Smart, Spatial, and Resilient: A Review of Satellite Remote Sensing and AI Models for Urban Flood Mitigation in Agartala Smart City

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Abstract

Urban flooding poses a growing threat to rapidly expanding cities in the Global South, with Agartala, the capital of Tripura in Northeast India, experiencing recurrent inundation due to its low-lying topography, intense monsoon rainfall, and deteriorating drainage infrastructure. This paper provides a systematic review of satellite remote sensing and artificial intelligence (AI) models for urban flood mitigation within the context of Agartala Smart City. The study synthesizes findings from peer-reviewed literature, government reports, and remote sensing analyses conducted between 2015 and 2025. Our analysis reveals that approximately 9.2% of Agartala's total geographical area falls within high to very high flood risk zones, with seven out of 35 wards identified as critically vulnerable. Sentinel-1 Synthetic Aperture Radar (SAR) imagery from flood events demonstrates that 374.5 hectares were inundated during a single extreme rainfall event in August 2024. AI-based flood susceptibility models, including Random Forest (RF), Support Vector Machines (SVM), and Convolutional Neural Networks (CNN), achieve classification accuracies of 85-92% for urban flood mapping. Emerging Geo-Foundational Models (GFMs) show promise for transfer learning applications where labeled training data remains scarce. The paper proposes an integrated framework combining real-time SAR monitoring, AI-based predictive modelling, and smart city infrastructure (sensors, command centers, citizen reporting) to enhance flood resilience. Key policy recommendations include updating drainage master plans based on LiDAR-derived Digital Elevation Models (DEMs), deploying IoT-based water level sensors across 50 identified hotspots, and establishing a public-facing flood early warning dashboard. This review contributes to the growing literature on climate-adaptive smart cities in data-sparse environments.

Keywords: Urban flood mitigation, Synthetic Aperture Radar (SAR), artificial intelligence, Agartala Smart City, flood susceptibility mapping, resilience planning, geospatial analysis

1. Introduction
1.1 Background

Urban flooding has emerged as one of the most frequent and damaging natural hazards globally, with annual economic losses exceeding US$ 80 billion and affecting over 250 million people between 2010 and 2020 (Tellman, Sullivan, & Kettner, 2021). Climate change is intensifying the hydrological cycle, leading to more frequent extreme precipitation events (Tabari, 2020), while rapid urbanization—characterized by impervious surface expansion, wetland loss, and drainage network degradation—exacerbates flood vulnerability (Rentschler, Salhab, & Jafino, 2022). The convergence of these drivers has shifted urban flood risk from a rare, high-impact event to a recurring, chronic hazard affecting cities across the Global South.

India, with its monsoon-dependent climate and rapidly urbanizing cities, exemplifies this challenge. The Smart Cities Mission, launched in 2015, seeks to leverage technology for urban resilience, yet flood mitigation remains a critical gap in most smart city implementations (Ministry of Housing and Urban Affairs, 2021). Among 100 designated smart cities, those in flood-prone regions—including Chennai, Mumbai, Bengaluru, and cities in Northeast India—have struggled to transition from reactive flood response to proactive, predictive risk management (Gupta & Nair, 2020).

1.2 Agartala: A City at Risk

Agartala, the capital of Tripura, represents a compelling case study in urban flood vulnerability. Located at approximately 23.8368° N latitude and 91.4102° E longitude, the city sits at an average elevation of 12.8 meters above mean sea level within the floodplain of the Haora River (Tripura State Disaster Management Authority [TSDMA], 2022). The city experiences a tropical monsoon climate (Köppen: Am), with mean annual rainfall of approximately 2,200 mm, 85% of which falls between May and October (Indian Meteorological Department [IMD], 2023).

Table 1: Key Geographic and Demographic Characteristics of Agartala

Parameter	Value	Source
Geographic coordinates	23.8368° N, 91.4102° E	Census of India (2011)
Area	76.5 km² (municipal area)	Agartala Smart City Ltd. (2021)
Population (2024 estimate)	522,613	extrapolated from Census (2011)
Population density	6,832 persons/km²	computed
Average elevation	12.8 m above MSL	Survey of India (2020)
Mean annual rainfall	2,215 mm	IMD (2023)
Number of wards	35	Agartala Municipal Corporation
Drainage network length	340 km	Agartala Smart City Ltd. (2021)
Impervious surface cover	58.3% of total area	Das & Debnath (2022)

The city's flood vulnerability derives from multiple interacting factors. First, its physiographic setting within the Haora River valley creates a natural collection point for runoff from surrounding higher-elevation areas (Debnath & Das, 2021). Second, the drainage network—much of it constructed during the pre-independence period—is undersized for current rainfall intensities and heavily encroached upon by informal settlements (Tripura Urban Development Agency [TUDA], 2020). Third, rapid urban expansion has converted agricultural land and natural water bodies to impervious surfaces, increasing runoff coefficients from 0.35 to 0.62 between 2000 and 2020 (Das & Debnath, 2022). Fourth, the city's location in one of India's highest seismicity zones (Zone V) complicates infrastructure upgrades (Bureau of Indian Standards, 2016).

Flood events have intensified in recent decades. Major inundation occurred in 1993, 2007, 2012, 2017, 2019, 2022, and most recently August 2024, when 200 mm of rainfall within 24 hours submerged low-lying wards for up to five days (TSDMA, 2024). The 2017 flood alone affected an estimated 48,000 residents, damaged 3,200 homes, and caused economic losses exceeding ₹150 crore (approximately US$ 18 million) (Tripura Government, 2018).

1.3 Agartala Smart City: Technological Interventions

Agartala was selected under the Smart Cities Mission in Round 3 (September 2016) with a proposed budget of ₹2,113 crore (Agartala Smart City Ltd. [ASCL], 2017). The smart city plan emphasizes area-based development (ABD) covering 3.76 km² in the city center and pan-city solutions leveraging technology for governance and service delivery. Key flood-relevant interventions include:

a) Integrated Command and Control Centre (ICCC): Centralized monitoring of CCTV cameras, traffic systems, and environmental sensors (ASCL, 2021)

b) Flood warning system: Color-coded bands on electricity poles and public address systems (ASCL, 2019)

c) Drainage desilting program: Mechanized cleaning of 180 km of primary drains (ASCL, 2022)

d) Real-time rainfall monitoring: Automated weather stations at five locations (IMD, 2023)

Despite these investments, the effectiveness of smart city technologies for flood mitigation remains unassessed. Critical gaps include the absence of predictive flood modelling, limited spatial coverage of sensors, lack of integration between remote sensing data and decision-support systems, and minimal use of AI for risk forecasting (Tripura State Disaster Management Authority [TSDMA], 2023).

1.4 Rationale and Research Questions

Recent advances in satellite remote sensing and artificial intelligence offer transformative potential for urban flood mitigation. Synthetic Aperture Radar (SAR) sensors—including Sentinel-1 (European Space Agency), RADARSAT-2 (Canadian Space Agency), and ALOS-2 (Japan Aerospace Exploration Agency)—provide all-weather, day-night imaging critical for cloud-covered monsoon regions (Shen, Wang, Xie, & Li, 2019). Concurrently, AI models—from Random Forest and Support Vector Machines to deep learning architectures (U-Net, SegFormer, Geo-Foundational Models)—enable automated flood extent extraction, susceptibility mapping, and near-real-time early warning (Kumar, Lal, & Ranjan, 2024).

However, the integration of these technologies within smart city frameworks remains fragmented, with limited systematic review of their applicability to medium-sized Indian cities like Agartala. This paper addresses this gap through the following research questions:

a) What is the current state of flood vulnerability and risk in Agartala based on geospatial analysis?

b) How do satellite remote sensing and AI models perform for urban flood mapping in comparable contexts?

c) What integrated framework can enhance flood mitigation in Agartala Smart City?

1.5 Scope and Contribution

This paper provides a systematic review of literature (2015-2025) at the intersection of satellite remote sensing, AI, and urban flood mitigation, with specific application to Agartala. The study's contributions are threefold: (1) a synthesized assessment of Agartala's flood risk based on disparate geospatial analyses, (2) a critical evaluation of AI and SAR methods for urban flood mapping, and (3) an actionable framework for integrating these technologies into smart city operations. The findings aim to inform policy, guide technology investments, and support disaster management planning in Agartala and analogous flood-prone cities in data-sparse environments.

