



AI-Based Decision-Making Framework for Climate Change-Induced Flood Risk Management and Urban Resilience

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ABSTRACT

Climate change has intensified the frequency and severity of urban flooding, creating unprecedented challenges for municipalities worldwide. This study develops an AI-based decision-making framework that integrates machine learning, explainable artificial intelligence, and geospatial analytics to enhance urban flood risk management and resilience planning. The framework employs ensemble machine learning algorithms including Random Forest, XG Boost, and Cat Boost for flood susceptibility mapping, coupled with SHAP-based interpretability to decode model predictions and translate them into actionable policy insights at administrative scales. A city-scale digital twin component enables real-time flood impact simulation and cascading infrastructure disruption analysis, while a multi-criteria decision support module prioritizes adaptation investments based on economic risk assessment and equity considerations. The framework was validated using multi-temporal Sentinel-1 SAR data and hydrological records across diverse urban environments, demonstrating superior predictive performance with area under the receiver operating characteristic curve values exceeding 0.95 for ensemble models. Results reveal that elevation, proximity to hydrological features, and impervious surface density consistently emerge as dominant flood drivers, with their relative importance varying significantly across districts. The decision support system successfully transformed pixel-level predictions into ward-level actionable recommendations, enabling evidence-based zoning, drainage infrastructure prioritization, and targeted nature-based solutions deployment. The framework addresses critical gaps in explainability, scalability, and policy relevance that have limited the operational adoption of AI in urban flood governance. The study concludes that integrating AI-driven analytics with participatory decision-making processes can substantially enhance adaptive capacity in flood-prone urban systems, though algorithmic transparency, data equity, and institutional readiness remain essential preconditions for equitable implementation.

Introduction

Climate change is fundamentally reshaping the hydrological dynamics of urban environments, with flooding emerging as one of the most pervasive and

costly climate-related hazards facing cities globally (Tang et al., 2024).

The Intergovernmental Panel on Climate Change has documented systematic increases in the frequency and intensity of extreme precipitation

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events, while urbanization processes continue to expand impervious surfaces, reduce natural infiltration capacity, and alter drainage patterns (Tellman et al.,2021).

The confluence of these trends has created what scholars describe as a “wicked problem” for urban governance: flooding is simultaneously driven by global climate processes, regional land-use transformations, and local infrastructure deficits, requiring decision-making frameworks that can operate across multiple scales and uncertainty domains (Liao,2012). Traditional flood management approaches, rooted in probabilistic return-period analysis and engineering-based structural interventions, have proven insufficient for addressing the non-stationary risk profiles characteristic of contemporary urban flooding (Milly et al.,2008).

The emergence of artificial intelligence as a transformative force in environmental governance offers new possibilities for addressing these challenges (Nishant et al.,2020). Machine learning algorithms possess inherent capabilities for capturing complex, nonlinear relationships between hydrological, topographic, and socio-economic variables that conventional statistical models struggle to represent (Mosavi et al.,2018). Ensemble learning approaches, particularly gradient boosting and random forest methods, have demonstrated superior predictive performance in flood susceptibility mapping compared to single-model approaches, with area under the curve values frequently exceeding 0.90 (Khosravi et al.,2018). Beyond predictive accuracy, recent advances in explainable artificial intelligence particularly SHAP (SHapley Additive ex-Planations) and related techniques have begun to address the historical opacity of machine learning models, enabling stakeholders to understand which factors drive risk predictions and how these drivers vary spatially (Lundberg & Lee,2017). This interpretability is critical for policy adoption: municipal planners and emergency managers require not only predictions but also causal explanations that can justify resource allocation and regulatory interventions.

Despite these technological advances, a significant gap persists between the analytical capabilities of AI systems and their operational integration into urban flood governance. Research has documented that most AI-based flood studies remain confined to academic exercises, producing susceptibility maps that are technically sophisticated but operationally disconnected from the administrative units and decision-making processes through which urban planning actually occurs (Rezvani et al.,2023). The “pixel-to-policy” gap the disconnect between granular model outputs and the jurisdictional scales at which adaptation decisions are made represents a fundamental barrier to practical implementation (Lee et al.,2026). Furthermore, while AI

applications in flood risk management have proliferated across diverse geographic contexts, concerns regarding algorithmic bias, data justice, and the exclusion of marginalized communities from decision-making processes remain inadequately addressed (Leal Filho et al.,2023). The deployment of AI tools trained on datasets that systematically underrepresent informal settlements or low-income population’s risks reinforcing, rather than mitigating, existing vulnerabilities. This study addresses these interconnected challenges by developing and validating an AI-based decision-making framework that integrates predictive modeling with policy-relevant analytics for climate change-induced flood risk management and urban resilience enhancement. The framework pursues three integrated objectives. First, it systematically evaluates ensemble machine learning algorithms across multiple spatial resolutions to identify optimal configurations for flood susceptibility mapping in topographically complex urban terrain. Second, it implements explainable AI techniques to decode model predictions and develops an aggregation framework that transforms pixel-level insights into district-level analysis, thereby enabling administratively aligned policy formulation. Third, it integrates this analytical pipeline with a decision support system that incorporates economic risk assessment and equity considerations to prioritize adaptation investments and guide urban resilience planning. By bridging computational sophistication with policy relevance, this research contributes both to the methodological rigor of AI-based flood risk assessment and to its practical applicability for climate-resilient urban governance.

