DeepRisk: A Machine Learning Framework for Mapping Climate Gentrification and Migration Vulnerability Risk Map

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***Abstract*—Climate change is instigating a complex socio-economic phenomenon known as climate gentrification, where the creation of "safe zones" leads to the displacement of vulnerable populations through rising costs and market pressures. Existing tools for risk assessment and migration are often rendered ineffective during disasters due to their reliance on constant internet connectivity. To address this critical gap, this project proposes the development of a resilient, offline-first Climate Gentrification Risk Map application. The system integrates Geographic Information Systems (GIS) for visualizing vulnerable and safe zones, GPS for location tracking, and Google Maps API for real-time navigation when connected. A key innovation is the incorporation of Edge AI, utilizing TensorFlow Lite on mobile devices to enable real-time risk and safe zone predictions without cloud dependency. By combining offline functionality through cached maps and data with cutting-edge, on-device AI insights, this solution ensures reliable access to crucial information under all conditions. The project aims to provide a scalable and community-centric tool that empowers both individuals and policymakers to make informed decisions, thereby mitigating climate-driven displacement and promoting equitable climate adaptation.**

***Index Terms*—Climate Change, Climate Gentrification, GIS, Edge AI, TensorFlow Lite, Offline-first System, Risk Mapping, Safe Zones, GPS, Disaster Management, Climate Adaptation**

I. INTRODUCTION

Climate change has significantly intensified the frequency and severity of extreme environmental events such as floods, leading to the displacement of vulnerable populations and reshaping urban settlement patterns. This has contributed to the emergence of climate gentrification, where high-risk areas become increasingly uninhabitable while relatively safer regions become economically inaccessible to low-income communities, forcing vulnerable populations into hazard-prone areas and thereby amplifying existing social and economic inequalities. Addressing this issue requires a comprehensive approach that integrates environmental risk assessment with socio-economic vulnerability analysis.

To address these challenges, this project proposes a Climate Gentrification Risk Mapping System focused on flood risk assessment in Madhya Pradesh. The system integrates geospatial analysis with multiple datasets, including flood hazard zones, rainfall data, Digital Elevation Model (DEM), population density, land use and land cover (LULC), settlement vulnerability, and administrative boundaries to compute a composite district-level flood risk score. The solution is implemented as an interactive web-based dashboard that visualizes risk through maps, charts, and district-level insights, while a weighted model classifies regions into low, moderate, high, and critical categories. Additionally, a machine learning-based module utilizes historical and real-time data to estimate short-term flood risk and potential displacement patterns. Overall, the system provides a scalable and efficient platform for climate risk assessment, supporting informed decision-making and improved disaster preparedness.

II. LITERATURE REVIEW OF EXISTING SYSTEMS

Table 1. Literature Review of FloodNet-Lite: A Lightweight Deep Learning for Flood Mapping Using Remote Sensing Data with Optimized UNet and Edge Deployment Approach in 6G

PAPER 1	OBJECTIVE	CHNOLOGY USED	METHODOLOGY	EFFICIENCY	ISSUES
Title: FloodNet-Lite: A Lightweight Deep Learning for Flood Mapping Using Remote Sensing Data with Optimized UNet and Edge Deployment Approach in 6G Journal: IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS) Year: 2025 DOI: 10.1109/JSTARS.2025.3591406	1. Framework: Develop a lightweight, edge-optimized deep learning framework for real-time flood mapping. 2. Model: Optimize a UNet architecture using a MobileNetV3 backbone, depthwise convolutions,and attention mechanisms. 3. Deployment: Enable real-time processing on 6G edge networks using data from UAVs, sensors, and satellites.	1. Technologies: Optimized UNet with MobileNetV3 backbone, depthwise separable convolutions, attention mechanisms, model compression (quantization-aware training, structured pruning), knowledge distillation, edge AI deployment. 2. Software Tools: TensorFlow, PyTorch, Python, CUDA, NVIDIA Jetson Nano for edge deployment. 3. Input Format: Satellite imagery, UAV/drone images, and ground sensor data	1. Data: Collect multisource data from satellites, UAVs, and ground sensors. 2. Architecture: Design a lightweight UNet model using a MobileNetV3 backbone with attention mechanisms. 3. Compression: Apply pruning and quantization to minimize the model's size and complexity. 4. Distillation: Use knowledge distillation from a larger teacher model to enhance accuracy.	1. Model Size: The model is ultra-lightweight at 18 MB, making it suitable for deployment on resource-constrained edge devices like NVIDIA Jetson Nano. 2.Inference Speed: Achieves 14.3 frames per second on Jetson Nano, enabling real-time flood detection. 3. Prediction Accuracy: High performance with a Mean Intersection over Union (IoU) of 0.85, ensuring reliable flood mapping. 4. Edge Deployment Capability: Optimized for real-time processing on edge devices, minimizing latency and eliminating dependency on cloud servers.	1. Data Availability: Limited labeled data for training deep learning models, especially in specific regions. 2. Model Generalization: Ensuring the model performs well across diverse geographical areas and varying flood scenarios. 3. Real-Time Constraints: Maintaining high inference speed and low latency in real-time applications.

