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Managing urban floods with GIS, SWMM and green infrastructure: a critical review with implications for Central Asian cities

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Abstract: Urban flooding is intensifying with urbanization, climate change and ageing drainage infrastructure, particularly in data-scarce foothill cities. This critical narrative review, based on a transparently reported selection procedure informed by PRISMA 2020, examines how geographic information systems (GIS), hydrological-hydraulic models (EPA SWMM, StormCAD, HEC-RAS and related 1D/2D tools), green infrastructure (GI/LID/SUDS) and machine learning are combined in urban flood management, and what this implies for Central Asian cities drained by open aryk networks. Searches of Scopus, Web of Science and Google Scholar, supplemented by Russian and Kazakh-language sources and citation searching, were used to select 33 sources published in 2002–2026 (28 from database searching and 5 from other methods), of which 26 are primary case or modelling studies. A structured data-extraction table summarizes the study area, tools, input data, calibration/validation and quantitative outcomes of each primary study. GIS-hydrological-hydraulic model integration was the largest thematic cluster (14 of 33 sources), whereas calibration or validation against observed flood data was reported in only some primary studies and several reported none. Reported GI/LID effects are not directly comparable because they refer to different metrics and design storms: LID covering 9.81% of a catchment in Palembang reduced runoff volume by 21.0–35.4% and peak discharge by 11.3–37.7%, whereas a combined GI scenario in Istanbul reduced the flooded area by 36.94%. Peer-reviewed evidence on urban drainage in Central Asian cities remains scarce. We recommend combining digitized aryk networks, high-resolution DEM/LiDAR data and locally derived design rainfall with calibrated 1D/2D models and GI scenarios, and we outline research priorities for the region.

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1 Introduction

Urban flooding is one of the most widespread environmental and engineering hazards associated with urbanization, climate change and the deterioration of infrastructure. As impervious surfaces expand, less rainfall infiltrates into the soil, which leads to greater surface runoff, higher peak flows and increased hydraulic pressure on urban drainage systems. The problem becomes especially pronounced during short, intense rainfall events, when sewer networks, open channels and stormwater infrastructure no longer have sufficient capacity to convey the generated runoff (Price & Vojinovic, 2008; Guo et al., 2021).

In urban drainage management, GIS platforms provide the spatial basis for delineating catchments, characterizing land cover, mapping flood-prone areas and visualizing model outputs (Abedin & Stephen, 2019; Jahangiri, 2019). Hydrological–hydraulic models, including EPA SWMM, StormCAD and HEC-RAS, are widely used to simulate rainfall–runoff processes, the conveyance capacity of pipe networks and flood propagation in open channels (Rossman, 2015; Abd-Elhamid et al., 2020; Ertan & Celik, 2021; Palaka et al., 2021).

In recent years, green infrastructure (GI), Low Impact Development (LID) and Sustainable Urban Drainage Systems (SUDS) have increasingly been viewed as nature-based solutions for mitigating urban flood risk. These terms overlap but are not synonymous: LID originated in North American site-design practice, SUDS in the United Kingdom and water-sensitive urban design (WSUD) in Australia, whereas GI is a broader planning concept that also covers ecological and social functions (Fletcher et al., 2015). Rain gardens, bioswales, permeable pavements, green roofs and detention ponds slow surface runoff, enhance infiltration and improve water quality (Porse, 2018; Skrygan et al., 2018; Al Amin et al., 2024).

Several reviews have already synthesized parts of this field. Teng et al. (2017) reviewed flood inundation modelling methods, recent advances and uncertainty analysis; Guo et al. (2021) compared urban surface water flood models and discussed their future challenges; and Tom et al. (2022) reviewed flood modelling in developing cities and informal settlements using Nairobi as an example. The hydrological performance of LID practices has been reviewed by Ahiablame et al. (2012) and Eckart et al. (2017), and machine learning approaches to flood prediction by Mosavi et al. (2018).

However, these reviews usually address a single family of tools – inundation models, LID practices or data-driven methods – and mostly draw on cities with dense monitoring networks and fully digitized pipe systems. Much less attention has been paid to how GIS, network models of the SWMM type, open-channel hydraulic models and GI scenarios can be combined in data-scarce foothill cities whose stormwater is conveyed largely through open channels. This situation is typical of Central Asia, where cities such as Almaty, Bishkek and Tashkent rely on *aryk* networks – open channels originally built for irrigation that also convey stormwater – and where peer-reviewed studies of urban flooding are still few (Ceresa et al., 2025; Mirlas et al., 2025; Mukhanbet et al., 2026; Linh et al., 2026).

