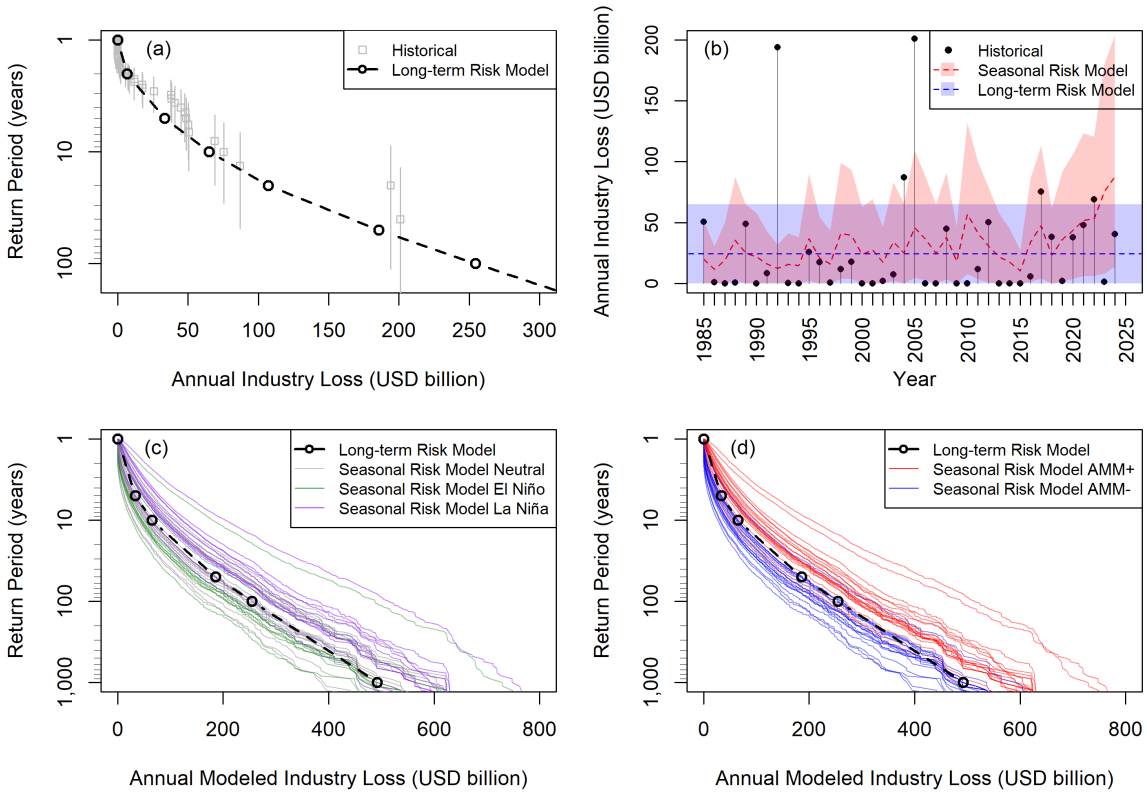


Figure 1: **Hurricane model validation and climate drivers.** (a) Exceedance frequencies of normalized historical annual losses[16] (gray squares) and annual losses simulated by the long-term catastrophe model[15] (black circles). Vertical lines show the 50% confidence intervals associated with the historical exceedance-frequency estimates. (b) Historical annual insured hurricane losses normalized to 2024 values (black circles), average annual insured losses generated by the long-term risk model (dashed blue line) and seasonal risk model (dashed red line). The shaded areas indicate the 80% inter-quantile ranges of modeled losses. (c, d) Annual loss exceedance probability curves generated by the seasonal model for each year in the 1985 to 2024 evaluation period, colored according to the forecast Relative Oceanic Niño Index (c) and Atlantic Meridional Mode sea-surface-temperature index (d). The long-term loss-exceedance curve is shown in black. La Niña conditions are defined by Relative Oceanic Niño Index values below -0.5, and El Niño conditions by values above 0.5.

Investment Strategy Evaluation

To evaluate the utility of climate-conditioned catastrophe modeling for insurance risk transfer, we simulate a systematic investment strategy over the 1985–2024 evaluation period (see Section 4.2). Annual capital allocations are optimized across a portfolio of 36 industry loss warranties (ILWs) covering different geographic regions and industry-loss trigger levels. We use ILWs as the empirical application because their explicit geographic scopes, industry-loss triggers, quoted premiums, and realized outcomes provide a transparent setting in which to evaluate the financial consequences of alternative risk distributions.

The analysis is grounded in real-world market and loss data, including stochastic loss output from a commercial catastrophe model widely used in the insurance industry (AIR North Atlantic Hurricane Model v25.1.0[15]), historical insured hurricane losses (Property Claim Services[16]), broker-quoted ILW premiums, and published U.S. property-catastrophe rate-on-line indices. The seasonal strategy uses loss distributions conditioned on June hurricane forecasts, issued before the start of the hurricane season, while the benchmark strategy uses the long-term catastrophe-model loss distribution. The 36 contracts correspond to the combinations of geographic scope and trigger level for which consistent broker-quoted market prices were available (see Section S2 of the Supporting Information).

The annual evaluation is pseudo-out-of-sample with respect to realized hurricane events and losses. For each year, the seasonal loss distribution and corresponding portfolio allocation are determined using forecast information available before the hurricane season, without using information about the hurricanes or insured losses that subsequently occurred during that year. Both strategies use the same underlying catastrophe-model loss table, exposure base, vulnerability assumptions, ILW definitions, price structure, and portfolio-optimization method. The difference between the strategies is therefore confined to the risk view used to estimate annual expected losses and loss covariances.

