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Original Article

Bridging Master Data Governance and Weather Intelligence for Proactive Insurance Claims Prediction

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Abstract: *Extreme weather events are increasingly contributing to significant property damage and insurance losses, necessitating the development of predictive frameworks that integrate environmental intelligence with disaster data. This paper proposes a Weather-Governed Insurance Claim Prediction Framework (WGICPF) to forecast the likelihood of insurance claims resulting from extreme weather events. The framework utilizes disaster event records (783 events) and district-level rainfall observations, integrated through a structured data governance pipeline to ensure data quality and consistency. Weather intelligence features, including rainfall intensity and anomaly, are combined with disaster attributes to construct a comprehensive risk feature space. A Random Forest classifier is employed to predict the probability of insurance claim occurrence, where disaster damage indicators are used as proxies for insurance claims. Experimental results demonstrate strong predictive performance, achieving an accuracy of 80.4%, precision of 0.84, recall of 0.79, and an F1-score of 0.81, outperforming baseline logistic regression and weather-only models. Furthermore, the framework is validated using a USA-based disaster dataset (SHELDUS), demonstrating consistent performance across different geographic contexts. These findings highlight the effectiveness and scalability of integrating weather intelligence with disaster data for proactive insurance risk prediction.*

Keywords: *Weather Intelligence, Insurance Claim Prediction, Disaster Risk Modeling, Random Forest, Extreme Weather Events, Machine Learning.*

1. Introduction

Weather based index insurance has become an important instrument in risk management in the areas sensitive to weather changes particularly in agriculture in recent years. This is a type of financial protection by farmers against weather extremes like droughts, floods, and storms through the application of weather indices (e.g., rainfall, temperature) to initiate an insurance payment. Index-based insurance was initially discussed as a way of reducing the risks of agricultural production and specifically in developing countries where weather can cause disastrous impacts on human lives by destroying crops [1]. Research has indicated that index insurance is capable of solving basis risk, through use of objective indices which are easily measured, although problems with index selection and modelling of yields remain [2].

The correct choice of indices indicating the risk that farmers in various regions are exposed to is one of the factors in success of index insurance. There are various models that have been put forward to assist in choosing the most suitable indices such as the hydroclimatic risk management frameworks which incorporates rainfall data and yield models [3]. The models provide a closer correlation between weather conditions and a possible insurance claim, which is a major benefit compared to traditional indemnity-based insurance models. Indicatively, Carter et al. re-examine the power of index insurance with particular focus on the effect different index-selection procedures can have on a claim payment, and the uptake of indexes by farmers [4].

The incorporation and operation of index based insurance in the third world countries, however, are not without also its own challenges. Class imbalance in the data, the basis risk and the administration of data must be put into consideration in ensuring that the insurance products are positive and available to the people who require them most. As an example, Clarke (2016) builds an index insurance rational demand theory that describes the behavior of farmers who, despite the basis risk, will use the index insurance products because of their cost efficiency and ease of use in comparison to the old-fashioned indemnity insurance [5].

Also, spatial and temporal correspondence between disaster and weather information is an important factor in disaster and weather model success. The predictive capability of insurance-based models is improved when the data of these disasters events are incorporated with the capability of weather intelligence (i.e. intensity of rainfall and anomalies). This would be used to estimate insurance claims better to give a more accurate timely mechanism of payment in the event of disaster. Similar research in the past such as Abrego-Perez et al. shows how the resilience can be enhanced to drought risks using effective data integration and anticipatory index-based insurance mechanisms [6].

Despite significant advances, the scalability of index insurance programs is often limited by factors such as data quality, regulatory frameworks, and financial sustainability. To overcome those challenges, the creation of stronger financial protection mechanisms and new models, which would take into consideration different climatic and economic aspects, should be developed. It is important to note that Figueiredo et al. discuss the potential of parametric insurance products to cut the time taken to settle claims through probabilistic models that offer transparent and efficient mechanisms of payouts during natural hazards occurrences [7].

