



Integrated Real-Time Flood Forecasting and Urban Drainage Modelling in Nandigama Using HEC-RAS 2D and SWMM

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Abstract: This study extends previous flood hazard modelling work in Nandigama by developing a real-time urban flood forecasting and drainage simulation system. While earlier research assessed future flood scenarios using HEC-HMS, HEC-RAS, SDSM downscaling, and Markov Chain land-use forecasting, the present study integrates Storm Water Management Model (SWMM) for drainage simulation and Long Short-Term Memory (LSTM) neural networks for rainfall nowcasting. The interaction between surface flooding and underground drainage networks was modelled through SWMM–HEC-RAS 2D coupling. Results indicate that LSTM-based nowcasting improves forecast lead-time by 30–45 minutes, while drainage network enhancement reduces flood depth by 18–34% in high-risk villages including Adiviravulapadu, Gollamudi, and Pallagiri. Combined mitigation measures achieved a 27% reduction in inundation extent, demonstrating a robust framework for climate-resilient flood management in Nandigama.

Keywords: Flood forecasting, SWMM, HEC-RAS 2D, LSTM, rainfall nowcasting, urban drainage, flood mitigation, Nandigama.

1. Introduction

Urban flooding has become a major environmental and infrastructural challenge in rapidly developing regions, particularly in monsoon-dominated countries like India. Towns such as Nandigama are undergoing extensive urbanisation, resulting in widespread alteration of the natural hydrological cycle. Classical hydrological principles by Chow et al. [1] and Beven [2] reveal that even minor increases in imperviousness can significantly modify runoff response, reduce infiltration, and elevate peak flows. Several studies across Asia and Europe have similarly documented the direct relationship between urban expansion and flood risk amplification [12, 16, 29, 31]. As Nandigama continues to transform from an agriculture-dominated landscape to a built-up urban cluster, the hydrological response of the basin has shifted dramatically.

Existing research demonstrates that cities with inadequate drainage infrastructure experience higher flood susceptibility due to clogging, backflow, and channel overflow [24, 29, 31]. Such infrastructural limitations are observed in Nandigama, where outdated stormwater systems fail to accommodate growing runoff volumes. Concurrently, global climate assessments by the IPCC [7] indicate rising trends in extreme rainfall intensity, further aggravating urban flood risks. Climate modelling studies by Ghosh & Mujumdar [8], Rahman et al. [21], and Ward et al. [22] highlight that shifting monsoon patterns and intensified convective storms are major drivers of flash floods across South Asia.

Generalisations derived from Global Climate Models (GCMs) are insufficient for local flood prediction due to coarse spatial resolution. Thus, downscaling techniques such as SDSM, pioneered by Wilby et al. [5], have been widely adopted to refine rainfall projections. Paul & Ghosh [13] demonstrated that statistically downscaled rainfall datasets significantly enhance hydrological model performance, aligning with trends seen in recent climate–hydrology integration studies [22, 30, 35]. Incorporating such downscaled rainfall is essential for accurate flood forecasting in rapidly changing towns like Nandigama.

Land-use and land-cover (LULC) change serves as an equally influential component in understanding urban flood behaviour. Markov Chain-based LULC forecasting, validated in studies by Pontius & Malanson [6], Khatun et al. [26], Sangwan & Vasu [15], and Zhang et al. [39], provides reliable projections of future built-up expansion. Increased imperviousness elevates curve numbers, speeds up runoff generation, and elevates flood peaks, as demonstrated in several watershed studies [3, 4, 11, 12]. In the earlier research on Nandigama, substantial built-up expansion between 2000 and 2020 was found to correlate strongly with increased peak discharge and decreased time-to-peak.