The aim of this review is to critically synthesize the methodological advantages, limitations and future directions of GIS, SWMM, StormCAD, HEC-RAS, GI/LID/SUDS and machine learning approaches used in urban flood management, and to derive implications for Central Asian cities. Three research questions guided the review: RQ1 – how are GIS, hydrological–hydraulic models, GI/LID/SUDS and machine learning combined in the reviewed studies, and which data do they require? RQ2 – how large and how comparable are the reported effects of GI/LID/SUDS measures, and why do they differ between cities? RQ3 – which model combinations are applicable under data scarcity, and what are the research gaps and practical priorities for Central Asian *aryk*-drainage systems? Compared with earlier reviews, this review (i) considers GIS, network, open-channel and GI modelling within one framework; (ii) provides a structured extraction of the included studies, including their calibration status and quantitative results; and (iii) explicitly addresses data-scarce foothill cities of Central Asia.

2 Materials and methods

2.1 Review type

This study is a critical narrative review (Grant & Booth, 2009) with a selection procedure informed by the PRISMA 2020 statement (Page et al., 2021). It is not a full systematic review: no protocol was registered in advance and no meta-analysis was performed, because the included studies use heterogeneous models, metrics and design storms. PRISMA 2020 was used as a reporting guideline for the search and selection stages, and the selection stages are shown in Figure 1. The PRISMA statement is cited as a methodological reference and is not part of the analysed corpus.

2.2 Information sources and search strategy

The searches covered Scopus, Web of Science Core Collection and Google Scholar, as well as Russian- and Kazakh-language scientific journals, theses and official project reports, which capture regional evidence that is rarely indexed in international databases. The searches were limited to publications from 2002 to 2026; the search strings and terms are given in Table 1. Because the review was designed as a narrative review, the numbers of records retrieved at the identification and screening stages were not recorded systematically; Figure 1 therefore shows the selection stages and reports numbers only for the documented stages (re-appraisal and final inclusion). During the revision in 2026, backward and forward citation searching of the included studies and a targeted search for peer-reviewed studies on Central Asian cities were also carried out; these yielded five additional studies.

Table 1. Search strategy

Source	Search string / terms
Scopus	TITLE-ABS-KEY (("urban flood*" OR "pluvial flood*" OR stormwater OR "urban drainage") AND (GIS OR SWMM OR "HEC-RAS" OR StormCAD OR LiDAR OR DEM) AND ("green infrastructure" OR "low impact development" OR LID OR SUDS OR "flood risk" OR "machine learning")) AND PUBYEAR > 2001
Web of Science Core Collection	TS = (same Boolean structure as for Scopus); publication years 2002–2026
Google Scholar	Combinations of: urban flood; stormwater management; GIS; SWMM; HEC-RAS; StormCAD; green infrastructure; LID; SUDS; DEM; LiDAR; flood risk assessment; urban drainage; machine learning flood prediction
Russian-/Kazakh-language sources	«городское наводнение», «ливневая канализация», «арычная сеть», «ГИС-моделирование», «отвод поверхностного стока»; «қалалық су тасқыны», «нөсер кәрізі», «арық желісі»
Other methods	Backward/forward citation searching; targeted search for peer-reviewed studies on Almaty, Bishkek, Tashkent and Central Asia (five studies included)

Source: compiled by the authors.

2.3 Eligibility criteria

The eligibility criteria are summarized in Table 2. Peer-reviewed journal articles, conference papers and reviews were the main type of included source. Theses and official project reports were admitted only when they were publicly accessible and provided unique evidence for an under-represented region (Central Asia) or a methodological contribution not available in the peer-reviewed literature; such sources are flagged as grey literature in Appendix A and are used for context rather than for quantitative comparison. The time frame was harmonized to 2002–2026: Burian and Edwards (2002) is the earliest included source and was retained as a historical–methodological reference on urban drainage.

Table 2. Inclusion and exclusion criteria

Criterion	Inclusion criteria	Exclusion criteria
Document type	Peer-reviewed article, conference paper or review; publicly accessible thesis or official project report providing unique regional or methodological evidence	Journalistic material; inaccessible full text; duplicate record; methodological guideline without urban flood content; journal outside the subject area or without a clear peer-review process
Thematic relevance	Urban drainage, GIS, SWMM/HEC-RAS/StormCAD and related models, GI/LID/SUDS, urban flood risk, flood susceptibility	Rural hydrology, coastal flooding or only indirectly related work
Spatial context	Urban or urbanized catchments, metropolitan areas, foothill cities; regional studies that report results for cities	Natural river basins without urban infrastructure
Methodological content	A model, map, scenario, numerical result or methodological conclusion is provided	Method not sufficiently described or results only stated in general terms
Time frame	Published 2002–2026	Publication year or publication status unclear

Source: compiled by the authors.

