



Impact of Climate Risks on Automobile Insurance Market: An Approach Based on the Risk Management of Nonlinear Systems

Jorge Skotiuk and Julio Skotiuk

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ABSTRACT

Climate risk introduces nonlinear dynamics, temporal dependence, and abrupt regime shifts that challenge traditional actuarial approaches based on historical averages and assumptions of stability. This essay reviews the main methods used to quantify climate risk—scenario analysis, exposure metrics, and capital models—and proposes Chaos Theory as a complementary framework to capture the complexity of the phenomenon. Through an application to loss experience from extreme precipitation in automobile insurance, the analysis shows how the identification of regime shifts and the use of observational indicators can strengthen pricing, reserving, and climate risk management.

INTRODUCTION

Climate change is substantially altering the behavior of multiple risks that are relevant to actuarial practice. Beyond a gradual increase in the frequency or severity of certain events, patterns are emerging that are characterized by extreme episodes, temporal concentration of losses, and abrupt transitions between seemingly stable states.

These behaviors challenge the traditional assumptions underlying many actuarial models, particularly those based on temporal dependence, parameter stability, and the extrapolation of historical averages. In this context, climate risk poses a challenge that is not only quantitative, but also conceptual.

This essay explores the value of Chaos Theory as a complementary framework for interpreting these dynamics, with the aim of enriching actuarial analysis of climate risk without replacing its classical tools. From this perspective, practical implications are discussed for pricing, reserving, and risk management in environments characterized by nonlinearity and structural uncertainty.

TRADITIONAL QUANTITATIVE APPROACHES TO CLIMATE RISK MEASUREMENT

The measurement of climate risk relies on three approaches that are widely used in financial and actuarial practice: scenario analysis, exposure metrics, and capital shortfall models. Each serves a different purpose, although all can be aligned under regulatory frameworks such as the Task Force on Climate-related Financial Disclosures (TCFD), which acts as a backbone to ensure coherence between disclosure and risk management.

CLIMATE SCENARIOS: ANTICIPATING POSSIBLE FUTURE STATES

Scenarios developed by institutions such as the Network for Greening the Financial System (NGFS) and the Intergovernmental Panel on Climate Change (IPCC) allow the exploration of physical and socio-economic pathways. These include physical risks (temperature increases, heat waves, floods) and transition risks (decarbonization policies, carbon pricing, technological change).

Their purpose is to raise awareness of potential impacts and to inform strategic decision-making. However, they present several challenges, including high uncertainty over long horizons and difficulties in capturing nonlinear effects.

EXPOSURE METRICS: QUANTIFYING VULNERABILITY

Indicators such as WACI (Weighted Average Carbon Intensity) and Climate Value-at-Risk (Climate VaR) allow the measurement of carbon intensity in portfolios and the estimation of potential losses under climate scenarios.

These metrics are useful for disclosure purposes and for comparisons across portfolios, but they depend on company-reported data and do not reflect complex dynamics such as clustering or abrupt changes.

CAPITAL MODELS: TRANSLATING RISK INTO SOLVENCY

Tools such as CRISK (Climate Risk, an extension of the SRISK methodology) estimate capital shortfalls under climate stress scenarios, incorporating parameters such as Long-Run Marginal Expected Shortfall (LRMES) and climate betas. Their objective is to assess financial resilience under severe scenarios. This approach is particularly relevant for institutions required to demonstrate capital adequacy in the face of emerging risks.

These limitations justify the incorporation of a complementary approach based on Chaos Theory and Fractal Geometry, which contributes three critical elements:

1. Dynamic diagnosis of sensitivity and regime shifts.
2. Estimation of realistic predictability horizons to avoid over-extrapolation.
3. Measures of complexity and nonlinearity that strengthen risk governance.

SOME TOOLS FROM CHAOS THEORY—LYAPUNOV EXPONENTS AND FRACTAL GEOMETRY

The Lyapunov exponent measures the rate at which two initially close trajectories diverge in a dynamical system. If the value of the maximum Lyapunov exponent is positive, the system is chaotic, as divergence grows exponentially. If it is zero or negative, the system is stable or periodic.

This indicator not only confirms the presence of chaos but also allows the calculation of the predictability horizon: the higher the exponent, the shorter the period over which projections retain informational value. In practice, this helps define how far a projection can be trusted (for example, weeks rather than months)

TCFD AS AN ARTICULATING FRAMEWORK

Although these methods are not designed to be technically integrated with one another, the TCFD requires coherence across governance, strategy, risk management, and metrics. This makes the TCFD the axis that allows scenarios, metrics, and capital models to be presented as parts of a consistent narrative for regulators and investors.

CHAOS THEORY APPLIED TO CLIMATE RISK MODELING

Traditional approaches to climate risk measurement—scenarios, exposure metrics, and capital models—are essential, but they exhibit limitations that may reduce their ability to capture the true complexity of climate risk. Among these limitations are:

- Dependence on average relationships and linear assumptions that fail to reflect the nonlinear nature of climate dynamics and abrupt regime changes.
- The need to project over very long horizons (20–30 years), which increases uncertainty and reduces operational usefulness for short-term decision-making.
- Reliance on historical data that do not adequately represent future extremes, such as more intense heat waves or prolonged wildfire seasons.

