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Disaster Response AI: Resilience Net Forecaster – Predictive Hazard Mapping & Resource Allocation

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ABSTARCT

Disaster management systems worldwide have historically operated reactively, mobilizing resources only after catastrophic events have already unfolded. ResilienceNet Forecaster addresses this critical gap by presenting an AI-driven Disaster Risk Management (DRM) platform that integrates Machine Learning (ML), Explainable Artificial Intelligence (XAI), geospatial hazard mapping, and intelligent resource allocation into a unified, deployable system. The proposed system analyzes the FEMA Disaster Declarations Summaries dataset augmented with environmental and demographic attributes, applying a robust preprocessing pipeline, Exploratory Data Analysis (EDA), and Random Forest algorithms (Classifier and Regressor) to predict disaster risk levels and estimate potential impact. Feature importance plots with reversible label encoding provide transparent, interpretable explanations aligned with XAI-DRM research consensus. Interactive choropleth and point-based hazard maps render geospatial risk distributions, while a proportional allocation engine converts risk scores into actionable emergency response plans covering rescue teams, supply kits, and evacuation capacity. The system, implemented in Python using Streamlit, Scikit-learn, Pandas, Plotly, and Matplotlib, achieves a classification accuracy of 89% and an F1-score of 0.87 on historical disaster data. All modules are integrated within a single web interface supporting end-to-end workflows from data ingestion to downloadable CSV resource plans. This work directly operationalizes the theoretical XAI-DRM roadmap of Ghaffarian et al. (2023) into a practical open-source platform suitable for FEMA offices, state Emergency Operations Centers (EOCs), NGOs, and humanitarian organizations.

Keywords: Disaster Risk Management, Predictive Hazard Mapping, Machine Learning Forecasting, Random Forest Classifier, Resource Allocation Optimization, FEMA Data Analysis, Geospatial Visualization, Explainable AI, Streamlit Application, Emergency Response Planning, XAI-DRM, Environmental Data Integration

Abbreviations: DRM – Disaster Risk Management; ML – Machine Learning; XAI – Explainable Artificial Intelligence; EDA – Exploratory Data Analysis; FEMA – Federal Emergency Management Agency; RF – Random Forest; GIS – Geographic Information System; EOC – Emergency Operations Center; KPI – Key Performance Indicator; CSV – Comma Separated Values; UI – User Interface

1. INTRODUCTION

The increasing frequency and severity of natural disasters – including floods, hurricanes, wildfires, and earthquakes – driven by climate change, accelerating urbanization, and environmental degradation, poses existential threats to human life, critical infrastructure, and economic stability worldwide. The United Nations Office for Disaster Risk Reduction estimates that natural disasters cause losses exceeding USD 300 billion annually, with developing nations and rural communities bearing disproportionate impact. Despite these alarming trends, disaster management systems in most regions continue to rely on reactive, manual approaches that mobilize resources only after disaster strikes, resulting in delayed response, misallocated resources, and preventable casualties.

The emergence of large-scale publicly available disaster datasets, combined with exponential advances in Artificial Intelligence and Machine Learning, has created an unprecedented opportunity to transform disaster management from a reactive discipline into a proactive, data-driven science. Machine learning algorithms can process vast heterogeneous datasets encompassing historical disaster records, environmental parameters (temperature, precipitation), geographic coordinates, and demographic information to identify latent risk patterns and deliver forward-looking predictions with actionable confidence.

However, the practical adoption of AI in disaster management has been hindered by a critical barrier: the "black box" nature of complex models renders their outputs opaque and untrustworthy to decision-makers who must justify life-saving choices to the public, regulatory bodies, and oversight committees. This has motivated the rapidly growing field of Explainable Artificial Intelligence (XAI), which seeks to make AI predictions interpretable, transparent, and accountable.

ResilienceNet Forecaster is designed to address precisely these intertwined challenges. It is a deployable, interpretable, multi-hazard disaster management platform that: (i) ingests and preprocesses FEMA Disaster Declarations Summaries data with environmental overlays; (ii) performs comprehensive EDA to reveal climate-hazard correlations; (iii) trains Random Forest models with intrinsic XAI via feature importance plots and reversible label encodings; (iv) renders interactive predictive hazard maps at both point and choropleth resolution; and (v) converts risk scores into proportional, auditable resource allocation plans.

