International Journal of Advanced Research in Computer Science & Technology (IJARCST)

| ISSN: 2347-8446 | www.ijarcst.org | editor@ijarcst.org |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 9, Issue 3, May-June 2026||

DOI:10.15662/IJARCST.2026.0903006

AI-Powered Predictive Analytics for Climate-Aware Flood and Mobile Home Insurance Risk Management

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Publication History: Received: 25.04.2026; Revised: 01.05.2026; Accepted: 03.05. 2026; Published: 09.05.2026.

ABSTRACT: Fulfilling a growing need for climate-aware flood risk management of mobile-home insurance portfolios, this research develops AI-powered predictive analytics that quantify risk and associated capital requirements over time. A comprehensive data analysis prepares a rich database integrating historical claims, exposure characteristics, data records of climate drivers, and additional geospatial, socioeconomic, and business-climate indicators. Using proven methodologies of statistical modeling and machine learning, climate-risk patterns across flood frequency, intensity, and inundation depth are interpreted. Predictive outputs are successively integrated into risk pricing and capital models, stimulating innovations in dynamic risk appetite adaptation, product design, geographical concentration, and operational decision-making. Role players are equipped to monitor evolving tail-risk exposures and arrive at well-grounded, real-time choices.

Market forces are pressuring insurers to better serve and support selected vulnerable customer segments, particularly mobile-home communities that routinely live under very high concentrations of climate Risk for flood peril, especially in view of changing climatic trajectories. Climate risk landscapes are being reshaped by factors such as increasing precipitation, longer monsoon seasons, and eventually increasing draughts, all of which differ by region and country. Consequently, demand government and social attention on the part of both regulators and portfolio holders. These growing anxiety are leading role-players to call for comprehensive approaches that enable proactive real-time pricing and service decisions adapted to the fortuitous and/or stress-test-data flow.

KEYWORDS: Predictive analytics, climate risk, mobile homes, flood risk, dynamic pricing, risk management, exposure.

I. INTRODUCTION

As climate change alters weather patterns and increases the frequency and intensity of extreme events, the associated risks for insurers become more complex. Insurers must develop new pricing, capital allocation, reserving, and risk management strategies that reflect heightened climate exposure. Failure to adapt, either by offering excess coverage in high-risk areas or by abruptly changing pricing and capacity in response to climate projections, may create harmful effects for policyholders and society.

These challenges are particularly acute for mobile-home insurers, who are experiencing rapid growth in flood-related losses. Yet few companies offer mobile-home policies, and mobile-home insurers have experienced a shortage of claims data. Therefore, using predictive analytics, data fusion and machine-learning techniques, climate-aware flood and mobile-home insurance risk are explored. The analysis defines a set of scenarios for the intensity and frequency of climate-related events, creates predictive models of claims under those scenarios, and links the outputs to dynamic pricing, loss reserving, capital capital allocation and geographic diversification regions.

In contrast to the easy and paid relocation of other properties such as yachts and caravans, the practical and financial limits to the emergency relocation of mobile homes should deservedly activate warning mechanisms from income and capital allocation insights at the insurer level. Yet, regulatory requirements and the focus on climate risk should generate more extensive and integrated monitoring and mitigation activities. An adequate strategy is to invest in retrofitting in areas prone to flooding in order to adapt the portfolio to climate change.