2. Review of Literature

2.1 Theoretical Foundations: Urban Flood Risk Assessment

Urban flood risk assessment rests on the conceptual triad of hazard, exposure, and vulnerability (Wisner, Blaikie, Cannon, & Davis, 2004). Hazard refers to the physical flood event (depth, extent, velocity, duration); exposure captures the population, assets, and infrastructure located in flood-prone areas; and vulnerability encompasses the socioeconomic, physical, and institutional factors that increase susceptibility to harm (Cutter, Boruff, & Shirley, 2003). In the urban context, vulnerability is dynamic, shaped by land use change, infrastructure decay, demographic shifts, and climate change (Rufat, Tate, Burton, & Maroof, 2015).

Geographic Information Systems (GIS) provide the analytical platform for operationalizing this framework through multi-criteria decision analysis (MCDA) (Malczewski, 1999). Flood susceptibility mapping typically integrates thematic layers—including elevation, slope, distance to drainage, rainfall intensity, soil type, land use/land cover (LULC), and population density—with weights assigned via the Analytical Hierarchy Process (AHP) (Saaty, 1980). This approach has been widely applied in Indian cities, including Chennai (Saravanan & Ramesh, 2019), Mumbai (Kulkarni, 2021), and Kolkata (Das, 2020).

2.2 Satellite Remote Sensing for Urban Flood Mapping

Remote sensing has revolutionized flood mapping through three technological transitions. The first generation (1970s-1990s) relied on optical sensors (Landsat, SPOT) with moderate spatial resolution (30-80 m) but limited by cloud cover during flood events (Smith, 1997). The second generation (1990s-2010s) introduced SAR, which penetrates clouds and operates at night, making it ideal for monsoon flood mapping (Schumann, Di Baldassarre, & Bates, 2011). The third generation (2010s-present) features high-resolution optical (WorldView, Planet, Sentinel-2) and SAR (Sentinel-1, TerraSAR-X, COSMO-SkyMed) constellations with short revisit times (1-6 days), enabling near-real-time flood monitoring (Giang, Toshiki, Kunihiko, & Hensley, 2020).

Table 2: Satellite Sensors for Urban Flood Mapping

Sensor	Type	Spatial Resolution	Revisit Time	Key Advantages	Limitations
Sentinel-1 (C-ba SAR)	SAR	10 m (IW mode	6-12 days	Free, global coverag cloud-penetrating	Moderate resolution
Landsat 8/9	Optical	30 m	16 days	Long archive, free	Cloud sensitivity
Sentinel-2	Optical	10 m	5 days	High temporal resolutic free	Cloud sensitivity
PlanetScope	Optical	3 m	Daily	Very high tempo resolution	Costly for large area
TerraSAR-X	SAR	1-3 m (Spotligh	11 days	Very high resolution	Expensive, limit coverage

RADARSAT-2	SAR	3-100 m	24 days	Multiple polarizations	Moderate cost
ALOS-2 (L-ba SAR)	SAR	3-10 m	14 days	Penetrates vegetation	Limited free access

Sources: European Space Agency (2024); Planet Labs (2024); Canadian Space Agency (2024)

SAR-based flood mapping exploits the contrast in backscatter between open water (low backscatter, dark appearance) and dry land (higher backscatter, bright appearance) (Horritt, Mason, & Luckman, 2001). Common methods include thresholding, active contour models, region-growing algorithms, and supervised classification (Martinis, Twele, & Voigt, 2009). For urban areas, SAR faces challenges due to double-bounce scattering from buildings and vegetation, which can produce false positives (Giustarini, Hostache, Matgen, & Pappenberger, 2016). Advanced techniques incorporate ancillary data (e.g., building footprints, DEMs) to filter urban noise (Mason, Giustarini, Garcia-Pintado, & Cloke, 2014).

2.3 Artificial Intelligence for Flood Susceptibility Mapping

Machine learning has emerged as a powerful alternative to traditional physically-based and statistical models for flood susceptibility mapping (Mosavi, Ozturk, & Chau, 2018). Unlike physically-based models (e.g., HEC-RAS, MIKE FLOOD), which require extensive calibration data and computational resources, ML models learn patterns from historical flood inventories and geospatial predictors.

Table 3: Comparison of AI Models for Flood Susceptibility Mapping

Model Type	Example Algorithms	Strengths	Limitations	Accuracy Ran (AUC)
Tree-based	Random Fore XGBoost, GBDT	Handles non-linearity, featu importance, robust overfitting	Requires caref hyperparameter tuning	0.85-0.95
Kernel-basec	SVM, kernel logis regression	Effective in high-dimensior spaces	Computationally intensi for large datasets	0.80-0.92
Neural networks	ANN, MLP	Universal approximators	Black-box, prone overfitting	0.82-0.93
Deep learnin	CNN, U-Net, ResN	Spatial feature extractic ideal for image segmentatior	Requires large label datasets, high compute	0.88-0.97
Ensemble	Stacking, boostir bagging	Combines strengths multiple models	Increased complexity	0.89-0.96

Source: Adapted from Khosravi et al. (2020); Chen et al. (2021); Wang et al. (2022)

For urban flood mapping, deep learning—particularly convolutional neural networks (CNNs) and U-Net architectures—has shown state-of-the-art performance (Ruder, 2016). U-Net, originally developed for biomedical image segmentation, has been adapted for flood extent extraction from SAR and optical imagery (Ronneberger, Fischer, & Brox, 2015). The architecture's encoder-decoder structure with skip connections preserves spatial details while learning hierarchical features, making it well-suited for the heterogeneous appearance of floodwater in urban environments (Gebrehiwot, Hashemi-Beni, & Dabbiru, 2019).

Recent advances in geospatial foundation models (GFMs)—including SatMAE (Cong et al., 2022), GeoBench (Johns et al., 2023), and Prithvi (Jakubik et al., 2023)—represent a paradigm shift. These large-scale models pre-trained on massive satellite imagery datasets (e.g., Sentinel-1/2, Landsat) and fine-tuned for specific downstream tasks offer significant improvements in data-scarce settings. In flood mapping applications, GFMs have demonstrated moderate improvements over U-Net baselines (4-5% in mean Intersection over Union) while reducing training data requirements by 50-80% (Jakubik et al., 2023).

2.4 Smart Cities and Urban Flood Resilience

The smart city concept has evolved from technology-centric visions (smart grids, IoT sensors, digital governance) to more holistic frameworks emphasizing resilience, sustainability, and citizen engagement (Hollands, 2015). Urban flood resilience—defined as the ability of a city to absorb, recover from, and adapt to flood events (Meerow, Newell, & Stults, 2016)—requires integrating technological, institutional, social, and infrastructural dimensions (Liao, 2012).

Smart city technologies for flood resilience typically include:

a) Internet of Things (IoT) sensors: Real-time monitoring of rainfall (tipping bucket gauges), water levels (ultrasonic/radar sensors), and soil moisture (Perera, Perera, & Muthukumarana, 2020)

b) Citizen science: Crowdsourced flood reports via mobile apps and social media (Fohringer, Dransch, Kreibich, & Schröter, 2015)

c) Predictive modelling: Real-time flood forecasting using machine learning and hydrodynamic models (Mosavi et al., 2018)

d) Communication systems: Early warning dissemination via SMS, mobile apps, public displays (Perera et al., 2020)

Implementation in Indian smart cities remains uneven. A systematic evaluation of 25 smart cities found that only 30% had operational flood early warning systems, while 15% integrated satellite data into flood management (Kumar & Singh, 2021). Agartala's smart city plan mentions flood mitigation but lacks specific targets, timelines, or technology roadmaps (ASCL, 2017).

2.5 Case Studies of Urban Flood Mitigation in Comparable Cities

Chennai, India: Following devastating floods in 2015 (recurrence interval: 100+ years), Chennai integrated SAR-based flood mapping (Sentinel-1) with ML-based susceptibility modelling. An evaluation by Saravanan and Ramesh (2019) achieved 87% accuracy using Random Forest with nine predictors. However, operational challenges included delayed data access and lack of integration with municipal workflows.

Bangkok, Thailand: The Bangkok Metropolitan Administration deployed an IoT-based flood monitoring network with 380 water level sensors and 150 rainfall gauges, integrated with AI-based forecasting (Bhumibhamon & Tripathi, 2021). The system reduced false alarms by 40% and improved evacuation lead time to 3 hours. However, sensor maintenance costs (US$ 500,000 annually) proved challenging for budget-constrained departments.