The climate-conditioned allocations respond to both the magnitude and geographic distribution of forecast risk. When seasonal forecasts indicate below-average risk along the entire U.S. coast, as in 1992, the climate-conditioned strategy redistributes capital toward riskier investments with higher premiums (larger allocations to low-attaching ILWs, Figure 2a,b). In years with regionally concentrated risk, as in 2012, the strategy shifts capital away from investments at higher risk toward less exposed ones (Figure 2c,d). In contrast, when forecasts signal elevated risk across several coastal regions, as in 2017, the strategy reduces allocations to low-attaching ILWs in favor of high-attaching ones (Figure 2e,f).

The annual allocations in these examples are based exclusively on information available before the corresponding hurricane seasons. Consequently, a forecast-informed allocation is not necessarily successful in every individual year. For example, the forecast for 1992 indicated below-average basin-wide activity, but Hurricane Andrew produced a major Florida industry loss. The investment analysis therefore evaluates whether the conditional risk distributions improve portfolio performance across the full 40-year period rather than whether they correctly anticipate every individual loss event.

Portfolio Performance Evaluation

The seasonal strategy generally produces better investment outcomes than the long-term benchmark across a wide range of risk-aversion parameter values. The average return (equation 4) is up to 30%

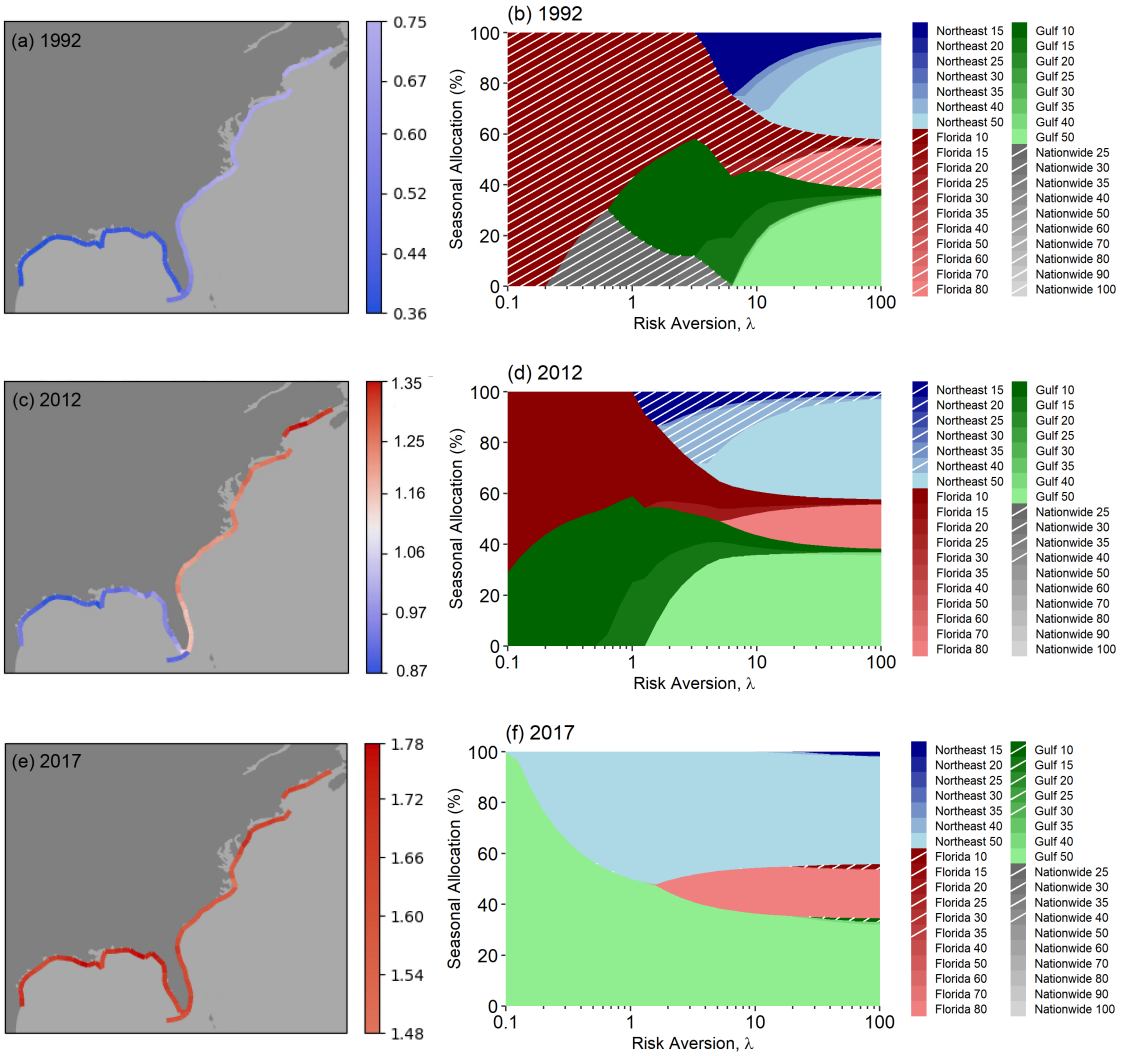


Figure 2: **Seasonal risk model.** (a, c, e) Hurricane landfall frequency ratios, as computed by the climate-based risk adjuster (CBRA), along the US East and Gulf Coasts in 1992, 2012, and 2017. Blue colors indicate that the seasonal risk is lower than the long-term risk, red colors otherwise. (b, d, f) Optimal ILW allocations informed by the seasonal risk model in 1992, 2012, and 2017. The optimized allocations vary depending on the risk-aversion parameter λ. Solid colors indicate loss-free ILWs, whereas striped areas indicate loss-affected ILWs in that specific year (Hurricane Andrew hit Florida in 1992, Hurricane Sandy hit New Jersey in 2012, and Hurricanes Harvey and Irma hit Texas and Florida, respectively, in 2017).

higher, with the greatest gains observed at intermediate levels of risk-aversion (Figure 3a). The compound annual growth rate (equation 5), quantifying the annual rate of return when gains are reinvested, is up to 35% higher for low-to-mid risk-aversion (Figure 3b). The risk-adjusted return, as measured by the ex-post Sharpe ratio (equation 6), is up to 40% higher (Figure 3c), indicating that the improvement in average returns is not accompanied by a proportionate increase in return volatility.