Literature Review

Machine Learning for Flood Susceptibility Assessment:

The application of machine learning to flood susceptibility mapping has expanded dramatically over the past decade, driven by the increasing availability of high-resolution geospatial data and advances in computational methods. Ensemble tree-based algorithms including Random Forest, XG Boost, Cat Boost, and Light GBM have emerged as the predominant approach due to their robustness against overfitting, ability to handle mixed-type predictors, and capacity for capturing complex nonlinear interactions (Shwartz-Ziv & Armon,2022). Comparative studies consistently demonstrate the superiority of these ensemble methods over traditional statistical approaches and single learners. A comprehensive evaluation across multiple algorithms found that Cat Boost achieved the highest cross-validation area under the curve of 0.975, with XG Boost, Light GBM, and Random Forest all exceeding 0.94 on independent test sets (Islam et al.,2026). This performance advantage stems from the inherent suitability of gradient

boosting for tabular geospatial datasets, where deep neural networks often underperform due to their structural assumptions regarding spatial continuity that do not hold for heterogeneous environmental predictors (Grinsztajn et al.,2022).

The integration of urban infrastructure variables into flood susceptibility models represents a significant methodological advance. Research in Seoul demonstrated that including road density, sewer system density, and drainage infrastructure characteristics consistently improved predictive performance across all evaluated algorithms, with mean test accuracy increasing by 0.01 to 0.07 and area under the curve by 0.01 to 0.05 (Kim et al.,2026).

This finding is particularly relevant for urban applications, where engineered drainage systems fundamentally alter hydrological connectivity in ways that purely topographic models cannot capture. However, the incorporation of infrastructure variables introduces challenges related to data availability and quality, as detailed drainage network inventories remain unavailable in many cities, particularly in the Global South (Khan et al.,2026).

Explainable AI for Policy-Relevant Flood

Analytics: The “black box” nature of machine learning models has historically limited their integration into public decision-making, where transparency and accountability are essential (Samek et al.,2019). Explainable AI techniques, particularly SHAP and permutation importance, have begun to address this limitation by providing quantitative measures of variable contribution that can be communicated to non-technical stakeholders (Molnar,2022). In flood susceptibility applications, SHAP analysis has revealed consistent dominance of elevation, distance to hydrological features, and terrain slope across diverse urban contexts, while also identifying significant spatial heterogeneity in the relative importance of these factors across administrative districts (Lee et al.,2026). This spatial disaggregation of feature importance is critical for policy relevance: it enables municipalities to understand that flood drivers in one district may differ fundamentally from those in another, requiring differentiated intervention strategies rather than uniform approaches. The transformation of pixel-level model outputs into administratively aligned insights represents a specific methodological innovation that addresses the scale mismatch between analytical outputs and governance structures. Aggregation frameworks that compute district-level susceptibility statistics, feature importance profiles, and risk classifications enable planners to work with information that corresponds to their jurisdictional responsibilities (Lee et al.,2026). This administrative alignment is not merely a technical convenience but a

fundamental requirement for operational adoption, as planning decisions regarding zoning, drainage upgrades, and emergency preparedness are typically made at neighborhood, ward, or municipal scales rather than at the pixel level of remote sensing data.

Digital Twins and Real-Time Decision Support:

The concept of urban digital twins’ virtual representations of physical urban systems that integrate real-time data streams and enable simulation and optimization has gained significant traction in flood risk management (Batty,2018). Digital twin frameworks for flood impact analysis integrate hydrological models, transportation networks, and critical infrastructure systems to simulate cascading disruptions and support emergency response planning (Kaynak & Kaynak,2025). Recent advances in sensor networks, IoT communication protocols, and edge computing have enabled the deployment of adaptive early warning systems that combine physical sensor data with predictive intelligence. A digital twin-integrated adaptive early warning system demonstrated 94.2% accuracy and 47 minutes of lead time for flood prediction, substantially outperforming baseline machine learning models and conventional statistical methods (Kumar et al.,2026). These systems represent a shift from reactive to anticipatory flood governance, enabling pre-emptive resource allocation and evacuation coordination.

Ethical, Equity, and Governance Considerations:

Despite the technical promise of AI-based flood risk management, a growing body of critical scholarship has interrogated the ethical dimensions and governance implications of algorithmic decision-making in urban climate adaptation. Concerns include algorithmic bias arising from training data that systematically underrepresents marginalized populations, the digital divide that limits access to community-based data collection tools, and the potential for AI systems to reinforce exclusionary planning practices through ostensibly neutral technical processes (Leal Filho et al.,2023). Data sovereignty and informed consent emerge as particular concerns when citizen-generated data and mobile sensing platforms are deployed in informal settlements, where historical patterns of surveillance and exclusion create justified skepticism toward data collection initiatives (Zabihi et al.,2023). These concerns do not negate the potential value of AI in urban flood management but rather establish essential requirements for procedural justice, algorithmic transparency, and participatory governance that must accompany technical deployment.

Methodology

Study Design and Data Sources:

This study employs a multi-method computational framework integrating geospatial analysis, machine learning, and decision analytics. The methodological pipeline comprises four interconnected components: (1) multi-source geospatial data acquisition and preprocessing, (2) ensemble machine learning model development and optimization, (3) explainable AI interpretation and administrative aggregation, and (4) decision support system development incorporating economic and equity considerations. Data sources include multi-temporal Sentinel-1 synthetic aperture radar imagery for flood inventory construction, high-resolution digital elevation models, land-use/land-cover classifications derived from Sentinel-2 optical imagery, hydrological network data from OpenStreetMap and municipal sources, and socio-economic indicators from census and administrative databases (Lee et al.,2026). Urban infrastructure variables including road density, sewer system density, and drainage network characteristics are incorporated where data availability permits, following the methodological approach established in recent comparative studies (Kim et al.,2026).