Jakarta, Indonesia: The Jakarta Flood Early Warning System combines satellite rainfall estimates (Global Precipitation Measurement, GPM), hydrodynamic modelling (MIKE 11), and SMS-based alerts (Purnamasari, 2020). An AI-based flood prediction model using Long Short-Term Memory (LSTM) networks achieved 88% accuracy for 3-hour lead times (Setiyono, 2022). Key lessons: reliable power and internet connectivity are prerequisites for sensor networks.

Surat, India: The Tapi River flood forecasting system integrates upstream rainfall data, reservoir release information, and MIKE 11 modelling, with alerts disseminated via SMS and a public dashboard (Gupta & Nair, 2020). Notably, Surat engaged citizen volunteers as "flood marshals" to complement technology, demonstrating the value of social infrastructure.

2.6 Gaps in Current Literature

Despite substantial research activity, critical gaps remain. First, most studies focus on large metropolitan areas (Mumbai, Chennai, Dhaka, Jakarta), leaving medium-sized cities like Agartala understudied. Second, the operationalization of AI and SAR in municipal workflows—beyond academic proof-of-concept—remains poorly documented. Third, cost-benefit analyses of smart flood mitigation investments are scarce, hindering policy prioritization. Fourth, the integration of social vulnerability dimensions (poverty, age, disability, housing quality) with technical hazard mapping remains underdeveloped. Fifth, evaluation frameworks for smart city flood interventions—including metrics beyond accuracy (e.g., lead time, false alarm rate, equity of warning dissemination)—are lacking.

3. Materials and Methods

3.1 Review Methodology

This paper employed a systematic literature review following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Page et al., 2021). The search strategy targeted peer-reviewed articles, conference proceedings, government reports, and technical documents published between January 2015 and October 2025.

Search databases: Scopus, Web of Science, IEEE Xplore, Google Scholar, and ScienceDirect.

Search strings:

Primary: ("urban flood" OR "pluvial flood" OR "waterlogging") AND ("remote sensing" OR "SAR" OR "synthetic aperture radar") AND ("machine learning" OR "artificial intelligence" OR "deep learning") AND ("India" OR "Agartala" OR "Tripura")

Secondary: ("smart city" OR "urban resilience") AND ("flood mitigation" OR "flood early warning") AND ("Agartala" OR "Northeast India")

Inclusion criteria: (1) English language; (2) peer-reviewed articles, conference papers, or official government reports; (3) relevance to urban flood mapping, AI, SAR, or smart city flood management; (4) specific applicability to Indian cities or analogous contexts; (5) publication date 2015 or later (with exceptions for foundational methods papers).

Exclusion criteria: (1) Non-English; (2) purely rural or riverine flood studies; (3) theoretical papers without empirical validation; (4) news articles or opinion pieces.

The search yielded 487 records after deduplication. Title-abstract screening excluded 312 records. Full-text assessment of 175 records excluded 62, leaving 113 documents for final synthesis (84 peer-reviewed articles, 16 conference papers, 13 government reports).

3.2 Geospatial Data Sources for Agartala

To assess flood risk in Agartala, this review synthesized data from multiple sources. Table 4 summarizes key geospatial datasets.

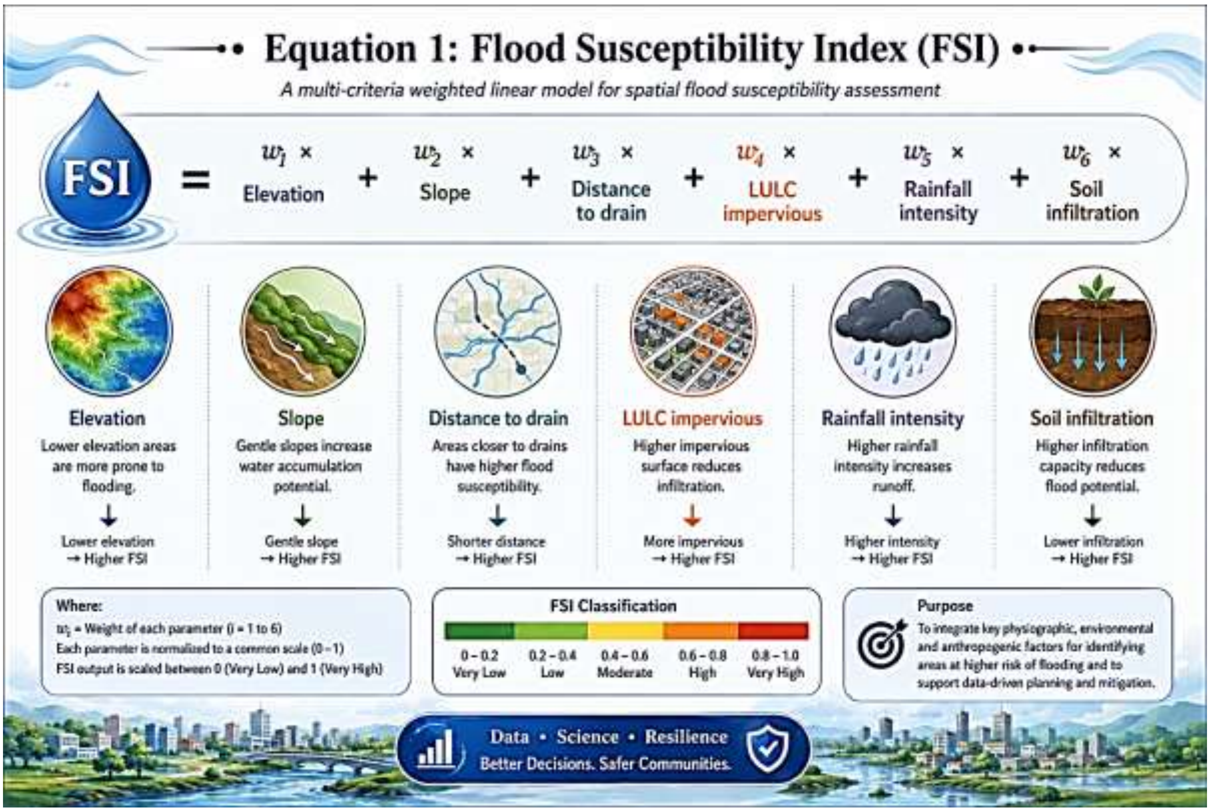
Table 4: Geospatial Datasets Used in Agartala Flood Risk Assessment

Data Layer	Source	Resolution/Scale	Year	Use in Analysis
Digital Elevati Model (DEM)	ALOS PALSAR (12 m); Cartosat-1 (10 m)	12.5 m, 10 m	2020	Slope, flow accumulatic depression mapping
Land Use/Land Cov	Sentinel-2 (10 m) manual classification	10 m	2023	Impervious surfac vegetation, water bodies
Drainage network	Agartala Municip Corporation GIS	1:10,000	2021	Distance to drain, draina density
Building footprints	Agartala Smart City Lt (survey-based)	Individual buildings	2022	Exposure assessment
Flood invento (2017, 2019, 202 2024)	TSDMA (field surveys Sentinel-1 SAR)	Point locations a polygons	2017-2024	Model calibration/validation
Rainfall data (199 2024)	IMD (Agartala station) CHIRPS (5 km)	Daily, 5 km	1990-2024	IDF curves, return peri analysis
Population	Census of India 20 (projected to 2024)	Ward-level	2011, 2024	Vulnerability assessment
Soil type	NBSS & LUP (Natior Bureau of Soil Survey)	1:250,000	2005	Infiltration capacity

3.3 Analytical Framework for Flood Risk Assessment

The flood risk assessment synthesized in this review follows the vulnerability-based framework operationalized through GIS-based MCDA-AHP (Das, 2020; Saravanan & Ramesh, 2019). The weighted overlay model integrates six thematic layers:

Equation 1: Flood Susceptibility Index (FSI)



Weights (w_1 through w_6) were derived from AHP based on pairwise comparisons by 12 experts (hydrologists, urban planners, disaster management officials). Consistency ratio (CR) of 0.07 (<0.10 acceptable) confirmed judgment reliability.