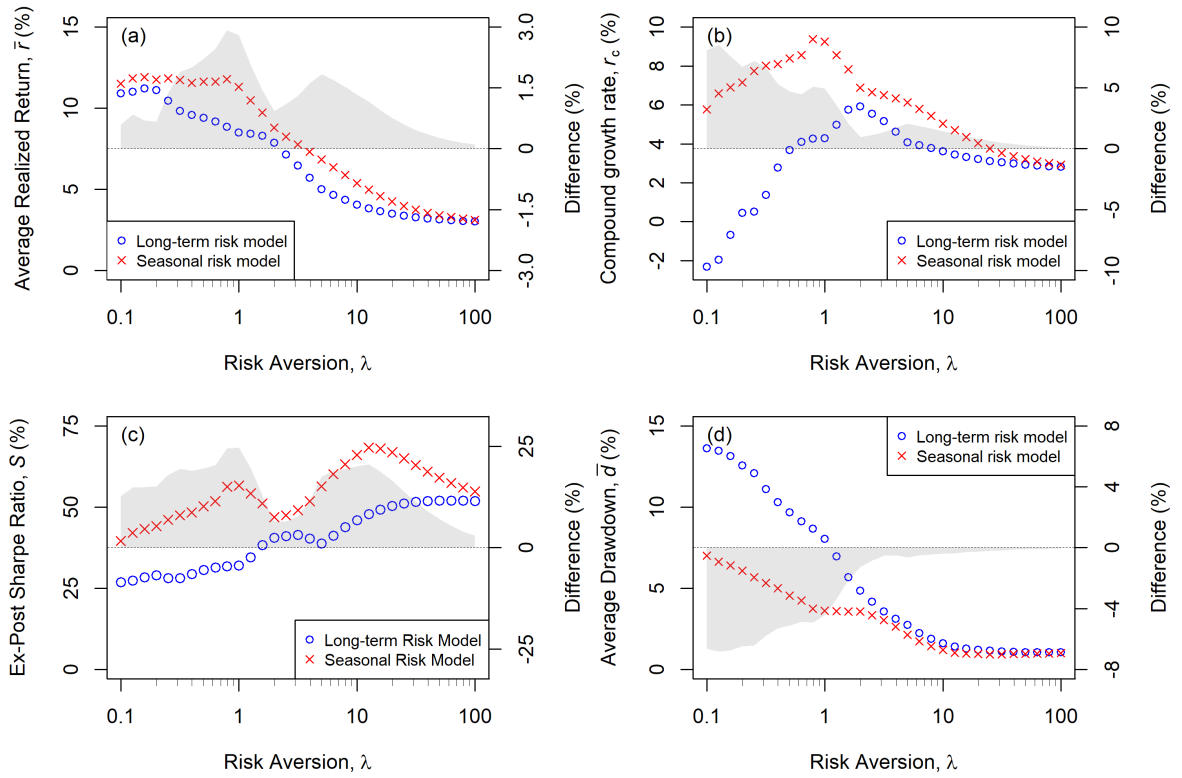


Figure 3: **Investment performance across risk-aversion levels.** (a) Average realized returns (equation 4), (b) compound annual growth rates (equation 5), (c) Sharpe ratios (equation 6), and (d) average drawdowns (equation 7) generated by the seasonal investment strategy (red crosses) and the long-term strategy (blue circles) over the 1985 to 2024 historical evaluation period. Drawdowns are reported as positive loss magnitudes, so smaller values indicate less severe average losses in negative-return years. Shaded gray areas indicate the difference between the seasonal strategy and the benchmark (vertical axis on the right side of each plot).

Furthermore, the seasonal strategy produces average drawdowns (equation 7) up to 50% smaller than those of the benchmark (Figure 3d). These results demonstrate the value of incorporating seasonal forecasts into capital allocation decisions.

Our analyses further suggest that the climate-conditioned framework produces broadly consistent improvements in investment performance when initialized with either April or June forecasts (Supporting Information, Section S3). The April forecasts are issued at a longer lead time and therefore provide additional time for translating risk assessments into investment decisions. Although individual performance metrics differ slightly between the two forecast initializations, both produce superior investment

outcomes relative to the long-term benchmark.

Fixed Risk-aversion Profiles

We further assess performance under two distinct risk profiles: an aggressive profile ($\lambda = 1$) that prioritizes returns over volatility, and a conservative profile ($\lambda = 10$) that emphasizes capital preservation. The aggressive profile produces an average return of approximately 15% under the scaling and constraints applied in this study, whereas the conservative profile produces an average return of 5% (Section S4 in the Supporting Information shows investment outcomes for a larger set of λ values).

For both profiles, the seasonal strategy yields higher capital gains (equation 8) than the benchmark over the 1985 to 2024 evaluation period (Figure 4). Under the aggressive profile, the difference in accumulated capital ranges from 100% to 400% after 2017 (Figure 4a), reflecting differences in allocations during several years with large hurricane losses. Under the conservative profile, the advantage is smaller but remains positive throughout the evaluation period (Figure 4b).