Climate phenomena and actuarial loss rates do not follow linear patterns or normal distributions; instead, they exhibit fat tails, clustering, and temporal dependence. Multifractal analysis allows the identification of periods of high persistence (for example, consecutive weeks of extreme temperatures) and regime shifts. This information is valuable for adjusting severe loss models, defining activation thresholds, and reinforcing reserves during critical windows.

In this sense, Chaos Theory and Fractal Geometry complement traditional techniques along three dimensions:

- Predictability horizon: the Lyapunov exponent helps define how far projections remain reliable, avoiding excessive extrapolation and guiding strategy toward realistic temporal windows, particularly for phenomena such as heat waves or prolonged droughts.
- Regime shift detection: multifractal analysis and recurrence plots identify abrupt transitions between regimes, that is, shifts from one stable pattern to a fundamentally different one, which are common in climate phenomena and loss series.
- Nonlinear sensitivity: tools such as nonlinear causality may reveal hidden links between climate variables and loss experience, improving the calibration of actuarial models.

Incorporating Chaos Theory and Fractal Geometry does not replace traditional approaches but rather enhances them by providing quantitative criteria to define horizons, detect regime shifts, and manage uncertainty.

APPLICATIONS IN ACTUARIAL PRACTICE

CLIMATE RISK AND LOSS RATE FROM EXTREME PRECIPITATION

In automobile insurance, a relevant share of loss rates are associated with extreme weather events, particularly intense precipitation, and urban flooding, which constitute a growing risk in many regions. These events not only increase claim frequency, but also alter temporal patterns, generating abrupt concentrations of claims over very short periods and increasing average severity.

From an actuarial perspective, this behavior is particularly relevant, as it challenges the traditional assumptions of independence and parameter stability embedded in many pricing and reserving models.

TRADITIONAL ACTUARIAL APPROACH

Let N_t denote the number of flood-related claims during period t (for example, a day or a week). A classical actuarial model assumes that the random variable N_t follows a Poisson distribution, i.e., $N_t \sim \text{Poisson}(\lambda)$, with independent severities X_i having mean μ .

This approach is appropriate under “normal” climatic conditions; however, it presents significant limitations when extreme events begin to dominate the behavior of the system.

EMPIRICAL EVIDENCE: CLUSTERING AND TEMPORAL DEPENDENCE

Recent experience shows that claims associated with intense rainfall are not uniformly distributed over time. On the contrary:

- Most days exhibit no material claims activity.
- A limited number of days concentrate an extraordinary volume of claims.
- These days tend to cluster during persistent meteorological episodes.

This phenomenon, commonly referred to as clustering, implies that the occurrence of one event increases the likelihood of additional events over a short time horizon, thereby violating the independence assumption implicit in homogeneous Poisson models.

REGIME SHIFTS AND RISK NONLINEARITY

Under normal climatic conditions, claim occurrence can be reasonably modeled through a counting process with stable parameters. However, once certain critical thresholds are exceeded—such as cumulative precipitation levels surpassing urban drainage capacity—the system transitions into a different regime, characterized by simultaneous increases in claim frequency and severity.

This behavior is consistent with the principles of Chaos Theory, particularly the existence of abrupt regime shifts and sensitivity to initial conditions. Meteorological events with apparently similar characteristics may lead to markedly different outcomes in terms of the magnitude of insured losses.

ILLUSTRATIVE NUMERICAL EXAMPLE

Consider an automobile insurance portfolio exposed to urban flood risk. Two operating regimes are identified:

Normal regime:

Expected frequency of relevant events:

$$\lambda_N = 2 \text{ events per year}$$

Average severity per event:

$$\mu_N = \$5,000$$

Extreme regime:

Expected frequency of relevant events:

$$\lambda_E = 10 \text{ events per year}$$

Average severity per event:

$$\mu E = \$12,000$$

If the annual probability of entering an extreme regime is assumed to be 20%, while the system operates under normal conditions during the remaining 80% of the time, the expected annual loss can be approximated as:

$$E[S] \approx 0.8 (\lambda N \cdot \mu N) + 0.2 (\lambda E \cdot \mu E)$$

Substituting values:

$$E[S] = \$32,000$$

This expected value, however, completely masks the underlying risk dynamics. In particular, extreme years account for a disproportionately large share of total losses, implying a level of volatility significantly higher than that suggested by the average.

At this point, it is worth referring to the Actuarial Climate Index (ACI), which measures changes in selected climate extremes relative to a baseline period, disaggregated by region, without aiming to establish causality or make predictions. Since the probability of entering an extreme regime can be conceptually linked to observed indicators of the climatic environment, the extreme precipitation sub-indices of the ACI provide an objective reference for identifying periods in which the climate system departs from its historical regime.