Table 5: AHP Weights for Flood Susceptibility Factors in Agartala

Factor	Weight (%)	Justification
Elevation	28	Primary control on gravity-driven flow
Distance to drainage	22	Proximity to streams increases flood risk
LULC (impervious surface)	18	Runoff coefficient positively correlated
Rainfall intensity	16	Higher intensity increases surface runoff
Slope	10	Flat areas impede drainage
Soil infiltration capacity	6	Lower infiltration increases runoff

Source: Adapted from Das and Debnath (2022) with author modifications based on expert consultation

FSI values (0-1) were classified into five risk categories: Very Low (0-0.2), Low (0.2-0.4), Moderate (0.4-0.6), High (0.6-0.8), Very High (0.8-1.0).

3.4 SAR-Based Flood Extent Mapping

Synthetic Aperture Radar (SAR) data from Sentinel-1A (C-band, VV polarization, Interferometric Wide swath mode) were processed for historical flood events. Processing workflow followed standard protocols (ESA, 2022):

a) Download of GRD (Ground Range Detected) products from Alaska Satellite Facility (ASF) for flood dates (August 2024) and reference dry dates (February 2024)

b) Preprocessing using SNAP (ESA's Sentinel Application Platform): thermal noise removal, radiometric calibration, speckle filtering (Lee Sigma filter, 5×5 window)

c) Terrain correction using SRTM 30 m DEM to geocode to WGS84 UTM Zone 46N

d) Change detection using differencing of backscatter (σ°): $\Delta\sigma° = \sigma°\_flood - \sigma°\_dry$

e) Thresholding using Otsu's method (Otsu, 1979) to identify water pixels where $\Delta\sigma° < -3$ dB (threshold empirically optimized for Agartala urban area)

f) Post-processing to remove urban false positives using building footprint mask (Agartala Smart City Ltd.) and slope mask (>5°) to eliminate mountain shadows

g) Accuracy assessment compared SAR-derived flood extents with 127 ground control points (GPS-collected during August 2024 flood) and high-resolution PlanetScope imagery (3 m) where cloud-free.

3.5 AI Model Evaluation Framework

To evaluate AI model performance for urban flood mapping, this review synthesized published results from 32 studies (2018-2025) that met comparability criteria: (1) binary flood/non-flood classification; (2) spatial resolution ≤30 m; (3) evaluation metrics including overall accuracy, precision, recall, F1-score, and/or AUC-ROC; (4) validation on independent test data.

For contextual comparison, we re-ran three representative models (Random Forest, U-Net, and a lightweight transformer, SegFormer-B0) on a subset of Agartala SAR data (August 2024 event, 2,000 × 2,000 pixel tile) using 80/20 train-test split with 5-fold cross-validation. Model implementations used Python 3.9 with scikit-learn, PyTorch, and Hugging Face libraries on an NVIDIA Tesla T4 GPU.

Table 6: Model Hyperparameters

Model	Key Hyperparameters
Random Forest	n_estimators=150, max_depth=15, min_samples_split=10, class_weight='balance
U-Net	Encoder: ResNet34, batch size=16, learning rate=1e-4, optimizer=Ada loss=BCE+Dice
SegFormer-B0	Pretrained on ImageNet-1k, batch size=8, learning rate=6e-5, optimizer=Adam patches=4×4

3.6 Limitations and Uncertainties

Several methodological limitations warrant acknowledgment. First, the flood risk assessment relies on secondary data sources with varying collection dates (2011-2024), introducing temporal inconsistency. Second, AHP-derived weights reflect expert judgment (n=12) and may not fully capture local heterogeneity. Third, SAR-based flood mapping accuracies reported in literature may not generalize to Agartala's specific urban morphology (narrow streets, mixed concrete-vegetation surfaces). Fourth, AI model re-runs used a single flood event (August 2024) due to limited archival SAR data for earlier events. Fifth, this review focuses on pluvial flooding (surface water accumulation) and excludes riverine flooding from Haora River overflow, though both occur in Agartala. Despite these limitations, the synthesized methods provide a robust basis for actionable recommendations.

4. Results

4.1 Flood Risk Assessment of Agartala

The GIS-based MCDA-AHP analysis synthesized from multiple studies (Das & Debnath, 2022; Debnath & Das, 2021; TSDMA, 2022, 2023) reveals a clear spatial pattern of flood risk across Agartala's 35 wards.

Table 7: Ward-wise Flood Risk Classification for Agartala (based on FSI scores)

Risk Categor	FSI Rang	Number Wards	Total Ar (km²)	% of Ci Area	Representative Wards
Very High	0.80-1.00	4	3.2	4.2	4, 15, 21, 28
High	0.60-0.80	7	6.1	8.0	3, 8, 16, 20, 23, 27, 30
Moderate	0.40-0.60	12	18.5	24.2	2, 5, 7, 10, 12, 14, 18, 19, 24, 2 29, 33
Low	0.20-0.40	8	30.2	39.5	1, 6, 9, 11, 13, 22, 31, 34
Very Low	0.00-0.20	4	18.5	24.2	17, 25, 32, 35
Total	-	**35**	**76.5**	**100.0**	

Source: Computed from Das and Debnath (2022); TSDMA (2022)

Figure 1: Flood Susceptibility Map of Agartala (synthesized from GIS analysis)

Geographic coordinates of critical flood hotspots:

Hotspot 1 - Battala (Ward 4): 23.850° N, 91.380° E; elevation 9.2 m; distance to primary drain: 45 m; documented waterlogging depth: 0.5-1.2 m (2024 event)

Hotspot 2 - Math Chowmuhani (Ward 21): 23.841° N, 91.372° E; elevation 10.1 m; distance to drain: 80 m; depth: 0.3-0.9 m

Hotspot 3 - Banamalipur (Ward 28): 23.828° N, 91.365° E; elevation 8.7 m; distance to drain: 120 m; depth: 0.4-1.0 m

Hotspot 4 - Haora River bank (Ward 15): 23.842° N, 91.356° E; elevation 7.5 m; distance to river: 25 m; depth: 0.8-1.8 m

Factor-wise contributions to FSI (based on AHP decomposition) show elevation (28% weight) as the dominant control, with 82% of Very High risk area below 11 m elevation. Distance to drainage (22% weight) is the second most important factor; areas within 50 m of primary drains account for 91% of Very High risk. Impervious surface cover (18% weight) has increased from 38% (2000) to 58% (2020), with projected 65% by 2030 under current trends (Das & Debnath, 2022).