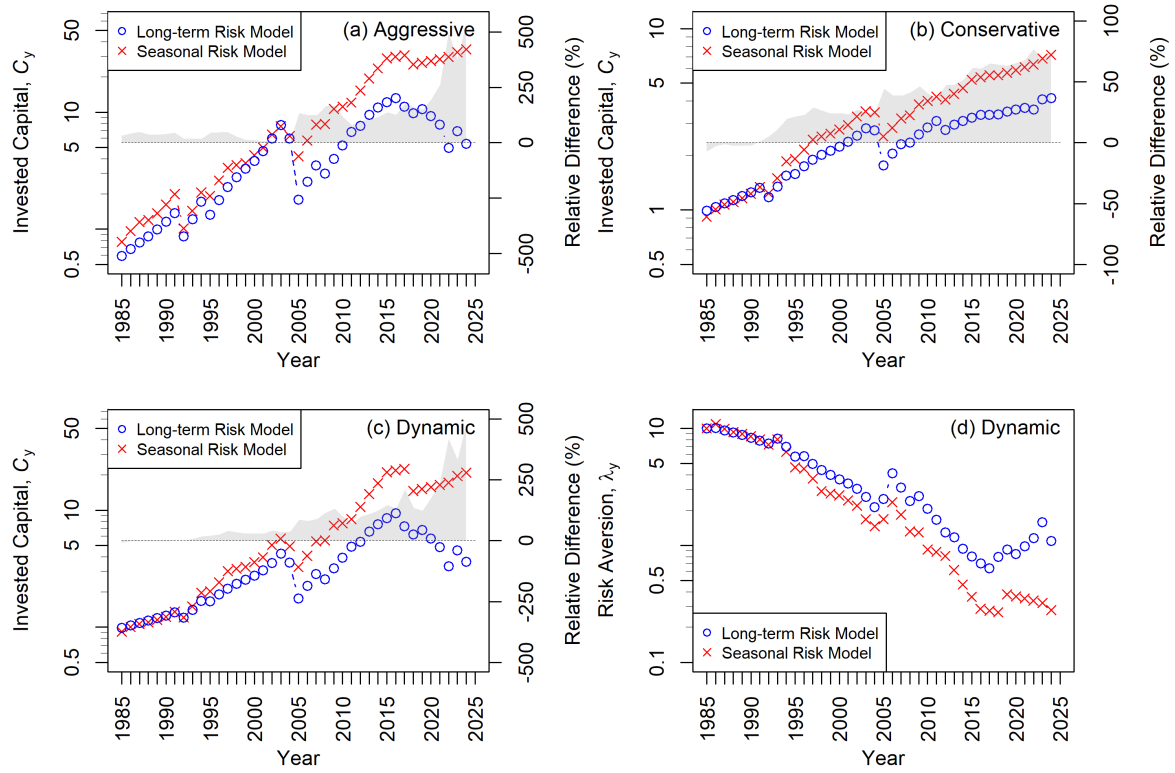


Figure 4: **Capital evolution under fixed and path-dependent risk-aversion.** (a) Evolution of invested capital (equation 8) over the 1985 to 2024 evaluation period for the aggressive risk profile (risk-aversion $\lambda = 1$), (b) the conservative risk profile (risk-aversion $\lambda = 10$), and (c) the path-dependent risk profile in which λ responds to the return realized in the preceding year (equation 9). (d) Annual evolution of the risk-aversion parameter under the path-dependent strategy. Red crosses represent the results obtained with the seasonal risk model, blue circles those from the long-term risk model, and shaded gray areas the relative difference between the two (vertical axis on the right side of the plot).

The climate-conditioned strategy reduces losses or improves returns relative to the benchmark in several high-loss years, including 2005 (Hurricanes Wilma and Katrina), 2012 (Hurricane Sandy), 2017 (Hurricanes Harvey and Irma), and 2022 (Hurricane Ian). In contrast, the aggressive seasonal strategy performs less well in 1992, when the pre-season climate information indicated below-average activity but Hurricane Andrew generated a severe Florida loss. For the conservative profile, the 1992 seasonal allocation instead produces a slightly smaller loss than the long-term allocation, owing to a significant shift from Florida-exposed to Gulf-exposed ILWs (Figure 2b). The annual results for the selected high-loss years are summarized in Table 1.

	Aggressive		Conservative	
Year	Long-term	Seasonal	Long-term	Seasonal
1992	**-37%**	-49%	-11%	**-8%**
2005	-70%	**-33%**	-36%	**-26%**
2012	+14%	**+27%**	-11%	**-4%**
2017	-16%	**+3%**	0%	**+3%**
2022	-37%	**+4%**	-2%	**+3%**

Table 1: **Investment performance in loss-heavy years.** Comparison between the investment performances of the seasonal and long-term investment strategies in years with heavy historical industry losses, including 1992 (Hurricane Andrew), 2005 (Hurricanes Wilma and Katrina), 2012 (Hurricane Sandy), 2017 (Hurricanes Harvey and Irma), and 2022 (Hurricane Ian). Investment outcomes are reported for both the aggressive (risk-aversion $\lambda = 1$) and conservative risk profiles (risk-aversion $\lambda = 10$). Numbers in boldface indicate the strategy generating the higher investment performance.

The sensitivity of the results to investment horizon and evaluation period was assessed by repeating the analysis for durations from 5 to 40 years and all feasible starting years within the 1985–2024 record. The seasonal strategy produces a higher compound annual growth rate than the long-term strategy in 78% of the evaluated windows for the aggressive profile and 97% for the conservative profile. Negative differences occur predominantly over shorter investment periods, whereas the relative performance becomes more stable and generally positive as the investment horizon increases (Section S5 of the Supporting Information).

Additionally, the sensitivity to the limited number of years in the historical record is evaluated using a historical-sequence bootstrap, in which sequences of 40 annual outcomes are sampled with replacement while retaining the returns associated with each single year (Section S6 of the Supporting Information). The resulting compound growth distributions indicate that the seasonal model performs better than the long-term model in 95% and 99% of the samples for the aggressive and conservative profiles, respectively. This suggests that the differences in the investment outcomes are not attributable solely to the exact composition and frequency of loss years in the observed historical record.