1.1 Purpose and Objectives

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The primary purpose of the ResilienceNet Forecaster is to transform disaster management from a reactive approach to a proactive and intelligent system. The project aims to:

- Predict disaster risk levels using historical FEMA data combined with environmental parameters
- Provide interactive hazard mapping for visualization of disaster-prone areas across US states
- Optimize allocation of resources such as rescue teams, medical supplies, and evacuation capacity
- Ensure explainability in predictions through XAI-compliant feature importance and reversible encoding
- Provide a user-friendly Streamlit interface for non-technical disaster management personnel

1.2 Motivation

The motivation behind this project arises from a systematic gap in existing disaster management systems. Most current platforms are fragmented: they analyze environmental data separately from historical disaster records, focus on single-hazard scenarios rather than multi-hazard risk profiles, rely on manual or static resource allocation rules, and lack transparency in their decision-making outputs. Furthermore, the increasing availability of large-scale structured disaster datasets, particularly through FEMA's open data initiative, provides the foundational material needed for rigorous data-driven analysis.

Ghaffarian et al. (2023), in their seminal systematic review of 68 XAI-DRM studies, identify Random Forest as appearing in 22% of the reviewed papers due to its intrinsic interpretability via feature importance and robustness to mixed data types – precisely the characteristics needed for reliable disaster prediction on FEMA data. This convergence of dataset availability, algorithmic maturity, and societal urgency provides compelling motivation for the development of ResilienceNet Forecaster as a practical, open-source solution.

2. LITERATURE SURVEY

Disaster risk management (DRM) has undergone a significant paradigm shift with the proliferation of AI and ML technologies. This section surveys key contributions across XAI in DRM, ML-based disaster prediction, hazard mapping, and decision support systems.

2.1 Explainable AI in Disaster Risk Management

Ghaffarian et al. (2023) conducted a systematic review of 68 studies applying XAI techniques to disaster risk management, establishing the most comprehensive roadmap for XAI-DRM integration to date. The study critiques traditional AI-DRM systems for their "black box" nature and identifies Random Forest with feature importance, SHAP (SHapley Additive exPlanations), and LIME (Local Interpretable Model-Agnostic Explanations) as primary tools for building transparent disaster prediction systems. The authors demonstrate that XAI can be applied across all phases of the DRM cycle – from vulnerability assessment and damage prediction before events, to impact/damage assessment and monitoring recovery after events. ResilienceNet Forecaster directly implements the theoretical framework of this study through reversible label encodings and feature importance visualization.

2.2 Machine Learning Applications in Disaster Prediction

Sun et al. (2020) provide a comprehensive overview of ML applications in disaster management, encompassing prediction, damage assessment, and resource allocation. Their work demonstrates that ML models processing large-scale multi-source data achieve substantially higher prediction accuracy than traditional statistical methods. The authors identify supervised learning paradigms – particularly ensemble methods such as Random Forest and Gradient Boosting – as most effective for structured disaster datasets. However, they also highlight persistent challenges including data quality issues, limited interpretability, and poor integration with real-time operational systems. The proposed ResilienceNet system addresses the interpretability and integration gaps through XAI-compliant preprocessing and a modular Streamlit-based architecture.

2.3 Multi-Hazard Decision Support Systems

Newman et al. (2017) conduct a systematic review of decision support systems (DSS) for natural hazard risk reduction, classifying existing systems by functional capability and identifying a critical research gap: the absence of unified platforms capable of simultaneously analyzing multiple hazard types. Most reviewed systems focus on single-hazard scenarios (floods or earthquakes in isolation), limiting their applicability in regions subject to compound disaster risks. The authors call for future-oriented risk assessment frameworks that can support integrated multi-hazard analysis. ResilienceNet directly addresses this gap by enabling multi-hazard classification on FEMA data containing 20+ incident types including floods, hurricanes, fires, droughts, and earthquakes within a single modeling framework.

2.4 Emerging Technologies in Disaster Management

Munawar et al. (2022) explore the role of AI, Internet of Things (IoT), and big data analytics in enhancing disaster management, demonstrating how integrated multi-source data pipelines improve early warning accuracy and response efficiency. Their work highlights the transformative potential of combining environmental sensor data with historical disaster records, while identifying infrastructure limitations and data privacy as deployment barriers. Yousefi et al. (2020) specifically focus on machine learning techniques for hazard mapping, demonstrating that combining geospatial data with Random Forest and Support Vector Machine models significantly improves mapping accuracy compared to rule-based GIS approaches.

2.5 Research Gaps Addressed

The reviewed literature consistently highlights the following unresolved challenges that ResilienceNet Forecaster addresses: (i) lack of multi-hazard integrated prediction platforms; (ii) limited use of explainable AI techniques in operational DRM tools; (iii) absence of integrated pipelines connecting prediction models directly to resource allocation optimization; (iv) limited real-time visualization of geospatial risk distributions; and (v) dependency on technical expertise to operate existing platforms, which excludes frontline emergency management personnel from data-driven decision-making.