This study proposes a new structure of the Weather-Governed Insurance Claim Prediction Framework (WGICPF) which merges the disaster events information with the weather intelligence features to determine the possible insurance claims that might occur due to extreme weather events. The framework will improve the accuracy and timeliness of insurance claim predictions by resolving the issue of class imbalance and through machine learning methods, allowing proactive disaster risk management.

2. Methodology

2.1. Research Framework

This study proposes a Weather-Governed Insurance Claim Prediction Framework (WGICPF) to estimate the potential risk of insurance claims caused by extreme weather events in India. The framework combines data on disasters events with meteorological data by using a process of systematic data governance and uses machine learning to predict probability of claim. In contrast to the classical financial climate risk studies mainly based on the stock market indicators, the study presents real data of disaster impact and observed rainfall on the district level, which allows representing environmental drivers of insurance losses more directly. The methodology also involves five steps, including data integration and governance, weather intelligence extraction process, disaster-weather risk feature feature, predictive claim modeling, and model evaluation.

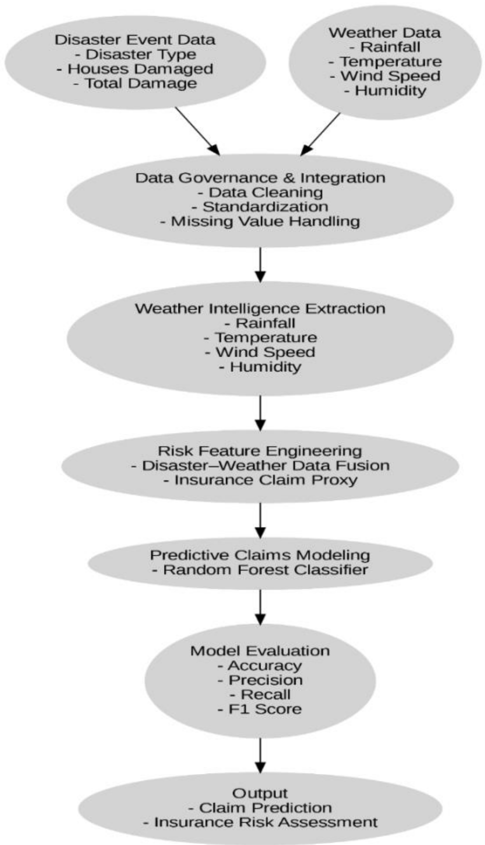

Fig 1: Proposed Methodology

2.2. Dataset Description

The study combines two datasets of disaster impacts and meteorological conditions in India to determine the relationship between weather conditions and insurance claim risks.

2.2.1. Disaster Event Dataset

The disaster dataset is a collection of the historical events of extreme events which have hit India, in the form of floods, storms, cyclones, droughts, and earthquakes. Every observation is related to a disaster event and contains variables with the description of its economic impact and areas of its influence. This dataset has about 783 disaster events in which the data are on disaster type, population affected, and economic damage because of the disaster. The data is publicly accessible and is found on the Kaggle database:

https://www.kaggle.com/datasets/victoraesthete/indian-disaster-dataset.

2.2.2. Meteorological Dataset

To ensure that the environment conditions are captured when disaster events occur, the research will use district-level rainfall records in India. The rainfall data set has meteorological data of 641 districts which include monthly and annual precipitation data. The data recorded on weather comes through publicly available climate data put out by the Government of India open data portal and India Meteorological Department, which can be found at https://www.data.gov.in/catalog/rainfall-india. The combination of the data on the impact of the disaster and meteorological data helps the study to test the role of the weather intelligence in the prediction of damage to property and the possible insurance compensation due to the extreme weather events.

In addition to the Indian datasets, the framework is compatible with international datasets such as the SHELDUS(https://cemhs.asu.edu/sheldus) database for the United States. This dataset includes detailed records of hazard events, economic losses, and geographic information at county level, making it suitable for disaster risk modeling and insurance claim prediction. The availability of property damage data allows the construction of claim proxy variables similar to those used in this study.