This study presents a lightweight deep learning framework, FloodNet-Lite, designed for real-time flood mapping using edge computing. It leverages optimized architectures and model compression techniques to achieve efficient and accurate flood detection on resource-constrained devices. The research explores multiple objectives: Framework Development to design a lightweight deep learning model optimized for real-time flood mapping. Model Optimization using a MobileNetV3 backbone with depthwise separable convolutions and attention mechanisms. Edge Deployment to enable real-time processing on low-resource devices like NVIDIA Jetson Nano. The study employs advanced technologies including: Deep Learning Frameworks (TensorFlow, PyTorch) for model development. Edge Computing Devices (NVIDIA Jetson Nano) for real-time inf.

Table 2. Literature Review of Typologies of multiple vulnerabilities and climate gentrification across the East Coast of the US

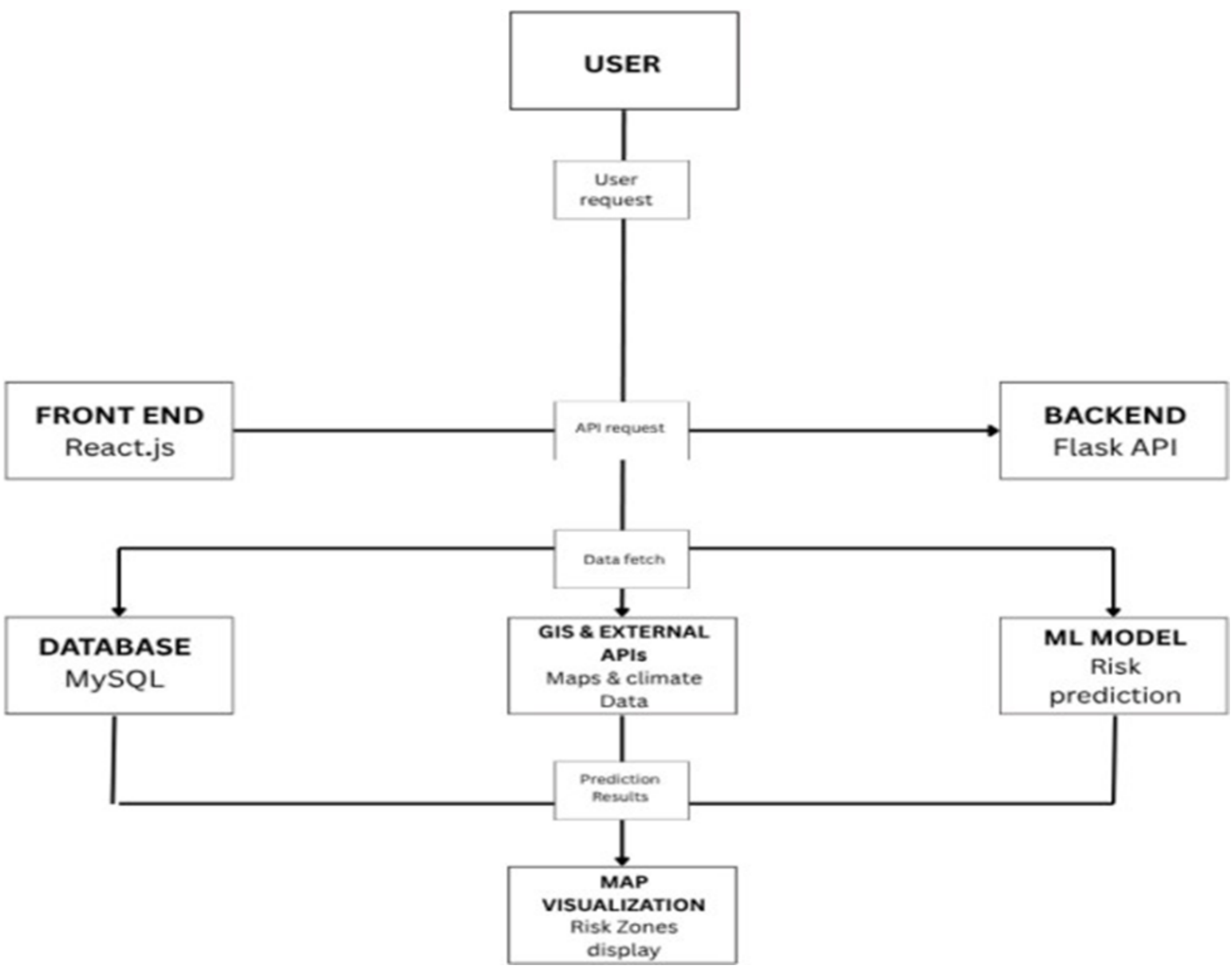
PAPER 2	OBJECTIVE	CHNOLOGY USED	METHODOLOGY	EFFICIENCY	ISSUES
Title: Typologies of multiple vulnerabilities and climate gentrification across the East Coast of the United States Journal: Urban Climate (2023) DOI: 10.1016/j.uclim.2023.101430	1. Cluster Vulnerabilities: Use unsupervised ML to map social, housing, and environmental vulnerability clusters in 51 East Coast counties. 2. Identify Gentrification Pathways: Analyze how climate risks interact with socioeconomic factors to drive potential climate gentrification. 