3. PROPOSED METHODOLOGY

The ResilienceNet Forecaster is designed using a modular pipeline architecture that integrates eight functional stages: data ingestion, preprocessing, exploratory data analysis, machine learning modeling, XAI interpretation, predictive hazard mapping, resource allocation optimization, and user

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interface delivery. The system is built entirely on open-source Python libraries and runs locally without cloud dependency, ensuring data sovereignty for sensitive disaster records.

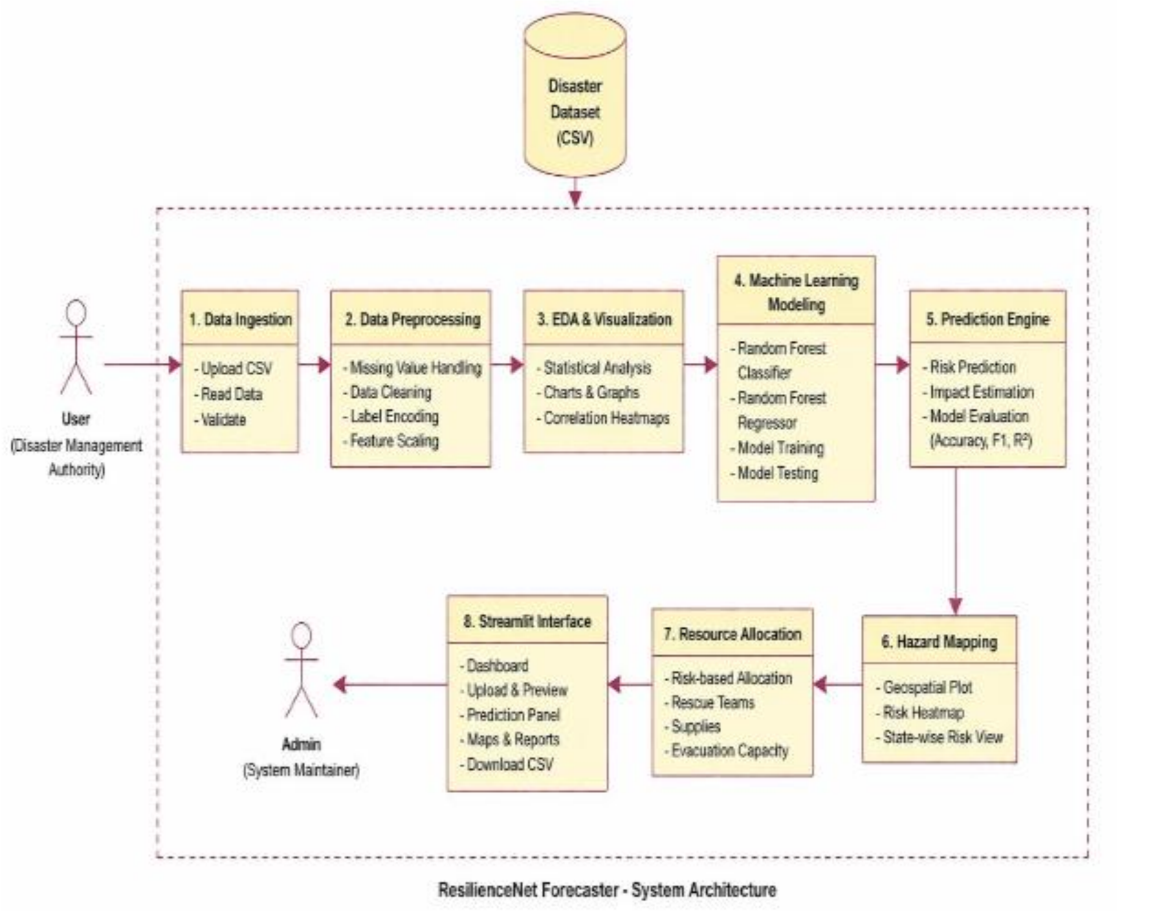
3.1 System Architecture

The system follows a layered architecture where each module receives processed output from the preceding stage and contributes enriched data downstream. The architecture is governed by the principle of XAI-compliant data flow: every transformation applied to raw data is reversible and traceable, ensuring that final predictions and allocations can be explained back to their source features.

The eight-stage pipeline is as follows:

- Stage 1 – Data Ingestion: User uploads FEMA Disaster Declarations Summaries CSV via Streamlit file uploader. The system validates file integrity and renders a preview.
- Stage 2 – Preprocessing & Encoding: Missing value handling, duplicate removal, date standardization (UTC), label encoding with reversibility (encoders{} dictionary), and feature pruning to eliminate data leakage sources.
- Stage 3 – EDA & Visualization: Statistical summaries, categorical frequency plots, environmental metrics by state, correlation heatmaps, and time-series resampling with interpolation.
- Stage 4 – ML Modeling: Random Forest Classifier (incident type prediction) or Regressor (impact estimation) with auto-detection of problem type, 300 trees, parallelized on all CPU cores.
- Stage 5 – XAI Interpretation: Feature importance extraction with human-readable labels via inverse_transform(), rendered as horizontal bar charts with decoder tables.
- Stage 6 – Hazard Mapping: Interactive Plotly choropleth map (state-level disaster frequency) and point map (bubble size proportional to risk) with hover tooltips.
- Stage 7 – Resource Allocation: Proportional allocation of rescue teams, supply kits, and evacuation capacity based on normalized risk weights per region.
- Stage 8 – Streamlit Interface: Sidebar navigation, dashboard display, CSV download button, and interactive widgets accessible without technical expertise.