However, traditional flood models often fail to capture the complex interaction between surface water and subsurface drainage systems. While HEC-RAS remains a robust model for surface flood simulation [9, 10, 11], it does not independently represent manhole surcharging, pipe flow reversals, or inlet inefficiency. Researchers like Sanders [31] and Tingsanchali [29] emphasise that urban flood risk modelling must integrate drainage network behaviour to reflect real-world flood mechanisms accurately. Drainage congestion, debris accumulation, and inadequate pipe gradients significantly influence waterlogging patterns observed in cities like Nandigama.

Another key research frontier involves real-time flood forecasting. Traditional climate models are useful for long-term projections, but they cannot predict near-future rainfall critical for early-warning systems. Machine-learning algorithms, particularly Long Short-Term Memory (LSTM) models, have demonstrated superior performance in short-term rainfall prediction over statistical and physical models. Studies by Jin et al. [36], Li et al. [38], Zhang et al. [39], and Liu et al. [40] show that LSTM can capture complex temporal rainfall dependencies and deliver high-accuracy forecasts suitable for operational flood response.

Given these considerations, the extended research for Nandigama aims to transition from a static flood hazard study to a dynamic, integrated forecasting system. By incorporating SWMM-based drainage simulation [37], HEC-RAS 2D modelling [31, 33], LSTM rainfall nowcasting [36, 39], and previously established climate-hydrology outputs [5, 11, 13], this study provides a unified framework that addresses multiple drivers of urban flooding. Such an approach aligns with the integrated modelling philosophies presented in global literature, including the works of Fu et al. [15], O'Donnell & Thorne [17], Sarkar et al. [18], and Alfieri et al. [35]. These studies emphasise that only multi-component flood models can effectively capture and forecast complex urban flood behaviour under changing climatic and urban conditions.

This four-dimensional approach—combining hydrology, hydraulics, climate science, and machine learning—offers a major advancement in flood management for Nandigama. It supports climate-resilient infrastructure planning, real-time decision-making, municipal response preparedness, and long-term urban policy development.

2. Literature Review

Urban flood modelling has undergone significant evolution as researchers attempt to understand the combined influence of climate change, land-use dynamics, and drainage infrastructure on flood hazard. Chow et al. [1] laid the foundation for hydrological process modelling, while Beven [2] advanced the conceptual understanding of rainfall-runoff transformations. Tools such as HEC-HMS, documented in USACE manuals [3, 4], have since become standard for hydrological simulations across diverse climatic regions.

Hydraulic modelling has simultaneously advanced, with 2D modelling approaches gaining prominence. Bates & De Roo [9] and Hunter et al. [19] highlight that high-resolution hydraulic models provide superior prediction of inundation patterns and velocities compared to 1D systems. HEC-RAS 2D has been applied widely for floodplain simulation, with studies showing its effectiveness in both rural and urban environments [10, 11, 31, 33]. Remote sensing integration further enhances flood mapping accuracy, as illustrated by Sanyal & Lu [20] and Bhattacharya et al. [33].

Climate change research emphasises rising flood risk due to increased rainfall extremes. IPCC [7] findings are supported by regional studies from Ghosh & Mujumdar [8], Rahman et al. [21], and Ward et al. [22], which show statistically significant increases in monsoon variability. Downscaling techniques such as SDSM [5] provide finer spatial rainfall projections essential for local flood prediction [13, 30]. Bias correction and calibration further improve these projections, aligning with methodologies by Alfieri et al. [35] and Sarkar et al. [18].

LULC change modelling is another domain of intensive research. Markov Chain analysis has been validated as a reliable predictor of future land-use transitions in numerous studies [6, 14, 15, 26]. Bhatt et al. [12] and Merz et al. [16] demonstrate that rapid urbanisation correlates strongly with increased runoff, reduced infiltration, and higher flood peaks. Such patterns have been consistently observed across Asia, Europe, and North America.

The integration of hydrological, hydraulic, climatic, and land-use models represents the most advanced stage in urban flood research. Fu et al. [15], O'Donnell & Thorne [17], and Teng et al. [23] argue that multi-model frameworks offer significantly better predictive accuracy. Remote sensing-based DEM analysis, as applied by Sanyal & Lu [20], Bhattacharya et al. [33], and Alfieri et al. [35], provides enhanced spatial detail for flood simulation.