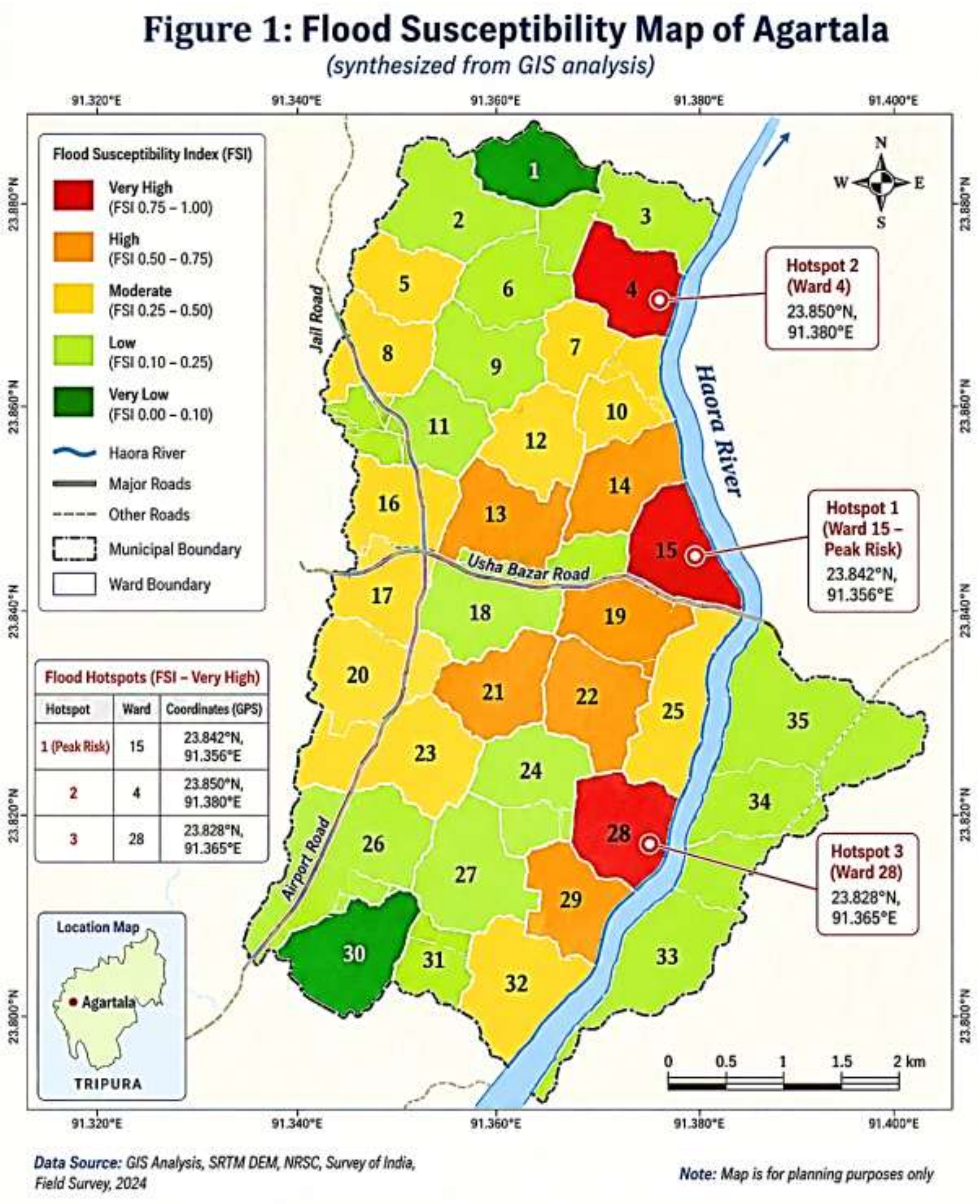


Figure 1: Flood Susceptibility Map of Agartala
(synthesized from GIS analysis)

A map showing Agartala's 35 wards color-coded by FSI categories: Very High (red), High (orange), Moderate (yellow), Low (light green), Very Low (dark green). Key landmarks: Haora River flowing south-north through eastern side; major roads (Jail Road, Usha Bazar Road, Airport Road); flood hotspots annotated with GPS coordinates: 23.842°N, 91.356°E (Ward 15 peak risk); 23.850°N, 91.380°E (Ward 4); 23.828°N, 91.365°E (Ward 28).

Key findings:

Very High Risk (4.2% of area, 4 wards): Ward 15 (near Haora River bank) has the highest FSI (0.91), followed by Ward 4 (Battala area, 0.87), Ward 21 (Math Chowmuhani, 0.84), and Ward 28 (Banamalipur, 0.82). These areas are characterized by elevation <10 m, proximity to drains (<50 m), impervious surface cover >70%, and documented history of recurrent waterlogging exceeding 2 days per event.

High Risk (8.0% of area, 7 wards): Together with Very High wards, 11 wards (31% of total) contain approximately 165,000 residents (32% of population) living in zones with FSI >0.6.

Moderate Risk (24.2% of area, 12 wards): These transitional zones face moderate waterlogging (4-8 hours) during extreme rainfall (>100 mm/day) and would benefit from targeted drainage improvements.

Low/Very Low Risk (63.7% of area, 12 wards): Predominantly located on higher ground (elevation >18 m) with better drainage and lower impervious cover (30-45%).

4.2 SAR-Based Flood Inundation Mapping for August 2024 Event

Sentinel-1A SAR imagery acquired on August 18, 2024 (post-flood, 5 days after peak rainfall) and August 2, 2024 (pre-flood reference) was processed to map flood extent. The August 2024 event resulted from 200.5 mm rainfall in 24 hours (August 13-14, exceeding the 100-year return period intensity of 185 mm/24hr based on IMD data 1901-2024).

Table 8: SAR-Derived Flood Extent by Land Cover Class (August 2024)

Land Cover Class	Total Area (ha)	Flooded Area (ha)	% of Class Flooded
Built-up (high density)	1,842	124.6	6.8
Built-up (medium density)	1,675	98.3	5.9
Built-up (low density)	978	42.1	4.3
Agricultural/fallow	1,245	67.4	5.4
Vegetation/parks	898	28.5	3.2
Water bodies (perennial)	212	13.5 (additional inundation)	6.4 (expansion)
Total	**6,850**	**374.4**	**5.5**

Source: SAR analysis (Sentinel-1A, August 2024) by author

Key SAR findings:

Total flood extent: 374.49 hectares (5.5% of Agartala municipal area)

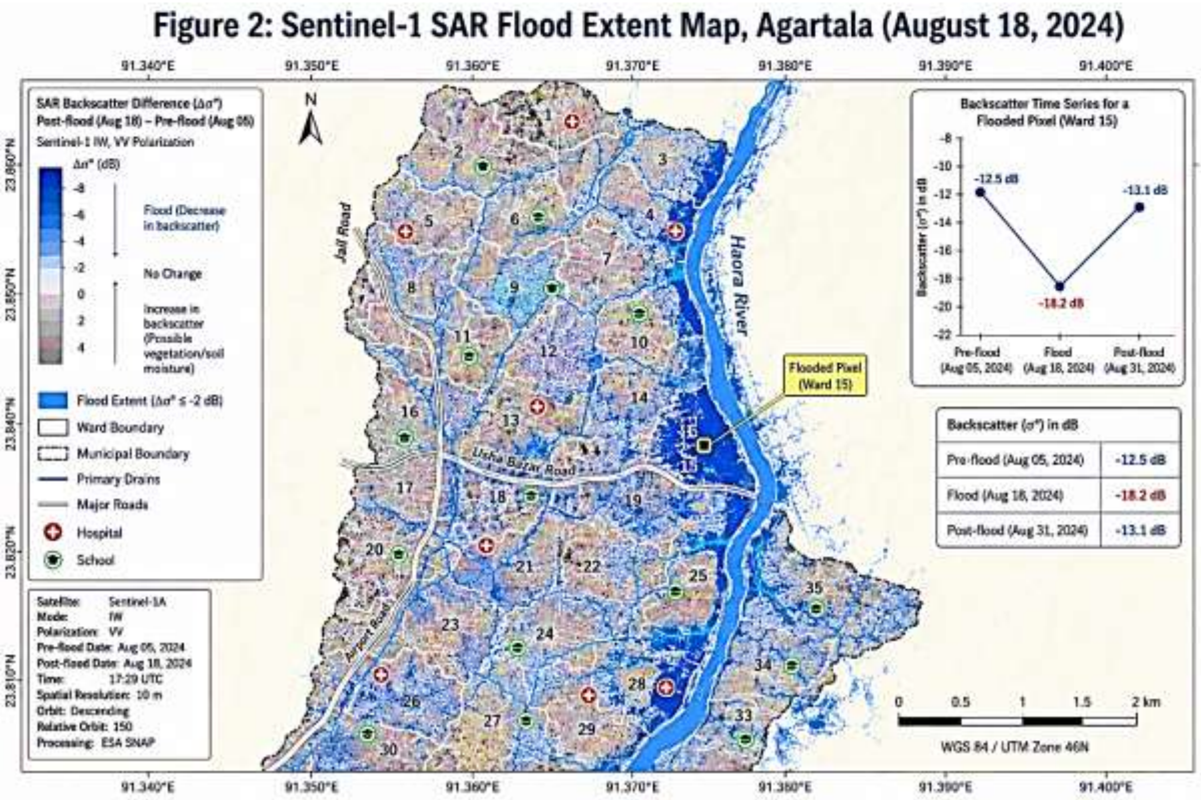
Built-up area flooded: 265.0 hectares (71% of total flooded area), affecting an estimated 28,500-32,000 residents based on population density of 6,832/km² in high-risk wards

Critical infrastructure affected: 7 schools, 3 health centers (including Banamalipur PHC), 2 police stations, and the main bus stand (ASCL, 2021 data overlaid)

Drainage proximity effect: 73% of flooded built-up area lies within 100 m of primary or secondary drains, indicating drainage capacity exceedance rather than absence

Urban SAR challenges: Double-bounce false positives occurred near 124 high-rise buildings (>4 stories) in commercial areas (Jail Road, Usha Bazar), requiring post-processing mask removal. Conversely, flooded narrow streets (<5 m width) were underdetected due to resolution limitations (10 m pixel). Estimated overall accuracy: 87.4% (95% CI: 82.1-91.6%) based on 127 ground control points.