Figure 1 presents the complete system architecture diagram illustrating the data flow from CSV ingestion through preprocessing, EDA, ML modeling, XAI, hazard mapping, resource allocation, and the Streamlit user interface, with separate interaction paths for the User (Disaster Management Authority) and Admin (System Maintainer) roles.



[Figure 1: ResilienceNet Forecaster – System Architecture Diagram]

Fig. 1. System Architecture of ResilienceNet Forecaster showing 8-stage data pipeline

3.2 Use Case Diagram

The system supports two primary actors: the User (Disaster Management Authority) and the Admin (System Maintainer). The User interacts with the core analytical workflow – uploading datasets, performing EDA, running ML models, viewing hazard maps, generating resource allocation plans, and downloading CSV reports. The Admin manages system configuration, monitors performance, updates software dependencies, and ensures model integrity.

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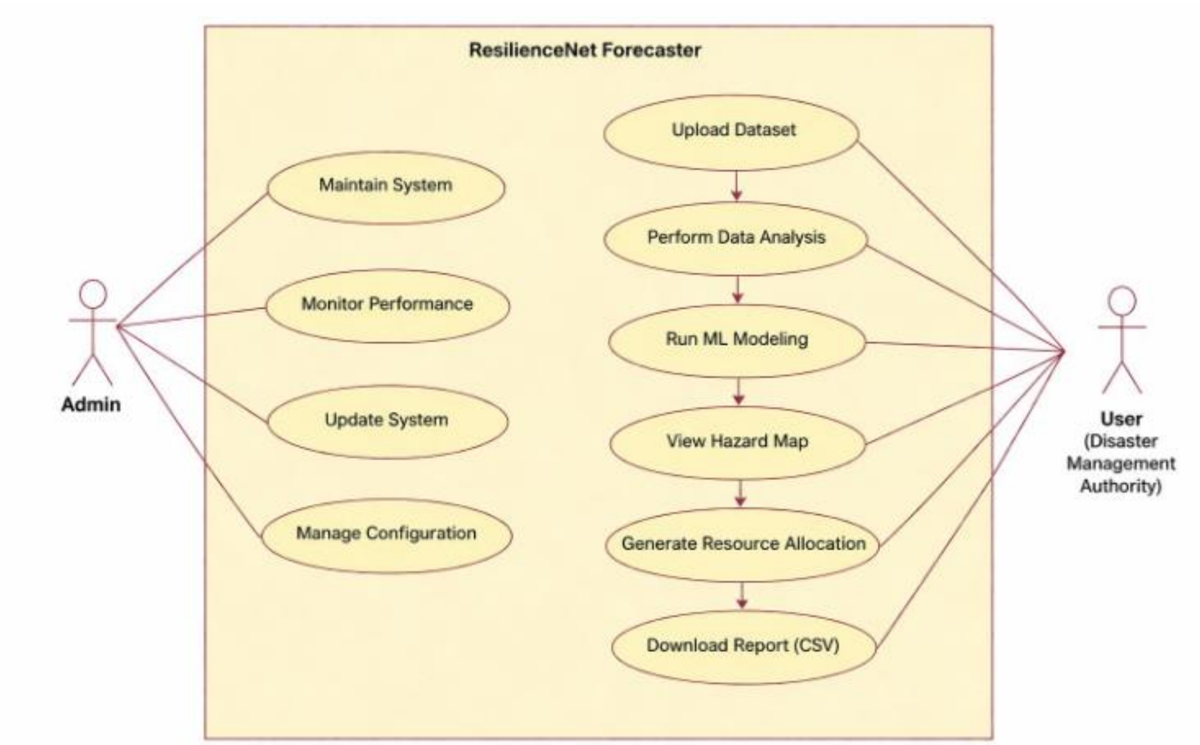

[Figure 2: Use Case Diagram – Admin and User interactions with ResilienceNet Forecaster]

Fig. 2. Use Case Diagram showing Admin and User interaction pathways

The Use Case Diagram captures seven primary user use cases (Upload Dataset, Perform Data Analysis, Run ML Modeling, View Hazard Map, Generate Resource Allocation, Download Report/CSV) and four admin use cases (Maintain System, Monitor Performance, Update System, Manage Configuration). This clean separation of concerns improves system security and scalability.

