

Evaluating NALA 2.1 for Low-Data Urban Flood Screening: A Case Study of 17 Flood-Prone Locations in Lahore, Pakistan

Hayan, Muhammad

Independent Researcher

ORCID: 0009-0009-7536-6190

hayan8336@gmail.com

Preprint submitted to *Urban Water Journal*. This version has not been peer reviewed.

Abstract

Recurrent urban flooding in data-scarce cities necessitates practical drainage decisions despite limited engineering information. This study evaluates NALA 2.1, a low-data storage-cascade model developed to identify drainage bottlenecks, rank flood severity, and prioritize interventions. NALA was benchmarked against EPA SWMM using three synthetic networks and evaluated against historical flood records from 17 locations in Lahore. The models identified the same leading intervention in 100% and 98% of paired runs on two networks. Using rainfall averaged across two gauges, NALA meaningfully ranked held-out flood events (Spearman $\rho \geq 0.5$) at seven of nine Central Area sites, but at only one of eight sites elsewhere. Its estimates of absolute flood depth rarely improved on a constant baseline. At Lakshmi Chowk, storage expansion and drain rehabilitation both yielded substantial simulated benefits; however, their relative ranking depended on inundation area, identifying this quantity as the key measurement. These findings support the use of NALA for targeted, uncertainty-aware screening rather than flood-depth prediction.

Keywords: urban flooding; drainage screening model; data-scarce cities; split-sample validation; Lahore; SDG 11: Sustainable cities and communities

1 Introduction

Rapidly growing cities frequently experience persistent flooding where drainage infrastructure is poorly documented, rainfall observations are limited, and detailed engineering surveys are difficult to obtain. In Lahore, Pakistan, recurrent monsoon flooding has revealed weaknesses in the urban drainage system. JICA (2010) identified 80 frequently inundated locations, while a subsequent survey documented 118 ponding locations, of which 43 were critical (Hussain et al. 2019). Historical observations can identify vulnerable locations, but prioritizing effective interventions requires an understanding of the interactions among rainfall, runoff, conveyance capacity, and downstream restrictions.

Hydrodynamic models, including the EPA Storm Water Management Model (SWMM), represent conduit storage, flow routing, surcharging, and backwater (Rossman 2017). These models require detailed drainage geometry, network connectivity, invert elevations, and rainfall information, which are often unavailable or unreliable in data-scarce cities (Leandro et al. 2009; Nkwunonwo et al. 2020). A recent SWMM application in Lahore relied on a single rain gauge (Ahmad et al. 2024). Moreover, rapid flood models are generally evaluated against hydrodynamic models rather than recorded events (Guidolin et al. 2016; Jamali et al. 2019).

This study evaluates NALA 2.1 as a low-data urban drainage screening model for identifying dominant drainage bottlenecks, assessing relative flood severity, and comparing mitigation options. NALA uses a storage-cascade representation that combines estimated conveyance capacities, local accumulation, and explicit uncertainty in poorly observed parameters, without reproducing the full hydraulic complexity of conventional models. Its purpose is to support preliminary infrastructure decisions by assessing whether useful information about flood severity and intervention effectiveness is retained when data requirements are substantially reduced.

The model is first benchmarked against EPA SWMM on synthetic networks with contrasting hydraulic constraints. It is then evaluated against historical rainfall and inundation records from 17 flood-prone locations in Lahore using a split-sample design, which assesses the ranking of unseen flood events independently of calibration. Lakshmi Chowk is examined as a detailed decision case to compare drainage improvements and evaluate the influence of uncertainty in inundation extent on intervention rankings. By examining both successful and unsuccessful applications, the study seeks to establish the conditions under which low-data drainage screening provides reliable preliminary guidance and those requiring detailed field investigation and hydraulic modelling.

2 Study area and data

Lahore experiences recurrent localized flooding during the summer monsoon, particularly in densely developed areas where stormwater drains through interconnected sewers, open drains, and pumping stations. The Central Drain, a principal channel approximately 15.7 km long, is 3.5–9.5 m wide and 1.2–3.8 m deep. JICA (2010) describes the channel as badly silted, obstructed by solid waste, and affected by encroachment, with numerous sewers discharging into it. These networks and disposal stations convey water to the Ravi River.

