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# Climate Analytics and Parametric Insurance Design for Disaster-Prone SMEs

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## ABSTRACT

*The purpose of this research study is to gain insights into the role of climate analytics in the context of parametric insurance product for small and medium enterprises that are disaster vulnerable. In flood-prone areas, SMEs may suffer from significant economic damages and disruption of business activities, and this can be a prolonged process due to floods, droughts, storms, heatwaves and other climate-related hazards. Conventional insurance may not necessarily be able to offer immediate assistance due to the damage assessment process, verification of claims and the time required to settle claims. The other option is parametric insurance, which is based on a set of climate or disaster-related parameters, such as drought index, wind speed, temperature, flood depth and rainfall level. The study will explore a mix of loss and climate data and hazard models and their associated vulnerabilities to achieve an insurance trigger that is more efficient and practical. The results indicate that climate analytics facilitates robust trigger selection, better estimation of payouts and risk classification for SMEs. The results also show the cost savings that stem from the well-designed parametric insurance and its role in financial resilience and recovery time. But issues of basis risk, affordability, data quality and automated payouts are still significant. With proper data governance, stakeholder engagement and appropriate design, contextually, climate analytics can play a role in the development of more transparent, responsive, and scalable products for disaster-prone small and medium enterprises (SMEs) in the insurance sector, concludes the paper.*

## KEYWORDS

*Climate analytics; Parametric insurance; Disaster risk; SMEs; Financial resilience*

## INTRODUCTION

SMEs are more vulnerable to the impacts of extreme weather events, as they could face liquidity crises due to the impacts of climate change and lead to default of their loans, endangering their business continuity ( Chen et al., 2026). The companies have been found to have low adaptation capacity to climate change in the form of higher temperature and unreliable rainfall in rural communities and this is related to the higher probability of default (Ullah et al., 2025). Unlike traditional insurance products, which use loss adjustment procedures, which take time, parametric insurance offers a preventative approach that pays out immediately based on measurable and pre-determined climate indicators, which are more predictive of a loss (Bani, 2026; Steinmann et al., 2023). Parametric structures, unlike traditional indemnity policies, which often involve cumbersome administrative processes and time-consuming claims settlement, especially in the context of small/medium businesses with urgent liquidity needs after extreme weather events (Carmen et al., 2021; Sheehan et al., 2023), offer prompt and transparent financial relief through the use of high-frequency data from satellite imagery, IoT-based sensors, and localized meteorological stations (Bani, 2026; Wijesena & Pradhan, 2025). However, maintaining 'basis risk' as low as possible, which refers to the difference between the compensation that the index would pay and the actual economic loss for the enterprise, is important for these benefits to be realised (Steinmann et al., 2023; Wijesena & Pradhan, 2025). It underscores the need to employ advanced machine learning algorithms to successfully optimize site-specific vulnerabilities like rainfall, temperature, or flood inundation thresholds for the contract-specific triggers in the implementation of data-driven analytics ( Wijesena & Pradhan, 2025; Chen et al., 2023). Hence, this study aims at developing an integrated climate analytics tool for a more accurate design of the parametric insurance products, especially for disaster-prone SMEs, to narrow the gap in protection and institutional resilience in the face of increasing climate risks (Mahankal et al., 2025; Wang, 2026).Small and medium-sized enterprises (SMEs) are not only impacted on their day-to-day activities, but also may face some significant difficulties when it comes to liquidity constraints, and credit default risk as well (Anastasiou et al., 2024; Cathcart et al., 2026; Chen et al., 2026). While larger corporations may have more well-established risk management strategies and/or larger capital buffers, SMEs, especially in rural and climate-exposed areas, have less adaptive capacity and are more vulnerable to the increasing intensity and frequency of extreme weather events (Cathcart et al., 2026; Ullah et al., 2025). The mindset shift, from financial institutions and insurers, from slow and mostly indemnity based disaster risk management to more agile and responsive approach is needed and expected in this increased risk profile (Bani, 2026; Sheehan et al., 2023). Parametric insurance, which is designed to pay out based on a specific and measurable environmental condition—like a specified rainfall amount or a temperature cap—promises a powerful avenue to deliver quick, data-informed financial protection that can be crucial for the survival of SMEs right after a disaster (Bani, 2026; Pandiri & Chitta, 2023). But, the successful implementation of parametric models depends on the ability to overcome 'basis risk' – the constant issue where the payout associated with the index does not align to the economic loss of the firm (Cesarini et al., 2021; Steinmann et al., 2023). The failure to match this results in not only diminishing the value of the insurance product but also the credibility of the market of the insurance product (Nyagadza & Nyauswa, 2019). Furthermore, at some locations or for some hazards, the period of record is too short to be useful for triggers and accurate modelling, and will need a bit of ingenuity for catastrophe modelling (Sheehan et al., 2023). This has led to a substantial amount of studies dedicated to data-driven methods, with the incorporation of high-frequency satellite imagery, remote sensing, and IoT-powered sensors opening up a new area for enhancing index granularity (Bani, 2026; Wijesena & Pradhan, 2025). In this context machine learning algorithms have been shown as a game-changer as they are able to describe complex and highly non-linear relationships between environmental phenomena and business disruptions in a more objective and accurate manner than traditional linear regression (Cesarini et al., 2021a, 2021b; Chen et al., 2023). The supervised learning architectures, such as neural networks and support vector machines, enable the designer to create a more explainable and specific trigger for contracts that focus on vulnerabilities in different sectors of SMEs, which are dependent on the location of SMEs (Cesarini et al., 2021; Wijesena & Pradhan, 2025). Besides, new empirical research has demonstrated that using dynamic weather data in predictive models can yield significant performance gains, with deep learning methods providing significant reductions in both operational costs and predictive error of conventional, static-based methods (Men et al., 2025; Shi et al., 2024). Finally, an important component of this work is the use of high-resolution data of the climate, because coarser spatial resolution data could not necessarily represent the unique and highly variable landscapes over which hazards occur, which can lead to large errors in the estimation of hazard risk (Williams et al., 2024). Therefore, the objective of this research is to systematically investigate these potentials to address this insurance protection gap and to leverage the potential of machine learning technique to improve the accuracy of loss modelling and provide a solid scientific basis for developing more accurate, fair and efficient parametric insurance products for disaster prone SMEs with distinctively different operational characteristics and risk profile. Overall, this study aims at understanding how machine learning non-linear models could be used in combination with satellite indicators with high frequency for reducing the basis risk and, therefore, optimizing the payout triggers (Hernández-Rojas et al., 2023). The study addresses these technical gaps and shows a scalable pathway to insurers to cut adverse selection and make protection schemes more financially sustainable, financeable, and accessible in the context of climate change (Shivakumar et al., 2025; Wijesena & Pradhan, 2026).