Path-dependent Risk-aversion Profile

The fixed-profile analyses assume that the risk-aversion parameter remains constant throughout the evaluation period. To examine the potential effect of changes in risk appetite following investment gains or losses, we additionally evaluate a stylized path-dependent strategy in which the value of λ used for each annual allocation responds to the return realized in the preceding year (equation 9). The comparison therefore evaluates whether the relative performance of the climate-conditioned risk view persists when portfolio risk-aversion is allowed to respond to prior investment outcomes.

Under this profile, a negative annual return increases subsequent risk-aversion and results in a more conservative allocation, whereas a positive return reduces subsequent risk-aversion. The climate-conditioned and long-term strategies are initialized at $\lambda_1 = 10$ and are subjected to the same updating rule. Differences between their risk-aversion paths arise because differences in annual allocations can produce different realized returns, which subsequently affect the value of λ used in the following year.

Throughout the evaluation period, the path-dependent seasonal strategy shifts toward lower values of risk-aversion more rapidly than the benchmark (Figure 4d). The shift is not monotonic, because negative-return years, including 1992, 2005, and 2017, generate increases in risk-aversion. By the end of the 40-year evaluation period, the seasonal strategy produces approximately 300% more accumulated capital than the long-term strategy (Figure 4c).

Note that this path-dependent formulation is intended as a sensitivity analysis rather than as a structural model of investor utility, which would require a dynamic utility function defined over investor wealth.

3 Discussion

Seasonal climate predictability has long been recognized as a valuable scientific resource, yet its integration into catastrophe modeling and financial risk assessment has remained limited. The framework introduced here demonstrates that seasonal climate information can be systematically translated into dynamically updated loss distributions that materially improve financial decision-making. Applied to an insurance-linked investment strategy, the climate-conditioned risk view generally improves portfolio performance relative to a benchmark based on long-term climatological risk across multiple investment periods, forecast initialization dates, and risk-aversion profiles. The comparison is constructed to isolate the effect of seasonal hazard conditioning. The seasonal and long-term strategies use the same commercial catastrophe-model loss table, 2024 exposure base, vulnerability assumptions, financial contract definitions, ILW price structure, and optimization method. Moreover, annual seasonal allocations are

determined using forecasts issued before the corresponding hurricane season and without information about the events or losses that subsequently occurred.

A central contribution of this work is the demonstration that probabilistic seasonal forecasts can be used to adjust catastrophe-model stochastic loss tables without altering the underlying exposure, vulnerability, and financial assumptions. This separation of hazard conditioning from financial modeling enables a modular approach in which advances in climate prediction can be incorporated directly into existing catastrophe-modeling workflows without reconstructing the remaining components of the underlying model.

Climate-conditioned risk assessment may also benefit the broader insurance system by supporting earlier capital planning and more informed risk-transfer decisions by insurers and reinsurers. Policyholders could benefit indirectly from more stable insurance capacity, while municipalities and public risk pools could use seasonal risk information to review contingency funding, preparedness priorities, and risk-transfer arrangements before hurricane season. These potential downstream benefits are not quantified in the present study and would require further institutional and policy analysis.

The results should nevertheless be interpreted in the context of the heavy-tailed nature of hurricane damages. Previous studies[19;20] have shown that the extreme tail of hurricane losses is influenced not only by meteorological hazard but also by the highly heterogeneous spatial distribution of exposed assets. Improved prediction of hurricane frequency, intensity, and landfall therefore cannot eliminate the substantial loss uncertainty arising from whether an event affects a densely exposed location. Although we verified that the portfolio optimization method is stable with respect to stochastic catalog size (Section S10 of the Supporting Information), this convergence does not eliminate uncertainty concerning the catastrophe model's representation of the extreme-loss tail or demonstrate robustness across alternative catastrophe models.

These findings have implications that extend beyond the specific case of North Atlantic hurricanes and touch on broader questions of how dynamic climate information can augment traditional catastrophe modeling in an era of increasing climate volatility. Many climate-sensitive perils, including wildfire, flood, drought, and severe convective storms, exhibit seasonal predictability driven by large-scale climate modes. Extending the framework to these hazards could enable a unified climate-aware risk assessment system capable of supporting global insurance and reinsurance markets. Such a system would represent a significant step toward integrating climate predictability into financial risk management at scale.

Several limitations warrant consideration. First, both strategies use catastrophe-model output based on a common 2024 industry exposure. Historical insured losses are normalized to 2024 values, accounting

for changes in inflation, insurance penetration, population, and wealth per capita. The analysis should therefore be interpreted as a comparison of strategies under a standardized present-day exposure basis, rather than as a reconstruction of the insurance market, asset base, available ILW contracts, or investment returns that existed in each historical year. Second, while the climate-conditioned event sets capture predictable variations in hurricane activity, they do not eliminate uncertainty in landfall location or intensity, which remains a dominant source of loss variability. Third, the analysis adopts the perspective of a price-taking ILW investor and assumes that quoted ILW premiums do not adjust fully and immediately to the same seasonal information used to condition the risk estimates. If sellers fully incorporated that information into contract-specific prices, part of the expected-return advantage could be transferred from investors to sellers through repricing. However, reinsurance pricing has historically been influenced mainly by broader supply-demand dynamics in reinsurance capital markets, with prices typically softening as capital accumulates following periods of limited catastrophe activity and hardening after major loss events. In such settings, seasonal climate information may not be materially reflected in quoted prices, providing a plausible rationale for the price-taking framework considered here.

Despite these limitations, the results show that seasonal climate information can improve catastrophe-model-based risk assessment and capital-allocation decisions when it provides a more informative conditional representation of hazard than long-term climatology. As climate variability intensifies and capital markets become increasingly exposed to weather-related shocks, integrating dynamic climate information into catastrophe modeling may be important for maintaining the stability of the risk-transfer ecosystem. The framework presented here offers a scalable, scientifically grounded approach for achieving this integration and highlights the broader potential for climate science to inform financial decision-making.