3. Inform Equitable Adaptation: Generate insights to guide adaptation planning that protects disadvantaged communities.	1. Technologies: Unsupervised machine learning (k-medoids clustering), spatial analysis of vulnerability indices, coastal vulnerability assessment. 2. Software Tools: Likely Python (scikit-learn) or R for clustering, GIS tools for mapping (e.g., ArcGIS or QGIS). 3. Input Format: County-level datasets including social, housing, and environmental variables, FEMA disaster frequencies, census data.	1. Data Collection: Gathered demographic, socioeconomic, housing, and environmental data for 51 East Coast counties. 2. Clustering Analysis: Applied k-medoids clustering to classify counties into four clusters representing multifaceted vulnerabilities. 3. Spatial Mapping: Mapped cluster results at county and finer census tract levels (North Carolina case study) to visualize geographic patterns of vulnerability.	1. Four Distinct Clusters: Captured multifaceted vulnerability dimensions (social, housing, environmental). 2. Case Study Validation: Methodology validated at finer spatial scales for North Carolina counties. 3. Insightful Policy Guidance: Provides a framework to target adaptation and planning efforts effectively, mitigating disproportionate impacts on vulnerable populations.	1. Data Granularity: County-level data may mask local variations; finer resolution data may improve precision. 2. Generalization: Findings specific to the East Coast of the U.S.; may require adjustment for other regions.