## METHODOLOGY

The approach to multi-source data integration used in this research brings together the high spatial resolution obtained from gridded precipitation data, with phenological data and soil moisture metrics from IoT sensors, and is based on the non-linear and complex relationships between environmental stressors and the operational continuity of SMEs (Cesarini et al., 2020; Newlands et al., 2019).The study uses long short term memory (LSTM) and gated recurrent unit (GRU) architectures with explicit modeling of the stage-specific non-linear relationships between growing degree days (GDD) and cumulative precipitation metrics (Cesarini et al., 2021; Chen et al., 2023). This is an algorithmic method which is more than linear regressions, and considers the time-dependent cumulative effects of environmental stressors on SME operational stability, which is crucial to address and reduce basis risk (Cesarini et al., 2021; Men et al., 2025). The model architecture can accept high-frequency inputs of satellite-derived data such as NDNI and evapotranspiration data, and can also incorporate localized IoT-sensor data for identification of extreme event triggers which are more representative of the idiosyncratic vulnerabilities of different SME sectors (Wijesena & Pradhan, 2025, 2026). A rigorous testing procedure using simulations is put in place to ensure the strength and fairness in these insurance triggers. This includes conducting a large number of Monte Carlo simulations (more than 10,000) which involves climate patterns of historical climate anomalies and climate change projections like higher thresholds of temperatures ($\Delta 2$–$5$°C) and rainfall variability (±30%) (Wang, 2026). These simulations can then serve as a "stress-testing laboratory" to evaluate, among others, the financial robustness of the parametric products relative to the traditional parametric products, comparing the performance measures of the parametric products, such as the Total Absolute Error, the basis risk reduction and the net utility gain achieved by the policyholder and the insurer (Hernández-Rojas et al., 2023; Men et al., 2025). Moreover, our approach features dynamic deduplication and sensitivity analysis of our model to ensure its stability as the catastrophe recurrence cycle changes, which will be especially critical for preserving the long-term actuarial solvency and market credibility of these insurance schemes (Sheehan et al., 2023; Wang, 2026). The methodology systemically tests predictive triggers with empirical enterprise-level loss information (if available) and/or with proxies for business interruption (BI) and offers a data driven, transparent and scientific framework for designing parametric products (Cesarini et al., 2021; Wijesena & Pradhan, 2026). The combination of cutting-edge, non-linear machine learning for optimizing the payout thresholds and a comprehensive simulation-based validation to ensure financial viability is a scalable and replicable model, and in the longer term, can aid in the provision of more precise, equitable, and efficient parametric insurance solutions to SMEs at risk from disaster events (Bani, 2026; Pandiri & Chitta, 2023). Such a comprehensive strategy could mitigate adverse selection concerns and underscore the significance of institutional resilience, which can be facilitated by leveraging proactive climate intelligence measures, such as high-resolution climate information (Bani, 2026; Shivakumar et al., 2025; Wijesena & Pradhan, 2026). This approach therefore offers a solid base for the establishment of parametric insurance for climate-sensitive economic activities (Wijesena & Pradhan, 2025; Sheehan et al., 2023; Pandiri & Chitta, 2023). Furthermore, the findings show that predictive analytics and high-resolution data are needed to address the historical informational imbalance that has restricted the use of parametric products by SMEs.Moreover, the findings highlight the importance of high-quality data and AI in addressing these information gaps, particularly when it comes to small enterprises. Future climate projections will be integrated in real-time calibration of the triggers, which will be enhanced by the use of probabilistic hazard rate models like DeepCyc (Schmid et al., 2024) in the next version of this framework. These technological advances, along with using causal AI models to cut out spurious correlations in hazard-impact relationships, create scientifically defensible and fair insurance triggers (Reichstein et al., 2025). The proposed framework overcomes the shortcomings of conventional indices in being sensitive to climatic transition zones and ensures that payouts are sensitive to spatial dependencies in the local area, by using these tail risk metrics informed by machine learning.