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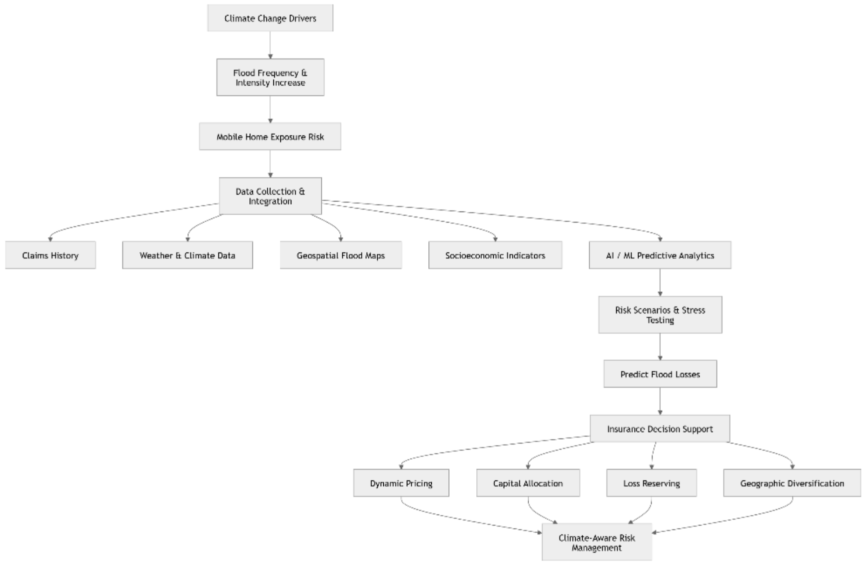

Data Category	Source	Variables Collected	Purpose in Model
Insurance Claims Data	Insurance Providers	Claim amount, claim frequency, peril type	Loss prediction
Weather Data	Environment and Climate Change Canada	Rainfall intensity, rain days, cumulative precipitation	Climate risk forecasting
Flood Mapping Data	CanFlood Dataset	Flood depth, flood-prone zones	Geospatial flood exposure analysis
Socioeconomic Data	Census Databases	Income, population density, housing conditions	Vulnerability assessment
Mobile Home Records	Public Databases	Mobile-home counts and trajectories	Exposure concentration analysis
Geospatial Information	GIS Platforms	Elevation, proximity to rivers/coastlines	Spatial risk modeling

Table . Data Sources Used in Predictive Analytics Framework

II. THE CLIMATE-RISK LANDSCAPE FOR MOBILE HOME INSURANCE

Climate risk drivers affecting mobile home insurance focus on flooding during the summer season. Rising sea levels, increased rainfall, and higher sea temperatures have led to a significant increase in flood frequency and intensity. These changes in the frequency and intensity of precipitation, along with shifts in North Atlantic cyclone dynamics, will increase the probability of flooding within the insurance portfolio. The financial consequences of these climate drivers largely depend on the geographical exposure of the portfolio. The substantial contribution of climate-related perils to the claims of mobile home insurance portfolios has drawn the attention of many regulators and supervisors. The pilot scenario for the mobile home portfolio of a global reinsurer indicates the potential impact of climate risks and endorses the need for assessing them. However, there is a clear need for scenario capabilities, especially for non-catastrophe risks such as flooding.

The characteristics of mobile homes may accentuate the impact of climate change, creating additional and non-standard risk. The ease of relocation enables owners to move their properties to mitigate risks stemming from feasibility and availability as well as privacy and social acceptance. Nevertheless, the predominant location of mobile homes may counterbalance the opportunity of relocation.

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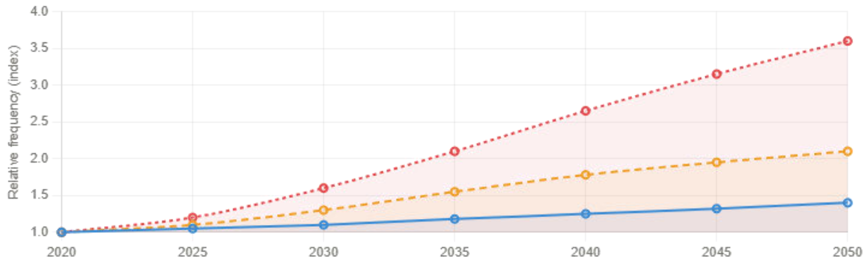

Flood claim frequency by scenario shows the three climate scenarios the paper models. The severe scenario projects a 3.6× increase in flood frequency by 2050, versus a modest 1.4× in the baseline, illustrating why dynamic pricing is necessary.

