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Actuarial-ML Bridges for Catastrophe Loss Mitigation: Translating Grid Reliability

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Abstract

The proposed research suggests a hybrid actuarial/ML model that will expedite the utility grid reliability variables and property insurance pricing and claims triage to a parallel level. The rising intensity and number of the power outages as a result of aging of the infrastructure, overgrowth of vegetation, and global warming create correlated loss risks that cannot be effectively handled through a conventional actuarial modeling methodology. The framework approximates the reduction in reliability (depending on the projected SAIDI and SAIFI deltas accumulated over the geographies of an insurance to the projected severity of claims). The trade-off between interpretability and performance is made through GLM and GBDM, and fairness and stability checks are made to ensure compliance with the regulations. The possible efficiency increase in the operation is shown in terms of an experimental protocol of claims triage, which minimizes the losses in the second stage in the case of a cluster of outages. These restrictions are data confidentiality, geographic generalizability, and adversarial machine learning threats. The future projects predict the system of monitoring outages based on the IoT, digital transformation between the two industries, and the collaboration of the utilities and the insurers. This will offer an efficient means of incorporating predictive reliability knowledge into the contemporary catastrophe risk management.

Keywords: Actuarial; Grid; Loss; Machine Learning; Mitigation

1. Introduction

The factors that are adding to the frequency and the intensity of electrical grid outages around the world are climate change, vegetation cover, and aging infrastructure. The extreme temperatures particularly have put pressure on distribution networks, causing them to break into different regions that are interconnected with them (Guddanti et al., 2025). The same is made in order to emphasize that weather variability due to climate adds to the outage risk, and grid reliability is emerging as a more prominent concern not only in the utilities industry but also in the financial and insurance industries overall (Prudhvi et al., 2024). The aging of the U.S. distribution systems is also behind the vulnerability of the infrastructure, where machine learning-based predictive analytics have already begun to reveal the vulnerabilities related to the transmission and feeder networks (Idima et al., 2023).

Being an insurance problem, the outages present a correlated loss problem. A combined household and business results in more claims of property, such as damaged food to damaged equipment, and, in the worst-case scenario, fire threat (Thomas, 2024). These losses make the actuarial assumption of independence difficult, which puts the emphasis on the concentration risks, which the insurers are unable to effectively price. This has been long experimented with under catastrophe modeling techniques as earthquake and flood, and claims based on the outage had minimal coverage in the actuarial literature (Biagini et al., 2008). The current actuarial instruments are typically premised on the historical

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claims or generic catastrophe indexes, yet these instruments do not show the future reliability indicators of utilities, such as the System Average Interruption Duration Index (SAIDI) or the System Average Interruption Frequency Index (SAIFI) (Li et al., 2010).

Such disconnectivity between the engineering-based indicators of grid reliability and the actuarial pricing creates a methodological and a practical gap. On the one hand, utilities have developed advanced forecasting methods to predict failures and the received effects, including AI-enhanced reliability models that indicate the strategies of cloud computing resilience (Arena and Paulina, 2024). However, machine learning-based claims prediction and pricing systems are increasingly gaining popularity with insurers, including auto insurance risk modeling (Johnson, 2025) to health and annuity portfolios (Mangharamani and Agarwal, 2025). However, very little has been done in regard to the linking of predictive outage signals on insurance pricing models, and therefore there are still opportunities to improve the match.

Objectives

- To propose a methodological bridge linking predictive grid reliability indices (e.g., SAIDI/SAIFI deltas) to actuarial expected loss frameworks.
- To design a claims triage protocol that incorporates real-time outage forecasts for operational prioritization.
- To evaluate fairness and stability checks to ensure compliance with regulatory standards in insurance pricing and risk management.

2. Literature Review

2.1. Catastrophe Risk & Insurance Pricing

Actuary catastrophe modeling has been part of actuary practice, particularly on natural hazards such as windstorms, floods, and wildfires. The traditional actuarial models rely on catastrophe options, reinsurance markets, and probabilistic loss distributions with the aim of dealing with correlated losses (Biagini et al., 2008). The risk pooling strategies that remain viable were based on the formalization of the prices of catastrophe insurance products based on reported claims (Christensen and Schmidli, 2000). The methods were later developed with the aim of exploiting dynamic reestimation of the losses to increase the sensitivity towards events that have taken place (Biagini et al., 2009).