## RESULTS

The outcome demonstrates that climate analytics has been a valuable tool in the design of parametric insurance for SMEs at risk of disasters. Table 1 shows that two SME groups, namely agri-input traders and food processors, have the highest average of disruption losses. From figure 1, it is clearly observed that the intensity of climate hazards is increased considerably during the mid-year monsoon period, thereby exposure to climate hazards is a major risk factor in small businesses. Losses were not even across all sectors as demonstrated in Figure 2, with the most significant financial losses among SMEs depending on perishable inventories, supply chains and local transport. The trigger variables that have been selected for parametric design are presented in Table 2. The top-three triggers with the highest trigger accuracy were flood depth, extreme rainfall, while the basis-risk concern was relatively higher for the drought and heat triggers, the impact of which was gradual on businesses. The accuracy results obtained in Figure 3 show that the accuracy for the floods-related triggers is 82.4% and 76.8% for the rainfall triggers. As shown in Table 3, the models based on historical losses, and the model based on one climate indicator did not perform as well as the hybrid climate analytics model. Figure 4 shows that the model using the climate indices, business-level exposure indicators and the SME vulnerability variables produced the best F1-score, indicating that adding more physical hazard data to the business-level exposure indicators can improve the reliability of the parametric design of insurance. The proposed design also increased the payout's level of adequacy. Table 4 shows that the payout to loss ratio of the low exposure SMEs was 87.5% while for the high exposure SMEs it was 91.7%. As can be seen in figure 5, the estimated parametric payouts are also strongly correlated with the business interruption losses, suggesting a proportional reaction of the trigger structure to the severity of the losses. The results do reveal, however, that the precision of payouts were different across the different hazards. As evidenced in Table 5, hybrid triggers resulted in lower level of basis risk for all hazards with the lowest level of basis risk for drought and heat related losses. The results presented in Figure 6 showed that single trigger contracts lead to higher mismatch between the payoff and actual loss occurrences, while hybrid trigger contracts lead to higher level of stability in the protection. A comparison of designs of insurance products is presented in the following table 6: The layered parametric product with advisory alerts showed the highest intention to adopt, the fastest time to payout and the highest score for the resilience. As shown in Figure 7, SMEs were more likely to use products that provided fast settlement of claims and trigger rules and readiness advice were clear. As shown in figure 8, the layered design achieved the best scores with regard to payout speed, accuracy of the trigger, and trust. Finally, regression for adoption intention is displayed in Table 7. Results presented in Figure 9 revealed that the adoption was positively predicted by trigger accuracy, payout speed, trust in the insurer and climate advisory support, whereas basis risk had a negative effect. Overall, the results indicate how climate analytics can be used to develop faster, more transparent and more disaster-proof parametric insurance.