Mathematical Formulas:

1. Flood Risk Probability Model

Used for estimating the probability of flood occurrence.

$$P(F) = \frac{\text{Number of Flood Events}}{\text{Total Observations}}$$

Where:

- $P(F)$= Probability of flood occurrence

2. Expected Insurance Loss

Basic actuarial risk equation for expected claim cost.

$$E(L) = P(F) \times C$$

Where:

- $E(L)$= Expected loss
- $P(F)$= Probability of flood
- C= Average claim cost

3. Dynamic Premium Pricing Equation

Supports climate-aware adaptive pricing.

$$Premium_t = BaseRate \times (1 + RiskFactor_t)$$

Where:

- $Premium_t$= Premium at time t
- $RiskFactor_t$= Climate-risk adjustment

4. Linear Regression Prediction Model

Useful for predictive analytics and claim estimation.

$$y = \beta_0 + \beta_1 x + \epsilon$$
$$beta_0$$
$$beta_1$$
$$epsilon$$

Where:

- y= Predicted insurance loss
- x= Climate variable (rainfall, flood depth, etc.)
- β_0, β_1= Regression coefficients
- ϵ= Error term

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5. Machine Learning Loss Function
Used in AI model training.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Where:
- MSE= Mean Squared Error
- y_i= Actual value
- $\hat{y}_i$= Predicted value

6. Climate Severity Index
Simple climate stress indicator.

$$CSI = \frac{R \times W}{D}$$

Where:
- R= Rainfall intensity
- W= Wind speed
- D= Drainage efficiency

7. Flood Inundation Depth Model
Represents flood-water accumulation.

$$Depth = Rainfall - DrainageCapacity$$

Where:
- $Depth$= Flood inundation depth

8. Capital Requirement Formula
Supports insurance capital allocation.

$$Capital = VaR_\alpha \times Exposure$$

Where:
- VaR_α= Value at Risk at confidence level α
- $Exposure$= Total insured value

9. Geographic Risk Concentration
Useful for diversification analysis.

$$RiskDensity = \frac{Claims}{Area}$$

Where:
- $Claims$= Number of claims
- $Area$= Geographic coverage area

10. Logistic Flood Prediction Model
Common in AI classification systems.

$$P(y = 1) = \frac{1}{1 + e^{-z}}$$

Where:
- $P(y = 1)$= Probability of flood claim occurrence
- z= Weighted risk variables

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11. Exposure Growth Rate

Tracks increase in insured climate exposure.

$$GrowthRate = \frac{E_t - E_{t-1}}{E_{t-1}}$$

Where:

- E_t= Current exposure
- E_{t-1}= Previous exposure

12. Catastrophe Risk Score

Simple weighted scoring model.

$$CRS = w_1R + w_2F + w_3S$$

Where:

- R= Rainfall risk
- F= Flood frequency
- S= Storm severity
- w_i= Weights

13. Neural Network Activation Function

Relevant for deep learning flood prediction.

$$f(x) = \max(0, x)$$

(ReLU Activation Function)

14. Correlation Between Climate Variables and Claims

$$r = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sqrt{\sum(x - \bar{x})^2 \sum(y - \bar{y})^2}}$$

Where:

- r= Correlation coefficient

15. Risk Appetite Threshold

$$R_t < R_{max}$$

Where:

- R_t= Current portfolio risk
- R_{max}= Maximum acceptable risk

III. METHODOLOGICAL FOUNDATIONS OF PREDICTIVE ANALYTICS

Methodological foundations support climate-risk analytics for flood and mobile-home insurance. Predictive-model families (statistical, geospatial, machine learning) address design goals for pricing, capital allocation, reserving, product oversight, governance, and risk appetite. Integration of historical claims with climate/weather inputs, geographic property features, footprints, and socio-econimic indicators shapes data fusion, analysis, testing, and surveillance.