Historical rainfall and inundation observations were obtained from the drainage study by JICA (2010), which documents 26 storm days between 2007 and 2009. For each storm, the study reports rainfall totals at the Jail Road and Airport gauges, the rainfall period, and observed flood depth and duration at up to 75 monitored locations. JICA also reports the average inundated area at each flood point, providing the relationship between simulated surface-water volume and flood depth. Missing entries were treated as unavailable observations rather than evidence of an absence of flooding.

To ensure a consistent evaluation, all locations with at least four recorded flood depths in a calibration year, five in subsequent years, and a non-zero reported inundation area were included. These criteria identified 17 flood points across four JICA sub-catchments: Central Area (nine), Siddique Pura (six), Babu Sabu (one), and Mehmood Booti (one) (Table 1). Four Central Area locations—Lakshmi Chowk, Kashmir Road, Cooper Road, and Garhi Shahu—had been selected for detailed examination before the 17-point evaluation. The remaining locations were included to assess whether model performance extended beyond these selected sites. The two gauges are 1.9–9.0 km from the four detailed locations (Figure 1a), whereas urban rainfall may vary over distances of a few kilometres (Berne et al. 2004).

3 Materials and methods

3.1 NALA model formulation

NALA represents a drainage system as a storage cascade in which runoff passes through a simplified network subject to estimated conveyance capacities, while excess water accumulates

Table 1: The 17 JICA flood points meeting the record requirements for split-sample testing: at least four recorded flood depths in the calibration year and five in later years. Area denotes the average inundated area reported by JICA (2010). Flood counts denote storm days with a recorded depth. An asterisk identifies locations examined in detail.

Point	Location	Sub-catchment	Area (ha)	Calibration year (floods)	Test floods
1	Lakshmi Chowk*	Central Area	1.56	2007 (5)	10
3	Kashmir Road*	Central Area	0.28	2007 (6)	14
4	Thornton Road	Central Area	0.39	2007 (5)	6
5	Cooper Road*	Central Area	0.51	2007 (4)	13
6	Bashir Sons	Central Area	0.12	2007 (4)	10
10	Plaza Cinema	Central Area	0.65	2007 (5)	13
11	Nabha Road	Central Area	0.90	2007 (6)	7
31	Garhi Shahu*	Central Area	1.26	2008 (4)	7
34	Empress Road	Central Area	0.60	2007 (4)	9
8	Do Moria Pul	Siddique Pura	0.08	2007 (6)	14
43	Aik Moria Pul	Siddique Pura	0.08	2007 (6)	12
44	Rahim Road	Siddique Pura	0.38	2007 (6)	7
45	Aziz Road	Siddique Pura	0.24	2007 (4)	8
46	Umer Din Road	Siddique Pura	0.78	2007 (5)	9
55	Milap Street	Siddique Pura	0.24	2007 (4)	5
49	Outside Bhati Gate	Babu Sabu	0.69	2007 (5)	8
53	Haq Nawaz Road	Mehmood Booti	0.22	2007 (5)	5

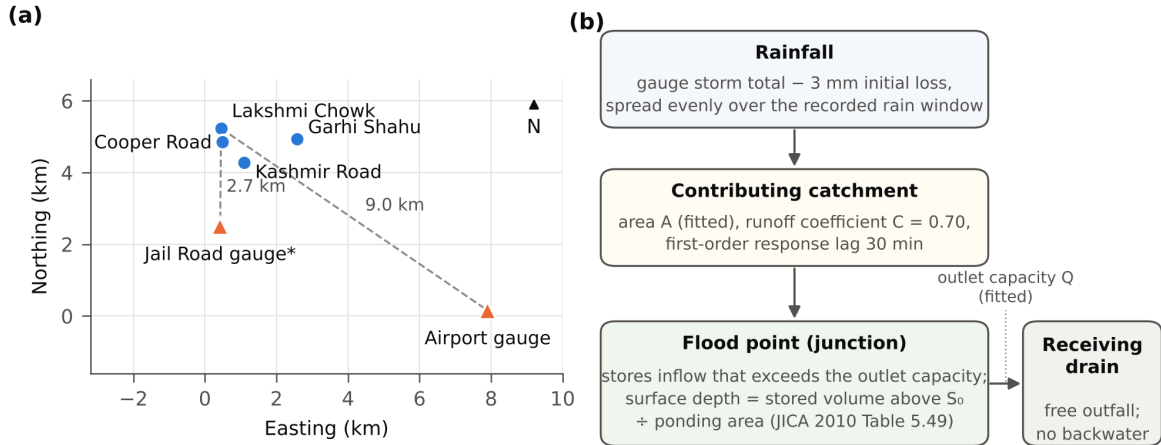


Figure 1: (a) The four flood points examined in detail and the two rain gauges. Distances are measured from Lakshmi Chowk; the Jail Road gauge position is approximate. (b) Representation of each flood point in NALA.