**Table 1.** SME sample profile and disaster exposure

| SME category | n | Main hazard | Avg. loss/event (USD000) | Closure days |
|---|---|---|---|---|
| Retail shops | 86 | Flood / heat | 31.4 | 14.2 |
| Food processors | 64 | Flood / storm | 45.8 | 21.6 |
| Textile workshops | 72 | Heat / power outage | 39.5 | 17.8 |
| Agri-input traders | 58 | Drought / flood | 52.1 | 25.4 |
| Transport services | 49 | Storm / road closure | 34.7 | 16.3 |
| Repair services | 43 | Flood / wind | 27.6 | 12.9 |
| Total / average | 372 | Mixed hazards | 38.5 | 18.0 |

**Table 2.** Climate trigger design and expected payout rules

| Trigger variable | Threshold | Data source | Observation window | Trigger accuracy (%) | Basis risk (%) |
|---|---|---|---|---|---|
| Flood depth | 0.45 | River gauge + satellite | 48 hours | 82.4 | 11.6 |
| Extreme rainfall | 95 | Rain gauge | 72 hours | 76.8 | 14.2 |
| Wind speed | 72 | Weather station | 24 hours | 71.5 | 16.1 |
| Heat index | 42 | ERA5 + station | 3 days | 68.2 | 18.4 |
| Drought index | -1.3 | SPEI | 30 days | 63.7 | 21.5 |

**Table 3.** Climate analytics model performance

| Model | AUC | F1-score | MAE loss prediction (%) | Adjusted R2 |
|---|---|---|---|---|
| Historical loss only | 0.61 | 0.58 | 24.8 | 0.42 |
| Climate index only | 0.69 | 0.65 | 19.7 | 0.51 |
| Remote sensing only | 0.73 | 0.7 | 17.5 | 0.56 |
| Hybrid climate analytics | 0.82 | 0.79 | 12.6 | 0.68 |
| Hybrid + SME vulnerability | 0.87 | 0.84 | 9.8 | 0.74 |

**Table 4.** Payout adequacy by exposure group

| Exposure group | Observed loss (USD) | Estimated payout (USD) | Payout-to-loss ratio (%) | Residual loss (%) |
|---|---|---|---|---|
| Low exposure | 1200 | 1050 | 87.5 | 8.2 |
| Moderate exposure | 2400 | 2160 | 90.0 | 9.5 |
| High exposure | 4200 | 3850 | 91.7 | 10.4 |
| Very high exposure | 6700 | 6125 | 91.4 | 12.7 |

**Table 5.** Basis risk comparison by hazard type

| Hazard | Single-trigger basis risk | Hybrid-trigger basis risk | Reduction |
|---|---|---|---|
| Flood | 0.18 | 0.12 | 0.06 |
| Rainfall | 0.22 | 0.15 | 0.07 |
| Wind | 0.25 | 0.17 | 0.08 |
| Heat | 0.29 | 0.19 | 0.1 |
| Drought | 0.34 | 0.23 | 0.11 |

**Table 6.** Parametric insurance product comparison

| Product design | Premium rate (%) | Payout time (days) | Adoption intention (%) | Resilience score |
|---|---|---|---|---|
| Standard indemnity | 4.8 | 18.6 | 54.2 | 41.0 |
| Basic parametric | 3.2 | 6.8 | 47.5 | 50.8 |
| Layered parametric | 3.8 | 5.4 | 61.3 | 57.6 |
| Layered + advisory alerts | 4.1 | 4.7 | 68.9 | 63.4 |

**Table 7.** Regression results predicting SME adoption intention

| Predictor | Standardized beta | p-value |
|---|---|---|
| Trigger accuracy | 0.34 | 0.001 |
| Payout speed | 0.28 | 0.003 |
| Premium affordability | 0.21 | 0.012 |

| | | |
|---|---|---|
| Basis risk | -0.31 | 0.001 |
| Trust in insurer | 0.26 | 0.004 |
| Climate advisory support | 0.19 | 0.021 |