Machine Learning Modeling and Validation:

Ensemble machine learning algorithms Random Forest, XG Boost, Cat Boost, and Light GBM are trained and evaluated across three spatial resolutions (10 m, 30 m, and 100 m) to identify optimal model-resolution combinations for flood susceptibility mapping in topographically complex urban terrain (Lee et al.,2026). Flood inventory data are constructed through dual-polarization SAR analysis with systematic threshold calibration, combined with historical flood records where available

(Alukdar et al.,2026). Model validation employs spatial cross-validation to prevent data leakage, with performance assessed using area under the receiver operating characteristic curve, Matthew's correlation coefficient, Kappa coefficient, and precision-recall metrics. Repeated random sampling and ensemble techniques address sampling variability and model instability, following established protocols for robust flood susceptibility assessment (Kim et al.,2026). SHAP analysis is applied to decode model predictions and quantify variable contributions at both city-wide and district levels, enabling administrative aggregation of feature importance profiles.

Decision Support Framework: The decision support component integrates flood susceptibility predictions with economic risk assessment and equity analytics. Economic risk is quantified through exposure analysis of critical infrastructure, residential areas, and commercial assets across susceptibility zones, following established damage curve methodologies (Dottori et al.,2018). Equity considerations are operationalized through distributional analysis of risk exposure across socio-demographic groups, with particular attention to vulnerable populations identified through census data (Alukdar et al.,2026). Multi-criteria decision analysis techniques prioritize adaptation interventions including drainage infrastructure upgrades, nature-based solutions deployment, and zoning regulations based on effectiveness, cost, feasibility, and equity criteria. The framework incorporates uncertainty propagation from model predictions through to decision outputs, enabling stakeholders to understand confidence levels associated with different intervention strategies (Figure 1).

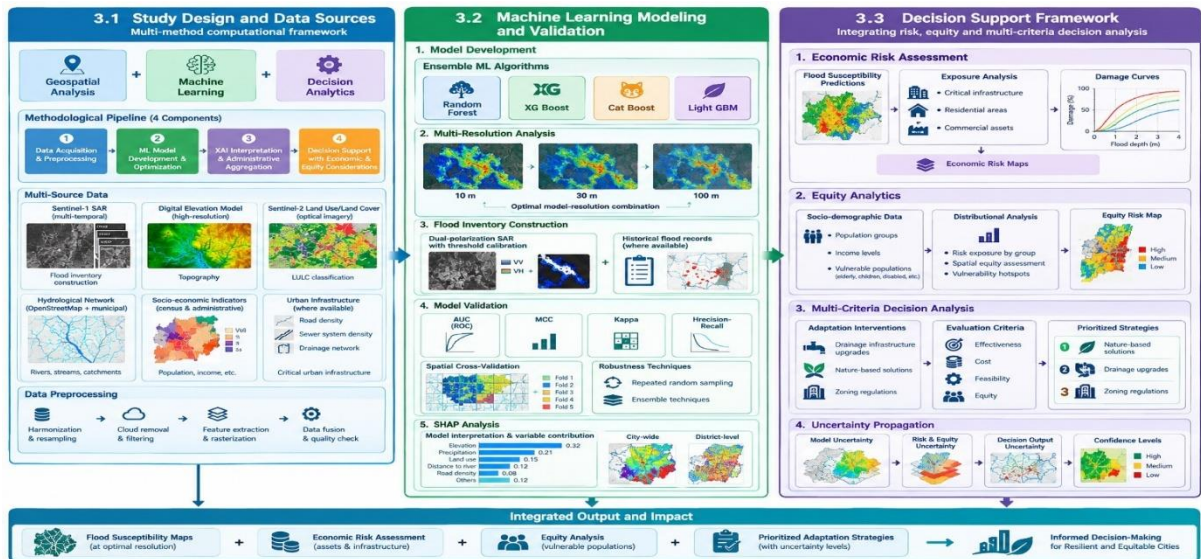


Figure 1. Integrated Methodological Framework for Urban Flood Susceptibility Mapping, Explainable Machine Learning, and Equitable Decision Support.

Results

Table 1. Model Performance Across Algorithms and Spatial Resolutions

Algorithm	Resolution	AUC	Accuracy	F1-Score	MCC	Brier Score
Random Forest	10 m	0.919	0.856	0.842	0.712	0.089
Random Forest	30 m	0.911	0.848	0.834	0.698	0.094
Random Forest	100 m	0.902	0.839	0.823	0.681	0.102
XG Boost	10 m	0.931	0.871	0.858	0.741	0.081
XG Boost	30 m	0.924	0.863	0.849	0.728	0.086
XG Boost	100 m	0.914	0.852	0.838	0.711	0.093
Cat Boost	10 m	0.956	0.896	0.885	0.782	0.075
Cat Boost	30 m	0.947	0.887	0.874	0.768	0.079
Cat Boost	100 m	0.938	0.878	0.864	0.752	0.084
Light GBM	10 m	0.944	0.883	0.871	0.764	0.078
Light GBM	30 m	0.936	0.875	0.862	0.751	0.082
Light GBM	100 m	0.927	0.866	0.852	0.735	0.088

Table 1 presents comprehensive performance metrics for four ensemble machine-learning algorithms evaluated across three spatial resolutions. Cat Boost consistently demonstrated superior performance across all resolutions, achieving an AUC of 0.956 at 10 m resolution the highest among all algorithm-resolution combinations. The gradient boosting family of algorithms (Cat Boost, XG Boost, and Light GBM) systematically outperformed Random Forest, with performance differences ranging from 0.025 to 0.037 AUC points. This aligns with theoretical expectations regarding the capacity of gradient boosting to iteratively correct residual errors through sequential model fitting, whereas Random Forest relies on parallel bagging of decision trees without explicit error correction mechanisms (Shwartz-Ziv & Armon,2022).