Table 3. Literature Review of Predictive modeling of climate change impacts using Artificial Intelligence: a review for equitable governance

PAPER 3	OBJECTIVE	CHNOLOGY USED	METHODOLOGY	EFFICIENCY	ISSUES
Title: Predictive modeling of climate change impacts using Artificial Intelligence: a review for equitable governance and sustainable outcome Journal: Environmental Science and Pollution Research, Vol 32, 2025 Year: 25 DOI: https://doi.org/10.1007/s11356-025-36356-w	Investigate AI Models: To investigate how AI-based predictive models summarize the consequences of climate change. Compare Models: To compare AI applications to conventional climate models. Promote Sustainability: To look into whether and how AI can add to sustainable development and management that is equitable.	AI/ML Algorithms: Neural networks, decision trees, ensemble methods like Random Forests and Gradient Boosting. Deep Learning Models: CNNs, RNNs, LSTM. Data Sources: Meteorological, oceanographic, environmental datasets, satellite data, ground-based monitoring, and climate model outputs. Tools for Interpretability: LIME, SHAP, Explainable AI (XAI).	Systematic Review Process: PRISMA Framework for selecting and reviewing ~320 studies; thematic analysis of AI applications in climate science. Data Handling: Pre-processing, data cleaning, imputation, dimensionality reduction (PCA). AI Model Development: Train/validate/test split, hyperparameter tuning. Evaluation: MSE, Accuracy, ROC-AUC, Cross-validation.	High Accuracy: At the regional level, AI models perform better than conventional models. Adaptability: AI is capable of learning dynamic and non-linear climate patterns. Decision Support: Offers legislators useful information. Hybrid Models: By combining physical and AI models, robustness is increased.	Data Gaps: Model accuracy is decreased by missing or low-resolution climate data. Interpretability Issues: XAI is required because AI models behave like "black boxes." Socio-economic Integration: Human and economic factors are not fully included.

Table 3. Literature Review of Harper 2019 Ecological Gentrification in Response to Apocalyptic Narratives of Climate Change

PAPER 5	Objective	Technolog Y Used	Methodol Ogy	Efficiency	Issues
Title: Harper 2019 Ecological Gentrification in Response to Apocalyptic Narratives of Climate Change Journal: International Journal of Urban and Regional Research (IJURR), Volume 44(1) Year: 019 DOI: 10.1088/1748-9326/ab6668 Link:https://iopscience.iop.org/article/10.1088/1748-9326/ab6668	To explore how apocalyptic climate change narratives influence urban planning and regeneration projects. To analyze how "sustainability" is used as a justification regime for ecological gentrification.	Ecological gentrification (urban redevelopment justified through green/sustainable goals). Immuno-politics (feeling of safety/immunity from climate crisis through urban design). Apocalyptic discourse from media, films, and scientific reports as a driver of urban change.	Theoretical analysis combining urban studies, political ecology, and psychoanalytic theory (Lacan, Esposito, Žižek). Case study observations of urban regeneration projects (e.g., Elephant & Castle in London, NOMA in Manchester).	Ecological redevelopment projects appear sustainable but often lead to gentrification and displacement. Sustainability works as an "empty signifier", easily used to justify capitalist urban growth. Instead of empowering citizens, such projects depoliticize urban subjects, creating passive eco-consumers.	Displacement of vulnerable populations in the name of green regeneration. Illusion of immunity: residents feel protected from climate change but continue unsustainable consumption. Depoliticization: sustainability narratives suppress real political resistance and critical engagement.



III. PROPOSED SYSTEM DESIGN

The proposed system is structured as a multi-layered architecture consisting of data acquisition, backend processing, prediction, and visualization layers. It follows a pipeline-based approach where data flows sequentially through different components, enabling efficient processing and analysis. The system integrates both real-time and static datasets, which are processed in the backend to extract relevant features for prediction. The machine learning model analyzes these features to generate risk scores, which are further refined using additional parameters such as rainfall anomalies, forecast data, and population exposure. The final results are then delivered to the frontend through REST APIs for visualization. The architecture ensures continuous data updates, where the frontend periodically fetches processed data from the backend to maintain up-to-date risk information. This enables users to view dynamic changes in risk levels across different regions. The use of a modular design ensures that each component operates independently while contributing to the overall system functionality.