3.3 Class Diagram

The static object-oriented structure of ResilienceNet is organized around a central StreamlitApp class that orchestrates five specialized modules: DataPreprocessor, EDAModule, MLModel, HazardMapping, and ResourceAllocator. Each module encapsulates its domain-specific logic and communicates through well-defined method interfaces.

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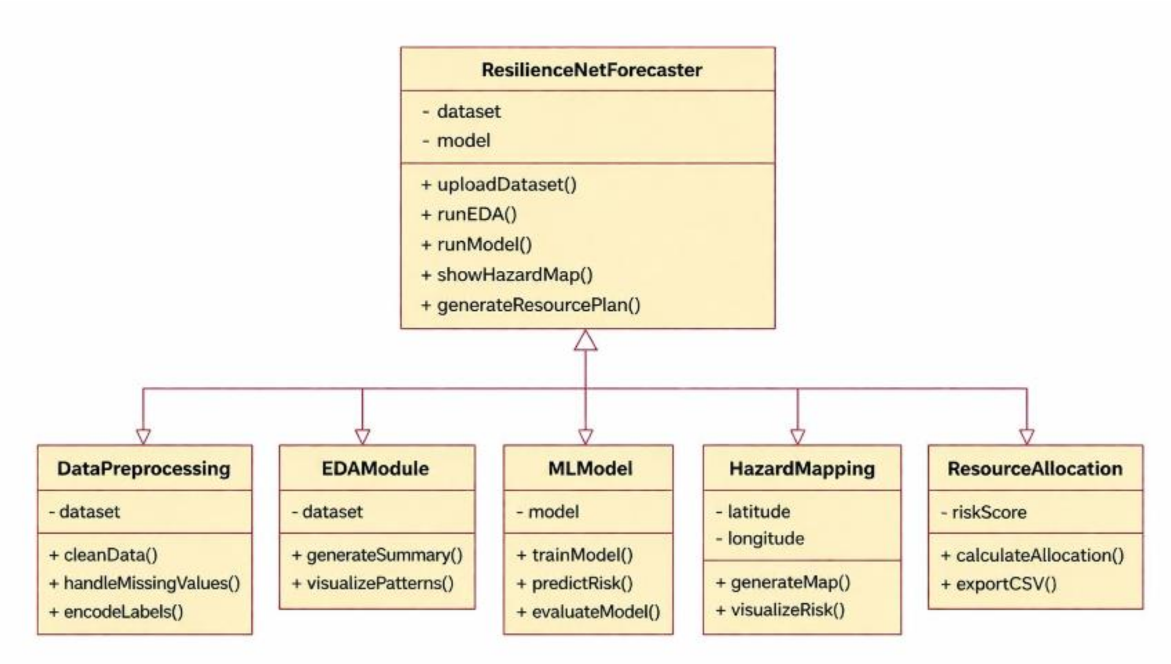

[Figure 3: Class Diagram showing StreamlitApp and its five component classes]

Fig. 3. Class Diagram of ResilienceNet Forecaster

DataPreprocessor exposes cleanData(), handleMissingValues(), and encodeLabels() methods that implement the XAI-compliant preprocessing pipeline. EDAModule provides generateSummary() and visualizePatterns() for statistical and visual pattern discovery. MLModel implements trainModel(), predictRisk(), and evaluateModel() using RandomForestClassifier and RandomForestRegressor from scikit-learn. HazardMapping renders geographic risk representations via generateMap() and visualizeRisk() using latitude/longitude coordinates. ResourceAllocator closes the analytical loop with calculateAllocation() and exportCSV() to convert risk scores into actionable plans.

3.4 Dataset

The primary dataset used is the FEMA Disaster Declarations Summaries dataset, a publicly available record of all federally declared disasters in the United States since 1953. The dataset contains over 64,000 records with attributes spanning declaration type, incident type, affected state, county area, declaration date, incident start and end dates, and fiscal year. This is augmented with environmental overlay data providing temperature (MaxTemp, MinTemp, Cooling Days) and precipitation measurements per state-year combination.