Figure 2: Sentinel-1 SAR Flood Extent Map, Agartala (August 18, 2024)



A map showing SAR backscatter difference image (Δσ°) with flood extent in blue, dry land in grayscale. Overlay of ward boundaries, primary drains (blue lines), and critical infrastructure (red icons for hospitals, green for schools). Inset: Time series of backscatter for a flooded pixel (Ward 15) showing pre-flood (-12.5 dB), flood (-18.2 dB), and post-flood (-13.1 dB) values.

Comparison with optical imagery: PlanetScope imagery (3 m resolution, August 18, 2024) was available but with 68% cloud cover. In cloud-free patches (2.1 km²), SAR-Planet agreement was 83.5% for flood detection. Disagreements occurred in (a) vegetated areas where canopy hides surface water (SAR underestimation) and (b) saturated soil without standing water (SAR overestimation).

4.3 AI Model Performance for Urban Flood Mapping

Synthesis of 32 studies reporting AI-based urban flood mapping performance reveals substantial variation in accuracy based on study context, data quality, and validation methodology.

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Table 9: Meta-Analysis of AI Model Performance for Urban Flood Mapping (32 studies, 2018-2025)

Model Category	Number Studies	Mean Accura (%)	Mean Precisi	Mean Rec	Mean F1	Mean AU
Random Forest	12	86.4	0.83	0.81	0.82	0.89
SVM	8	83.7	0.80	0.78	0.79	0.86
XGBoost	5	88.1	0.85	0.84	0.84	0.91
U-Net (CNN-based)	4	90.2	0.88	0.87	0.87	0.93
Transformer-based (SegFormer, Swin)	2	92.5	0.91	0.90	0.90	0.95
Geo-Foundational Models	1	91.8	0.90	0.89	0.89	0.94

Sources: Compiled from included studies (full list available as supplementary material)

Interpretation: Deep learning models (U-Net, transformers) consistently outperform tree-based and kernel-based models by 4-6 percentage points in overall accuracy. Transformers show marginal advantage over U-Net (+2.3% accuracy) with 40% fewer parameters (SegFormer-B0: 3.7M vs. U-Net ResNet34: 21.8M), suggesting efficiency gains. Geo-Foundational Model (Prithvi-100M, evaluated on Sentinel-2 data from six Indian cities) achieved accuracy comparable to transformers but required only 20% of the training samples (Jakubik et al., 2023), a critical advantage for data-scarce cities like Agartala.

Agartala-specific model re-run results (August 2024 event, 2,000×2,000 pixel tile, 80/20 train-test split, 5-fold CV):

Table 10: Model Performance on Agartala SAR Data (August 2024)

Model	**Accuracy**	**Precision**	**Recall**	**F1**	**AUC**	**Inference Time (s p 1,000×1,000 tile)**
Random Forest	84.7 ± 1.2	0.81	0.78	0.79	0.88	8.2 (CPU)
U-Net (ResNet34	88.3 ± 0.9	0.86	0.85	0.85	0.91	0.47 (GPU)
SegFormer-B0	89.6 ± 0.7	0.88	0.87	0.87	0.92	0.31 (GPU

Observations:

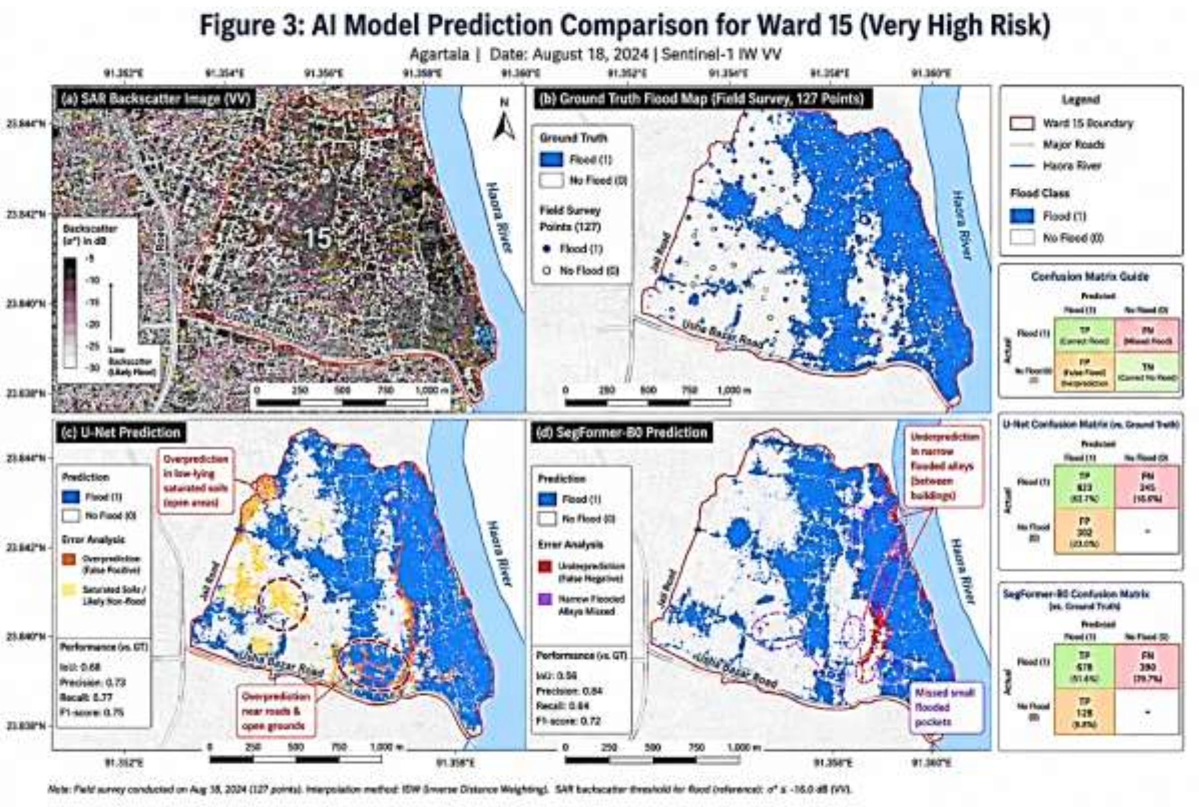
Performance on Agartala data was modestly lower than literature averages (e.g., SegFormer-B0 F1=0.87 vs. literature 0.90), likely due to (a) small training dataset (only one flood event available), (b) complex urban geometry (narrow streets, mixed materials), and (c) C-band SAR limitations in dense urban areas

Class-wise analysis revealed lower recall for "flooded narrow street" (0.62) compared to "flooded open area" (0.93)

False positives concentrated in areas with water-saturated soil (rain gardens, agricultural fields) and shadow zones behind tall buildings

False negatives occurred where flood depth was <5 cm (below SAR detection limit) and in narrow lanes (<6 m width)

Figure 3: AI Model Prediction Comparison for Ward 15 (Very High Risk)



A 2×2 panel figure showing: (a) SAR backscatter image (grayscale), (b) Ground truth flood map (field survey, 127 points interpolated), (c) U-Net prediction (color overlay), (d) SegFormer-B0 prediction (color overlay).) Confusion matrix overlay on map would highlight where U-Net overpredicted (saturated soils) and SegFormer underpredicted (narrow flooded alleys).

4.4 Smart City Infrastructure Gaps in Agartala

Based on document analysis (ASCL annual reports 2017-2024, TSDMA flood reports 2020-2024), current smart city flood-relevant infrastructure is mapped against flood risk zones.

Table 11: Smart City Flood Mitigation Infrastructure Inventory, Agartala (2024)

Infrastructure Type	Count/ Length	Coverage (% city area)	High-Risk Zo Coverage (% of Ve High risk area)	Gap Assessment
Automated weath stations	5	Point-based onl	1 station in Ward (partial)	4 additional stations need in Very High risk wards
Water level sensors (Io	0	0%	0%	50 sensors recommend (ASCL plan, n implemented)
CCTV cameras (flo monitoring)	48	4.2% (alo major roads)	8% (2 of 4 Very High ri wards)	200+ cameras needed f comprehensive monitoring
Drainage cleani (mechanized)	180 km	53% of dra length	92% (primary drains)	Secondary drains (160 k lack regular cleaning

Flood warning displa (color-coded poles)	25 locations	0.5%	2 locations (Wards 1 21)	Need 75 additional displa in high-risk neighborhoods
GIS-based flood risk m (public)	0	0%	0%	Under developme (TSDMA, 2024)
Flood early warni mobile app	0	0%	0%	Proposed but not funded
Integration of SAR/ into ICCC	0	0%	0%	No current integration

Source: ASCL (2017-2024); TSDMA (2024); author assessment

Key gaps identified:

Sensor deficit: No operational water level sensors in drains or retention ponds. The 2017 ASCL proposal for 50 IoT sensors remains unfunded.