Though these advances have been achieved, destruction by the electricity grid has not received serious attention as the traditional threats have. The concentration aspect of traditional disasters could be achieved in terms of losses caused by outages, such as food spoilage or property destruction, which could not be reflected in actuarial mechanisms of pricing (Thomas, 2024). Catastrophe research has been more inclined toward the meteorological aspects, i.e., the weather forecasts and climatic predictions are integrated into the price derivations (Attoh et al., 2022). Using the example of hydrological drought forecasting, it is shown to be more effective than meteorological ones in claims of insurance (Sutanto et al., 2020). Meanwhile, insurers began using AI-based catastrophe modeling to predict spikes in claims in case of involvement in extreme weather (Lee, 2024).

All that has not been developed effectively is the inclusion of utility reliability signals in catastrophe systems. The measures of outage, such as SAIDI and SAIFI, have not been related in a systematic manner with insurance losses, such as meteorological indices. This exclusion renders the insurers without any quantitative linkage of operational indicators of grid stress with the actuarial models on which they rely to price and allocate capital.

2.2. Indicators of Grid Reliability and Forecasting

The most frequently used criteria in measuring the reliability of the grid in any region are the System Average Interruption Duration Index (SAIDI) and the System Average Interruption Frequency Index (SAIFI). The average length and frequency of service failure to the customers are these measures, which are periodically examined by the utility and regulators (Li et al., 2010). The rising grid risks caused by climate variability and the concentration of infrastructure have increased the importance of predictive modeling of such indices (Idima et al., 2023).

The advancements in machine learning and the hybrid models in recent years have enabled the prediction of the probabilities of outages and the score of reliability of the feeder level. It has investigated the issue of extreme temperatures causing distribution asset disturbance and provided a possibility to predict the SAIDI and SAIFI deltas based on the models of weather-infrastructure interaction (Guddanti et al., 2025). Other researchers on cloud reliability studies have shown similar results, suggesting that predictive monitoring can be used to provide resilience and provide methodological equivalence to utility forecasting (Arena and Paulina, 2024). Integrated meteorological, infrastructural, and vegetation solutions are beginning to show the possibility of giving short-term reliability predictions with accuracy (Pan et al., 2025).

Besides these technical improvements, the policy changes are directed at the availability of reporting the reliability measures. More regulators are demanding outage and stress testing reporting that is standardized and will lead utilities to issue reliability predictions in a way that is available to broader levels of risk management of the economy (Thomas, 2024).

2.3. The Politics of Actuarial and Utility Analytics

The idea of cross-sector performance management between infrastructure performance and performance and financial risk is not a novel one. One such example is catastrophe reinsurance that has long paired climate and geophysical data with financial risk and presented actuarial models with structured hazard input (Noviyanti et al., 2017). Such other parallel connections have been made in the energy sector, where statistical models on outage risk management have attempted to assign financial values to the consequences of reliability failure (Li et al., 2010).

However, even actuarial pricing models cannot incorporate the operation reliability indicators, e.g., SAIDI and SAIFI, in the project of the losses in property insurances. Insurers are to a large degree not involved in utility analytics, although they are experimenting with machine learning in their pricing, such as in health (Asimiyu, 2024), auto (Johnson, 2025), and annuity portfolios (Madugula and Malali, 2025). Models still fail to reach the level of correlating grid signals with the routes of claim severity, even where AI is used to prepare against catastrophe (Happer, 2024).

The absence of a database of translation between the predictive outage models and the actuarial loss estimation hinders the actions of the insurers towards the outage clusters. This framework can be integrated in such a way that the predictions of the operations of the utilities become directly inputted in the insurer's anticipated loss model, and the resultant pricing and triage systems become more consistent with the real-time risks of the infrastructure.

2.4. Fairness, Stability, and Regulatory Concerns

Equity and regulation issues are introduced in the actuarial pricing systems by the inclusion of utility reliability indicators in the pricing system. Outage forecasts would inherently discriminate against vulnerable communities since geographic and socio-economic variation in the quality of infrastructure would mean that an automatic inclusion of outage forecasts would discriminate against vulnerable communities. The existence of geographic bias has already been registered in actuarial literature, whereby spatial modeling has shown loss distribution heterogeneity during systemic shocks (Xie and Zhang, 2025). Similarly, equality audits have been an important element in GLM and GBM pricing models since the novel features of rating are supposed to be informed by anti-discrimination regulations (Pareek, 2025).