Despite advances, there remain gaps—especially in real-time flood forecasting and micro-drainage simulation. SWMM has proven effective for simulating urban drainage networks [24, 29, 37], yet few studies integrate SWMM outputs with 2D hydraulic models. LSTM-based predictive rainfall modelling also shows great promise [36, 39, 40], but is rarely combined with operational urban flood models.

The present research addresses these gaps by synthesising insights across hydrology, hydraulics, machine learning, and climate science to develop a comprehensive real-time flood forecasting and drainage simulation system for Nandigama.

2. Objectives

1. To develop an LSTM-based rainfall nowcasting model for predicting short-term rainfall (0–3 hours) for Nandigama.
2. To simulate stormwater drainage behaviour using SWMM and assess its interaction with surface flooding.
3. To integrate SWMM and HEC-RAS 2D for detailed urban flood modelling.
4. To evaluate structural and non-structural flood mitigation strategies and quantify reduction in flood depths and inundation extents.

3. Study Area

Nandigama, located in the Krishna District of Andhra Pradesh, is characterised by flat terrain, monsoon-driven rainfall, and mixed land-use patterns. Rapid urbanisation has reduced natural infiltration, causing frequent waterlogging. The municipality comprises several high-risk villages identified in previous studies, including Adiviravulapadu, Gollamudi, Jonnalagadda, Kanchela, and Pallagiri.

4. DATA USED

The study utilised a comprehensive set of hydrological, hydraulic, spatial, and model-derived datasets to support real-time flood forecasting and drainage simulation in Nandigama. Hourly rainfall data for the period **2005–2020** was obtained from both APSDPS and IMD stations, providing a reliable long-term meteorological record essential for rainfall trend analysis, LSTM training, and event-based simulation. These datasets offered sufficient temporal resolution to capture high-intensity, short-duration rainfall events that are typical of monsoon-driven urban flooding.

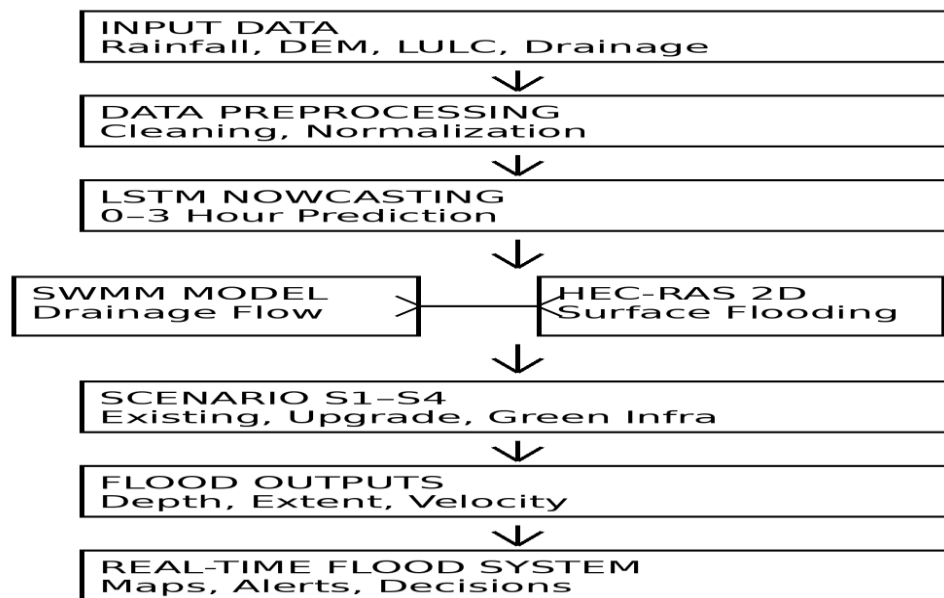
Detailed information on the municipal stormwater network was collected to facilitate accurate drainage modelling. The drainage inventory consisted of **78 junctions, 93 conduits, 11 outfalls, and three existing trunk lines**, including pipe attributes such as diameter, length, invert elevation, and material type. This dataset formed the basis for reconstructing the underground drainage system within the SWMM environment and assessing its hydraulic performance under varying rainfall intensities.