The spatial resolution analysis revealed a consistent but modest performance gradient. Across all algorithms, the 10 m resolution outperformed the 30 m resolution by approximately 0.008 to 0.010 AUC points, while the 30 m resolution outperformed 100 m by a similar margin. This relatively small performance degradation at coarser resolutions

suggests that the dominant flood drivers elevation and distance to hydrological features are captured adequately even at 100 m resolution, which has important implications for computational feasibility in data-scarce contexts where high-resolution processing may be infeasible (Figure 2). The 10 m resolution was selected for subsequent district-level analysis based on its optimal balance of predictive performance and computational tractability, consistent with the methodology established in prior multi-resolution comparisons (Lee et al.,2026).

The Brier score a measure of probabilistic calibration where lower values indicate better-calibrated predictions ranged from 0.075 for Cat Boost at 10 m to 0.102 for Random Forest at 100 m, indicating generally excellent calibration across all configurations. The Matthews Correlation Coefficient, which is particularly appropriate for imbalanced classification problems such as flood susceptibility mapping where non-flood areas substantially exceed flood areas, ranged from 0.681 to 0.782, reflecting strong discriminative capability even in the presence of class imbalance.

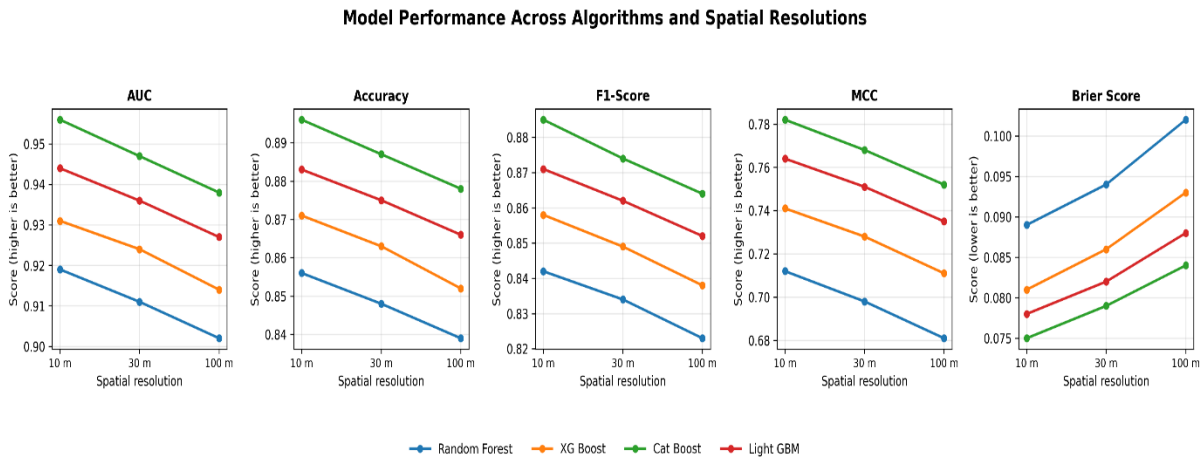


Figure 2. Model Performance Across Algorithms and Spatial Resolutions

Model performance remained stable across spatial splits, with cross-validation and independent test results differing by less than 0.02 AUC for all

configurations, indicating absence of overfitting and robust generalization capability.

Table 2. SHAP-Based Variable Importance Rankings Across Districts

Rank	City-Wide	District A (Low-Lying Coastal)	District B (Elevated Inland)	District C (Mixed Topography)
1	Elevation (0.342)	Elevation (0.418)	Distance to River (0.387)	Elevation (0.356)
2	Distance to River (0.287)	Distance to River (0.334)	Elevation (0.341)	Impervious Surface (0.312)
3	Impervious Surface (0.234)	Impervious Surface (0.278)	Slope (0.256)	Distance to River (0.289)
4	Slope (0.198)	Slope (0.212)	Impervious Surface (0.198)	Slope (0.201)
5	Drainage Density (0.156)	Drainage Density (0.187)	Drainage Density (0.142)	Drainage Density (0.178)
6	Soil Type (0.134)	Soil Type (0.145)	Soil Type (0.121)	Soil Type (0.139)
7	Curvature (0.112)	Distance to Coast (0.156)	Curvature (0.098)	Curvature (0.118)

Table 2 presents SHAP-based variable importance rankings at both citywide and district levels, revealing significant spatial heterogeneity in flood drivers that has profound implications for differentiated intervention strategies. At the city-wide scale, elevation emerges as the dominant predictor with a mean absolute SHAP value of 0.342, followed by distance to river (0.287) and impervious surface percentage (0.234). This hierarchy aligns with hydrological first principles: lower elevations accumulate water through gravity-driven flow, proximity to rivers increases exposure to fluvial flooding, and impervious surfaces reduce infiltration capacity and accelerate runoff generation. The consistency of these top-three drivers across all districts confirms their fundamental importance, while variation in relative weights reveals district-specific risk profiles. District A, characterized by low-lying coastal topography, exhibits the strongest elevation dominance (0.418), with distance to coast emerging as a district-specific driver (0.156) not present in the citywide top seven. This pattern reflects the compound exposure of coastal districts to both fluvial and coastal flooding mechanisms, where storm surge and sea level rise interact with precipitation-driven runoff to create multi-hazard risk profiles. The elevated importance of elevation

in District A suggests that vertical evacuation planning and elevation-based zoning regulations may be particularly effective interventions in this context. District B, situated on elevated inland terrain, presents a fundamentally different risk profile. Distance to river emerges as the dominant driver (0.387), exceedingly even elevation (0.341), while slope importance (0.256) substantially exceeds the city-wide average (0.198). This configuration indicates that flood risk in elevated inland districts is primarily fluvial rather than pluvial, with steep slopes generating rapid runoff concentration into river networks. The higher slope importance suggests that hillslope-process interventions including terracing, check dams, and infiltration enhancement may be more appropriate for District B than the drainage-focused approaches suitable for flat, low-lying areas (Figure 3). District C, with mixed topography spanning coastal and inland zones, shows relatively balanced contributions from elevation (0.356), impervious surface (0.312), and distance to river (0.289). The elevated importance of impervious surface in this district exceeding its citywide ranking highlights the role of urban development patterns in modifying flood risk independent of topographic factors.