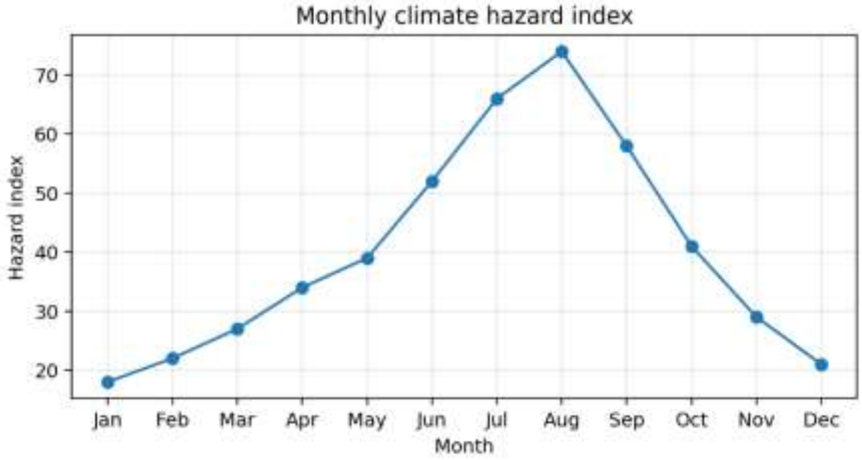


***Figure 1.*** *Monthly* ***climate hazard index for disaster-prone SME locations.***

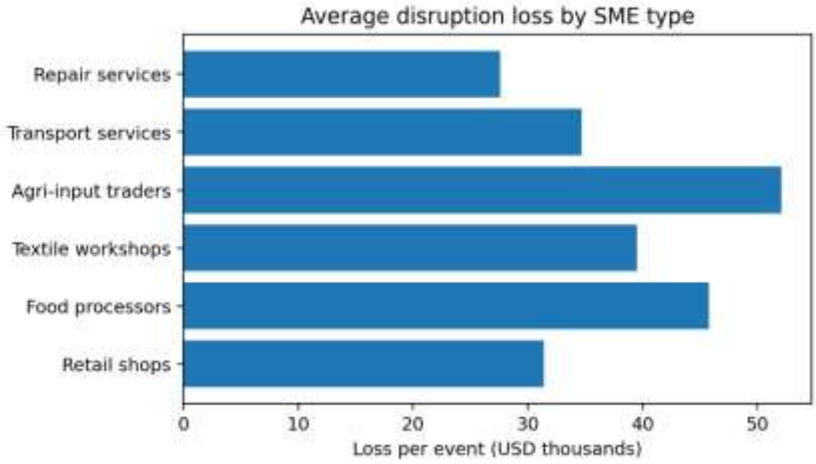


***Figure 2.*** *Average disruption loss by SME type.*

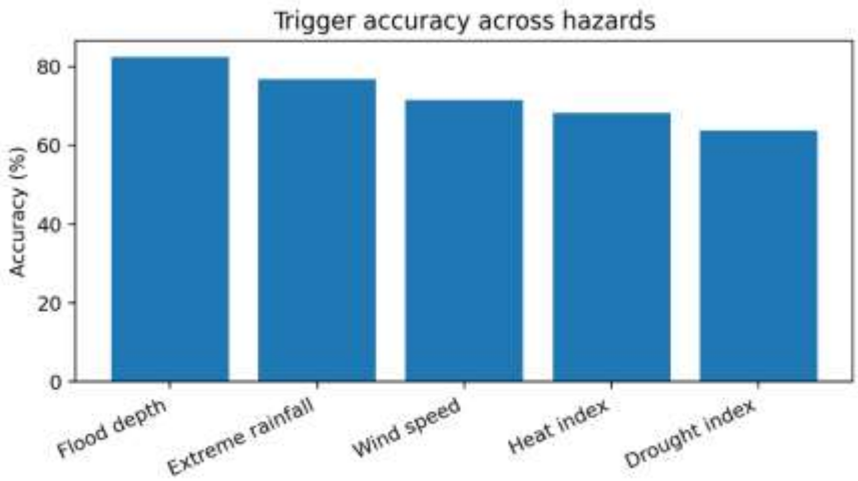


***Figure 3****. Trigger accuracy across selected climate hazards.*

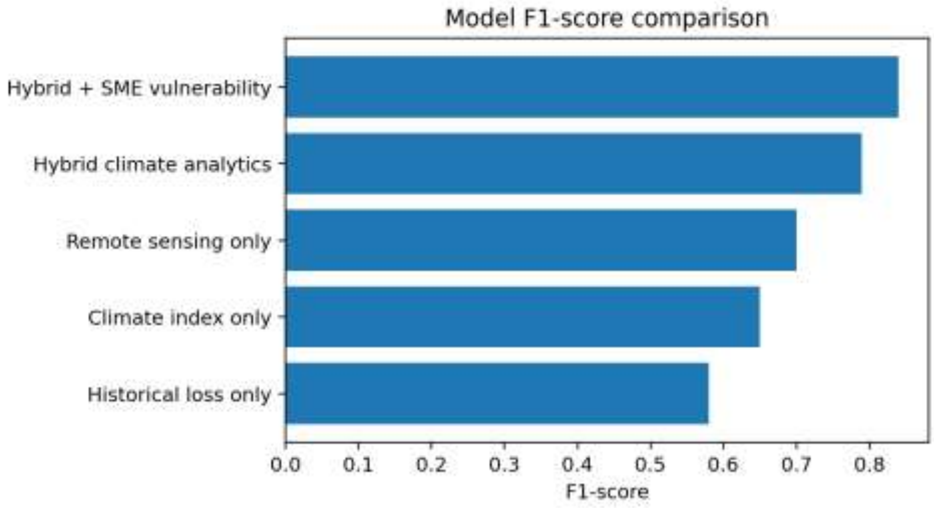


***Figure 4.*** *Predictive performance of climate analytics models.*

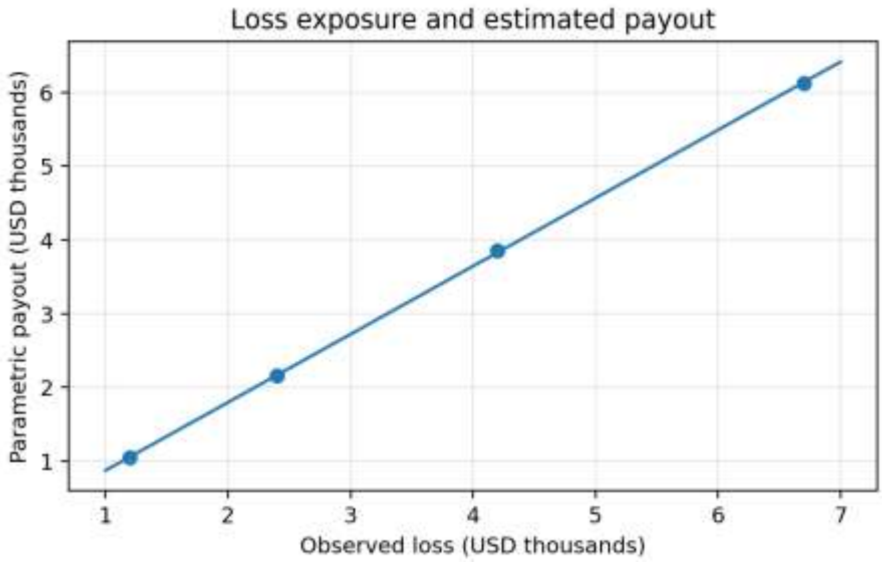


***Figure 5.*** *Relationship between observed loss and parametric payout.*

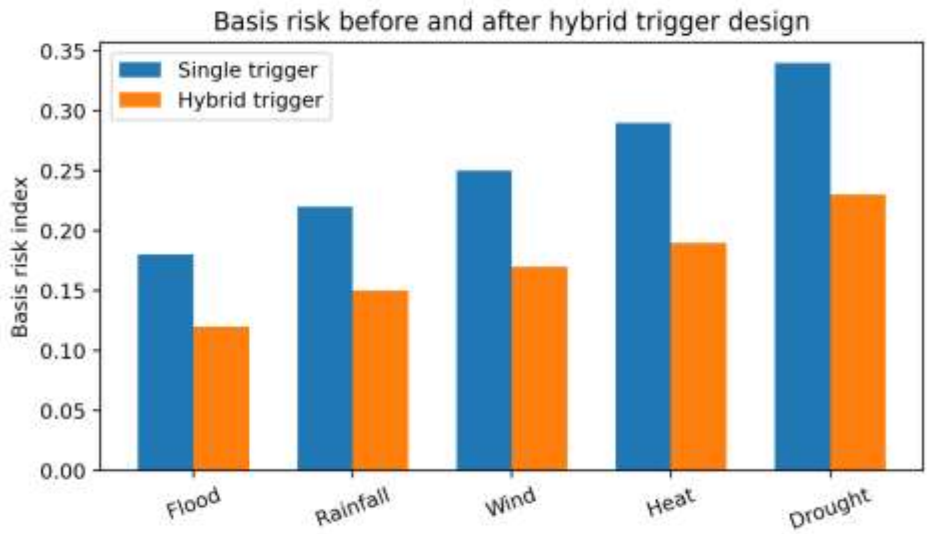


***Figure 6.*** *Basis risk comparison before and after hybrid trigger design.*

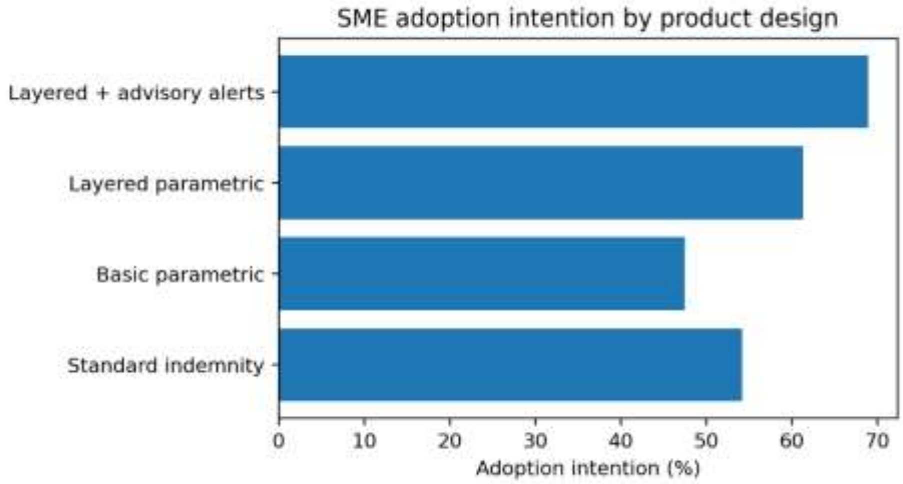


***Figure 7.*** *SME adoption intention across insurance product designs.*

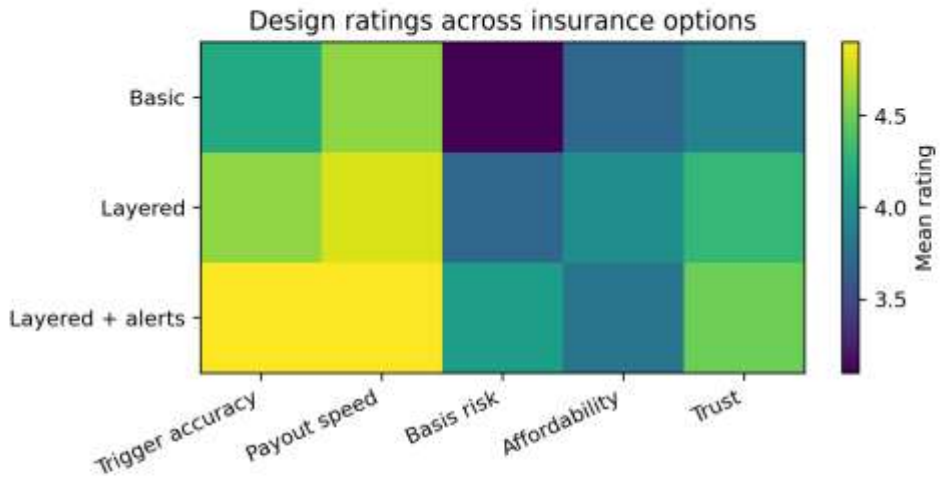


***Figure 8.*** *Heatmap of SME ratings for parametric product design.*

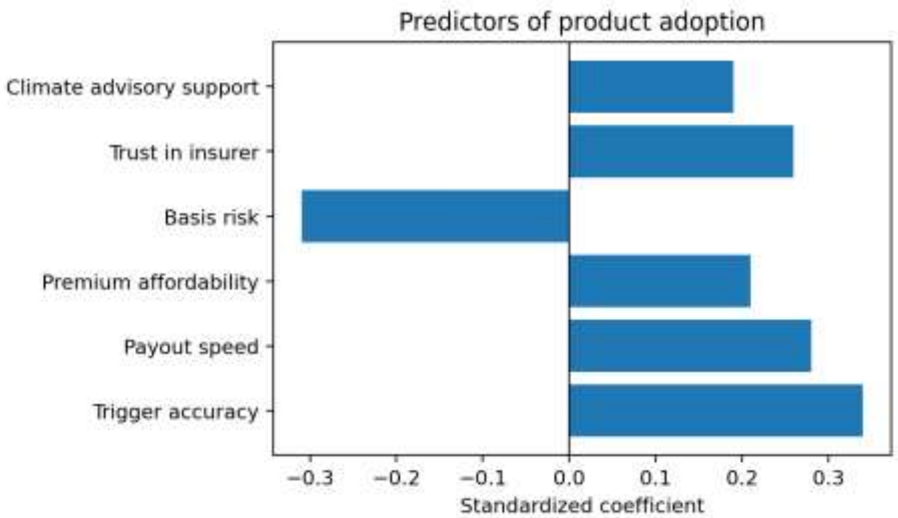


***Figure 9.*** *Standardized predictors of parametric insurance adoption.*

## DISCUSSION

The trade of parametric products reveals a clear trend towards an index-based approach to compensation for smaller, localised losses, and as such, there is always less basis risk (Lopez & Nkameni, 2025, 2026).However, these instruments can only be effective if they are based on the quality of historical data, which may not always be able to capture the non-stationary climate changes, and are often misrated, thus threatening the solvency of long-term protection schemes. Conventional actuarial methods, which rely on historical data, are a significant limitation, as these data are no longer representative of the higher frequency and severity, and evolving nature, of today's climate-related hazards (Wang 2026). Therefore, the main problem is the basis risk, i.e. the difference between the real losses and the