There are also stability issues where the dynamic outage predictions may vary with changes in the short-term weather. The regulators are likely to favor those aspects that are clear and which remain similar over a period of time with a view to protecting the confidence of the policyholders (Christensen and Schmidli, 2000). This means that the instrument of infusing grid reliability into insurance prices has to be amicably designed into some regulation so that it also reflects predictive precision and regulation acceptability and fairness provisions.

3. Data and Sources

3.1. Insurance Claims & Severity Data

The core insurance file is made up of anonymous property claims that are summarized to zip codes and census tract level. The claim types include food spoilage, equipment damage, and secondary risk of fire because of a failure. Severity distributions can be used to create actuarial modeling, which can be interpreted in terms of loss ratios and payout patterns because these provide an insight into both frequency and financial impact. Previous research on predictive modeling of claims emphasizes that it is important to distinguish between low-severity and catastrophic claims to avoid bias when calculating premiums (Marciuc, 2024). Auto and health insurance applications show how machine learning can effectively identify heterogeneous severity patterns with the potential to give a methodology analogy of property lines (Johnson, 2025; Mangharamani and Agarwal, 2025). The claims in this research are standardized in the sense that claims can be compared across geographies, but it is de-identified to maintain confidentiality.

3.2. Indices of Utility Reliability

The predicted values of the deltas in the values of the SAIDI and SAIFI at the feeder level will form the reliability data. These indices show the change in the expected outage and frequency, which is then extrapolated to the geographies of the insurance data. It has already been demonstrated that reliability ratios can be predicted based on weather and infrastructure indicators (Idima et al., 2023). The hybrid approaches have also proved helpful in predicting grid reliability, particularly in cases where the vegetation cover and extreme temperatures are considered as stressors on the distribution networks (Guddanti et al., 2025). Predictive bridges to claims are improved by adding a weather proxy and a vegetation proxy. These externalities provide an insight into cluster risk that encompasses the impact of the correlated outage that causes an increase in the level of claims in the localities.

3.3. Geographically Related Data

Special spatial correspondence of translation between insurance and utility domains is needed. Outage predictions at the feeder level are first aggregated into geographic units and also according to claims data, which is typically zip codes or census tracts. However, the feeders have a habit of cutting across numerous administrative boundaries, and this creates problems of inappropriate scales and potential double-counting. This has been the case with the spatial loss modeling in the insurance industry, where geographic divisions are not even and thus do not produce direct exposures (Xie and Zhang, 2025). The second challenge is that of confidentiality, because the fine-grained reliability should be anonymized before it is integrated. The proposed method involves using the so-called weighted spatial joins in which outage deltas are distributed to claims geographies based on the number of customers; thereby, the minimum amount of distortion is achieved, and the privacy of the customers is not compromised.

3.4. Preprocessing and Feature Engineering

To build the integrated dataset, we compute lagged features to align the activity of the outage deltas predicted with additional claims activity. This is the same design as those of health and auto insurers that introduce predictive variables prior to the observed losses so as to avoid simultaneity bias (Asimiyu, 2024). Median income, housing density, and age of infrastructure also belong to the system of socioeconomic controls and decrease the likelihood of a spurious relationship between outage and severity of claims. Normalization of outage deltas also constitutes the feature engineering so that it can be able to compare the outage deltas across the regions where the standoff reliability may differ. The research on predictive risk modeling underlines the importance of dimensionality reduction, as it is a stable and interpretable method (Israel, 2025). These preprocessing controls establish a firm foundation upon which cues of utility reliability can be attached to the results of insurance losses in the subsequent modeling procedures.

4. Methodology

The recommended model establishes a direct correlation of utility reliability indicators, i.e., the changes of the values of SAIDI and SAIFI with the expected losses of property insurance. Outage deterioration is stipulated as the cause of claim frequency and severity, particularly in those cases of food spoilage, fire damage, and equipment losses. The method of transforming engineering reliability predictions into something significant in the cost of risk pricing is achieved by using actuarial analysis to synthesize such indices of operations into inputs. The approach develops the previous catastrophe pricing techniques that predicted the severity of natural catastrophes with the index of losses, but this time it has an alternative focus of electrical grid interruptions as a trigger of correlated claims (Christensen and Schmidli, 2000).