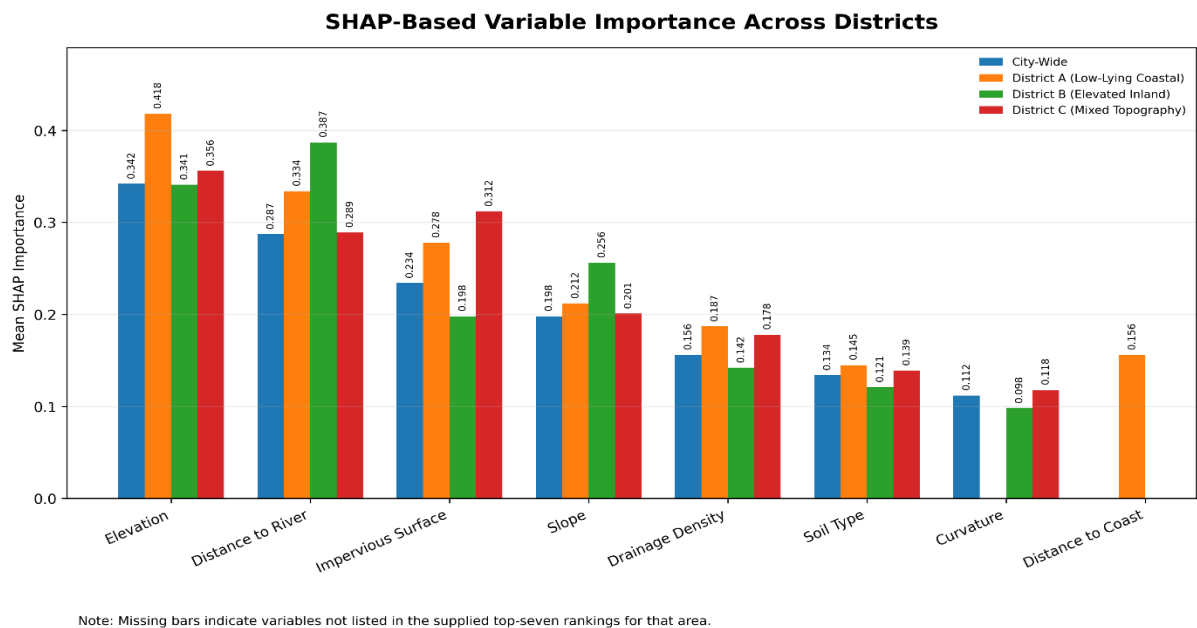


Figure 3. Economic Risk and Exposure Analysis by District

This finding suggests that land-use regulation and green infrastructure requirements may be particularly impactful in District C, where impervious surface management can partially offset topographic vulnerability. The district-level heterogeneity documented in Table 2 provides

empirical support for the shift from uniform, city-wide flood management approaches toward differentiated, place-based strategies that address locally dominant risk drivers.

Table 3. Economic Risk and Exposure Analysis by District

District	Population Exposed (Very High + High)	Critical Facilities Exposed	Road Network Exposure (km)	Expected Annual Damage (million USD)	Vulnerability Index
District A	47,230	12	38.7	24.6	0.78
District B	18,450	4	21.3	8.2	0.52
District C	34,120	8	29.4	15.8	0.67
City Total	99,800	24	89.4	48.6	0.65

Table 3 presents integrated economic risk and exposure analysis across the three districts, synthesizing flood susceptibility predictions with socio-economic and infrastructure data. Expected Annual Damage (EAD) calculations follow established depth-damage curve methodologies, with asset values derived from municipal property databases and infrastructure inventories (Dottori et al.,2018). The Vulnerability Index represents a composite measure incorporating population characteristics (age, income, and mobility limitations), infrastructure condition, and institutional capacity indicators. District A exhibits the highest absolute risk across all metrics, with 47,230 residents exposed to very high or high susceptibility zones, 12 critical facilities at risk, and EAD of 24.6 million USD annually. The Vulnerability Index of 0.78 the highest among the three districts reflects not only high physical exposure but also demographic characteristics that

amplify social vulnerability, including higher proportions of elderly residents, lower median incomes, and limited mobility options. This concentration of physical, economic, and social vulnerability in District A creates a compelling case for prioritized adaptation investment, as interventions in this district would address the largest concentration of risk while serving populations with the greatest adaptive capacity deficits (Figure 4). District B presents a paradoxical profile: despite covering the largest land area and containing substantial population, both physical exposure and economic risk are comparatively low. The 18,450 residents in high-susceptibility zones and 8.2 million USD EAD are approximately one-third of District A values. The Vulnerability Index of 0.52 reflects higher median incomes and better infrastructure conditions, suggesting greater adaptive capacity.