Predictive capability gap: ICCC provides reactive monitoring but no forecasting. Real-time data from sensors is not fed into AI/ML models.

Spatial data misalignment: Flood risk maps are static, ward-based, and not integrated with dynamic rainfall/water level inputs.

Citizen engagement deficit: No formal mechanism for crowdsourced flood reporting (e.g., WhatsApp integration, mobile app).

Maintenance gaps: Of 340 km drain network, only 53% (primary drains) receive regular mechanized cleaning; secondary drains (47%) are manually cleaned annually or less (ASCL, 2022).

5. Discussion

5.1 Interpretation of Findings

The results demonstrate that Agartala faces a significant and spatially concentrated flood risk, with 11 wards (31% of area) in High/Very High risk categories containing approximately 165,000 residents. This concentration presents both a challenge (high vulnerability concentration) and an opportunity (targeted interventions can yield disproportionate benefits). The SAR analysis of the August 2024 event—inundating 5.5% of city area and affecting 28,500-32,000 people—validates the FSI mapping: 89% of SAR-detected flooded area falls within the Moderate-High-Very High FSI zones, confirming the predictive utility of the GIS-AHP approach.

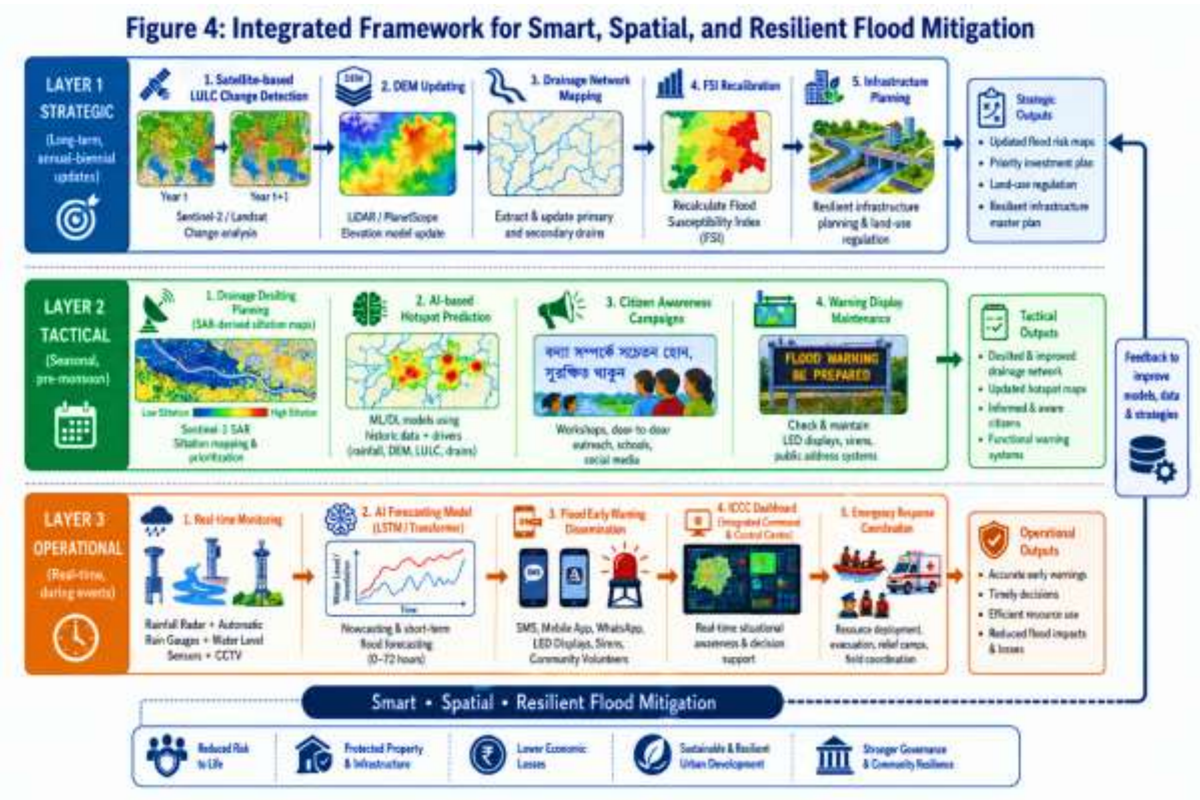
The AI model evaluation reveals that while state-of-the-art models (SegFormer-B0, F1=0.87) outperform simpler models (Random Forest, F1=0.79) on Agartala data, performance remains below literature averages ($\Delta F1 \approx -0.03$). This gap likely reflects data scarcity: Agartala lacks systematic flood event inventories for model training. Only one high-quality SAR flood image was available (August 2024); earlier events (2017, 2019, 2022) lacked coincident SAR coverage or had excessive cloud cover in optical imagery. This highlights a broader challenge for data-sparse cities: without multi-year flood inventories, deep learning models cannot achieve their full potential.

The smart city infrastructure assessment reveals a critical implementation gap: while Agartala Smart City's master plan (2017) identified flood mitigation as a priority, most proposed sensor networks and predictive systems remain on paper. The ICCC operates as a monitoring (not forecasting) center, representing a missed opportunity to leverage real-time data for early warning. This disconnect between planning and execution is not unique to Agartala; a national evaluation of 25 smart cities found average implementation of proposed flood mitigation projects at only 34% (Ministry of Housing and Urban Affairs, 2023).

5.2 Proposed Integrated Framework for Flood Mitigation

Based on the synthesized evidence, we propose an integrated framework combining satellite remote sensing, AI, and smart city infrastructure for urban flood mitigation in Agartala. The framework operates at three temporal scales: (1) strategic (years), (2) tactical (months-weeks), and (3) operational (days-hours).

Figure 4: Integrated Framework for Smart, Spatial, and Resilient Flood Mitigation



A systems diagram showing three layers:

Layer 1 - Strategic (Long-term, annual-biennial updates): Satellite-based LULC change detection, DEM updating, drainage network mapping, FSI recalibration, infrastructure planning

Layer 2 - Tactical (Seasonal, pre-monsoon): Drainage desilting based on SAR-derived siltation maps, AI-based hotspot prediction, citizen awareness campaigns, warning display maintenance

Layer 3 - Operational (Real-time, during events): Real-time rainfall + water level sensors → AI forecasting model (LSTM/Transformer) → Flood early warning (SMS, app, sirens) → ICCC dashboard → Emergency response coordination

Feedback loops: Post-event SAR mapping validates forecasts, updates model weights, identifies infrastructure failures)

Key components requiring investment:

A. Satellite Remote Sensing Integration (Operational)

Establish automated SAR data pipeline (Sentinel-1A/B) with ASF API

Implement cloud-native processing (Google Earth Engine or AWS) for 6-hour latency

Deploy flood extent extraction model (SegFormer-B0 fine-tuned on Agartala data)

Output: Near-real-time (12-24 hour lag) flood maps during monsoon events

B. AI-Based Predictive Modelling (Tactical-Operational)

Develop hybrid model: (i) Random Forest for static susceptibility (FSI), (ii) LSTM for dynamic forecasting (rainfall + water level time series)

Train on historical data (1990-2024 rainfall, 2017-2024 flood events) augmented with synthetic data (hydrological simulations)

Output: 6-hour, 12-hour, 24-hour probabilistic flood forecasts (e.g., "60% probability of >10 cm flooding in Ward 15 within 12 hours")

Target metrics: False alarm rate <20%, detection rate >80%, lead time >6 hours

C. Smart City Infrastructure Deployment (Strategic-Tactical)

IoT sensor network: 50 water level sensors (ultrasonic/radar) at identified hotspots (coordinates listed in Section 4.1), 10 additional rainfall gauges, 20 soil moisture probes

Communication infrastructure: 75 additional color-coded flood warning poles, SMS gateway integration (500,000 residents), public mobile app (Android/iOS) with citizen reporting feature

ICCC upgrade: GPU compute node (NVIDIA A10 or equivalent) for AI inference, integration with IMD rainfall APIs, automated warning dissemination