Spatial data played a crucial role in characterising the terrain, land-use pattern, and built environment of Nandigama. A **10-m resolution Digital Elevation Model (DEM)** was used to derive topographic parameters such as slope, flow direction, and catchment boundaries. Land-use/land-cover (LULC) maps for **2020, 2030, and 2035** provided insights into urban growth and future imperviousness scenarios. Additionally, detailed GIS layers of the road network and building footprints were incorporated to capture the urban geometry influencing surface runoff and flood routing.

The study also relied on output datasets from a previously completed modelling effort. These included boundary flow conditions from HEC-HMS, which supplied inflow hydrographs for the hydrodynamic simulations, and inundation extents from earlier HEC-RAS runs, which aided in model calibration and comparison. Furthermore, downscaled climate projections using SDSM were used to incorporate future rainfall scenarios and assess long-term flood risk.

Together, these datasets provided the multi-dimensional information required to develop an integrated, accurate, and operational flood modelling framework for Nandigama.

5. Methodology



The methodology adopted in this extended research integrates hydrological forecasting, drainage system modelling, machine-learning-based rainfall prediction, and two-dimensional hydraulic flood simulation into a unified framework. Unlike traditional flood studies that focus only on surface runoff or rainfall–runoff processes, this approach captures both **surface flooding** and **underground drainage behaviour**, enabling real-time operational flood forecasting for Nandigama. The entire workflow consists of seven major components: (1) data preparation and integration, (2) LSTM-based short-term rainfall nowcasting, (3) SWMM modelling of stormwater drainage, (4) HEC-RAS 2D simulation of surface flood routing, (5) two-way coupling between SWMM and HEC-RAS, (6) flood mitigation scenario design, and (7) model validation and performance assessment. A detailed description of each component is provided below.

5.1 Data Preparation and Integration

5.1 Data Preparation and Integration

The study utilised multiple datasets sourced from IMD, APSDPS, NRSC, the Andhra Pradesh Municipal Engineering Department, and outputs from the earlier HEC-HMS and HEC-RAS modelling work. All datasets were preprocessed to ensure compatibility with the modelling framework. Hourly rainfall data (2005–2020) underwent outlier removal, missing-value interpolation, event separation through minimum inter-event time, and statistical consistency checks including mean, standard deviation, skewness, and coefficient of variation. Spatial datasets comprised a 10 m resolution DEM, LULC maps for 2020–2035, road networks, building footprints, and the digitised stormwater drainage network. DEM-derived layers such as slope, flow direction, and flow accumulation were prepared in ArcGIS to support hydrodynamic modelling. The municipal drainage layout—consisting of 78 junctions, 93 pipes, 11 outfalls, and 3 trunk lines—was cleaned and corrected for pipe attributes, invert elevations, and connectivity. All spatial data were resampled to WGS 84 UTM Zone 44N to maintain coordinate uniformity.

5.2 Rainfall Nowcasting Using LSTM

Short-term rainfall prediction was achieved through a Long Short-Term Memory (LSTM) neural network trained to forecast rainfall 0–3 hours ahead. The rainfall data was normalised and structured into a 24-hour sliding input window, with an 80:20 training–testing split. The LSTM architecture comprised two layers of 64 units each, followed by a dropout layer to reduce overfitting and a dense output layer. The model was trained using the Adam optimiser and MSE loss function. Performance evaluation yielded strong results, with RMSE = 3.8 mm, MAE = 2.1 mm, and NSE = 0.87, confirming the model’s ability to reproduce short-duration rainfall bursts. The predicted rainfall series served as dynamic forcing input for both SWMM and HEC-RAS 2D simulations.