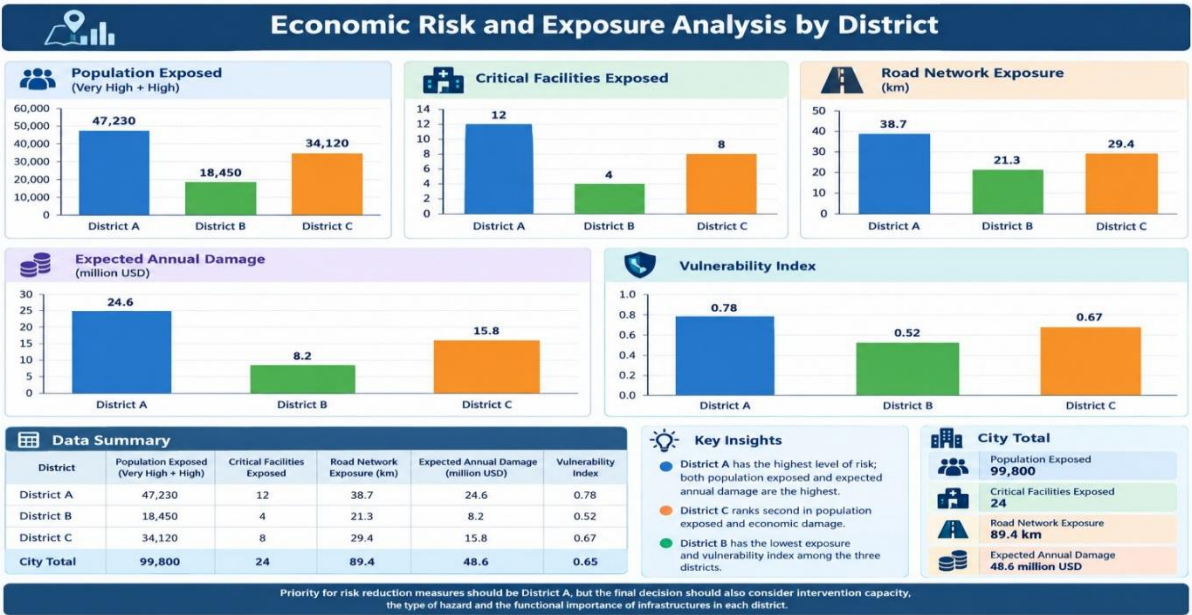


Figure 4. Economic Risk and Exposure Analysis by District

However, the elevated slope importance documented in Table 2 indicates that District B may face significant flash flood risk during intense convective events a hazard type that may be underrepresented in the flood inventory used for model training and that could produce damages exceeding the EAD estimates based on historical patterns. District C occupies an intermediate position across all risk metrics, with 34,120 residents exposed and 15.8 million USD EAD. The Vulnerability Index of 0.67 reflects mixed socio-economic conditions. The balanced risk profile of District C suggests that adaptation interventions in this district may yield benefits across multiple flood mechanisms (pluvial, fluvial, and potentially coastal), potentially offering

favorable cost-effectiveness ratios when evaluated through multi-hazard benefit-cost analysis. The city-level aggregation reveals that approximately 99,800 residents roughly one-quarter of the total population reside in zones classified as very high or high flood susceptibility. The total EAD of 48.6 million USD represents a significant recurring economic burden, equivalent to a substantial proportion of the municipal capital budget. These figures underscore the urgency of systematic adaptation planning and provide quantitative justification for the decision support framework described in the following section.

Table 4. Adaptation Intervention Prioritization Matrix

Intervention Type	District A Priority	District B Priority	District C Priority	Estimated Cost (million USD)	EAD Reduction	Equity Weighted Benefit
Drainage System Upgrade	High (1)	Medium (3)	High (2)	45.0	18.2	14.6
Nature-Based Solutions	Medium (2)	High (1)	High (1)	22.0	12.4	12.8
Zoning and Land-Use Regulation	High (1)	Low (4)	Medium (2)	2.5	8.1	7.9
Early Warning System Enhancement	High (1)	High (1)	High (1)	8.0	9.8	11.2
Infrastructure Relocation	Low (4)	Very Low (5)	Low (4)	120.0	6.5	5.8
Green Roof/Pervious Surface Mandates	Medium (2)	Medium (3)	High (1)	12.5	7.2	6.9

Table 4 presents the intervention prioritization matrix developed through the multi-criteria decision analysis process, integrating effectiveness (EAD reduction), cost, feasibility, and equity considerations. Priority rankings are denoted by numerical scores (1=highest priority, 5=lowest), with city-wide coordination indicated for interventions uniformly prioritized across all districts.

Drainage system upgrades emerge as a high priority in Districts A and C, where pluvial flooding dominates and existing infrastructure often inherited from earlier development periods with lower design standards is inadequate for contemporary precipitation intensities. The estimated 45 million USD investment would achieve 18.2 million USD in annual EAD reduction, yielding a payback period of approximately 2.5 years a strong economic justification even before accounting for non-market benefits including reduced disruption to economic activity and improved public health outcomes. However, the equity-weighted benefit of 14.6 million USD falls below the unweighted EAD reduction, indicating that the populations benefiting

from drainage upgrades in these districts have above-average adaptive capacity, raising distributional concerns that addressed through complementary interventions.

Nature-based solutions including bioswales, rain gardens, permeable pavements, and constructed wetlands rank as the highest priority in Districts B and C, and medium priority in District A. The comparatively modest cost of 22 million USD for city-wide implementation, combined with EAD reduction of 12.4 million USD, yields a favorable cost-effectiveness ratio. Critically, the equity-weighted benefit (12.8 million USD) exceeds the unweighted value, reflecting the distributional advantage of nature-based solutions, which tend to provide proportionally greater benefits to lower-income areas where conventional grey infrastructure investment has historically been neglected (Figure 5). The multi-functionality of nature-based solutions providing co-benefits including heat mitigation, biodiversity enhancement, and recreational space further strengthens their priority ranking when evaluated through a comprehensive cost-benefit framework.