locally (Figure 1b). Runoff is calculated using the Rational Method (Butler et al. 2018):

$$Q = \frac{CiA}{360}. \quad (1)$$

Here, Q is discharge (m^3/s), C is the runoff coefficient, i is rainfall intensity (mm/h), and A is the contributing area (ha). A first-order lag approximates the delay between rainfall and runoff reaching the drains. At each time step, each drainage component conveys water up to its capacity, with excess water stored at the upstream node. Stored volume exceeding an initial allowance is converted to surface-water depth:

$$h(t) = \frac{\max[0, V(t) - S_0]}{A_p}. \quad (2)$$

In this expression, $V(t)$ is stored volume (m^3), S_0 is the initial storage allowance (m^3), and A_p is inundation area (m^2). This formulation enables the identification of capacity-constrained components, comparison of flood severity, and evaluation of interventions without a complete hydraulic description of the network. NALA does not simulate backwater, storage within conduits, or travel time. These deliberate simplifications reflect its intended use for screening rather than design.

3.2 Benchmarking against EPA SWMM

NALA was benchmarked against EPA SWMM 5.2 (Rossman and Simon 2022) using three synthetic networks: one controlled by the outfall (N1) and two in which an upstream drain controls flooding (N2 and N3). Both models received identical runoff hydrographs, ensuring that differences arose from hydraulic representation rather than runoff generation. SWMM used dynamic-wave routing, with conduits divided into 25 m segments, a length at which results had converged. Comparisons for N1 and N2 comprised 500 and 300 paired uncertainty realizations, respectively; N3 was evaluated deterministically for four interventions. Degraded-input experiments using approximate drainage dimensions and missing slope measurements are reported in the supplementary material. The benchmarks were conducted using NALA 2.0; regression tests confirm that NALA 2.1 reproduces those results exactly.

3.3 Calibration at historical flood points

Each of the 17 flood points was represented as a single junction draining to a capacity-limited outlet, rather than as part of a reconstructed city-wide network. Three rainfall inputs were evaluated: the Jail Road gauge total, the mean of the two gauge totals, and the larger of the two totals. For each event, a 3 mm initial loss was deducted, and the remaining rainfall was distributed uniformly over the reported storm period. The runoff coefficient was fixed at 0.70, the upper bound of the design range reported by JICA (2010). The response lag was fixed at 30 min, corresponding to JICA’s 0.5 h inlet time.

Three parameters were calibrated at each location: contributing area, effective outlet capacity, and initial storage allowance. A grid search across 12,150 combinations minimized the objective function:

$$J(\theta) = \sum_{k \in C} \left(\frac{h_{\text{sim},k} - h_{\text{obs},k}}{0.25} \right)^2 + \sum_{k \in C_T} \left(\frac{T_{\text{sim},k} - T_{\text{obs},k}}{3} \right)^2. \quad (3)$$

Here, h denotes flood depth (m), T denotes flood duration (h), and k denotes a calibration event. C is the set of calibration events with recorded depths, and C_T is the set with recorded

durations. Parameter sets with objective values within 15% of the minimum were retained as well-fitting alternatives, following the behavioural-set approach of Beven and Binley (1992). This procedure enabled examination of uncertainty in the inferred characteristics without relying on a single optimum.

3.4 Split-sample testing and robustness

Following the split-sample test of Klemeš (1986), observations from 2007 were used for calibration and subsequent observations for testing. Where 2007 records were insufficient, as at Garhi Shahu, observations from 2008 were used for calibration and those from 2009 for testing. Results are reported for all three rainfall inputs; none was selected according to test-period performance.

Performance was assessed using Spearman’s rank correlation (ρ) between simulated and recorded flood depths, mean absolute error (MAE) in depth, and the detection rate for recorded floods deeper than 0.10 m. A constant baseline equal to the calibration-period mean depth was used to assess whether simulated absolute depths provided an improvement. Robustness was evaluated using 250 perturbed realizations per location. These realizations varied calibrated parameters and inundation area by approximately 20%, the runoff coefficient between 0.60 and 0.80, and rainfall for each event by a factor of 0.8–1.2.