IV. METHODOLOGY AND ALGORITHMS USED

This section describes the core working of the system, including data processing, machine learning models, and risk computation techniques used for climate risk prediction. Machine Learning Algorithm : Random Forest Regressor, The primary predictive model used in the system is the **Random Forest Regressor**, an ensemble learning technique that combines multiple decision trees to improve prediction accuracy and robustness. The model is designed to capture non-linear relationships between environmental and socio-economic factors such as rainfall, elevation, and population density. It utilizes approximately 200 decision trees, making it suitable for handling complex interactions among multiple variables. Training Process: The model is trained on a structured dataset representing district-level conditions. It considers multiple input features, categorized as, Static Features: Elevation (DEM), population density, river proximity. Dynamic Features: 24-hour rainfall, 7-day cumulative rainfall forecasts. Performance: The model achieves a high level of accuracy with a Coefficient of Determination ($R^2 \approx 0.92$), indicating strong predictive capability. Methodology: Composite Risk Scoring, The system adopts a hybrid methodology that combines machine learning predictions with real-time environmental indicators. Normalization: All input variables are scaled to a common range for consistency. Weighted Risk Calculation: A composite risk score (0–100) is computed by combining model predictions with live anomaly factors. Risk Categorization: The final score is classified into four levels:

- Critical: > 80
- High: 60–80
- Medium: 40–60
- Low: < 40

This approach ensures both predictive accuracy and real-time responsiveness.

V. PROJECT FUNCTIONAL MODULES IMPLEMENTATION

The system is divided into multiple functional modules, each responsible for a specific operation, Data Acquisition & Integration Module Collects real-time weather data using APIs (e.g., OpenWeatherMap).ntegrates static datasets such as census data, elevation, and flood hazard zones. Ensures seamless data flow between sources. Data Processing Module. Performs data cleaning, normalization, and transformation. Handles missing and inconsistent data. Extracts relevant features for model input. Predictive Engine (ML Layer), Implements the Random Forest model for risk prediction. Processes live data inputs to generate real-time risk scores. Ensures model availability through initialization at system startup. RESTful API Layer, Developed using FastAPI to provide structured JSON responses. Supports endpoints for real-time risk data and historical analysis. Implements middleware (CORS) for secure frontend-backend communication. Visualization Module, Uses mapping libraries (e.g., Leaflet.js) for geospatial visualization. Displays risk levels hrough color-coded regions. Integrates charts (Chart.js) for trend analysis and comparison. Alert and Insights Module, Provides warnings for high-risk regions. Generates actionable insights for decision-makers. Enhances user awareness and preparedness.

VI. METHODOLOGY FOR SYSTEM DEVELOPMENT

The development of the system follows a structured and systematic approach: Requirements Analysis & Data Sourcing, Identification of key risk factors such as rainfall, elevation, and population density. Collection of environmental and socio-economic data from public datasets and APIs. System Architecture Design, Implementation of a three-tier architecture: Data Layer: Storage using databases or CSV files. Logic Layer: Backend processing and ML model integration. Presentation Layer: Interactive user interface and visualization Machine Learning Pipeline Development, Data preprocessing and feature scaling, Model selection using Random Forest algorithm, Training and validation using cross-validation techniques, Performance evaluation using accuracy and R^2 metrics. Backend Development & API Integration, Implementation using asynchronous programming for efficient data handling, Real-time data fetching and processing without performance delays, Frontend Development, evelopment of an interactive dashboard with map-based visualization, Integration of charts and analytics for better data interpretation, Auto-refresh mechanisms for real-time updates. Deployment and Maintenance, Deployment using containerization tools (e.g., Docker), Ensuring scalability, consistency, and performance optimization, Continuous updates and improvements based on new data and feedback.