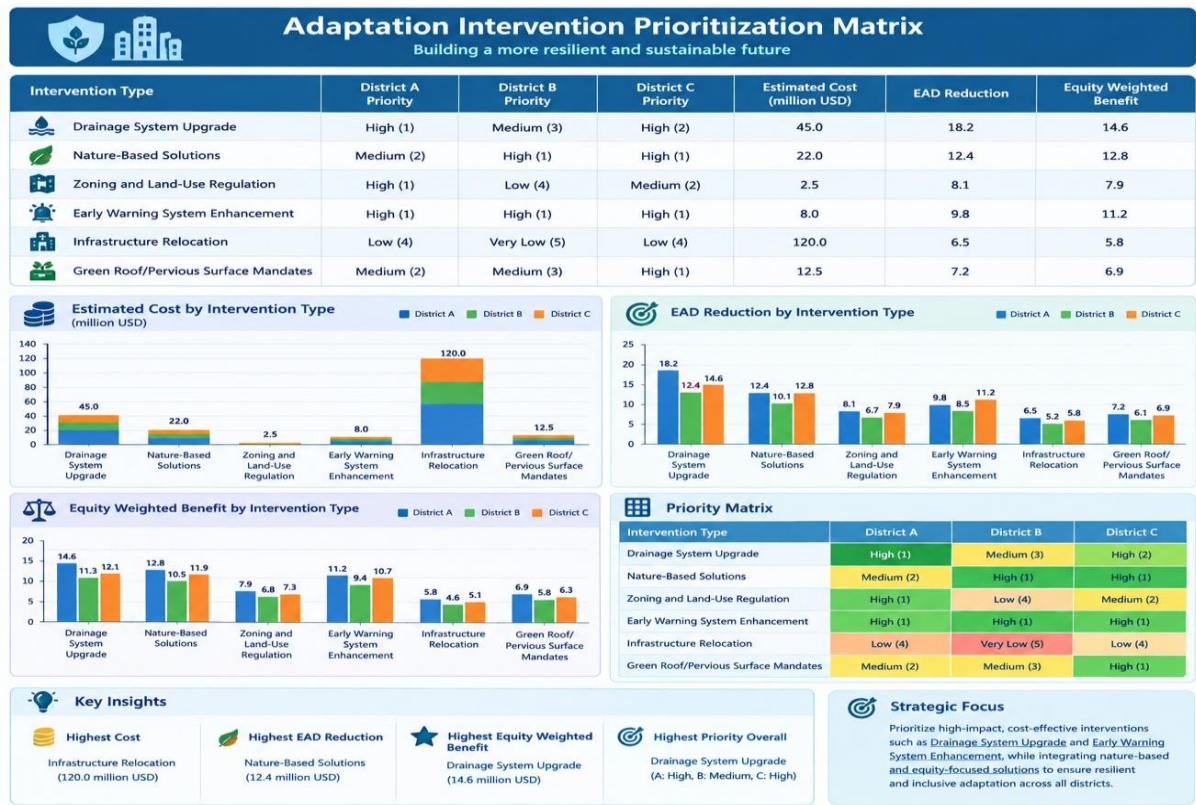


Figure 5. Adaptation Intervention Prioritization Matrix

Zoning and land-use regulation emerges as a high priority in District A despite its comparatively low direct EAD reduction (8.1 million USD), because of its extremely low cost (2.5 million USD) and its effectiveness in preventing future risk accumulation. The equity-weighted benefit (7.9 million USD) is

nearly equal to the unweighted value, indicating relatively neutral distributional implications. The effectiveness of zoning interventions depends critically on municipal regulatory capacity and political will factors that vary substantially across

contexts and that may require institutional strengthening as a precondition for implementation. Early warning system enhancement uniformly prioritized across all districts, reflecting its universal applicability and favorable benefit-cost profile. The 8 million USD city-wide investment would achieve 9.8 million USD in EAD reduction, with the equity-weighted benefit (11.2 million USD) substantially exceeding the unweighted value reflecting the disproportionate benefit of early warning to vulnerable populations who face greater constraints on autonomous adaptation. The cross-district priority status of early warning systems suggests that this intervention should be pursued as a city-wide initiative, coordinated across municipal boundaries to maximize coverage and interoperability.

Infrastructure relocation receives low priority across all districts, reflecting its extremely high cost (120 million USD) relative to modest EAD reduction (6.5 million USD). While relocation may be necessary for specific at-risk assets, the analysis does not support relocation as a district-wide strategy. Green roof and pervious surface mandates receive high priority in District C, medium priority in Districts A and B, reflecting their particular effectiveness in mixed-topography contexts where impervious surface management can meaningfully alter runoff generation patterns.