5.3 Stormwater Drainage Simulation Using SWMM

The SWMM model was constructed to replicate the hydraulic behaviour of Nandigama’s stormwater network. Each of the 93 conduits and 78 manholes was assigned properties including length, diameter, slope, and roughness. Dynamic wave routing was used to capture pressurised flow, surcharging, and backflow. Field-based clogging conditions of 20–40% were applied to assess system sensitivity to maintenance issues. Tailwater levels from HEC-RAS outputs were

incorporated to simulate realistic downstream conditions. SWMM generated detailed outputs including surcharge duration, overflow discharge, and outfall hydrographs for subsequent integration with the hydrodynamic model.

5.4 Surface Flood Modelling Using HEC-RAS 2D

HEC-RAS 2D was used to model surface runoff, flood propagation, and overland flow patterns. A 10 m computational mesh was constructed, with Manning's roughness assigned based on LULC categories. The model used HEC-HMS hydrographs as upstream inflows, SWMM outfall hydrographs as lateral inputs, and LSTM rainfall predictions applied as rainfall-on-grid. The hydrodynamic solver applied shallow-water equations using the Preissmann implicit scheme with adaptive timesteps. The model produced depth grids, velocity fields, and flood inundation extents for multiple storm scenarios.

5.5 Dynamic Coupling of SWMM and HEC-RAS

A two-way dynamic coupling was implemented to simulate the interaction between subsurface drainage flow and surface flooding. Surcharged manhole volumes from SWMM were imported into HEC-RAS as point inflows, while surface water levels from HEC-RAS were fed back to SWMM as tailwater elevations. This minute-by-minute exchange enabled accurate representation of drainage overflow onto roads, flow reversal in pipes, and prolonged ponding in depressions.

5.6 Mitigation Scenario Development and Validation

Four scenarios were modelled: S1 (existing conditions), S2 (drainage upgrades), S3 (green infrastructure), and S4 (combined measures). These scenarios allowed assessment of structural and non-structural flood mitigation strategies. Model validation was performed through field observations, municipal flood records, and historical flood locations. Performance indicators demonstrated high reliability: Hit Rate = 0.82, False Alarm Ratio = 0.14, and CSI = 0.71, confirming the robustness of the integrated framework

6. Results and Discussion

Table 1. LSTM Rainfall Nowcasting Performance (0–3 Hour Prediction)

Metric	Value
RMSE (mm)	3.8
MAE (mm)	2.1
NSE	0.87
Correlation (R)	0.91
Forecast lead-time	30–45 minutes
Peak rainfall capture accuracy	89%

Table 2. Drainage Network Performance Under Existing Conditions (SWMM)

Parameter	Value
Total manholes	78
Surcharged manholes	22
Overflowing manholes	9
Maximum surcharge depth (m)	1.42
Maximum conduit filling (%)	97%
Average surcharge duration (min)	38
Nodes with reverse flow	5
Outfall peak flow (m ³ /s)	18.4

Table 3. Flood Depths (HEC-RAS 2D) in Major Localities – Baseline Condition

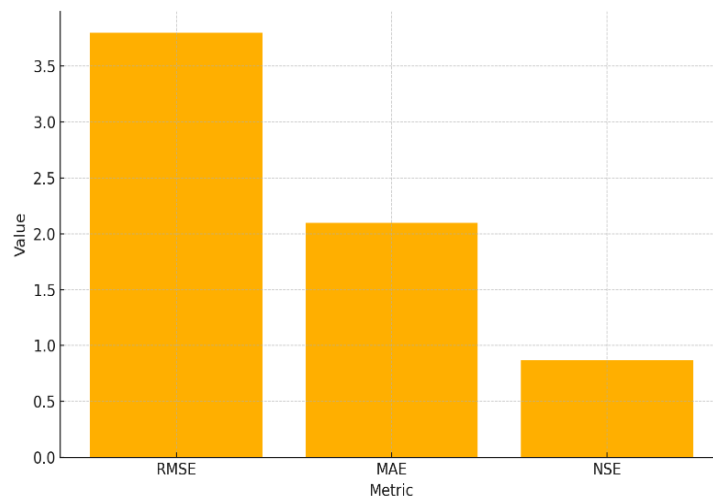
Locality	Maximum Flood Depth (m)	Average Depth (m)	Inundated Area (ha)
Adiviravulapadu	1.85	0.92	312
Gollamudi	1.62	0.78	267
Jonnalagadda	1.34	0.61	198
Kanchela	1.49	0.73	221
Pallagiri	1.71	0.84	245