2.4 Screening and selection

After removal of duplicates, the records were screened by the authors in two steps: first by title and abstract and then by full text against the criteria in Table 2; disagreements were resolved by discussion. During the revision of the manuscript, the corpus was re-appraised: the PRISMA 2020 statement (a methodological guideline) and one article published in a journal outside the subject area were removed, leaving 28 sources from database searching. Together with the five studies identified by other methods, 33 sources were included in the synthesis (Figure 1).

Stage	Records	Records removed / excluded
Identification	Records identified from Scopus, Web of Science, Google Scholar and Russian-/Kazakh-language sources (2002–2026)	Duplicates removed
Screening	↓ Records screened by title and abstract	Records excluded as not relevant to urban flooding, drainage modelling or GI
Eligibility	↓ Full texts assessed against the criteria in Table 2	Full texts excluded: not urban; no model, map or quantitative result; full text not available; duplicate publication
Re-appraisal during revision	↓ Sources retained from databases (n = 30)	Removed (n = 2): methodological guideline (PRISMA 2020 statement, n = 1); journal outside the subject area (n = 1)
Other methods	Citation searching and targeted search for peer-reviewed studies on Central Asian cities	Studies added (n = 5)
Included	↓ Studies included in the synthesis (n = 33): 28 from databases + 5 from other methods; 26 primary studies and 7 reviews/conceptual works	

Figure 1. Flow of records through the selection procedure (PRISMA 2020-informed)

Source: compiled by the authors.

2.5 Quality appraisal and data extraction

Each primary study was appraised with a simple four-item checklist: (Q1) the study area and input data are clearly described; (Q2) the model or method is described in sufficient detail to be reproduced; (Q3) calibration or validation against observed data is reported; and (Q4) quantitative results are reported. The appraisal was not used to exclude studies but to weight their interpretation; its key element, the calibration/validation status, is reported for every primary study in Appendix A. Data were extracted with a standard form containing the following fields: author and year; country and city; study type; tools and models; input data (DEM, rainfall, drainage network, land use); calibration/validation and performance metrics; scenarios; main quantitative result; and limitations. Extraction was carried out by the authors and cross-checked against the original publications. The completed extraction table is given in Appendix A (Table A1) and serves as the list of included studies.

2.6 Synthesis

The corpus was first described by publication period, study region and thematic cluster (Table 3, Figure 2). The primary studies were then compared narratively and critically along the three research questions, with particular attention to the metrics used to report effects, the design storms, the calibration status and the availability of input data. Figure 2 was produced in Python using the Matplotlib Basemap toolkit.

Bibliometric diagrams were not used in the revised version because several included sources are not indexed in bibliographic databases.

3 Results

3.1 Characteristics of the included literature

Of the 33 included sources, 26 are primary case or modelling studies and seven are reviews or conceptual works (Burian & Edwards, 2002; Price & Vojinovic, 2008; Merz et al., 2014; Tsakiris, 2014; Skrygan et al., 2018; Guo et al., 2021; Tom et al., 2022). The number of sources increased over time: three were published in 2002–2010, seven in 2011–2018, twelve in 2019–2022 and eleven in 2023–2026, so that 23 sources (69.7%) appeared after 2018 (Table 3). Early sources mainly address probabilistic flood risk and the historical development of urban drainage (Apel et al., 2004; Merz et al., 2014), whereas later ones are dominated by GIS–hydrology integration, 2D hydraulics, LID scenarios and machine learning (Guo et al., 2021; Al Amin et al., 2024; Linh et al., 2026).

Table 3. Distribution of the included sources (n = 33) by period, region and thematic cluster

Category	Number	Share, %	Sources / main content
Publication period			
2002–2010	3	9.1	Historical foundations of urban drainage; probabilistic flood risk
2011–2018	7	21.2	Flood risk concepts; GIS-based modelling; GI and open data
2019–2022	12	36.4	GIS–SWMM/HEC-RAS integration; GI scenarios; developing cities; machine learning
2023–2026	11	33.3	Modelling under data scarcity; LID scenarios; Central Asian studies; explainable machine learning
Study region			
South Asia	6	18.2	India (4), Pakistan (1), Bangladesh (1)
Central Asia	6	18.2	Kazakhstan (3), Uzbekistan (1), Kyrgyzstan (1), regional study of five countries (1); two of six are grey literature
North America	4	12.1	USA: Las Vegas, Philadelphia, Los Angeles, Sacramento
East and Southeast Asia	3	9.1	China, Thailand, Indonesia
Middle East	3	9.1	Saudi Arabia, Iraq, Iran
Africa	3	9.1	Senegal, Burkina Faso, Kenya (review of Nairobi)
Europe	2	6.1	Germany, Turkey
Reviews / conceptual (no single study area)	6	18.2	General reviews and conceptual works
Thematic cluster			
GIS and hydrological–hydraulic modelling	14	42.4	SWMM, StormCAD, HEC-RAS, PCSWMM, MODFLOW; drainage-area delineation; network capacity
GI/LID/SUDS	6	18.2	Rain gardens, bioretention, permeable pavements, green roofs, multifunctional channels
Flood risk, probabilistic and climate approaches	6	18.2	Monte Carlo, return periods, design rainfall, regional risk models
General reviews and drainage practice	5	15.2	Model reviews, developing cities, history of drainage, aryk-network project
Machine learning and flood susceptibility	2	6.1	GARP/QUEST, explainable machine learning

Note: shares are calculated from n = 33 and may not sum to 100 because of rounding. Source: compiled by the authors from Table A1.