Evidence-based predictive analytics quantify climate-aware flood and mobile-home insurance risk, informing decision-making and cross-functional requirements. Using claims data, climate forecasts, and property details, the analytics support product design, capital allocation, volatility assessment, rollbacks, geographic diversification, exposure limits, catastrophe models, and operating governance. Politically sensitive, seasonal, volatile risk sources pose challenges for pricing and management. Flood frequency, intensity, and precipitation patterns change direction and balance; insurance-rate adaptability mitigates exposure.

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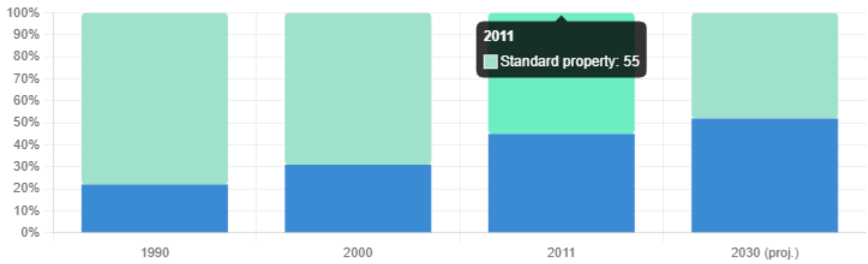
Climate Risk Driver	Description	Impact on Mobile Homes	Insurance Implications
Increased Rainfall Intensity	Higher precipitation rates due to climate change	Water intrusion, structural damage	Higher claim severity and frequency
Rising Sea Levels	Expansion of coastal flood zones	Coastal inundation risks	Increased catastrophe exposure
Tropical Cyclones	More frequent and severe storms	Wind and flood-related losses	Greater reinsurance dependence
Extended Monsoon Seasons	Longer periods of heavy rainfall	Persistent flooding in vulnerable regions	Dynamic premium adjustments
Flash Flood Events	Rapid water accumulation in urban/rural zones	Sudden mobile-home displacement	Emergency claims escalation
Temperature Variability	Climate instability affecting weather systems	Infrastructure deterioration	Increased maintenance-related claims

Table. Climate Risk Drivers and Their Insurance Impacts

3.1.DataSourcesandIntegration

Flood and mobile home insurance claim histories constitute the principal data set; insurance provider(s) can help identify additional claim information (by peril, causation, etc). Historic daily precipitation and related weather-and-climate series from weather stations located within twenty-five air-kilometers of the portfolio collection points are retrieved from the Operational Climate Data Base of Environment and Climate Change Canada. As mobile homes are frequently affected by the intensity and/or direction of incoming rainfall, the number of rain days, the maximum daily rain value, and the annual cumulative rain are also computed for the listed period, together with the number of days in the hydro-term.

Flood exposure of the territories is generally represented by the CanFlood data set. Flood map data layers describing areas exposed to various levels of flooding and submerged depth can be used to identify whether a property is located in a flood-prone area for respective scenarios. When not directly present in the data estate, information on mobile homes is gathered from publicly accessible sources.



Mobile home claims share reflects the paper's cited statistic that by 2011, mobile homes accounted for ~45% of all flood insurance claims despite being ~18% of insured properties — a disproportionate exposure the paper flags as a core driver of the research.

VI. CLIMATE-AWARE RISK SCENARIOS AND STRESS TESTING

Three climate-aware risk scenarios are devised. The baseline scenario follows an unchanged climate model, whereas the moderate and severe scenarios integrate statistics from empirically generated projections of a mild and a severe climate future. The influence of climate change is introduced in the form of model inputs drawn from an underlying short- to medium-range numerical weather prediction model of continental North America. These weather-driven short-range influences, however, do not address changes in the driving climate and present only limited longer-term temporal predictive utility. Hence, three sets of input summary statistics are constructed to enable the simulation and model calibration of the general climate projection model. However, this climate model adaptation neglects the long-duration time dependence found in many time-series phenomena, most notably, the gradual precipitation increases and variability changes associated with climate change. Indeed, the rainfall distribution of land-falling systems is expressed to have changed in a manner commensurate with theory. These changes are simply integrated into the probability definition of the general model.