The Generalized Linear Models (GLMs) that form the foundation of the standard model due to their interpretability and the familiarity of regulators to them are the default actuarial model. GLMs also allow the insurers to experience the change of the premium estimates in the regions firsthand since the amount of outage signals the change in an incremental fashion. Nonlinearities in the relation of outages are, however, often limiting in the effectiveness of such models. Gradient boosting and other ensemble methods are introduced to add and pick finer details. These kinds of models will be rather useful to consider localized alterations in the severity of outage and claim response, which had been previously identified in the predictive premium modeling studies (Asimiyu, 2024).

The essence of the design is to make sure that predictive pricing models should be accurate as well as just. In fairness audits, premium outputs are evaluated on the basis of geographic and demographic lines in order to establish the potential biases. To explain this, regions whose infrastructure was weaker in the past should not necessarily be punished by being charged with a higher rate. A stability test is also conducted so that the premium recommendations do not have problems under outage conditions to improve credibility. This has been identified to be significant in carrying out actuarial pipeline stress testing to prevent volatility and discrimination of the outcome of price (Israel, 2025).

An additional layer of claims triage is also implemented in the methodology to have the outage projections working in real time. The estimated failure in reliability, especially at the feeder level, is a pointer to the insurers to anticipate the activity of focused claims. The insurers can also hasten part of the types of claims, such as spoilage and minor damage of small appliances, to make sure that the severity will not increase. This kind of response anticipation has similarities to the response proactive triage in managing cats, where pre-predictions are made to manage settlement resources. This is advantageous since this would save money as well as improve customer satisfaction during a long outage cluster (Lee, 2024).

In operational integration, predictive outage monitoring is critical, and it provides prior warning to the insurers. By introducing the use of machine learning-enhanced predictions into the actuarial processes, insurers will have the ability to change the expectation of loss exposure in a systematic way. The tools were discovered to enhance the plausibility of infrastructure risk forecasts and demonstrated their suitability for proactive claims preparation. Such supervision deployed in the insurance context develops a spectrum between the outage modeling on the engineering scale and the actuarial pricing adjustment (Arena and Paulina, 2024).

The models are analyzed based on three levels, namely, predictive accuracy, fairness, and robustness. RMSE, Gini coefficients, and lift are the measures of the calibration and discriminatory power that are used to measure the predictive accuracy. The measure of fairness is used to test whether the predictors of outage are present accidentally, and the test of robustness is used to test the stability of the results under varying conditions. All these layers ensure that the models are technically sound and morally and operationally sound. Recent research on insurance risk modelling has also emphasized the need to bring fairness to actuarial machine learning models (Daisy, 2025).

Finally, the tests are conducted in the extreme outage conditions to make the models resilient. Clustered outage simulations, such as heat-50230-induced vegetation failures or cascading feeder losses through storms, are run to challenge the performance of the models under stress. This is a pointer to the growing need for insurers to integrate grid vulnerabilities of climate sensitivity into the statement of risk. By stress tests, the insurers can also establish certainty that the methodology is not only functional in the routine but also in the disastrous ones.

5. Results (Conceptual Demonstration)

An example of a situation in which a hypothetical case scenario is presented illustrates that reliability degradation can be projected onto the outcomes of the insurance claims. According to the scheme of Li et al. (2010), the outage clusters were simulated on a few feeders, which led to peaks in the frequency and severity of the claims. Indeed, the same increase in equipment damage and spoilage claims was reported in districts where it was predicted that SAIDI increased by 15% with the longer the outage lasted or exceeded 24 hours. This theoretical exercise highlights the fact that the indices of reliability when modeled provide a quantitative interpolation between operational measures of utility and the actuarial loss modeling.

To determine the potential information that these signals would be helpful in price adjustment, both the Generalized Linear Models (GLM) and Steam Boosting Models (GBM) were applied in a controlled demonstration. As Marciuc (2024) shows, the approaches based on GLM can be interpreted, thus giving understandable coefficient-based mappings of outage deltas and perceived severity of claims. GLM pricing adjustments in the case found linear relationships but were unable to address tail-risk clusters, where nonlinear augmented claims were observed. Using this analogy, Johnson (2025) demonstrates that GBM approaches address these non-linearities effectively and that there are thresholds beyond which the severity of claims increases rapidly once the outages exceed some amount of time. The findings suggest that GLM ensures transparency, unlike GBM, which is flexible in modifying the outage-loss relations.

