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Scenario-Based Flood Susceptibility Mapping using Machine Learning: A Case in Manila City, Philippines

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INTRODUCTION & AIM

Manila City faces severe flooding from intense rainfall, exacerbated by low elevation, dense population, and urbanization. Traditional hydrodynamic models, though accurate, are computationally costly and impractical for rapid scenario testing. This study develops a machine learning framework for scenario-based flood susceptibility mapping, trained on FastFlood hydrodynamic simulations using synthetic rainfall scenarios. Multiple rainfall scenarios (5-, 10-, 15-, 30-, and 60-minute intervals) generate flood extent data used to train Support Vector Machine, Random Forest, and XGBoost classifiers. The framework integrates maps such as digital elevation model data, soil type, land use categories, and rainfall hyetographs to predict flood susceptibility across four classes. Three supervised classification algorithms were systematically trained and comparatively evaluated to assess the viability of machine learning for flood prediction under the Chicago rainfall design. This approach enables rapid assessment of flood risk while reducing computational requirements associated with physics-based modeling techniques.

METHOD

Synthetic rainfall scenarios were generated using the Chicago Rainstorm Design method at five intervals (5, 10, 15, 30, 60 minutes). FastFlood simulations converted these hyetographs into classified flood extent maps with flood level categories (0-4). Spatial features underwent standardized preprocessing: DEM data were resampled to 256×256 resolution, imputed, and then min-max normalized, yielding three channels. Soil and land use maps were similarly resampled and normalized for each layer. Ground-truth flood maps were aligned to the DEM resolution and converted to tensors. Hyetograph arrays were normalized and tiled as conditional features. A Manila boundary mask excluded non-mainland areas. Spatial splitting allocated quadrants to training and validation. Three ML classifiers: Random Forest, SVM, and XGBoost were trained on identical feature sets and evaluated via confusion matrices.

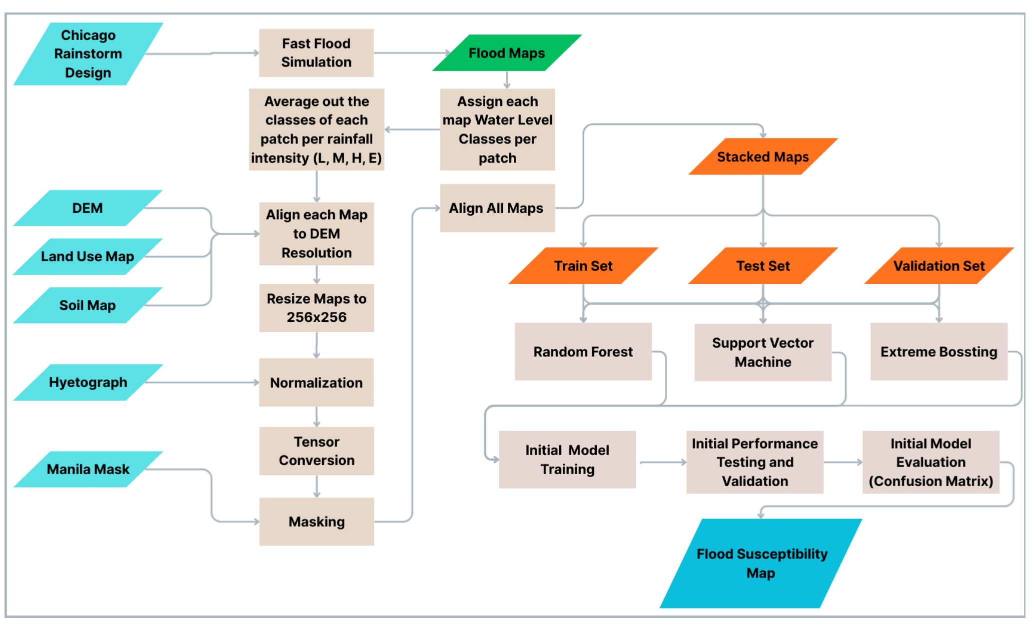

FIGURE 1: Flood Susceptibility Modeling Framework Using RF, SVM, and XGBoost

RESULTS & DISCUSSION

Random Forest achieved 94.14% overall accuracy but demonstrated critical classification failures in minority flood classes. Precision values declined sharply from 0.4118 for Light flooding to 0.1170 for Medium, with complete failure (0.0000) for Heavy and Extreme categories. Recall metrics exhibited severe deficiencies across all flood classes: 0.0131 (Light), 0.0440 (Medium), and 0.0000 for higher flood levels. XGBoost recorded 96.92% accuracy yet performed worse, yielding zero precision and recall across all non-baseline flood categories. In contrast, SVM obtained 86.63% accuracy with substantially improved minority class detection capabilities. While precision remained modest at 0.07 (Light), 0.06 (Medium), and 0.02 (Heavy), recall metrics demonstrated functional classification, with values of 0.46 (Light), 0.09 (Medium), and 0.06 (Heavy).