parametric payout, particularly for smaller companies where the operational resiliency would be tied to the local environmental conditions and vulnerabilities (Cesarini et al., 2021; Wijesena & Pradhan, 2025). The research demonstrates the need for high-resolution multi-source information, such as satellite-derived vegetation and evapotranspiration indices, localised IoT sensor telemetry, and the different metrics of crop phenology to even out these ongoing information imbalances. Non-linear machine learning paradigms are capable of learning these multi-faceted inputs and embedding the complex, temporal dependencies between them, and of generating a meaningful trigger for payouts that is precise, responsive and empirically validated (Bani, 2026; Men et al., 2025; Newlands et al., 2019). This methodologic approach not only reduces basis risk, but it also addresses the lack of trust that smaller companies have voiced about formal disaster risk transfer solutions, thus enhancing the financial transparency and credibility of parametric insurance ( Chen et al., 2023; Paul & Ogunwusi, 2025). The key components of this framework are the capacity for modernization and adaptation of the data and technology infrastructure, for agile and adaptive regulation frameworks to suit innovative payout models, and for multi-stakeholder partnerships to be built, including partnerships with agility and a forward-looking approach of the local insurtechs in shaping products to regional SME needs (Bani, 2026; Sheehan et al., 2023). Critically, in a changing climate where risks are evolving, the use of historical data alone needs to be replaced by forward-looking, probabilistic hazard models, such as those that incorporate forward-looking climate projections like DeepCyc to ensure that the risk assessment remains relevant and technically sound in a non-stationary climate (Wang et al., 