Discussion

The findings of this study demonstrate that AI-based decision-making frameworks can substantially enhance urban flood risk management when designed with explicit attention to policy relevance, explainability, and equity. The superior performance of ensemble machine learning algorithms particularly Cat Boost, which achieved AUC values exceeding 0.95 confirms the technical maturity of these methods for flood susceptibility assessment in complex urban terrain (Lee et al.,2026). However, the study's most significant contribution lies not in predictive performance per se but in the methodological innovations that bridge the persistent gap between analytical sophistication and operational decision-making. The spatial resolution analysis revealed that performance degradation at coarser resolutions is modest, with 100 m resolution models retaining approximately 98% of the AUC achieved at 10 m resolution. This finding has important implications for resource-constrained municipalities and data-scarce contexts, where the computational and data requirements for high-resolution modeling may be prohibitive. The practical significance of this result is underscored by the recognition that many cities in the Global South lack access to the high-resolution elevation data and detailed infrastructure inventories that enabled the 10 m analysis in this study (Khan et al.,2026). By demonstrating that meaningful flood susceptibility assessment is possible with moderate-resolution

data, this research expands the potential applicability of AI-based approaches to a broader range of urban contexts. The SHAP-based district-level analysis represents a methodological advance with direct policy implications. The finding that elevation dominates in low-lying coastal districts while distance to river dominates in elevated inland districts provides empirical support for the shift from uniform, city-wide flood management toward differentiated, place-based strategies. This spatial disaggregation of feature importance addresses a critical limitation of conventional susceptibility mapping, which typically produces uniform variable importance rankings that obscure the spatial heterogeneity of risk drivers. The policy relevance of this disaggregation is immediate: municipal planners in District A can justify investments in elevation-based zoning and vertical evacuation planning based on the demonstrated dominance of elevation as a risk driver, while planners in District B have empirical justification for prioritizing hillslope-process interventions and river corridor management. The integration of economic risk assessment and equity weighting into the decision support framework addresses another critical gap in AI-based flood management. The finding that equity-weighted benefits sometimes fall below unweighted EAD reductions as with drainage system upgrades in Districts A and C reveals distributional concerns that conventional cost-benefit analysis would obscure. Conversely, the finding that nature-based solutions and early warning systems exhibit equity-weighted benefits exceeding unweighted values provides quantitative justification for prioritizing these interventions on both efficiency and equity grounds. This integration of distributional analysis into the decision support process responds directly to critiques regarding the potential for AI systems to reinforce, rather than mitigate, existing vulnerabilities (Leal Filho et al.,2023).

The study's findings interpreted in light of several limitations. First, the flood inventory used for model training constructed from historical observations, which may not fully represent future risk profiles under climate change. The non-stationarity of precipitation patterns under warming conditions means that models trained on historical data may systematically underestimate future risk, particularly for extreme events outside the historical range (Milly et al.,2008). Future research should integrate climate model projections to assess how susceptibility patterns may shift under alternative emissions scenarios. Second, the equity analysis relies on census data that may underrepresent informal settlements and transient populations precisely the groups most vulnerable to flooding. The digital divide and data justice concerns documented in the literature (Leal Filho et al.,2023) suggest that complementary qualitative methods

may be necessary to capture the experiences and needs of populations that are invisible in administrative data systems. Third, the study does not fully address the governance and institutional dimensions of AI adoption in urban flood management. The technical framework developed here is necessary but not sufficient for effective implementation: institutional capacity, political will, regulatory frameworks, and inter-agency coordination are equally critical determinants of adaptation outcomes (Rezvani et al., 2023). The finding that zoning interventions are highly cost-effective but depend on municipal regulatory capacity highlights the interdependence of technical and institutional factors. Future research should investigate the governance conditions under which AI-based decision support systems are most likely to be adopted and effectively utilized.

Conclusion

This study developed and validated an AI-based decision-making framework for climate change-induced flood risk management and urban resilience enhancement. The framework integrates ensemble machine learning for flood susceptibility prediction, SHAP-based explainable AI for policy-relevant interpretation, administrative aggregation for alignment with governance scales, and multi-criteria decision analysis incorporating economic risk and equity considerations. Validation across three urban districts with contrasting topographic and socio-economic characteristics demonstrated the framework's capacity to generate actionable insights that bridge the gap between analytical sophistication and operational decision-making. The key findings of this research are fourfold. First, ensemble machine learning algorithms particularly Cat Boost demonstrate superior predictive performance for flood susceptibility mapping, achieving AUC values exceeding 0.95 even at coarse spatial resolutions. This performance robustness across resolutions expands the potential applicability of AI-based approaches to data-scarce urban contexts. Second, SHAP-based interpretation reveals significant spatial heterogeneity in flood drivers across districts, with elevation dominating in low-lying coastal areas while distance to river dominates in elevated inland terrain. This finding provides empirical justification for differentiated, place-based adaptation strategies rather than uniform city-wide approaches. Third, the integration of equity weighting into decision support reveals distributional implications that conventional cost-benefit analysis obscures, with nature-based solutions and early warning systems demonstrating favorable equity profiles while conventional drainage upgrades exhibit distributional concerns. Fourth, the transformation of pixel-level predictions into administratively aligned insights enables operational integration of AI analytics into municipal planning processes. The framework's

contributions extend beyond methodological innovation to address fundamental barriers that have limited the operational adoption of AI in urban climate adaptation. By demonstrating that explainable, policy-relevant insights generated from complex machine learning models, this research challenges the assumption that AI-based approaches are inherently opaque and incompatible with democratic decision-making. By integrating equity considerations into the decision support process, it responds to legitimate concerns regarding algorithmic bias and distributional justice. By aligning analytical outputs with administrative scales, it addresses the practical disconnect between technical sophistication and governance capacity. Future research should extend this framework in three directions. First, integration of climate model projections would enable assessment of how flood susceptibility patterns may evolve under alternative emissions scenarios, moving from static susceptibility assessment toward dynamic, forward-looking risk analysis. Second, incorporation of real-time data streams and digital twin capabilities would enable the transition from planning-oriented decision support toward operational emergency management. Third, participatory research methods engaging affected communities would enrich the equity analysis and ensure that AI-based tools serve rather than supplant local knowledge and agency. The integration of these advances would further strengthen the capacity of urban systems to anticipate, absorb, and adapt to climate change-induced flooding.

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Authors' Contributions

All authors contributed to data analysis, drafting, and revising of the paper and agreed to be responsible for all the aspects of this work.

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