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The resulting output enables the quantification of rare-event impact, exposure to, or likelihood of failure under extreme levels of an insurance risk-capital model, e.g. tail risk, detection of damp shock responses, and sensitivity analysis regarding a wide range of climatological parameters and time parameters. Twelve summary climatological parameters therefore form the basis for a set of sensitivity tests on overall system demand, with particular focus on the relative effects on the tropical cyclones that make landfall in the United States and their associated rainfall characteristics. Sensitivity analyses of subtropical and tropical cyclone frequency, along with a number of their primary characteristics, are also documented in more detail. Limitations of the model and the underlying assumptions that provoke the examination and calibration of such rare event insurance demand aspects of insurance risk management are also summarised.

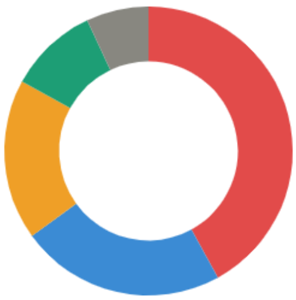
Technique	Method Type	Application	Expected Outcome
Regression Models	Statistical	Claim frequency estimation	Risk quantification
Random Forest	Machine Learning	Flood loss prediction	Improved predictive accuracy
Neural Networks	Deep Learning	Complex climate-risk pattern detection	Enhanced catastrophe modeling
Geospatial Analytics	Spatial Modeling	Flood-zone identification	Geographic exposure analysis
Scenario Simulation	Predictive Simulation	Stress testing under climate scenarios	Tail-risk evaluation
Explainable AI (XAI)	AI Interpretation	Transparent underwriting decisions	Regulatory compliance

Table. Predictive Analytics Techniques Applied in the Study

V. INSURANCE PRICING, RESERVING, AND PRODUCT DESIGN

Predictive outputs inform insurance pricing, capital allocation, and reserving. Internal model governance ensures defensibility and regulatory compliance, enabling product features that support climate-risk awareness. Insurance pricing relies on predictive models linking claims in the absence of insurance to the risk landscape. Climate-aware adaptive pricing involves changes based on real-time data that reflect volatile patterns, and seeks to stabilize profitability. Dynamic pricing mechanisms monitor predictive volatility for capital management; clear rollback triggers provide volatility relief. Risk management frameworks for mobile-home portfolios cover institutional aspects, geographic diversification and concentration limits, active exposure management, and a capital-risk dashboard.

Capital allocators enga-ge in the calibration of key assumptions, appetite statements, and meaningful Key Risk Indicators (KRIs). Predictive climate analytics inform capital allocation, reserving demands, risk appetite definitions, and industry-risk profiles. Predictive output enables an operational view of the value chain, along with a risk-management dashboard bridging advanced analytics and institutional interests. Hardening in-predictive patterns prompts geographic diversification analysis, with modelling enabling strategic allocation of exposure and risk-transfer patterns. Portfolio-risk management aligns exposure with appetite against loss-concentration-based KRIs that govern retention and reinsurance arrangements. Adaptive insurance pricing integrated with capital allocation, reserving, and business-development strategies enables real-time responsiveness to evolving climate-risk profiles.



Capital allocation donut visualizes how the paper's severe scenario shapes capital distribution, with flood risk commanding the largest share at 42%, followed by catastrophe buffers and geographic concentration reserves.