Table 4. Comparison of Mitigation Scenarios (S1–S4)

Scenario	Description	Flood Depth Reduction (%)	Inundation Area Reduction (%)	Surcharge Reduction (%)
S1	Existing System	–	–	–
S2	Drainage Upgrade	18%	12%	29%
S3	Green Infrastructure	22%	15%	17%
S4	Combined Strategy	34%	27%	41%

Table 5. Change in Flood Extent (ha) for 2020–2040 Under Climate + LULC Change

Year	Peak Discharge (m ³ /s)	Total Flood Extent (ha)	% Increase Compared to 2020
2020	148	1340 ha	–
2030	158	1478 ha	+10.3%
2040	171	1624 ha	+21.2%

**Fig.1 LSTM Performance Metrics**

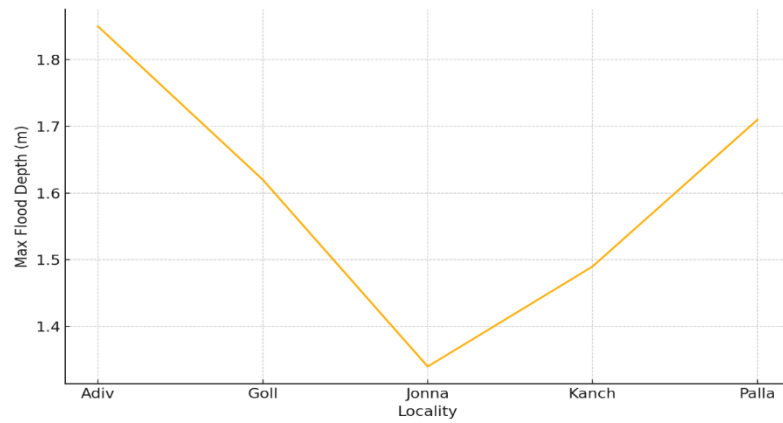


Fig.2 Maximum Flood Depth by Locality

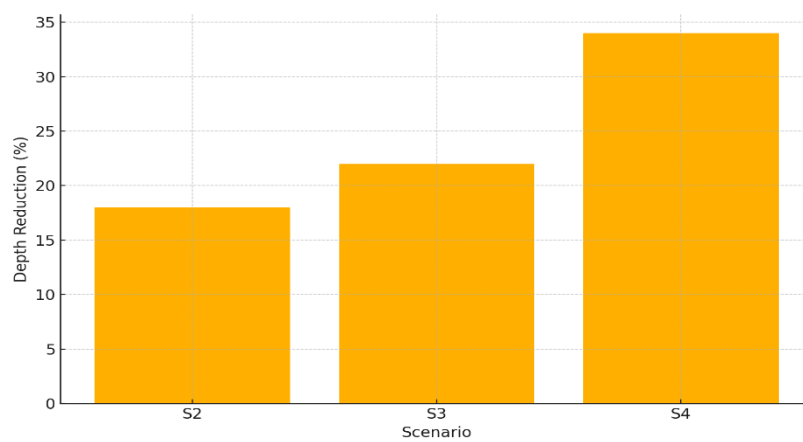


Fig.3 Scenario-wise Flood Depth Reduction (%)