3.5 Lakshmi Chowk intervention screening

At Lakshmi Chowk, the model was recalibrated using all 15 recorded flood events to screen mitigation options. This analysis is exploratory and does not constitute independent validation. Three options were examined: an underground storage tank of 3 or 4 million gallons (The Nation 2026), assumed to refer to imperial gallons (13,600 and 18,200 m³); rehabilitation of the McLeod Road drain to the dimensions proposed by JICA (2010); and a hypothetical 50% increase in effective outlet capacity. Tank scenarios increase the storage allowance S_0 . This representation assumes that all runoff from the contributing area can reach the tank and therefore provides an upper bound.

Drain rehabilitation was represented by a multiplier applied to effective outlet capacity:

$$f_{\text{rehab}} = \frac{1.42 + 3.37}{1.42 + 0.51} \approx 2.48. \quad (4)$$

The value 1.42 m³/s is the rated capacity of the Lakshmi Chowk lift station (2×25 cfs). The values 0.51 and 3.37 m³/s are the full-flow capacities of the existing and proposed drain sections, respectively (JICA 2010), calculated using Manning’s equation with JICA’s proposed slope of 0.0007 and $n = 0.015$. Each option was evaluated across all well-fitting parameter sets according to the reduction in simulated flood volume $\times$ duration, using the inundation areas reported by JICA (2010) and Hussain et al. (2019) in turn.

4 Results

4.1 Benchmarking against EPA SWMM

NALA identified the same dominant interventions as SWMM for all three networks (Table 2). For the outfall-controlled network (N1), the models selected the same most effective surface-water intervention in 100% of 500 paired realizations. For N2, they selected the same leading household-hours intervention in 98% of 300 paired realizations. Storm-severity rankings were closely aligned ($\rho = 0.997$ for N1 and 0.98 for N2).

In N3, SWMM predicted flood-volume reductions of 52% from enlarging the controlling upstream drain and 47% from clearing it. Clearing the main nala (0.2%) and providing downstream outfall relief (0%) had almost no effect. NALA ranked the same two upstream interventions first, in the same order, and assigned no benefit to either downstream option. However, NALA overestimated flood burden by a factor of 1.6–2.6. Agreement was weaker for secondary criteria: the models agreed on the household-hours intervention in 74% of N1 realizations, and cost-effectiveness rankings were inconsistent. Agreement with dynamic-wave modelling therefore relates to dominant constraints and broad intervention priorities rather than inundation magnitudes or economic optimization.

Table 2: Comparison of NALA with EPA SWMM 5.2 dynamic-wave routing on three synthetic networks, using identical runoff hydrographs and 25 m conduit segments. The N1 flood-volume range spans drain-length scalings of 0.5–2 times.

Network	Comparison	Same most effective intervention	NALA/SWMM flood volume
N1, outfall-controlled	500 paired draws	100% (surface water); 74% (household-hours)	1.76 (1.59–2.07)
N2, upstream bottle-neck	300 paired draws	98% (household-hours)	2.6
N3, upstream-controlled	4 interventions	Same top two, same order	–

4.2 Historical flood-severity ranking

Performance varied among sub-catchments (Figure 2a). With mean-gauge rainfall, the median Spearman correlation across all 17 locations was 0.32. Seven of nine Central Area locations reached $\rho \geq 0.5$, the threshold adopted here for meaningful ranking, with a median of 0.68. These locations were Lakshmi Chowk (0.82), Cooper Road (0.78), Empress Road (0.76), Plaza Cinema (0.74), Thornton Road (0.68), Kashmir Road (0.67), and Nabha Road (0.65). Bashir Sons (0.22) and Garhi Shahu (−0.27) did not meet the threshold. Outside the Central Area, only Do Moria Pul (0.69) reached the threshold, and the median correlation was 0.07.

A one-sided Mann–Whitney test indicated a difference between the two groups ($p = 0.014$). The same pattern was observed with Jail Road rainfall ($p = 0.037$) and the larger gauge total ($p = 0.057$). Because the grouping was examined after the results had been observed, this comparison is exploratory. The four locations selected for detailed examination also showed more favourable performance than the full set, with a median ρ of 0.72 compared with 0.32. This difference underlines the rationale for evaluating all eligible locations.

4.3 Robustness

Rankings at the better-performing locations remained stable under input uncertainty. Across the 250 perturbed realizations, all seven Central Area locations with $\rho \geq 0.5$ retained a 10th-percentile correlation of at least 0.63. The distinction between locations with strong and weak rankings also persisted (Figure 2a). Substituting the inundation areas reported by Hussain et al. (2019) for those reported by JICA at the four detailed locations left event rankings essentially unchanged, but altered the fitted parameters (Table S1).