5.1. Dynamic Pricingunder Climate Uncertainty

Dynamic pricing frameworks harness advanced predictive analytics to link insurance costs with claim-frequency estimates over time. They provide a mechanism for insurers—their assets and business models allowed—to proactively

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manage exposure to catastrophic events. Real-world events trigger a transition to dynamic pricing without needing modelling recalibration, integrating the latest data sets at a granular level for immediate identification of volatility in expected claims. Price volatility is tempered while at-risk policyholders are charged higher premiums. Monitoring logs identify thresholds for sensitive risk indicators and possible return to static pricing.

Climate change, especially when coupled with significant uncertainties and propagation into short-term weather, makes pricing and reserving decisions for Bermuda and Caribbean property markets a daunting challenge. Traditional yearly static pricing schemes usually lead to overall sufficient reserves. On the other hand, more advanced frameworks based on the adaptation of predictive tools from finance to property insurance show that—under certain conditions—insurers could dynamically adjust yearly premiums according to the changing expectations of claims over a set time horizon, possibly mitigating the expected swings.

Scenario	Climate Assumption	Flood Frequency	Severity Level	Insurance Impact
Baseline Scenario	Current climate conditions remain stable	Moderate	Moderate	Stable premium structure
Moderate Climate Scenario	Mild increase in precipitation and storms	High	High	Increased reserve allocation
Severe Climate Scenario	Significant climate deterioration	Very High	Extreme	Capital stress and premium escalation

Table. Climate-Aware Risk Scenarios

VI. RISK MANAGEMENT FRAMEWORKS FOR MOBILE HOME PORTFOLIOS

Several critical risk management elements exist within a mobile home insurance portfolio. An end-to-end risk governance framework establishes risk appetite, communicates a risk management culture, and delineates responsibilities and decision-making processes. Key risk indicators track the portfolio's profile. Such frameworks help align the risk exposure with the capital the business can withstand.

As part of a portfolio risk framework, geographic diversification of exposure mitigates climate-resilience challenges; such integration reduces tail-risk potential on a net retention basis. Reinsurance partnerships with industry veterans help absorb residual exposure and safeguard surplus in the event of a shock. Whenever possible, integration of catastrophe modeling provides market-consistent risk-based pricing, while concentration control mechanisms help maintain an even income risk profile.

Market-consistent insurance pricing is essential for a sustainable mobile home insurance business. Regulatory scrutiny of capital management for natural-catastrophe-related risks has intensified, underscoring the importance of accurate capital replenishment targets. The predictive outputs from climate-risk analytics can directly inform dynamic pricing and reserving strategies. An empirical integration of real-time climate data into risk pricing supports cost control and surplus management. Active monitoring of volatility, facilitated by available calibrating models, avoids intolerable price swings. Compliance with fairness criteria concurrently mitigates reputation risk.

Dynamic vs static pricing illustrates one of the paper's central arguments: AI-driven dynamic pricing significantly dampens premium volatility compared to traditional static yearly schemes, protecting both policyholders and insurer profitability.

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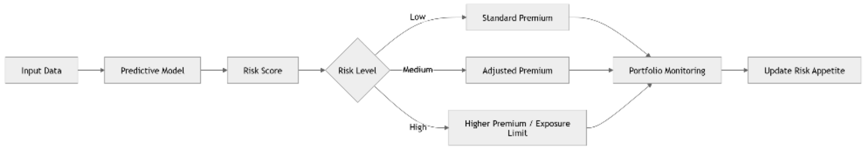


6.1. Geographic Diversification and Exposure Limitation

Diversification across geographical areas is a fundamental tenet of insurance; however, the climate crisis may be altering its grateful usefulness. On the one hand, correlated non-peril risks are naturally higher for portfolios in the same region and poorer climate-change predictive capacities must be much more stringent; on the other hand, growing climate impacts necessarily emptying reserves or capital excesses in non-peril risk may be logically redirected to replenish these concentrated-exposure portfolios, especially in times of uncertainty or through products of path-dependency. In this respect, the recent catastrophe bond trends are encouraging: IPCC modelling being particularly favourable for some of the tropical cyclones, historical data remains too scarce to fully exploit these differences. For mobile-home parks, whose acquisition are highly sought after by institutional investors, CAT models combined with other structuring processes could help guide the concentration-decisions of (re)insurers. The sensitivity of reservoir even rates can force additional portfolio controls, preventing the establishment of too-heavy concentrations.