4 Methods

The climate-conditioned investment strategy assessed in this study consists of two parts. The first generates season-specific risk distributions through a climate-conditioned catastrophe model. The second uses this risk information to inform a systematic investment algorithm. Each step is described in more detail below and depicted in Figure S7.

4.1 Climate-Conditioned Catastrophe Modeling

We develop a climate-conditioned catastrophe modeling framework that integrates probabilistic seasonal forecasts with stochastic event sets to generate dynamically updated loss distributions. The modeling framework consists of two components:

1. **Dynamic Hurricane Simulations:** Generating stochastic hurricane events conditional on annual climate patterns, using the Reask Unified Tropical Cyclone (UTC) model[21]. This step produces climate-aware hurricane landfall probabilities along the US coastline.

2. **Climate-Based Risk Adjustment:** Adjusting the static risk view of a widely used catastrophe model to reflect each season's expected hurricane activity and the corresponding loss distribution, using the Climate-Based Risk Adjuster (CBRA).

Each stage is described in more detail in the following sections and a schematic representation of the entire workflow is shown in the Supplementary Information (Section S7).

4.1.1 Dynamic Hurricane Simulations

To augment the catastrophe model output, our approach necessitates simulating hurricanes using a climate-aware generative model. We first simulate large ensembles of hurricane seasons conditional on a long-term climatology, designed to match that of the static catastrophe model. We next simulate hurricane seasons conditional on target climates, designed to reflect seasonal hurricane forecasts. The differences in hurricane patterns between the simulated seasons conditional on the two climates – seasonal and long-term – are used to resample the static model output to reflect the frequency, intensity, and spatial patterns of the target climate, as described in Section 4.1.2.

The climate-forced generative hurricane model we employ is the Reask UTC model[21;22]. The methods employed by this model are described in detail in the corresponding manuscript and are summarized in the Supporting Information (see Section S8). The UTC model has been assessed in previous published work, and the present study does not introduce a new seasonal hurricane forecasting methodology. Here, we evaluate its forward-looking probabilistic landfall skill (Supporting Information, Section S1) and whether its output provides useful information when translated into climate-conditioned loss distributions and portfolio allocations.

The UTC model is forced by global gridded monthly average values of sea surface temperature, zonal and meridional wind at 200 hPa and 850 hPa, and mean sea level pressure, and it produces simulated seasons of tropical cyclone tracks consistent with the climate of the forcing dataset. In this study, we choose the climate of 1951–2020 as our long-term climatology, using ERA5 reanalysis[23] as forcing for the corresponding UTC event set. To generate UTC event sets for the target seasonal climates, we utilize 6-month seasonal weather forecasts from the European Center for Medium-Range Weather Forecasts (ECMWF, SEAS5). For our primary analysis, we use the forecasts initialized each year in early June, which are late enough to contain information for peak hurricane season but early enough to

inform some ILS investment decisions. We additionally show results initialized with the April forecasts. These forecasts provide information at a longer lead time and can therefore support earlier investment decisions. Their probabilistic landfall skill is broadly comparable to that of the June initialization across the configurations evaluated in Section S1 of the Supporting Information.

While not identical in their underlying dynamical core and parameterizations, ERA5 and SEAS5 both rely on ECMWF's Integrated Forecast System[23;24]. This minimizes bias between the models used to force event sets for the baseline and target climates, allowing for the interpretation of differences in hurricane characteristics as driven by differences in expected climate, rather than in the underlying model representation.

We use 2500 UTC-simulated seasons per year of the ERA5 reanalysis, yielding 175,000 total simulations for the long-term climatology. For the target climates, we simulate 1,000 seasons for each of the 51 ensemble members produced by SEAS5, yielding a 51,000-year event set for each forecast year. The resulting 51,000-year event set represents two nested sources of uncertainty. Variation among the 51 SEAS5 members represents uncertainty in the forecast atmospheric and oceanic climate state, while the 1,000 stochastic simulations generated for each member represent intrinsic variability in hurricane genesis, occurrence, intensification, trajectories, and landfalls conditional on that state. The seasonal risk view therefore retains the joint distribution of these characteristics. Accordingly, the climate-conditioned model should not be interpreted as a deterministic forecast of annual hurricane counts but as a forecast-conditioned probability distribution of possible hurricane events and associated losses. Note that we do not separately perturb total storm counts, major-hurricane frequency, and spatial track distributions while holding the remaining characteristics fixed, because these quantities are jointly generated and are not independent within the stochastic hurricane model.

For each hurricane simulated by the UTC model, we extract all intersections between the storm track and 72 "landfall gates", representing contiguous near-shore line segments that span the Gulf and Atlantic coasts of the Continental US. For each intersection, we record the hurricane characteristics produced by UTC at the last hourly model timestep prior to the intersection. Such characteristics include the eye location, maximum wind speed, radius of maximum winds, angle of maximum winds, central pressure, heading, and translational speed. These landfall data are used as inputs into the CBRA tool, described below.

4.1.2 Climate-Based Risk Adjustment

The Climate-Based Risk Adjuster (CBRA) is a Python package developed to assist users in modifying the output of traditional catastrophe models, consisting of stochastic loss tables (see an example in the

data repository[25]), such that the output reflects risk from the peril under a desired climate. It estimates changes in the joint distribution of event frequency, intensity, and geographic location driven by climate variability and change. By doing so, it combines information from the loss table, which models how each given event simulated in a static climate will affect a specified economic or financial outcome, with that from the UTC event sets, which model how the patterns of such events will differ between a baseline and a target climatological regime.

CBRA takes as input a static loss table, in addition to the landfall simulations for the long-term climatology and seasonal climates described in Section 4.1.1. For this analysis, we use a loss table consisting of 10,000 years of stochastic events, sourced from a commercial catastrophe model widely used in the insurance industry (AIR North Atlantic Hurricane Model as implemented in TouchstoneRe v13[15]).