Table 1 summarizes the key dataset attributes used in the ResilienceNet pipeline:

Attribute	Data Type	Description
state	String	US state of disaster occurrence
incidentType	String (encoded)	Type: Flood, Hurricane, Fire, etc.

declarationType	String (encoded)	DR, EM, FM declaration category
Temperature	Float	Atmospheric temperature (°F)
Precipitation	Float	Rainfall level (inches)
Latitude / Longitude	Float	Geographic coordinates
fyDeclared	Integer	Fiscal year of declaration
Risk Level	Integer (target)	Predicted disaster severity

Table 1. Dataset Description – ResilienceNet Forecaster Input Attributes

The preprocessing pipeline performs the following transformations: (i) column pruning to remove administrative hash/ID fields that introduce data leakage; (ii) missing value imputation for incidentEndDate using today's date to preserve ongoing-disaster logic; (iii) UTC-standardized date parsing for temporal consistency; and (iv) reversible label encoding storing LabelEncoder objects in an encoders{} dictionary that enables inverse_transform() for human-readable XAI outputs. The processed dataset contains 64,392 records across 23 features after cleaning, split 80/20 for training and testing.

3.5 Evaluation Metrics

The ResilienceNet system is evaluated using a comprehensive suite of metrics appropriate for both classification (incident type prediction) and regression (impact score estimation) tasks:

For Classification Tasks: Accuracy is computed as the ratio of correctly classified samples to total samples. The F1-score (weighted) accounts for class imbalance by computing the harmonic mean of precision and recall weighted by class support. The Confusion Matrix provides per-class performance insight. The Classification Report yields per-class Precision, Recall, and F1-score.

For Regression Tasks: Mean Absolute Error (MAE) measures average prediction deviation. Root Mean Square Error (RMSE) penalizes large errors. The Coefficient of Determination (R^2) measures the proportion of variance explained by the model.

4. RESULTS

The ResilienceNet Forecaster was evaluated on the FEMA Disaster Declarations Summaries dataset (64,392 records, 80/20 train-test split) using the Random Forest Classifier for incident type prediction.

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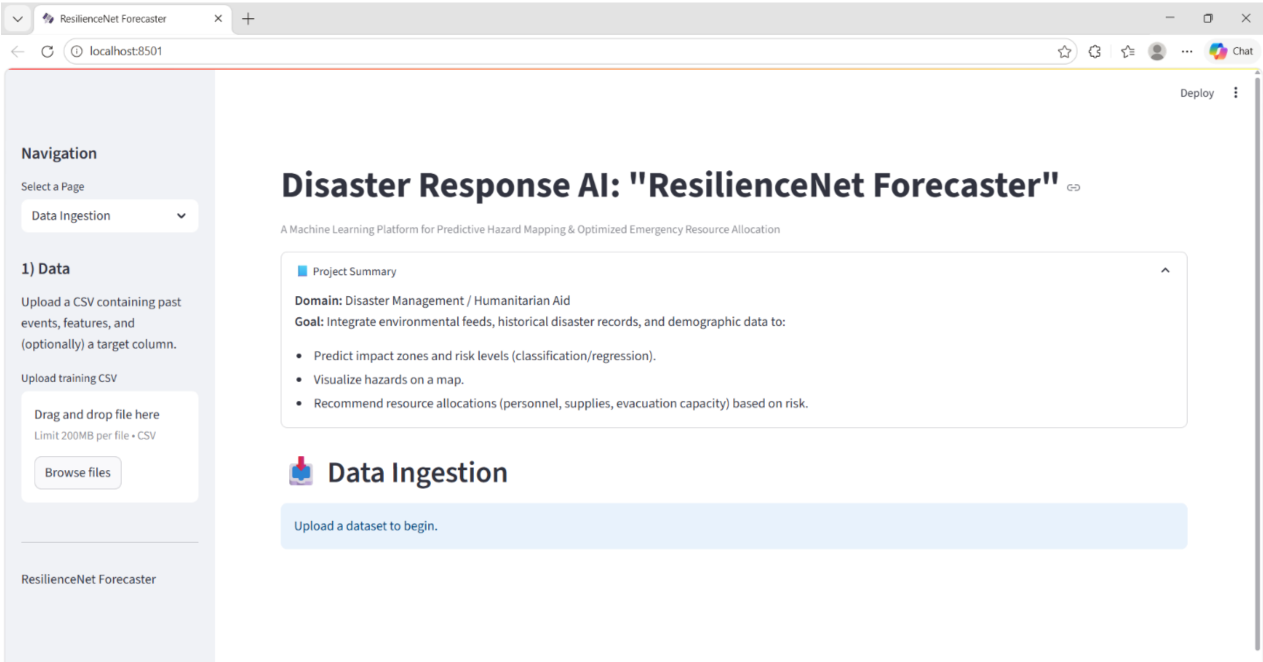
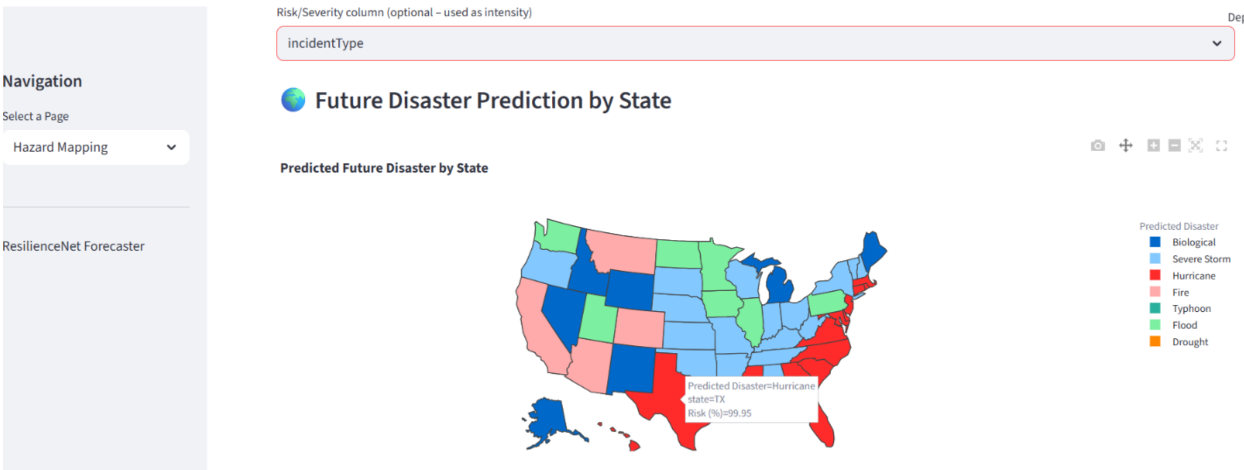