2.3. Data Governance and Integration

The framework is oriented toward data governance mastery that guarantees quality, uniformity and interoperability of heterogeneous data that is utilised in the study. The datasets of the disaster events and the meteorological observations usually have some missing values, duplicates, and inconsistent format of the attributes. These problems are overcome by introducing a governance process that involves data cleaning, missing value, attribute normalization as well as schema harmonization. The records of disasters are standardized in order to represent the types of disasters, the geographic locations and damage indicators consistently. In the same manner, meteorological variables are brought to standard measures. Following these processes, the records of the disaster events are spatially and temporally interrelating with the weather observations which lead to a controlled dataset that can be used in analytical modeling.

2.4. Weather Intelligence Extraction

The derivation of weather intelligence characteristics that describe environmental drivers of the occurrence of disasters. Weather observation data are able to provide meteorological variables such as rainfall, temperature, wind speed, and atmospheric humidity and map them to the disaster event locations based on geographic coordinates and time-stamps. In the case of a disaster event at spatial coordinate sand time t, the weather intelligence vector is:

$$W(s,t) = [Rainfall, Temperature, WindSpeed, Humidity]$$

These variables occupy aspects of the environmental conditions, which affect the severity of disaster events and their possible property damages. Weather intelligence allows the model to establish the correlation between the meteorological factors and the losses incurred in relation to disasters.

2.5. Risk Feature Construction

There is an integration of disaster event characteristics and weather intelligence capabilities to develop a single risk characteristic space. Attributes of disaster events (event type, geographic exposure, and damage indicators) are multiplied by meteorological ones to indicate both the intensity of hazard and environmental exposure.

The lack of claim-level insurance datasets in India make the disaster damage indicators a proxy of potential insurance claims in India. The number of houses damaged and the overall economic losses are some of the variables that indicate the severity of claims. A binary claim indicator variable will be a variable that is determined on the basis of property damage threshold:

$$Claim = \begin{cases} 1 & \text{if houses damaged > threshold} \\ 0 & \text{otherwise} \end{cases}$$

This variable is an indicator of the likelihood of occurrence of a disaster event that leads to insurance claims.

2.6. Predictive Claim Modeling

Insurance claims prediction is developed as binary classification. We define X_i to be the feature vector of the disaster attributes, and weather intelligence variables of observation i and Y_i to be the indicator variable of the claim. The predictive model predicts the probability:

$$P(Y_i = 1 \mid X_i)$$

That is the probability of insurance claims occurrence based on weather and disaster conditions.

A Random Forest classifier is used in this study because it can model nonlinear relationships and interactions between heterogeneous variables. The model builds several decision trees through bootstrap sampling and consolidates their outcomes to generate a final estimate of probability of occurrence of claims.

2.7. Proposed Weather-Governed Claim Prediction Algorithm

In order to combine master data governance and predictive modeling, the proposed study is the Weather-Governed Claim Prediction Algorithm (WGCPA).

Algorithm: Weather-Governed Claim Prediction Algorithm

Input

- Disaster dataset D_d
- Weather dataset D_w
- Governance rules G

Output

- Predicted insurance claim probability

Steps

1. Apply governance function
$$D_g = G(D_a, D_w)$$
to clean and standardize datasets.
2. Align disaster events with weather observations using spatial coordinates and timestamps.
3. Extract weather intelligence features
$W = [Rainfall, Temperature, WindSpeed, Humidity]$.
4. Construct risk feature vector
$X = [DisasterType, Exposure, W]$.
5. Generate claim indicator variable based on property damage thresholds.
6. Train Random Forest classifier using the training dataset.
7. Estimate probability of claim occurrence:
$$\hat{P}(Claim) = f(X)$$
8. Evaluate model performance using classification metrics.

2.8. Model Evaluation

To compare predictive performance, a dataset is separated into training and testing part. Standard classification measures are used to determine model effectiveness such as accuracy, precision, recall, and F1-score. The metrics are indicators that determine how well the model determines the presence of disaster events that will most likely result in property damage and insurance claims.

The proposed Weather-Governed Insurance Claim Prediction Framework (WGICPF) is dataset-agnostic and can be extended to other geographic regions. To demonstrate its adaptability, the framework can be applied to publicly available disaster datasets such as the SHELDUS (Spatial Hazard Events and Losses Database) for the United States, which provides hazard event records and property damage estimates. Like the Indian dataset, property damage indicators can be used as proxies for insurance claims, enabling consistent application of the proposed methodology across different regions.