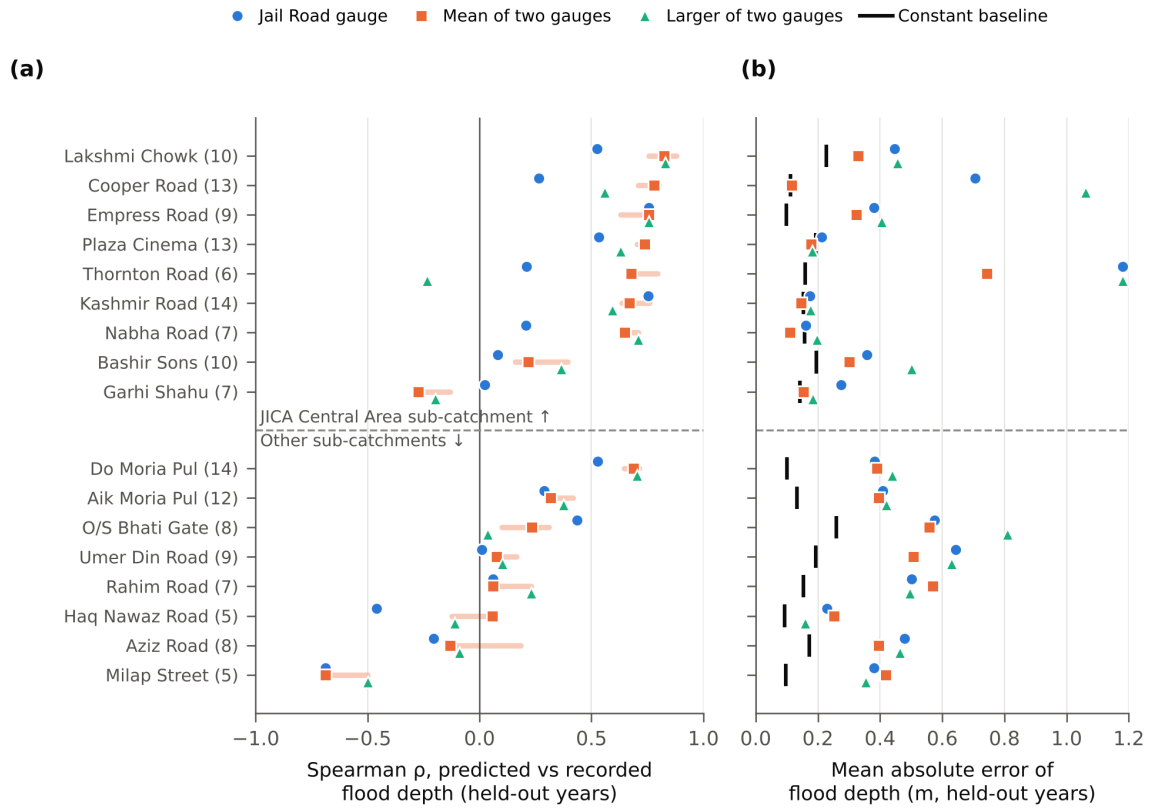


Figure 2: Split-sample results for the 17 flood points, grouped by JICA sub-catchment; bracketed values indicate the number of test floods. (a) Spearman correlation between simulated and recorded flood depths for three rainfall inputs. Shaded bars indicate the 10th–90th percentile across 250 perturbed realizations using the mean-gauge input. (b) Mean absolute depth error relative to a constant baseline equal to the calibration-period mean depth. Errors exceeding 1.2 m are shown at the axis edge.

4.4 Flood depth and event detection

Performance for absolute depths was less successful (Figure 2b). With mean-gauge rainfall, depth MAE was lower than that of the constant baseline at only 3 of the 17 locations. This number declined to one with the larger gauge total and to none with Jail Road rainfall alone. Improvements, where present, were small: at Kashmir Road, MAE was 0.147 m compared with 0.154 m for the baseline. NALA detected 38 of 62 recorded floods deeper than 0.10 m in the Central Area and 25 of 45 elsewhere. At the four detailed locations, every flood missed using larger-gauge rainfall followed rainfall of 28 mm or less at the wetter gauge. Thus, the model retained relative severity more successfully than it reconstructed flood depths or detected individual events, consistent with its screening purpose.