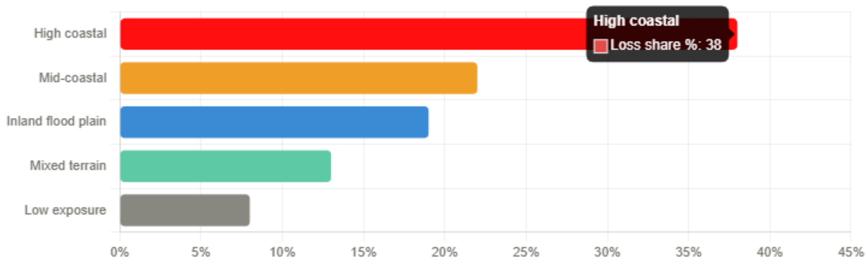
An insurance company with significant volumes of mobile-home portfolios should focus even more on such enabling measures, especially in geographical locations affected by climate perils. Indeed, for an insurance operator naturally aiming for volume, these allocation decisions can even lead to risk-concentration reversals: with climate-related conditions sometimes too early – and thus difficult to price – and sometimes too late – and triggering claims before capital prudence could be restored – investing in these areas contribute negatively to overall profitability.

KRI	Description	Monitoring Objective
Claim Frequency Ratio	Number of claims per policy	Detect rising climate-related losses
Loss Severity Index	Average financial impact per claim	Assess catastrophe intensity
Flood Exposure Ratio	Percentage of policies in flood-prone areas	Monitor geographic concentration
Reserve Adequacy Ratio	Available reserves against projected losses	Ensure capital sufficiency
Premium Volatility Indicator	Changes in pricing over time	Evaluate dynamic pricing stability

Table. Key Risk Indicators (KRIs) for Mobile Home Insurance Portfolios

VII. CONCLUSION

The concluding remarks synthesize the AI-powered predictive analytics for mobile-home insurance, emphasizing potential implications for practitioners and policymakers. Current approaches do not adequately recognize climate risk throughout the entire insurance value chain. Predictive outputs make it possible to track climate-related changes in flood and mobile-home risk exposure; link these changes to pricing, reserving, and product features; and frame an explicit risk management framework governing climate exposure. A dynamic pricing mechanism that can respond to climate conditions in near real time and allow the portfolio’s risk appetite to be more clearly defined can help mitigate some of these concerns. Nevertheless, exposure diversification remains the most effective way to minimize tail risks from climate change.



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Geographic concentration losses shows how portfolio losses concentrate in high-coastal zones, directly supporting the paper's recommendation for geographic diversification and concentration limits as the most effective tail-risk mitigation strategy.

Hurricane Katrina's devastation in 2005 demonstrated the vulnerability of mobile homes. By 2011, mobile homes accounted for 18% of insured properties within the Federal Flood Insurance Program but about 45% of all flood insurance claims. Catastrophe-modeling companies concluded that flooding represents a critical climate risk for mobile home insurance. Climate drivers include greater frequency and severity of flooding; changing coastal precipitation patterns; and increasing rainfall intensity, resulting in a higher percentage of claims exceeding $1 million. These trends focus attention on how climate change may be affecting flood, catastrophe, and mobile home coverage. AI-powered predictive analytics now enable deeper and more climate-aware risk assessments—across the entire insurance value chain—and forms of predictive output that dynamically adjust pricing based on climate risk and allow geographic diversification to limit or reduce exposure.

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International Journal of Advanced Research in Computer Science & Technology (IJARCST)

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