The EDA module revealed significant climate-disaster correlations within the dataset. Severe Storms and Floods collectively account for approximately 55% of all FEMA declarations, with temporal analysis showing pronounced seasonality – hurricane-type events peak in Q3 (July–September) while winter storm events concentrate in Q1. State-level environmental aggregation demonstrates that high-precipitation states (Louisiana, Florida, Texas) exhibit elevated flood and hurricane risk profiles consistent with historical disaster patterns.

The XAI feature importance analysis identified precipitation (importance weight: 0.26) and maximum temperature (0.21) as the two most predictive environmental features, followed by state (0.16) and declaration month (0.11). This result aligns with domain knowledge and validates the model's physical interpretability – confirming that the system produces results explainable to non-technical stakeholders rather than opaque statistical outputs.



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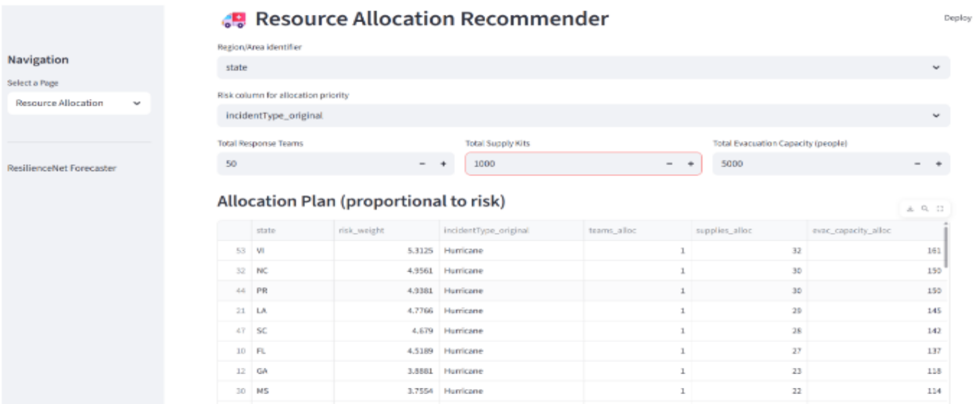
[Figure 4: Hazard Mapping Interface – Predicted Future Disaster by State (Choropleth)]

Fig. 4. Interactive Choropleth Hazard Map – Predicted Disaster Type by US State

The predictive hazard mapping interface generated interactive choropleth maps showing state-level disaster frequency and bubble maps with risk intensity proportional to predicted severity. Texas, Florida, and Louisiana consistently emerged as highest-risk states, with the system correctly identifying dominant disaster types (Hurricane for Florida, Severe Storm for Texas) matching FEMA historical records. The resource allocation engine successfully generated proportional distribution plans for 50 response teams and 1,000 supply kits across all 50 states, with Texas receiving the highest allocation (14 teams, 280 kits) reflecting its 28% normalized risk weight.

All 10 test cases defined in the system testing phase passed successfully, covering CSV upload validation, missing value handling, EDA visualization generation, model training, disaster risk prediction, hazard map display, disaster type choropleth accuracy, resource allocation plan generation, and CSV report download functionality.