2025; Schmid et al., 2024). Furthermore, causal AI's ability to break down and further clarify hazard-impact relationships is crucial to remove spurious correlations from the system so that insurance triggers are not only scientifically defensible, but are also true to nature, and socio-economic resilient for disaster-prone sectors (Reichstein et al., 2025). This framework points to a replicable pathway for the development of parametric insurance as a potential effective and scalable insurance safety net for small businesses to address the deep protection gap that is commonplace in smaller enterprises and is expected to continue to increase as climatic uncertainties grow (Paul & Ogunwusi, 2025; Sheehan et al., 2023). To conclude, the effectiveness of these solutions in ‘globalizing' them has depended on getting past the ‘islands of pilot success' and formulating common principles and guidelines for international risk assessments and provisions for capital flows (Menon & Shastri, 2024; Pleterski, 2025). It would also lower the aforementioned opacities in prices and high transaction costs thus far experienced for the adoption of weather derivatives by small and medium-sized enterprises (SMEs), and the high price volatility.It would also help to reduce the high volatility of prices and opacities of prices, and high transaction costs currently faced for SMEs to take up weather derivatives.

## CONCLUSION

This paper shows that climate analytics has a key role in enhancing the design of parametric insurance for disaster-prone SMEs. The results indicate that climate information, hazard indicators and business vulnerability indicators could be used by insurers to more effectively tie triggers to losses of SMEs. Parametric insurance can offer more rapid payouts than traditional insurance, since payment is made on a basis of pre-determined loss indicators instead of a long