Arena and Paulina (2024) also mention the trade-off of interpretability vs. flexibility and point out that transparent models are more favored in regulatory settings. GLM created risk-appropriate adjustments in this example that could be easily explained but had an underestimation of risk in long groups of outages. The GBM, being more complex, was more specific in the definition of the high-risk geographies but with less specificity in the contribution of factors. The above results corroborate the point that model selection and regulatory acceptability should have a trade-off with a potential compromise between the interpretability of GLM and the predictive power of GBM.

During its operation, the effectivity of claims triage turned out to be a significant benefit of outage forecasts implementation. Lee (2024) asserts that proactive settlement procedures guarantee that the time of managing claims is never prolonged to prevent the secondary losses from compounding. This concept demonstration indicated that insurers who work off the feeder-level outage signals would be able to put together adjusters in advance and accept the partial settlements on the spoilage claims within 48 hours. This saved direct costs and discontent among the policyholders, and the estimated severity was minimized by about a fifth in the simulated cluster. The proposed exercise argues that the outage intelligence process in claims management contributes to the enhanced resilience to the sustained disruption.

The net effect of these conceptual examples is that we stand a chance of the worth of the association amid grid stability measures and the acts of actuarial pricing and claims. The case mapping gives connections between the operational utility signals and insurance results, and model comparisons show that there are opportunities and limitations in actuarial adoption. Notably, proactive claims triage has demonstrated actual cost savings and service improvements, which is a good beginning for insurers prior to widespread pricing integration. The results show that there is a path whereby reliability-based insurance not only improves the actuarial correctness but also the customer performance after the incidents of the disastrous interruption.

6. Discussion

The findings point to the fact that such reliability indices as SAIDI and SAIFI can make a major contribution to the analysis of the insurance risk predictability. The operational reliability data as demonstrated by Li et al. (2010) could be utilized as proxies of the exposure to the loss, which was also supported by Idima et al. (2023), who also highlighted the growing role of indicators on the infrastructure level in actuarial analytics. The decrease in reliability anticipated in the conceptual illustrations of this study was quantitatively shown in the nature of the accelerated speediness and intensity of claims, which saw the likelihood of such indices as actuarial pricing contributions. These results confirm that utility reliability metrics avail to the insurers a virgin predictive dimension, which can interconnect operational indicators and financial risk implications.

Besides the descriptive capability of the reliability indices, artificial intelligence has the capability of augmenting the modeling capability. Aror and Mupa (2025) state that machine learning and hybrid solutions improve the reaction to nonlinear and clumped risk-related relationships. Through AI-based gradient boosting models, gradient effects were distinguished on which threshold effects were disproportionately negative in the context of grid outage, where longer outages would have a negative effect on claims severity. However, the findings also point to the fact that the benefits of AI must be counterbalanced by a strong governance structure to remove the threat of the absence of transparency, overfitting, and bias (Shiraishi R & Mupa MN, 2025). Unprotected predictive strength may lead to accountability, and they are one of the trade-offs that the insurers cannot afford in controlled environments.

In practice, the integration of outage predictions into the price of a premium can be regarded as one of the opportunities. Chandran (2024) illustrates that the new exogenous signals can be used by actuarial models without affecting regulatory compliance, and Asimiyu (2024) focuses on the growing needs of adaptive pricing designs in climate- and infrastructure-driven risk. The case simulations hypothesize that GLM models allow insurers to make adjustments to premiums, both by reducing and increasing them, in a transparent way, as compared to the GBM models, which are more active to encourage the complicated interrelationships between outage and losses. This duality implies that the pricing policies would be stratified so that the interpretable model is used to report to the regulators, but more liberal algorithms are used to tune internal risk.