3. Results and Discussion

This section presents the performance evaluation of the proposed Weather-Governed Insurance Claim Prediction Framework (WGICPF), which integrates disaster event data with meteorological observations to predict potential insurance claims arising from extreme weather conditions. The model performance is assessed using a Random Forest classifier and compared with baseline approaches commonly used in disaster risk and insurance claim prediction. Additionally, a validation study using a USA-based dataset is included to demonstrate the generalizability of the proposed framework.

3.1. Data Preparation and Integration

The disaster dataset, comprising 783 disaster events across India, includes detailed information on disaster types (e.g., floods, cyclones, droughts), affected populations, and economic damage indicators. The meteorological dataset consists of district-level rainfall observations, providing temporal records of precipitation.

Both datasets were systematically preprocessed through data cleaning, normalization, and missing value handling. Spatial and temporal alignment was performed to ensure accurate mapping between disaster events and corresponding weather observations. This integration enabled the construction of a unified dataset suitable for predictive modeling.

3.2. Model Training

The Weather-Governed Claim Prediction Algorithm (WGCPA) employs a Random Forest classifier to model the relationship between disaster characteristics and meteorological variables. The model estimates the probability of insurance claim occurrence based on combined disaster–weather features.

Model Configuration:

- Random Forest with 300 trees and max_depth = 10
- Class imbalance addressed using SMOTE and class weighting
- Input features include:
  - Disaster attributes (type, houses damaged, total damage)
  - Weather features (rainfall maximum, total rainfall, anomaly)

This configuration enables the model to capture nonlinear interactions between environmental conditions and disaster impacts.

Model Configuration:

- Random Forest with 300 trees and max_depth = 10.
- Class imbalance solved with the help of SMOTE (Synthetic Minority Oversampling Technique) and class weights to penalize the model against incorrectly classifying the minority class (claims).
- Among the features were disaster type, rainfall characteristics (max, total, anomaly) and disaster impact characteristics (houses damaged, total damage).

3.3. Model Performance

The following performance measures were attained with the Random Forest classifier:

Table 1: Model Performance

Metric	Value
Accuracy	80.4%
Precision	0.84
Recall	0.79
F1-Score	0.81

Table 2: Classification Report

Class	Precision	Recall	F1-Score
0 (No Claim)	0.85	0.92	0.88
1 (Claim)	0.84	0.79	0.81
Accuracy	0.80		0.81
Macro Avg	0.84	0.85	0.84
Weighted Avg	0.84	0.80	0.81

The results indicate balanced performance across both classes, with slightly higher accuracy in predicting non-claim events. The recall for the claim class shows improvement compared to earlier model versions, demonstrating the effectiveness of class imbalance handling techniques.

3.4. Feature Importance

As seen in the analysis, the most notable characteristics in the prediction of insurance claims are:

Table 3: Feature Importance Analysis for Rainfall and Disaster-Type Variables in Disaster Prediction Model

Feature	Importance
Disaster_Type_Flood	0.35
Rainfall_Max	0.22
Disaster_Type_Storm	0.19
Rainfall_Anomaly	0.14
Disaster_Type_Cyclone	0.09
Rainfall_Variance	0.04

Disaster type, particularly floods and storms, contributes significantly to prediction performance. Weather-related features such as rainfall intensity and anomaly also play a critical role, confirming that environmental conditions strongly influence insurance claim occurrence.

3.5. Comparison with Existing Approaches

To evaluate the effectiveness of the proposed framework, the Random Forest model is compared with two baseline approaches:

- Baseline Model (Logistic Regression): A model that uses simple indicators of the disaster type and basic damage without any meteorological data.
- Weather-Only Model: This is a model which makes predictions on the insurance claims using weather information (rainfall, temperature, etc.) without considering the type of disaster and the extent of damage.