CBRA groups landfalls in the input loss table, as well as the UTC model outputs, by two dimensions. These represent variations in landfall location and intensity, as described by the 72 landfall gates (Figure 1) and the Saffir-Simpson hurricane categories[26], respectively. We refer to each combination of landfall gate and intensity category as a unique storm "type". After assigning a type to each event within the three event sets (the input table and the UTC model outputs for both a baseline climatology and a specific season) based on these groupings, CBRA performs two stages of modeling to output an adjusted version of the input static loss table:

1. **Event count adjustment**: Adjusting the number of events of each type that occur in each simulated season in the input loss table
2. **Loss table resampling**: Using the adjusted counts of events by type, adding or removing events from the input loss table to yield an output loss table with the desired counts.

CBRA is agnostic to the algorithms used for each of these steps, which can be encoded and supplied by the user at runtime; however, it provides default approaches and a set of pre-packaged reasonable alternatives. For this analysis, we use the default methods described below.

To first order, the default count adjustment approach implemented in CBRA scales the number of events of each event type seen in the input loss table by the ratio of the landfalls of that type seen in the UTC event set for the target climate to that for the baseline climate. In other words, if there are twice as many events of a certain type in the UTC event set for the target climate as there are for the baseline climate, the number of events in the input loss table would also be doubled. Several additional measures are taken to (a) preserve correlation between event types across seasons as seen in the input event set, and (b) ensure that, grouping all intensity categories together, the number of landfalls at a given gate is scaled appropriately regardless of potential mismatches in the intensity distribution between

the baseline UTC event set and the input loss table (see Section S9 in the Supporting Information for additional details).

Once the event counts have been adjusted, CBRA then seeks to resample from the original loss table, creating new events of a certain type when additional events are indicated, and removing events of that type when fewer events are indicated. In the default algorithm, used in this paper, CBRA does this via an empirical resampling approach. When an event of a certain type occurs in a particular simulation in the input loss table but not in the output of the count adjustment step, we simply remove it. When an event is to be added, we sample randomly from all events of the appropriate type that exist in the input loss table across all simulations. The output of this step is a resampled loss table where events from the input table may occur zero or more times in the output, shifting the distribution of losses relative to the input.

4.2 Insurance-linked Investment Strategy

Following the implementation of the climate-conditioned catastrophe modeling framework, we simulate a systematic investment strategy for the 40-year period 1985–2024. For this purpose, we construct a portfolio comprising 36 industry loss warranties (ILWs), consisting of reinsurance contracts that trigger payouts when industry-wide property losses, as reported by an independent agency, exceed predefined strike levels within specific geographic regions, namely Nationwide, Florida, Gulf, and Northeast (see Table S1). The 36 contracts correspond to the combinations of geographic scope and trigger level for which consistent broker-quoted market premiums were available.

The multi-region portfolio permits both reallocation among geographic regions and selection among attachment levels within each region. ILW allocations are optimized using a Markowitz framework[27] that balances expected return against loss volatility. The investment performance of a dynamic portfolio informed by seasonal forecasts is compared with that of a benchmark strategy based on long-term climatology.

We assume ILWs with annual risk periods and occurrence loss triggers. If the strike level of an ILW is not breached by any hurricane losses in a given year, the investor earns the associated risk premium without incurring a claim. Conversely, if the strike level is exceeded by at least one loss event, the investor receives the premium but must pay the full claim, resulting in a net loss. The risk associated with each ILW is quantified by the model expected loss, defined as the average payout across a stochastic event set. In our climate-conditioned modeling framework, the expected loss is dynamic, updated annually based on seasonal hurricane forecasts, while the ILW risk premiums reflect historical phases of hardening and

softening reinsurance rates.

To back-test historical performance, we use proprietary market data obtained via commercial licenses. Specifically, we derive ILW risk premiums from 2024 market reports from leading reinsurance brokers Aon and Howden Re. These prices reflect the risk associated with a given geographical region and strike level (see Section S2 in the Supporting Information). We additionally utilize the US Property Catastrophe Rate-on-Line Index published by reinsurance brokers Guy Carpenter[28] and Howden[29] to account for the historical hardening and softening phases of reinsurance premiums (see Section S2 in the Supporting Information). The long-term event set, adjusted annually to reflect seasonal climate conditions, is sourced from a widely used catastrophe model in the insurance industry. Historical industry losses are provided by the official US reporting agency designated in the vast majority of ILW indemnity contracts. These losses are indexed to 2024 values, accounting for inflation, insurance penetration, population growth, and wealth per capita[30;31].

4.2.1 Portfolio Optimization

Annual allocations across the $n = 36$ ILWs are optimized using the Markowitz portfolio model[27], which identifies weights $\mathbf{w} = (w_1, \ldots, w_n)$ that maximize the return-volatility trade-off:

$$\max_{\mathbf{w}} \left(\mathbf{w}^T \langle \mathbf{r} \rangle - \frac{\lambda}{2} \mathbf{w}^T \mathbf{\Sigma} \mathbf{w} \right), \tag{1}$$

where $\langle \mathbf{r} \rangle = \mathbf{p} - \langle \mathbf{l} \rangle$ denotes expected returns, calculated as the difference between risk premiums $\mathbf{p}$ and model expected losses $\langle \mathbf{l} \rangle$, $\mathbf{\Sigma}$ is the loss covariance matrix, and λ is the risk-aversion coefficient. The model balances expected portfolio return $\langle R \rangle = \mathbf{w}^T \langle \mathbf{r} \rangle$ against loss variance $\sigma_l^2 = \mathbf{w}^T \mathbf{\Sigma} \mathbf{w}$. Smaller values of λ prioritize return maximization, while larger values emphasize risk minimization. For each forecast year, the expected-loss vector $\langle \mathbf{l} \rangle$ and covariance matrix $\mathbf{\Sigma}$ are estimated from the complete forecast-conditioned loss distribution. Consequently, the joint uncertainty represented by the SEAS5 ensemble and stochastic hurricane simulations is carried through the adjusted loss table into the portfolio moments and optimized allocations.