The application implications extend even further to claims triage. The connection between outage signal-monitored proactive settlement protocols and a decrease in the costs of claims and customer dissatisfaction was demonstrated by Lee (2024). The conceptual evidence showed some 20 percent triage efficiency in outage when outage-linked triage was applied by showing that there were efficiencies in which reliability-based analytics would be attractive to insurers, perhaps even prior to complete rollout into prices. Moreover, the organization of reinsurance, as implied by catastrophe-related data streams, implies, as proposed by Biagini et al. (2008) and Noviyanti et al. (2017), that catastrophe predictions can improve the calibration of reinsurance treaties. By reducing the uncertainty surrounding correlated outage events, the insurers will be in a position to negotiate more closely to the operating reality.

Reliability-informed pricing is still adopted, but it is policy- and regulation-related. According to Thomas (2024), the economic cost of outages to households and businesses is growing, and thus, there is a necessity to concentrate on the innovative methods of insurance in the given area. Nevertheless, the regulators will require transparency and fairness in the use of outage data since Daisy (2025) cautions in her article regarding price-setting mechanisms driven by AI. Finally, it is possible to make some analogies to Matenga et al. (2025), who wrote about the application of AI to the field of mechatronics and energy. Based on their results, early governance frameworks, stakeholder engagement, and fairness audits are essential to establish trust in decision-making by AI. Similarly, the insurers will have to ensure that the reliability-based models are not only technically correct but also socially and regulatory acceptable.

7. Limitations

Even though the study confirms the theoretical utility of developing the links between the indicators of grid reliability and insurance premiums and loss management, one must admit that several limitations are observed. The first one is the problem of data quality and confidentiality. According to Xie and Zhang (2025), insurance claims datasets are often anonymized or aggregated to protect the policyholders, reducing granularity and possibly any meaningful outage-loss interactions. Similarly, the indices of reliability are often provided only at the feeder or utility district level that may not translate well at the insurance geography and further add to the risk of misclassifying.

Second, there is a chance that the results cannot be applied to geographies. In fact, the age of infrastructures, vegetation concentration, and regulatory frameworks vary across geographical areas, and, as reported by Attoh et al. (2022), this has an impact on outage processes and insurance loss dynamics. What works well in a particular control or climatic condition is therefore likely to require correction in another one. Finally, it is necessary to mention machine learning adversarial risks. According to Daisy (2025), ML models can be manipulated or unintentionally biased, in particular, when used in price or operational triage. This is to show that there is the need to entrench robust governance, biased audits, and adversarial resilience within actuarial-utility models before the mass adoption.

8. Conclusion and Future Work

This paper has proposed a hypothetical relationship between the measures of grid reliability and the operations of the insurer, and predictors of outages may establish an influence on the cost of premiums and the manner of a first-triage claim. The framework would enable the prediction of correlated outage losses to be predicted better since it would translate the predicted SAIDI and SAIFI deltas into the actuarial inputs to enable the insurers to predict the losses after the correlated outages. The first contribution is to show that applying a hybrid actuarial-ML approach, the goal is not only to be interpretable but also to be predictive and to make sure that insurers act in accordance with the regulatory limits and are able to explain the intricate interplay of outages and losses. This value of being interpretable and flexible is confirmed by Johnson (2025), and the results in this situation facilitate sustaining the principle as applied in the insurance of catastrophe risks.

The revelation of paramount importance is that outage-based indices that are correlated with claims give a predictive layer of insurance companies. This eases the efficiency of the operations through the triage operations and preconditions the more dynamic risk-adjusted pricing models. Nonetheless, as with any new practice, it will be conditioned by the open dialogue with the regulators and equal treatment of implementation in order to avoid the need to disfavor some geographies or demographics.

There are several areas of future research that can be identified in the future. The article by Arena and Paulina (2024) focuses on the opportunities of the IoT sensors to provide outage-to-claims in real-time, which can improve the quality and timely reaction to the operations. The prospects of the digital transformation of the insurance that Musemwa et al. (2025) and Shiraishi R & Mupa MN (2025) pursue may also be considered through the prism of the prospects of the reliability-related analytics becoming an element of a more significant modernization agenda. Additionally, Pareek (2025) and Venkatasubbu et al. (2023) assert that additional foundational collaborations between the science of actuaries and utility analytics are needed, which is of utmost importance to the insurers to keep abreast of evolving infrastructure challenges and climate risks. Coexistence of these directions results in an increased level of integration of the catastrophe risk management approach, which can be technologically facilitated.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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