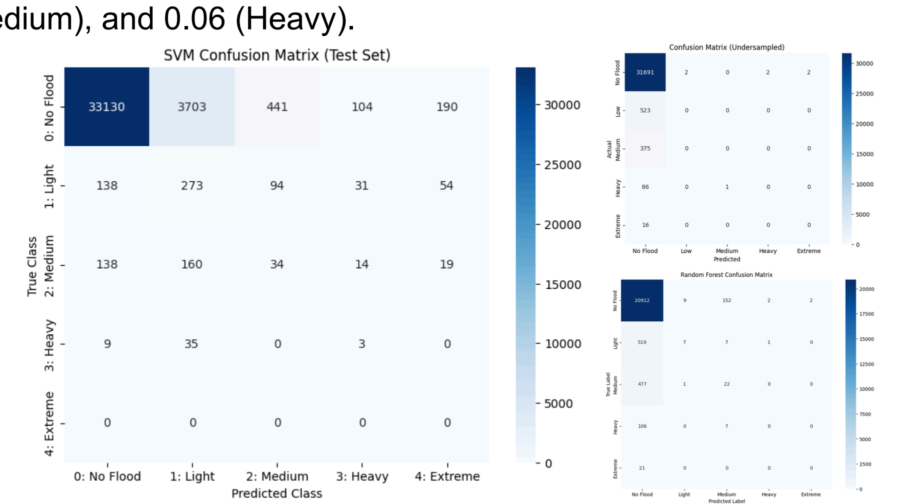

FIGURE 2: Confusion Matrix For SVM *(left)*, **XGBoost** *(right, top)*, **and RF** *(right, bottom)*

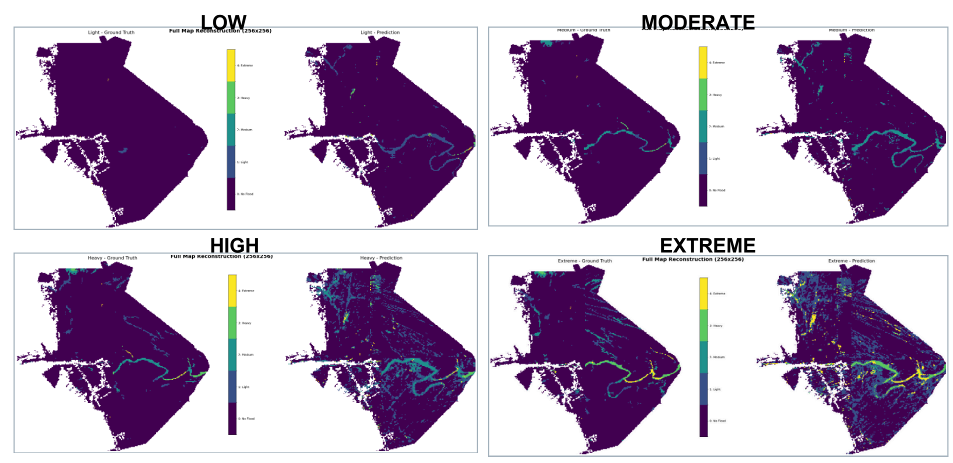

FIGURE 3: Ground Truth *(left)* **and Predicted** *(right)* **Flood Susceptibility Map for each flood levels by SVM**

CONCLUSION

SVM demonstrated superior minority flood class detection despite lower overall accuracy compared to Random Forest and XGBoost. Traditional ML classifiers struggle with severe class imbalance in flood mapping, necessitating alternative approaches for operationally reliable scenario-based susceptibility prediction systems.

FUTURE WORK / REFERENCES

Future work should address class imbalance using advanced resampling, incorporate additional hydrologic and urban features, test deep learning architectures, and evaluate temporal rainfall variability. Expanding datasets and integrating real flood observations may further enhance predictive reliability and model robustness.