VII. IMPLIMENTATION PROTOTYPE, ALGORITHM AND PROGRAM LOGIC

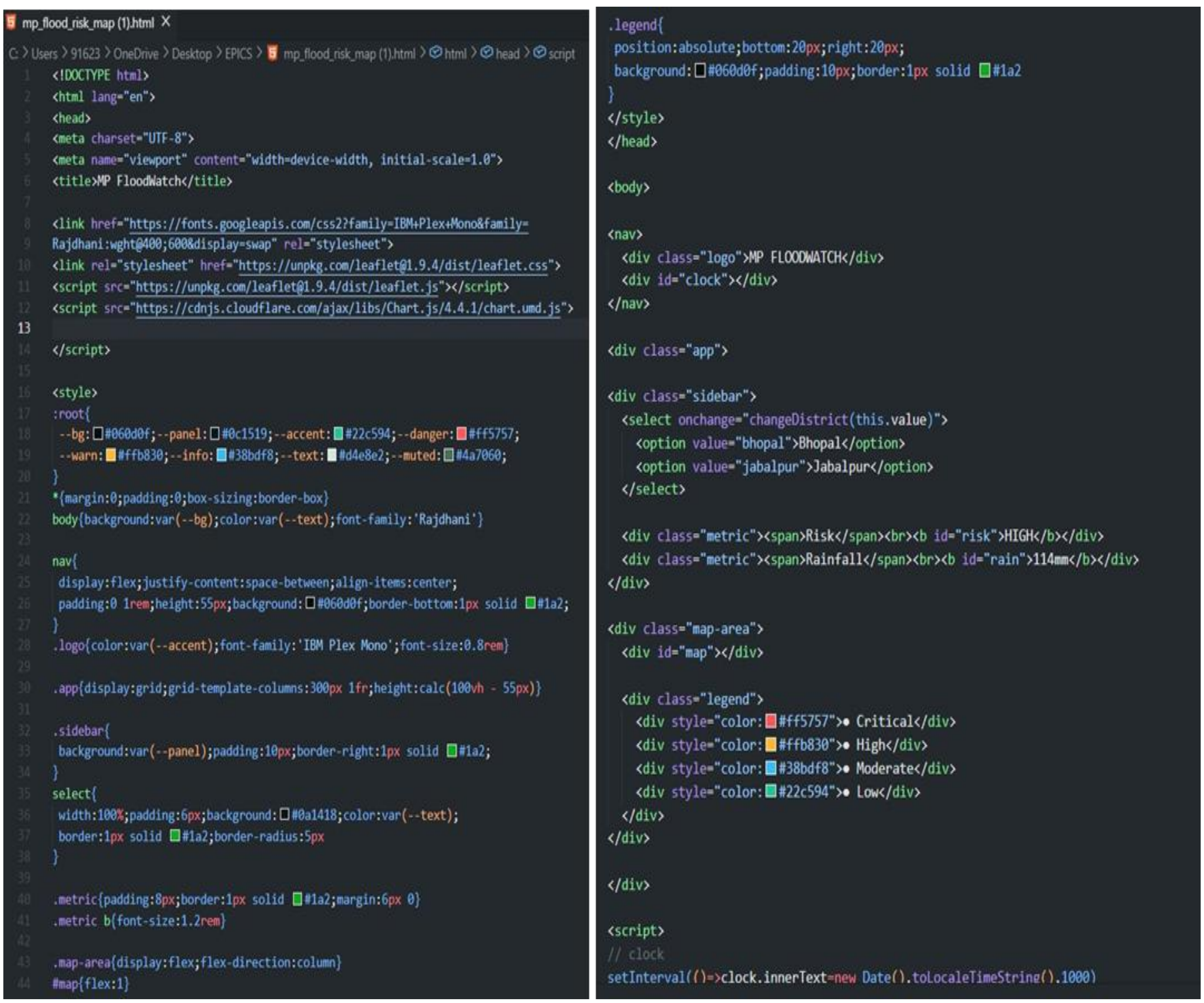


Fig 2: Building the front-end system Climate Gentrification - Migration Risk Map

Fig 3: Climate Gentrification - Migration Risk Map predictions

Fig 4: Prediction of Climate Gentrification - Migration Risk Map predictions

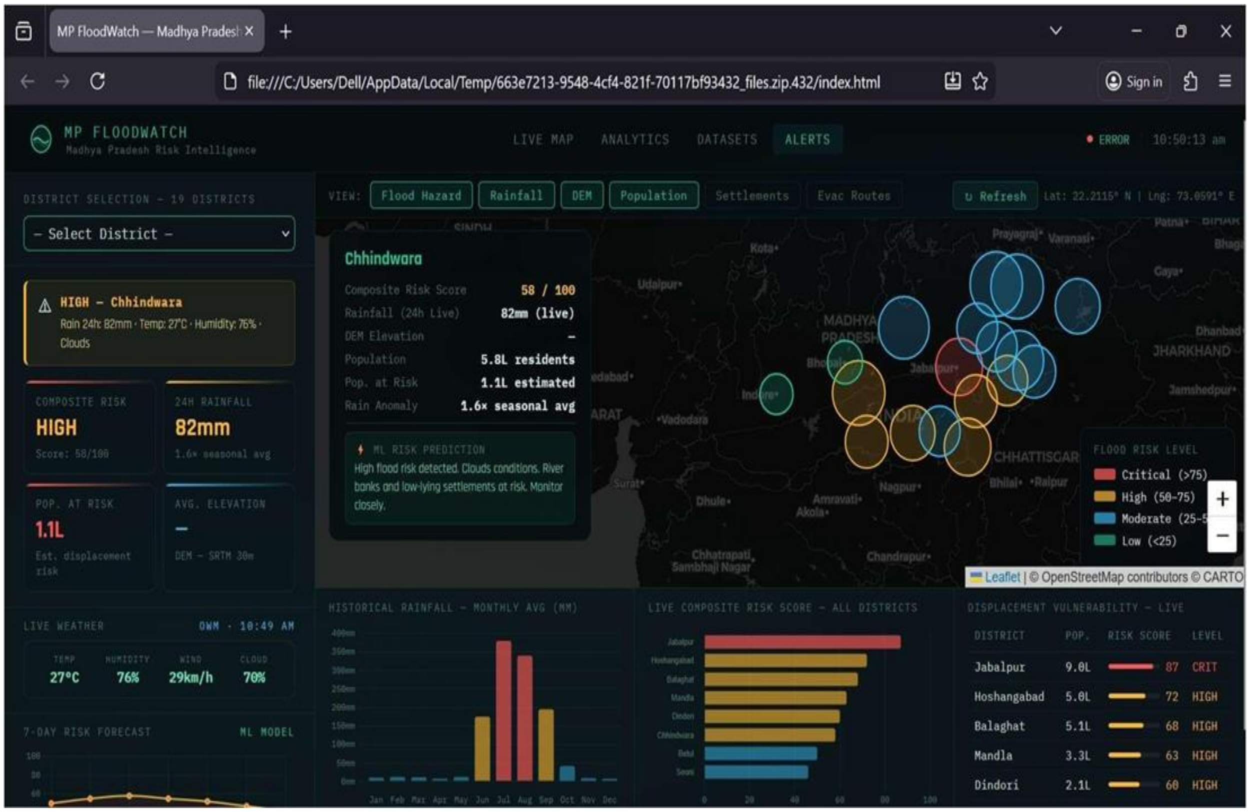


Fig 5: Flood Statistics Climate Gentrification - Migration Risk Map predictions

Fig 6: Madya Pradesh Migration Risk Map predictions

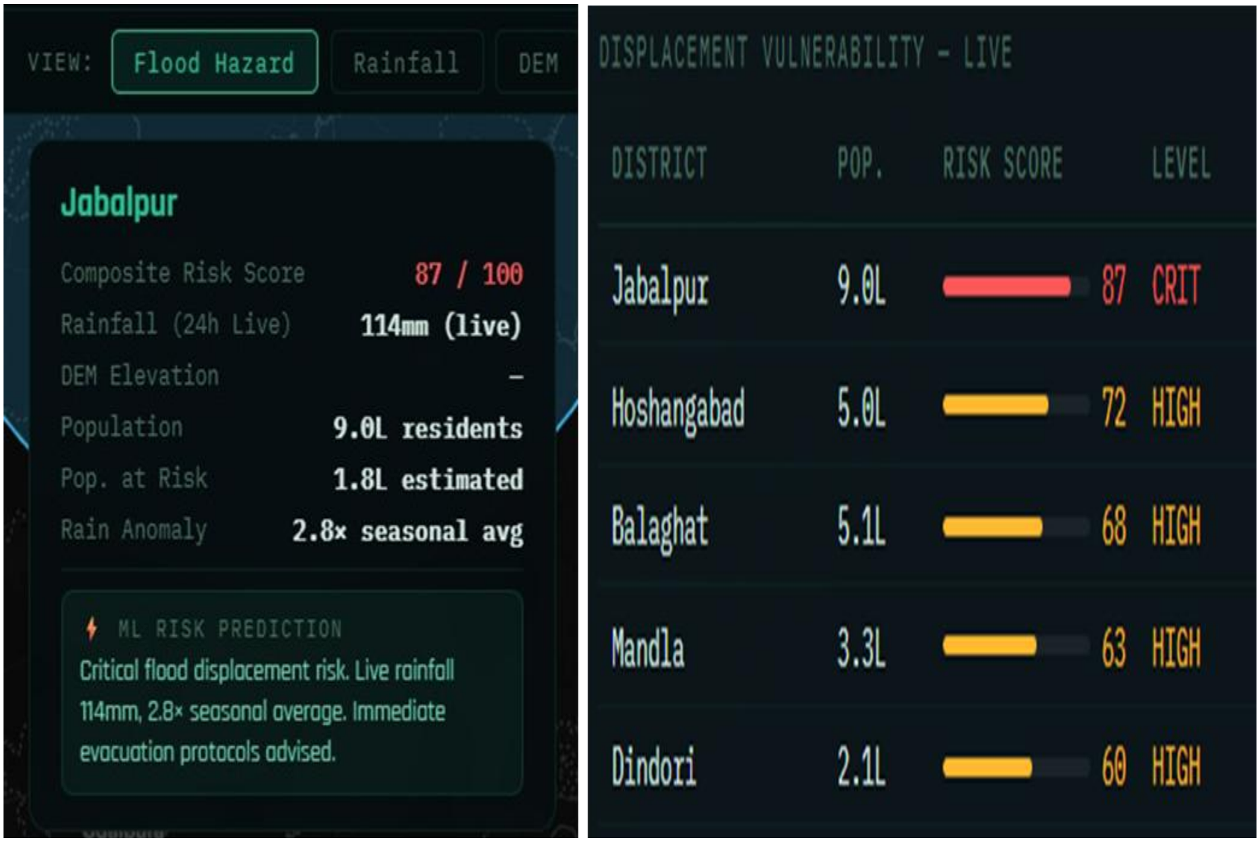


Fig 3: Jabalpur Climate Gentrification - Migration Risk Map predictions

6.1 Contribution and Findings: This work develops an Integrated Geospatial Risk Assessment Framework that combines real-time, historical, and socio-economic data into a unified system for urban planning. It uses a Random Forest-based risk engine to predict future threats and is built with a scalable architecture (FastAPI, Docker) along with