Because the portfolio optimization depends on the estimated loss covariance matrix $\mathbf{\Sigma}$, we evaluated both its numerical conditioning and its sampling stability with respect to the length of the stochastic catalog. The condition numbers indicate that the covariance matrices are sufficiently well conditioned for the numerical optimization. In addition, covariance matrices estimated from random subsets of the 10,000-year stochastic catalog converge progressively toward the full-catalog estimate as the number of stochastic years increases. The median relative Frobenius error falls below 5% at approximately 3,000

stochastic years and below 2% at approximately 8,000 years. These diagnostics indicate that, conditional on the catastrophe-model catalog used here, matrix conditioning and sampling variability associated with a small number of simulated extreme-loss events are unlikely to be material sources of instability in the estimated covariance structure. Full definitions and results are provided in Section S10 of the Supporting Information.

The optimization is subject to the following constraints:

$$\sum_{i=1}^{n} w_i = C \tag{2}$$

$$w_i \geq 0, \qquad i = 1, \ldots, n. \tag{3}$$

ensuring full deployment of capital C and prohibiting short positions. While these constraints could be relaxed to represent strategies involving leverage ($\sum_i w_i > C$) or retrocession ($w_i < 0$), we restrict the analysis to positive or zero allocation weights to retain a transparent investor perspective. Accordingly, the optimization evaluates the allocation of investment capital across quoted ILWs rather than the effectiveness of the contracts as hedges for a specified insurance portfolio. Hedge-effectiveness metrics would require an explicitly defined underlying exposure portfolio, its associated loss distribution, and an objective measuring the extent to which ILW payouts offset those losses. These inputs are not included in the present study. Extending the framework to buyer-specific insurance or reinsurance portfolios would provide a complementary assessment of the value of seasonal information from the perspective of protection buyers.

4.2.2 Assessment of Investment Performance

We evaluate the performance of the climate-aware investment strategy and the benchmark by comparing average realized returns $\overline{r}$, compound annual growth rate r_c, ex-post Sharpe ratios S, and average drawdowns $\overline{d}$:

$$\overline{r} = \frac{1}{N}\sum_{y=1}^{N} r_y \tag{4}$$

$$r_c = \left[\prod_{y=1}^{N}(1+r_y)\right]^{\frac{1}{N}} - 1 \tag{5}$$

$$S = \frac{\overline{r}}{\sqrt{\frac{1}{N}\sum_{y=1}^{N}(r_y-\overline{r})^2}} \tag{6}$$

$$\overline{d} = \frac{1}{N}\sum_{y=1}^{N}\delta_y^- r_y, \tag{7}$$

where $N = 40$ is the number of years in the investment period (1985–2024), $y = 1, \ldots, N$ is the year index, and r_y is the return generated in year y. The compound growth rate r_c measures the rate of return throughout the investment period, when annual returns are reinvested. The Sharpe ratio S (equation 6) is a measure of risk-adjusted returns and is defined as the ratio of average return to its standard deviation. In the expression for the average drawdown $\overline{d}$ (equation 7), δ_y^- is equal to -1 if $r_y < 0$ and 0 otherwise, so the average only takes into account years with negative returns and $\overline{d}$ is reported as a positive loss magnitude.

We then analyze two strategies with calibrated risk-aversion parameters: $\lambda = 1$ (aggressive, targeting $\sim$15% mean return) and $\lambda = 10$ (conservative, targeting $\sim$5%). For both, we track the evolution of invested capital over the investment period:

$$C_y = C_1 \prod_{y'=1}^{y}(1+r_{y'}), \tag{8}$$

where C_y denotes the investment capital accrued up to year y and $C_1 = 1$ is the assumed initial capital.

We further investigate a dynamic investment strategy where the risk-aversion parameter λ evolves depending on the return realized in the preceding year, i.e.,

$$\lambda_y = \lambda_{y-1}\exp(-\kappa r_{y-1}). \tag{9}$$

Under this specification, a negative return increases the subsequent value of λ, while a positive return decreases it. The magnitude of the update depends on both κ and the realized return. For the purpose of this analysis, we use a value of $\kappa = 1$ and an initial value of risk-aversion $\lambda_1 = 10$. This formulation is used

as a stylized sensitivity analysis rather than as an empirically calibrated model of investor utility.

Data Availability Statement

The climate-conditioned loss tables (1985–2024), ILW premiums, historical loss normalization factors, landfall gate definitions, and annual ENSO/AMM index forecasts used in this article are available in a public repository[25]. The catastrophe model loss table, historical hurricane insurance losses, and simulated seasonal hurricane event sets are subject to commercial confidentiality agreements and cannot be publicly disclosed. The event sets may be made available upon request for noncommercial use and for licensed commercial use by Reask (contact@reask.earth).

Code Availability Statement

The code used to simulate investment strategies and produce the figures shown in this article is available in the data repository[25]. The CBRA tool, used to generate the climate-conditioned loss tables provided in the public repository, may be made available upon request for noncommercial use and for licensed commercial use by Reask (contact@reask.earth). For this analysis, we use CBRA v0.30.11.

Competing interests

IB and JR are employees of, and own equity in, Reask. Reask is the provider of seasonal hurricane event sets and the CBRA package used in this study.

Author contributions

FC devised the project, designed the investment methodology, performed the calculations, and wrote the manuscript. IB designed the risk adjustment methodology and wrote the corresponding sections. YBM helped in designing the investment methodology and performing the computations. BM, JR, and HP supervised the project. All authors discussed the results and contributed to the final manuscript.

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