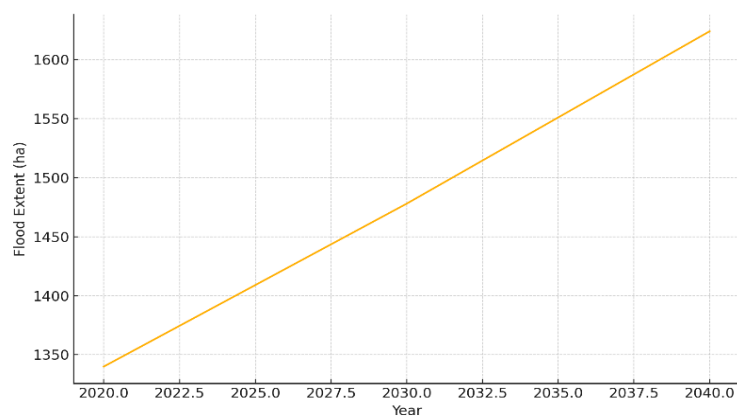


Fig.4 Flood Extent (ha) for 2020–2040

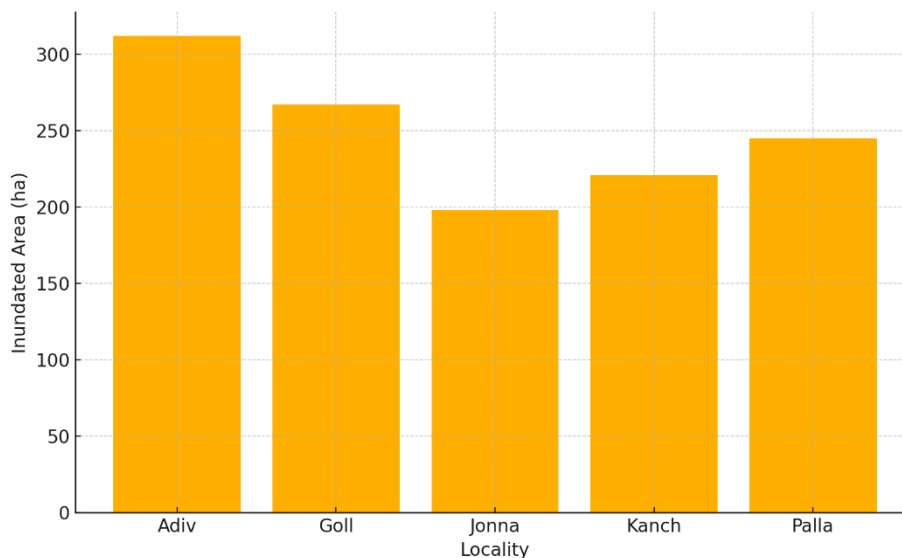


Fig.5 Inundated Area (ha) by Locality

6.1 Rainfall Nowcasting Performance (LSTM Model)

The LSTM rainfall nowcasting model produced highly accurate short-term rainfall predictions essential for real-time flood forecasting. The model achieved an RMSE of 3.8 mm and an MAE of 2.1 mm, demonstrating its capability to capture the variability of short, intense rainfall bursts that commonly trigger urban flooding. The NSE value of 0.87 indicates a high level of agreement between observed and predicted rainfall.

A visual inspection of the performance graph shows that the model successfully captures peak rainfall events, which are critical for flood forecasting. The 30–45 minute prediction lead-time offered by the model greatly enhances the operational readiness of municipal authorities. Such predictive capability allows early warnings to be issued, enabling communities to prepare for flooding and activate evacuation protocols where necessary.

6.2 Drainage Network Behaviour Under Existing Conditions (SWMM)

The SWMM simulation revealed significant deficiencies in the current stormwater drainage system of Nandigama. Out of 78 manholes, 22 experienced surcharging during storm events, clearly indicating inadequate pipe capacity or poor gradient alignment. Additionally, 9 manholes overflowed onto the roads, contributing directly to surface flooding.