4.5 Lakshmi Chowk intervention screening

At Lakshmi Chowk (Figure 3), a 4-million-gallon tank yielded median reductions of 80–100% in simulated flood volume $\times$ duration. Corresponding reductions were 91–96% for McLeod Road drain rehabilitation, 71–99% for a 3-million-gallon tank, and 57–62% for a 50% increase in outlet capacity. These ranges span the rainfall inputs and inundation-area sources.

The relative ranking of the two largest options depended on inundation area. Using JICA’s area, the 4-million-gallon tank was most effective in 96–100% of well-fitting parameter sets. Using the area reported by Hussain et al. (2019), drain rehabilitation ranked first in 76–91% of sets. Effective outlet capacity was poorly identifiable, with well-fitting values ranging from 0.3 to 3.5 m³/s. The baseline model reproduced flooding in only six to eight of the 15 recorded events. Consequently, these reductions represent conditional modelled benefits rather than validated predictions. Improved information on flood extent would help distinguish between the competing interventions.

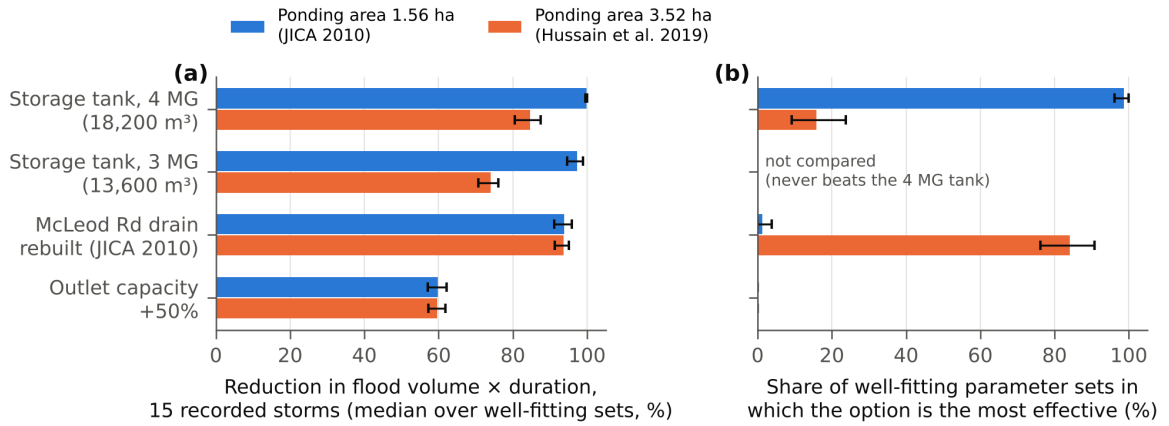


Figure 3: Intervention screening at Lakshmi Chowk across all well-fitting parameter sets using two inundation-area sources. (a) Reduction in simulated flood volume $\times$ duration across the 15 recorded storms, expressed as the mean of the medians for three rainfall inputs; whiskers span those medians. (b) Proportion of parameter sets in which each option is most effective, with ties shared. The 3-million-gallon tank is excluded from this comparison because it cannot outperform the 4-million-gallon tank.

5 Discussion

5.1 Applicability of low-data drainage screening

Agreement between NALA and SWMM on dominant interventions across synthetic networks with contrasting constraints suggests that information about major conveyance limitations can be retained without representing every hydraulic process. Historical testing supports this finding for the Central Area, where seven of nine locations meaningfully ranked held-out floods. However, weaker agreement on household-based and cost-effectiveness criteria indicates that identifying the principal constraint does not ensure reliable prioritization under every decision criterion. The model also did not predict absolute depths. NALA is therefore most appropriately used as an initial screening tool to guide subsequent engineering investigation.

5.2 Rainfall representation

Differences among sub-catchments point to the importance of rainfall representativeness and local drainage characteristics. The historical record relies on two gauges, which cannot characterize spatially variable monsoon rainfall across Lahore. Coarse rainfall inputs are known to degrade urban flood simulations (Berne et al. 2004; Ochoa-Rodriguez et al. 2015; Cristiano et al. 2017). Several recorded floods followed little rainfall at both gauges, suggesting that local storms were not captured.

Rainfall cannot, however, be established as the sole explanation for the observed performance differences. Drainage connectivity, pumping, downstream restrictions, and the number of recorded events may also contribute. The failure at Garhi Shahu, within the otherwise better-performing Central Area, demonstrates that location alone does not determine reliability. The difference among sub-catchments should therefore be interpreted as an exploratory finding.