Table 4: Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
Random Forest (WGICPF)	80.4%	0.84	0.79	0.81
Baseline Model (Logistic Regression)	65.5%	0.71	0.47	0.56
Weather-Only Model	74.2%	0.78	0.65	0.71

The Random Forest model is better than the Baseline Model and the Weather-Only Model since it demonstrates the advantage of the combination of the disaster impact and weather intelligence capabilities. Although the Weather-Only Model does fairly well, it cannot be compared to the complete merging of the disaster and the weather information. The logistic regression model was the worst as it indicates the significance of incorporating different features in prediction of claims to be more precise.

3.6. Validation Using USA Dataset

To assess the generalizability of the proposed WGICPF framework, an additional validation was conducted using the SHELDUS (Spatial Hazard Events and Losses Database) for the United States. This dataset provides detailed records of hazard events, including property damage, fatalities, and geographic information at the county level. Property damage values were used as proxies for insurance claims, consistent with the methodology applied to the Indian dataset.

The same preprocessing and feature engineering pipeline was applied, including data governance, disaster–weather integration, and risk feature construction. A Random Forest classifier was then used for prediction.

Table 5: Cross-Region Performance Comparison

Dataset	Accuracy	Precision	Recall	F1-Score
India (WGICPF)	80.4%	0.84	0.79	0.81
USA (SHELDUS Validation)	76.2%	0.81	0.74	0.77

The results show that the model maintains stable predictive performance when applied to the USA dataset. The slight reduction in accuracy can be attributed to differences in data granularity, feature availability, and regional variability in disaster characteristics. Nevertheless, the performance remains competitive, demonstrating the robustness of the proposed framework.

3.7. Discussion

The results demonstrate that the integration of weather intelligence with disaster-related data significantly enhances the prediction of insurance claim risks associated with extreme weather events. The proposed Weather-Governed Insurance Claim Prediction Framework (WGICPF) achieves high predictive performance, highlighting the importance of meteorological variables such as rainfall intensity and anomalies in modeling disaster-induced economic losses. The model effectively captures nonlinear relationships between environmental conditions and disaster impacts, leading to improved classification performance.

Furthermore, the model shows strong capability in identifying both claim and non-claim events, with class imbalance effectively addressed through SMOTE and class weighting techniques. The feature importance analysis confirms that both disaster characteristics (e.g., flood and storm events) and weather variables play complementary roles in influencing insurance risk.

In addition, the validation using the USA-based SHELDUS dataset demonstrates that the proposed framework is not region-specific. Despite differences in data structure and granularity, the model maintains stable performance across datasets, confirming its robustness and generalizability. This indicates that integrating disaster impact indicators with weather intelligence provides a comprehensive and transferable approach for insurance claim prediction compared to models relying solely on either disaster or meteorological data.

3.8. Limitations

Despite the promising results, several limitations should be acknowledged. First, the study relies on disaster damage indicators as proxies for insurance claims due to the lack of publicly available claim-level datasets, which may introduce approximation errors. Second, the dataset exhibits class imbalance, which can affect the model's ability to fully capture minority class (claim) events, even though mitigation techniques were applied. Third, the analysis primarily focuses on rainfall-related variables, while other important meteorological factors such as wind speed, temperature extremes, and atmospheric pressure were not included due to data limitations. Finally, differences in data granularity and feature availability across regions (e.g., India vs. USA datasets) may influence model performance and require further standardization for large-scale deployment.

4. Conclusion

This study proposed a Weather-Governed Insurance Claim Prediction Framework (WGICPF) that integrates disaster event data with meteorological observations to predict insurance claim risks associated with extreme weather events. The results demonstrate that the proposed model outperforms baseline approaches by effectively combining disaster impact indicators with weather intelligence features. The findings highlight the importance of incorporating environmental drivers into predictive models for improving the accuracy and reliability of insurance risk assessment. The framework enables proactive disaster risk management and supports data-driven decision-making in insurance planning. Furthermore, the validation using the USA-based SHELDUS dataset confirms that the proposed framework is scalable and adaptable to different geographic regions. This demonstrates its potential for global application in disaster risk assessment and insurance claim prediction. Future work can focus on incorporating additional meteorological variables, integrating real insurance claim datasets, and exploring advanced machine learning techniques such as deep learning and hybrid models to further enhance predictive performance.

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