an interactive interface showing risk zones and evacuation routes. The system achieved high accuracy ($R^2 \approx 0.92$) in flood prediction and revealed that so-called "sustainable" areas can still be highly vulnerable. It also highlights that socio-economic factors like population density and infrastructure often outweigh environmental factors, and that real-time data.

VII. CONCLUSION

Climate Gentrification (CG) transforms climate safety into an exclusive commodity, leveraging environmental risk to drive social inequality. This process works through market sorting, pushing low-income people into high-hazard areas (disinvestment) while securing low-risk zones for the wealthy (superior investment). CG projects are often masked by a "green paradox," acting as a justification regime for privatization, granting the wealthy a fantasy of "immunization". Effectively combating CG requires equitable policy coherence and mandating affordable housing in resilient zones, treating climate safety as an equitable social right. The Climate Gentrification Risk Map is not just a technological innovation but a community resilience enabler, designed to safeguard vulnerable populations from climate-driven displacement. By integrating GIS visualization, GPS tracking, Edge AI, and offline-first functionality, it ensures accessibility, reliability, and inclusivity even under disaster conditions. Beyond supporting individuals in locating safe zones, the system provides policymakers and planners with actionable insights to promote climate justice and equitable adaptation strategies. With its scalable and resilient framework, the project lays a strong foundation for future enhancements such as early warning systems, real-time disaster feeds, and multi-language accessibility—positioning it as a reliable tool for climate adaptation and disaster preparedness.

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