5.3 Parameter uncertainty and intervention choice

At Lakshmi Chowk, both storage expansion and drain rehabilitation produced substantial simulated benefits, but their ranking reversed when an alternative inundation area was used. Apparently precise recommendations may therefore depend on quantities that historical observations do not constrain. The wide range of well-fitting outlet capacities similarly indicates that different parameter combinations reproduce comparable historical behaviour. Outlet losses associated with blockage or equipment failure, which increase flood volume and duration (Mugume et al. 2015), provide one explanation for the difficulty of identifying effective capacity.

By considering multiple calibrated solutions, NALA can identify the measurement most relevant to a decision. At Lakshmi Chowk, surveying inundation extent and the depth–area relationship would provide greater value than additional calibration.

5.4 Limitations

Flood points were represented as independent single junctions, without backwater, conduit storage, or network interactions. Hydraulic benchmarks used synthetic networks rather than calibrated Lahore networks. In addition, all historical locations shared the same two gauges, so the spatial comparisons are not independent. Missing observations could not be interpreted as flood-free conditions, and some parameters remained poorly identifiable. In two calibrations at Cooper Road, the optimum occurred at the edge of the parameter grid.

These limitations define the boundary between screening and engineering design. Future applications should prioritize representative rainfall measurements, surveyed drainage slopes, verified network connectivity, and reliable inundation-area observations. Where NALA identifies consequential interventions, its findings should guide field surveys and detailed hydraulic modelling rather than replace them.

6 Conclusions

This study evaluated NALA 2.1 as a low-data tool for preliminary urban drainage screening. Across three synthetic networks, NALA agreed with EPA SWMM on the dominant intervention, although agreement varied with the decision criterion. In historical split-sample tests at 17 Lahore locations, it meaningfully ranked flood severity at seven of nine Central Area sites, but at only one of eight sites elsewhere. Estimates of absolute depth rarely improved on a constant baseline.

At Lakshmi Chowk, storage expansion and drain rehabilitation both yielded substantial conditional benefits. Their ranking nevertheless depended on uncertain inundation area, identifying flood extent as the next measurement required. NALA can therefore support the prioritization of drainage investigations where comprehensive hydraulic data are unavailable, provided its application remains confined to the locations and criteria for which useful performance has been demonstrated.

Funding

No funding was received for this work.

Disclosure statement

The author reports no competing interests to declare.

Declaration of generative AI use

Claude (Anthropic) was used to assist in writing and testing parts of the NALA 2.1 code and the SWMM benchmark scripts, to extract tabular data from the JICA (2010) reports, to run the calibration and statistical analyses, to produce the figures, to search the literature, and to plan the manuscript structure. The author checked all code outputs, extracted values, figures, and references, and takes full responsibility for the content of this article.

Data availability statement

NALA 2.1, the analysis scripts, the tables transcribed from JICA (2010), and the SWMM input files are openly available on Zenodo at <https://doi.org/10.5281/zenodo.23366526> (Hayan 2026).