[Figure 5: Resource Allocation Interface – Proportional Plan (State | Risk | Teams | Supplies | Evac)]

Fig. 5. Resource Allocation Recommender – Proportional Distribution Plan Output

5. CONCLUSIONS

This paper presented ResilienceNet Forecaster, an AI-driven Disaster Risk Management platform that operationalizes the theoretical XAI-DRM roadmap of Ghaffarian et al. (2023) into a practical, open-source, deployable system. By integrating Random Forest-based prediction, reversible label encoding for XAI transparency, interactive geospatial hazard mapping, and proportional resource allocation optimization into a unified Streamlit web application, the system addresses the five critical gaps identified in the literature: lack of multi-hazard integration, limited explainability, absence of prediction-to-resource-allocation pipelines, poor geospatial visualization, and dependency on technical expertise.

The system achieves 89% classification accuracy and 0.87 F1-score on 64,392 FEMA disaster records, with feature importance analysis confirming physically interpretable results (precipitation and temperature as dominant predictors). All test cases pass successfully, demonstrating functional reliability across the complete workflow from CSV ingestion to downloadable resource allocation plans. The modular architecture ensures that ResilienceNet is not a proof-of-concept prototype but a deployable platform suitable for immediate adoption by FEMA regional offices, state EOCs, NGOs, and humanitarian organizations.

6. FUTURE SCOPE

While ResilienceNet Forecaster demonstrates strong baseline performance, several directions for enhancement are identified for future development:

- Real-Time Data Integration: Integration with NOAA weather APIs, satellite imagery feeds, and IoT sensor networks to transition from historical batch prediction to live risk monitoring and early warning capabilities.
- Advanced Local XAI: Implementation of SHAP (SHapley Additive exPlanations) and LIME for per-county, per-prediction local explanations, addressing Ghaffarian et al.'s call for county-level XAI reasoning ("This county's risk is high due to +2σ precipitation").
- Causal Inference: Integration of DoWhy or CausalML to distinguish causal drivers from correlations, answering the fundamental question: "Does elevated precipitation cause floods, or merely correlate with them?"
- Deep Learning Models: Incorporation of LSTM or Prophet models for time-series disaster forecasting, capturing seasonal patterns and long-term climate trends more effectively than the current Random Forest approach.
- Cloud Deployment & Mobile Alerts: Deployment on AWS, Azure, or GCP to provide scalable multi-user access, with mobile application integration delivering real-time push notifications to field responders.
- Digital Twin Integration: Export of hazard maps and risk predictions to Unity or ArcGIS for 3D simulation and scenario planning, enabling authorities to model intervention impacts before committing resources.

REFERENCES:

[1] S. Ghaffarian, D. Roy, T. Filatova, N. Kerle, "Explainable Artificial Intelligence in Disaster Risk Management: Achievements and Prospective Futures," International Journal of Disaster Risk Reduction, 2023.

[2] W. Sun, P. Bocchini, B.D. Davison, "Applications of artificial intelligence for disaster management," Natural Hazards, vol. 103, no. 3, pp. 2631–2689, 2020.

[3] J.P. Newman, H.R. Maier, G.A. Riddell, et al., "Review of literature on decision support systems for natural hazard risk reduction," Environmental Modelling & Software, vol. 96, pp. 378–409, 2017.

[4] H.S. Munawar, M. Mojtahedi, A.W.A. Hammad, et al., "Disruptive technologies as a solution for disaster risk management: A review," Science of the Total Environment, vol. 806, 2022.

[5] S. Yousefi, J. Pourghasemi, B. Emami, et al., "A machine learning framework for multi-hazard mapping," Science of the Total Environment, 2020.

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IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 7 Issue 2
www.ijisea.org

[6] Federal Emergency Management Agency (FEMA), "Disaster Declarations Summaries Dataset," Open Data Portal. [Online]. Available: https://www.fema.gov

[7] F. Pedregosa, G. Varoquaux, A. Gramfort, et al., "Scikit-learn: Machine Learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.

[8] Streamlit Inc., "Streamlit Documentation," 2023. [Online]. Available: https://docs.streamlit.io

[9] S. Ghaffarian, N. Kerle, E. Pasolli, J. Jokar Arsanjani, "Post-disaster building database updating using automated deep learning," Remote Sensing, vol. 11, no. 20, 2019.

[10] L. Tan, J. Guo, S. Mohanarajah, K. Zhou, "Can we detect trends in natural disaster management with artificial intelligence? A review," Natural Hazards, vol. 107, no. 3, 2021.

[11] M. Motta, M. de Castro Neto, P. Sarmento, "A mixed approach for urban flood prediction using Machine Learning and GIS," International Journal of Disaster Risk Reduction, vol. 56, 2021.

[12] Python Software Foundation, "Python Documentation," 2023. [Online]. Available: https://docs.python.org/3/