From an actuarial perspective, these indicators do not directly determine expected losses ratios, but they are useful to justify stress scenarios and regime shifts in frequency and severity parameters. In this sense, the following modeling framework may be adopted:

- When the ACI is close to zero, parameters λN and μN are used.
- When the ACI is persistently above zero, parameters λE and μE are adopted.

SUMMARY OF ACTUARIAL IMPLICATIONS

- Pricing: Premiums based solely on historical averages may underestimate climate-related risk.
- Technical reserves: Temporal aggregation of claims during extreme events requires margins beyond traditional premium, claims, and IBNR reserves.
- Reinsurance: Event-based or excess-of-loss structures are justified.
- Risk management: Monitoring climate indicators may help anticipate regime shifts.

FINAL CONSIDERATIONS

The breakdown of temporal independence is evidenced by the tendency of extreme climatic events to cluster within specific periods. This aggregation is not random but rather associated with persistent climatic conditions that signal a departure from the historical regime.

Observational indicators such as the extreme precipitation sub-indices of the Actuarial Climate Index help identify contexts of elevated climatic stress without establishing direct causal relationships with claims experience. From an actuarial standpoint, their value lies in contextualizing the risk environment and highlighting periods in which the probability of extreme events ceases to be temporally independent. A limitation, however, is that the ACI currently covers only the United States of America and Canada.

Chaos Theory provides a conceptual framework for interpreting these patterns as abrupt regime transitions. Persistent elevated values in observational climate indicators may be interpreted as evidence that the system has temporarily exited its historical regime, simultaneously increasing claim frequency and severity from an insurance perspective.

Actuarially, such regime shifts can be represented by adopting different parameter sets for claim frequency and severity. During periods characterized by indicators close to their baseline, parameters associated with a normal regime are applied. When indicators display persistent deviations, parameters corresponding to a stress regime become appropriate.

In an environment characterized by nonlinearity, clustering, and regime shifts, uncertainty is structural rather than purely parametric. Under such conditions, the use of robust actuarial tools—such as scenario analysis, sensitivity testing, and conservative risk bounds that do not rely on strict distributional assumptions—is particularly appropriate.

CONCLUSIONS

Climate change poses a substantial challenge to actuarial science, not only due to the quantitative increase in uncertainty associated with certain risks, but also because of the qualitative transformation of their dynamics. Phenomena such as extreme precipitation, heat waves, and compound climate events introduce nonlinear behaviors that expose the limitations of approaches based exclusively on historical averages and stability assumptions.

Throughout this paper, it has been argued that Chaos Theory provides a useful conceptual framework for understanding these dynamics, by highlighting the existence of critical thresholds, sensitivity to initial conditions, and abrupt regime shifts. These elements help explain why risks that appear moderate under traditional metrics may materialize as highly concentrated and disproportionate losses.

The practical application presented in the context of automobile insurance illustrates how these concepts can be incorporated into actuarial work in a straightforward manner. The numerical example shows that even with moderate probabilities of extreme regimes, a significant share of aggregate risk is concentrated in a small number of episodes, with direct implications for pricing, reserving, and reinsurance design.

From this perspective, climate risk should not be viewed merely as a gradual shift in parameters, but rather as a phenomenon capable of inducing structural changes in risky behavior. For actuaries, this implies the need to complement traditional models with approaches based on scenarios, sensitivities, and regime analysis, capable of capturing the nonlinear nature of the problem without sacrificing technical rigor.

In this context, tools developed by the profession itself—such as the Actuarial Climate Index—illustrate how observational indicators can be used to contextualize the climate risk environment. Without seeking to establish direct causal relationships or make predictions, such indices are useful for identifying persistent deviations from historical regimes and for justifying stress scenarios and regime shifts in actuarial analysis.

Ultimately, the integration of concepts derived from Chaos Theory does not replace classical actuarial tools, but rather enriches them, providing a more realistic framework for climate risk management. In an environment characterized by increasing volatility and uncertainty, this expansion of the actuarial approach is essential to preserve the relevance and robustness of the discipline in the face of emerging challenges.

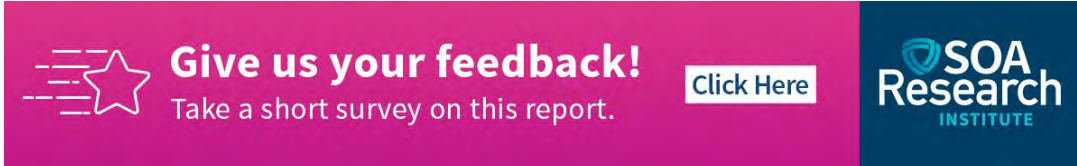
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Jorge Skotiuk is an independent actuarial consultant. He can be reached at jmskotiuk@gmail.com.

Julio Skotiuk is a financial risk management consultant with broad experience in the identification, management, quantification, and monitoring of market, credit, and liquidity risk. He can be reached at juliosk24@gmail.com.



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