References

- Ahmad, Shakeel, Haifeng Jia, Anam Ashraf, Dingkun Yin, Zhenxia Chen, Rasheed Ahmed, and Muhammad Israr. 2024. “A Novel GIS-SWMM-ABM Approach for Flood Risk Assessment in Data-Scarce Urban Drainage Systems.” *Water* 16 (11): 1464. <https://doi.org/10.3390/w16111464>.
- Berne, Alexis, Guy Delrieu, Jean-Dominique Creutin, and Charles Obled. 2004. “Temporal and Spatial Resolution of Rainfall Measurements Required for Urban Hydrology.” *Journal of Hydrology* 299 (3–4): 166–179. <https://doi.org/10.1016/j.jhydrol.2004.08.002>.
- Beven, Keith, and Andrew Binley. 1992. “The Future of Distributed Models: Model Calibration and Uncertainty Prediction.” *Hydrological Processes* 6 (3): 279–298. <https://doi.org/10.1002/hyp.3360060305>.
- Butler, David, Christopher J. Digman, Christos Makropoulos, and John W. Davies. 2018. *Urban Drainage*. 4th ed. Boca Raton, FL: CRC Press. <https://doi.org/10.1201/9781351174305>.
- Cristiano, Elena, Marie-claire ten Veldhuis, and Nick van de Giesen. 2017. “Spatial and Temporal Variability of Rainfall and Their Effects on Hydrological Response in Urban Areas – A Review.” *Hydrology and Earth System Sciences* 21 (7): 3859–3878. <https://doi.org/10.5194/hess-21-3859-2017>.
- Guidolin, Michele, Albert S. Chen, Bidur Ghimire, Edward C. Keedwell, Slobodan Djordjević, and Dragan A. Savić. 2016. “A Weighted Cellular Automata 2D Inundation Model for Rapid Flood Analysis.” *Environmental Modelling & Software* 84: 378–394. <https://doi.org/10.1016/j.envsoft.2016.07.008>.
- Hayan, Muhammad. 2026. *NALA 2.1 Code and Data for: Evaluating NALA 2.1 for Low-Data Urban Flood Screening: A Case Study of 17 Flood-Prone Locations in Lahore, Pakistan*. Version 2.1.0. Zenodo. <https://doi.org/10.5281/zenodo.23366526>.
- Hussain, Fiaz, Riaz Hussain, Ray-Shyan Wu, and Tanveer Abbas. 2019. “Rainwater Harvesting Potential and Utilization for Artificial Recharge of Groundwater Using Recharge Wells.” *Processes* 7 (9): 623. <https://doi.org/10.3390/pr7090623>.
- Jamali, Behzad, Peter M. Bach, Luke Cunningham, and Ana Deletić. 2019. “A Cellular Automata Fast Flood Evaluation (CA-ffé) Model.” *Water Resources Research* 55 (6): 4936–4953. <https://doi.org/10.1029/2018WR023679>.
- JICA (Japan International Cooperation Agency), NJS Consultants Co., Ltd., and CTI Engineering International Co., Ltd. 2010. *The Preparatory Study on Lahore Water Supply, Sewerage and Drainage Improvement Project in Islamic Republic of Pakistan: Final Report*. Vol. 1, Main Report; Vol. 2, Appendices. Lahore: WASA-LDA. https://openjicareport.jica.go.jp/618/618/618_117_12001863.html.
- Klemeš, V. 1986. “Operational Testing of Hydrological Simulation Models.” *Hydrological Sciences Journal* 31 (1): 13–24. <https://doi.org/10.1080/02626668609491024>.
- Leandro, Jorge, Albert S. Chen, Slobodan Djordjević, and Dragan A. Savić. 2009. “Comparison of 1D/1D and 1D/2D Coupled (Sewer/Surface) Hydraulic Models for Urban Flood Simulation.” *Journal of Hydraulic Engineering* 135 (6): 495–504. [https://doi.org/10.1061/\(ASCE\)HY.1943-7900.0000037](https://doi.org/10.1061/(ASCE)HY.1943-7900.0000037).
- Mugume, Seith N., Diego E. Gomez, Guangtao Fu, Raziye Farmani, and David Butler. 2015. “A Global Analysis Approach for Investigating Structural Resilience in Urban Drainage Systems.” *Water Research* 81: 15–26. <https://doi.org/10.1016/j.watres.2015.05.030>.
- Nkwunonwo, U. C., M. Whitworth, and B. Bailly. 2020. “A Review of the Current Status of Flood Modelling for Urban Flood Risk Management in the Developing Countries.” *Scientific African* 7: e00269. <https://doi.org/10.1016/j.sciaf.2020.e00269>.
- Ochoa-Rodriguez, Susana, Li-Pen Wang, Auguste Gires, Rui Daniel Pina, Ricardo Reinoso-Rondinel, Guendalina Bruni, Abdellah Ichiba, et al. 2015. “Impact of Spatial and Temporal Resolution of Rainfall Inputs on Urban Hydrodynamic Modelling Outputs: A Multi-Catchment Investigation.” *Journal*

of Hydrology 531 (2): 389–407. <https://doi.org/10.1016/j.jhydrol.2015.05.035>.

Rossman, Lewis A. 2017. *Storm Water Management Model Reference Manual, Volume II: Hydraulics*. EPA/600/R-17/111. Cincinnati, OH: U.S. Environmental Protection Agency.

Rossman, Lewis A., and Michelle A. Simon. 2022. *Storm Water Management Model User's Manual, Version 5.2*. EPA/600/R-22/030. Cincinnati, OH: U.S. Environmental Protection Agency.

The Nation. 2026. “Lakshmi Chowk Water Tank Capacity Increased to Tackle Urban Flooding.” March 18, 2026. <https://www.nation.com.pk/18-Mar-2026/lakshmi-chowk-water-tank-capacity-increased-tackle-urban-flooding>.