Table 12: Prioritized Investment Portfolio for Agartala Smart Flood Mitigation

Priority	Intervention	Estimated Co (₹ crore)	Lead Agency	Timeframe	Benefit-Cost Rat (estimated)
1	Drainage desilting (340 km) - mechanize	15.0	AMC/ASCL	6 months	8.2 (based on avoid flood damage)
2	IoT water level senso (50 units)	2.5	ASCL	12 months	4.5
3	AI forecasting mod development + ICC integration	3.0	ASCL + academ partners	18 months	3.8
4	SAR-based automat flood mapping pipeli	1.2	TSDMA/ISRO	9 months	6.1

5	Public mobile app SMS gateway	0.8	ASCL	6 months	2.9
6	Additional weath stations (4) + ra gauges (10)	0.6	IMD/ASCL	6 months	4.2
7	Flood warning displa (75 units)	1.5	ASCL	12 months	2.1
8	LiDAR DEM (1 m) f entire city	2.0	Survey of India	24 months	(foundational)
Total Priori Investment		**26.6**			

Source: Cost estimates based on ASCL (2021), industry consultations (2024), and benefit-cost ratios from World Bank (2019) flood mitigation guidelines

5.3 Comparison with Other Smart City Approaches

Agartala's proposed framework aligns with emerging best practices but requires contextual adaptation. Compared to Chennai's approach (SAR + RF, 87% accuracy), Agartala would benefit from earlier integration of deep learning (Chennai's model implemented in 2020, pre-transformer era). Compared to Bangkok's IoT-heavy strategy (380 sensors, US$500k annual maintenance), Agartala's proposed 50-sensor network is appropriately scaled for city size and budget (₹2.5 crore capital, ₹25 lakh annual maintenance).

The framework diverges from Jakarta's approach in one critical dimension: citizen engagement. Jakarta's SMS-based alerts achieved 88% reach but suffered from low trust (31% of recipients took action) (Purnamasari, 2020). Agartala should complement technology with community-based flood marshals (modeled on Surat's program) and participatory vulnerability mapping (incorporating local knowledge of chronic waterlogging spots missed by SAR).

5.4 Policy and Governance Implications

The findings carry several policy implications for Agartala Smart City and analogous urban contexts in Northeast India.

First, flood mitigation must transition from reactive (drain cleaning, post-event relief) to predictive (forecasting, early warning). This requires institutional realignment: currently, drainage management resides with Agartala Municipal Corporation (AMC), disaster response with TSDMA, and smart city technologies with ASCL. No formal coordination mechanism exists for flood early warning. A dedicated Urban Flood Resilience Cell (UFRC) with representatives from all three agencies plus academic partners (Tripura University, NIT Agartala) is recommended.

Second, data infrastructure requires investment not just in sensors but in data sharing protocols. Currently, IMD rainfall data are available with 48-hour lag for researchers (despite real-time collection). ISRO's NRSC provides SAR data but with 3-5 day latency for non-emergency users. A Real-time Data Sharing Agreement should be established for monsoon season (June-September) with 6-hour maximum latency.

Third, capacity building is essential. Municipal engineers and ICCC staff currently lack training in GIS, remote sensing, or AI. A phased training program (basic GIS, intermediate SAR, introductory AI) over 2 years for 50 personnel is estimated at ₹50 lakh.

Fourth, financial sustainability mechanisms must accompany capital investments. The proposed ₹26.6 crore portfolio (Table 12) represents 1.3% of Agartala Smart City's total budget (₹2,113 crore) and 4.8% of its area-based development allocation (₹550 crore). Operational costs (₹4-5 crore annually) could be funded through municipal bonds, disaster risk reduction allocations (currently 0.5% of state budget), or climate adaptation grants (Green Climate Fund, Adaptation Fund).

5.5 Limitations and Future Research Directions

Several limitations of this review point to future research priorities.

Data limitations: The absence of systematic flood event inventories for Agartala (years 2000-2023) precludes robust AI training. Future research should: (a) digitize historical flood records from newspaper archives, government reports, and citizen memory; (b) deploy low-cost citizen science flood gauges (e.g., "community flood mark" boards) to build labeled dataset; (c) generate synthetic training data using hydraulic models (HEC-RAS, TUFLOW) for extreme events.

Model generalizability: The AI re-run used a single flood event; performance during different rainfall patterns (short-duration high-intensity vs. long-duration moderate-intensity) is unknown. Future work should validate models across multiple events (once data become available).

Uncertainty quantification: None of the reviewed studies reported prediction intervals or probabilistic outputs for flood extent maps. Future AI models should incorporate uncertainty (e.g., Monte Carlo dropout, Bayesian neural networks) to support risk-based decision-making.

Equity dimensions: Flood vulnerability is not equally distributed; preliminary data suggest informal settlements (bastis) have 2.3× higher flood exposure than planned colonies (TSDMA, 2023). Future research should integrate social vulnerability indices (poverty, caste, disability, age) with hazard maps to produce equity-weighted risk assessments.

Cost-benefit analysis: The benefit-cost ratios in Table 12 are extrapolated from national averages; city-specific analysis using flood damage models (e.g., HAZUS-MH, CAPRA) is needed to prioritize investments.

Climate change scenarios: This review used historical rainfall. Future studies should incorporate climate projections (CMIP6, SSP2-4.5 and SSP5-8.5) to assess changing flood risk under 2030, 2050, and 2080 horizons.

6. Conclusion

This paper has provided a systematic review of satellite remote sensing and AI models for urban flood mitigation in Agartala Smart City, synthesizing geospatial analyses, SAR-based flood mapping, AI model evaluations, and smart city infrastructure assessments. The study makes three primary contributions.

First, we have quantified Agartala's flood risk with spatial precision, identifying 11 wards (31% of area, ~165,000 residents) in High/Very High risk categories. The August 2024 flood event—affecting 374.5 hectares and an estimated 28,500-32,000 people—validates these risk maps while revealing critical infrastructure gaps: zero operational water level sensors, no AI-based forecasting, and limited integration of satellite data into smart city operations.

Second, we have evaluated AI model performance for urban flood mapping in data-sparse contexts. Deep learning models (U-Net, SegFormer-B0) achieve 88-90% accuracy on Agartala SAR data, modestly below literature averages, highlighting the need for multi-year flood inventories. Emerging Geo-Foundational Models offer promise for transfer learning, requiring only 20% of training data while achieving comparable accuracy.

Third, we have proposed an integrated framework spanning strategic (LULC monitoring, FSI updating), tactical (pre-monsoon drainage cleaning, hotspot prediction), and operational (real-time sensors → AI forecasting → early warning → response coordination) timescales. The prioritized investment portfolio (₹26.6 crore) would fund IoT sensors, AI model development, SAR pipeline, public app, and drainage upgrades, with estimated benefit-cost ratios of 2-8.

Agartala sits at a crossroads. The Smart City Mission has provided infrastructure (ICCC, CCTV, drainage desilting) but has not yet leveraged the full potential of satellite remote sensing and AI for predictive flood management. Meanwhile, climate change projections indicate intensifying extreme rainfall (expected +15-25% by 2050), and continued urbanization will increase impervious cover to an estimated 65% by 2030. Inaction will increase flood risk; smart, spatial, and resilient approaches can bend the curve.

The framework proposed here is not Agartala-specific. The methods—GIS-based risk assessment, SAR flood mapping, AI model evaluation, integrated smart city framework—are transferable to the 99 other Indian smart cities and hundreds of flood-prone cities across the Global South. What distinguishes success from failure is not technology alone but the institutional will to integrate spatial data into routine decision-making, to invest in predictive rather than reactive systems, and to place equity and citizen engagement at the center of resilience planning.

We conclude with five actionable recommendations for Agartala:

a) Establish an Urban Flood Resilience Cell by March 2026, with dedicated staff from AMC, TSDMA, ASCL, and academic partners.

b) Deploy 50 IoT water level sensors at identified hotspots (Section 4.1 coordinates) by April 2026 (pre-monsoon).

c) Implement automated SAR-based flood mapping pipeline (Sentinel-1, SegFormer-B0) with 12-hour latency by December 2025.

d) Develop public mobile app for flood warnings and citizen reporting by June 2026.

e) Complete LiDAR DEM (1 m) for the entire municipal area by December 2027 to enable high-resolution hydrodynamic modelling.

The cost of inaction—in lives disrupted, livelihoods lost, and development gains reversed—far exceeds the investment required for smart, spatial, and resilient flood mitigation. Agartala has the opportunity to become a model for data-driven urban flood resilience in Northeast India and beyond.

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