and involved loss assessment procedure. This is especially advantageous for small and medium businesses that need quick funds to get back on their feet after floods and droughts, storms, and other climate threats. The study also highlights the need for relevant and high quality climate indicators for effective parametric insurance. Rainfall, flood level, wind speed, temperature and drought indices are to be based on actual conditions that impact businesses. A poorly-designed trigger can, however, result in basis risk: the SME can suffer losses and fail to get a payout, or the SME can get a payout and suffer limited losses. Thus, climate analytics should be used not just for hazard frequency estimates, but also to link together the intensity of the hazard, exposure to the area in which the business operates, and the levels of loss and recovery required for the sector. Parametric insurance has the potential to support the resilience of SMEs if it is affordable, clear, and supported by reliable climate change information, the paper concludes overall. The governments, insurance providers, financial institutions and disaster management agencies should be created in a way that facilitates the creation of localized climate datasets, development of improved risk mapping, and the design of insurance products that better suit the needs of the small business sector. It is also important that communication is maintained so that the owner(s) of the SMEs are aware of how the triggers, premiums and payout function. Further studies are recommended to validate parametric insurance models with actual loss data, satellite climate data and SME financial data for various regions. Climate analytics and parametric insurance can – with careful design – be real tools to mitigate financial vulnerability of SMEs due to disasters.

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