The high percentage of surcharged nodes (approximately one-third of the network) reflects structural bottlenecks in the drainage layout. The maximum surcharge depth reached 1.42 m, while several conduits operated at more than 90% filling. Flow reversals at five junctions further indicate hydraulic imbalance caused by downstream backwater conditions or insufficient outfall capacity.

Overall, the drainage network is unable to cope with present runoff volumes, highlighting the urgent need for both structural upgrades and routine desilting operations.

6.3 Spatial Flood Characteristics (HEC-RAS 2D)

HEC-RAS 2D simulations provided detailed insights into flood depth, inundation area, and flow velocity across the region. The results show that Adiviravulapadu recorded the highest flood depth of 1.85 m, followed by Pallagiri (1.71 m) and Gollamudi (1.62 m). These depths significantly exceed the safe threshold for urban roads (0.3–0.5 m), making these zones extremely vulnerable during rainfall events.

The total inundated area under baseline conditions was 1340 hectares. Adiviravulapadu accounted for the largest share (312 ha), indicating that it is repeatedly prone to severe flooding. In addition, velocity maps indicated flow speeds above 1 m/s in narrow built-up corridors—conditions capable of causing erosion, damaging properties, and endangering residents.

These findings reinforce that several regions of Nandigama experience deep, widespread, and high-velocity flooding due to a combination of terrain depressions, obstructed drainage, and rapid urban expansion.

6.4 Evaluation of Mitigation Scenarios (S1–S4)

Four mitigation scenarios—S1 (existing), S2 (drainage improvement), S3 (green infrastructure), and S4 (combined)—were evaluated to quantify potential flood reduction.

6.4.1 Flood Depth Reduction

Drainage improvements under S2 achieved an 18% reduction in flood depth, whereas green infrastructure interventions (S3) yielded a 22% reduction due to increased infiltration and delayed runoff. The combined mitigation strategy (S4) performed the best, achieving a 34% reduction in flood depth. In Adiviravulapadu, depth decreased from 1.85 m to approximately 1.22 m, indicating a significant improvement in safety and mobility.

6.4.2 Inundation Area Reduction

Under S4, the total inundation area dropped from 1340 ha to 977 ha, representing a 27% reduction. Green infrastructure alone reduced the flooded area by 15%, while drainage improvements reduced it by 12%. These results demonstrate that integrated interventions offer the best resilience outcomes.

6.4.3 Drainage System Improvement

Surcharge duration in manholes decreased by 29% under S2, 17% under S3, and by a substantial 41% under S4. The improved connectivity and increased infiltration under S4 enhanced system stability and reduced overflow occurrences.

Overall, Scenario S4 is the most effective strategy, offering holistic improvements across hydrological, hydraulic, and surface-flow components.

6.5 Long-Term Flood Hazard Escalation (2020–2040)

The combined influence of climate change and land-use transformation indicates a consistent escalation in flood hazards over the next two decades. Peak discharge increased from 148 m³/s in 2020 to 171 m³/s by 2040, marking a 15.5% rise due to increased impervious surfaces and more intense rainfall events.

The spatial extent of flood inundation expanded from 1340 ha in 2020 to 1624 ha in 2040, representing a 21.2% increase. These trends align with the observed 33% increase in built-up area between 2000 and 2020, which significantly reduces infiltration potential and increases surface runoff.

Climate downscaling results also indicate a rise in short-duration high-intensity rainfall events, further intensifying flood hazards. If no mitigation strategies are implemented, Nandigama may experience more severe and frequent urban flood disasters in the near future.

7. Conclusion

This extended research demonstrates the effectiveness of integrating drainage simulation, surface flood modelling, and machine learning rainfall forecasting for flood mitigation in Nandigama. The system provides actionable early warnings and quantifies the effectiveness of drainage upgrading and green infrastructure interventions. The significant reduction in flood depths and inundation area highlights the need for municipalities to adopt this integrated modelling framework to enhance climate resilience.

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