Geographically, the primary studies are spread across South Asia and Central Asia (six sources each), North America (four), East and Southeast Asia, the Middle East and Africa (three each) and Europe (two) (Table 3, Figure 2). The Central Asian group was strengthened during revision by four peer-reviewed studies on design rainfall and groundwater flooding in Almaty, regional flood risk in Central Asia and flood susceptibility in Kyrgyz cities; two further Central Asian sources are grey literature. GIS and

hydrological–hydraulic modelling is the largest thematic cluster (14 sources, 42.4%), followed by GI/LID/SUDS and flood-risk approaches (six each).

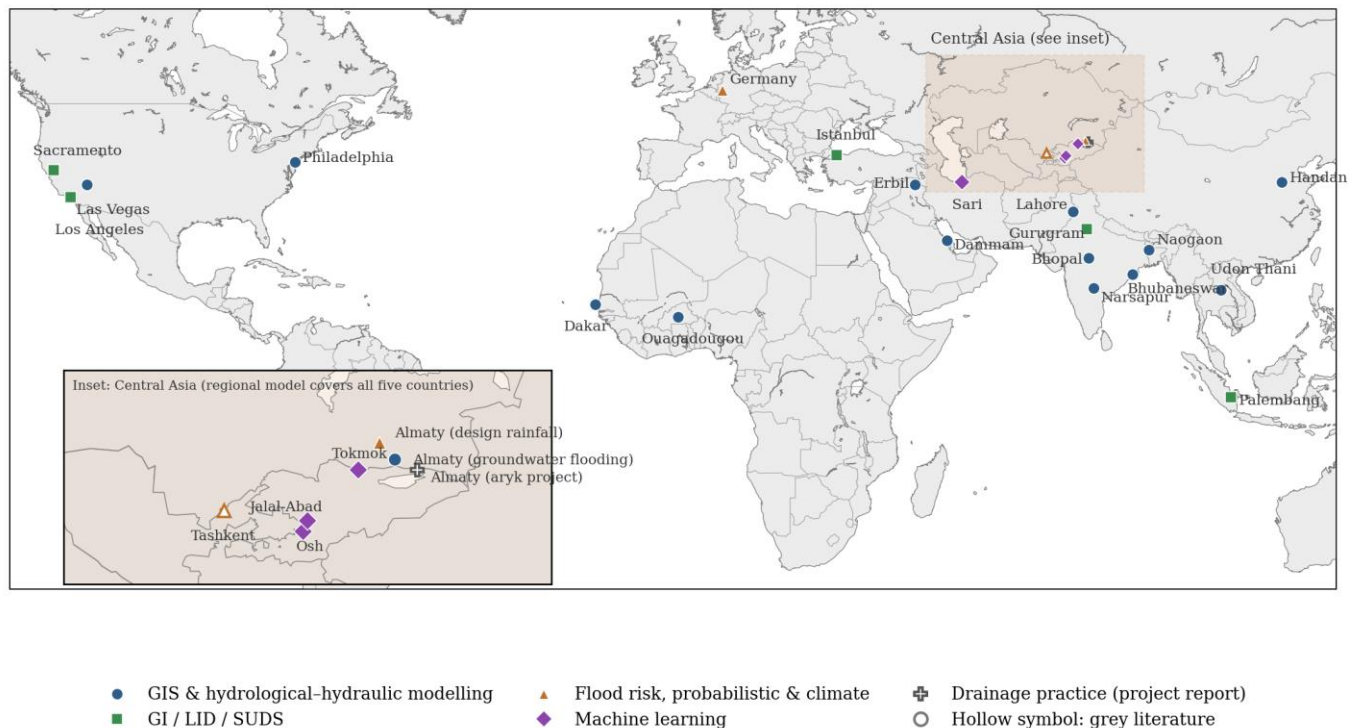


Figure 2. Study areas of the 26 primary studies by thematic cluster; the inset shows Central Asia, and the regional study of Ceresa et al. (2025) covers all five Central Asian countries

Source: compiled by the authors from Table A1; base map: Matplotlib Basemap toolkit.

3.2 Role of GIS platforms and DEM/LiDAR data

GIS platforms provide the initial spatial framework for studying urban drainage systems. ArcGIS, ArcHydro and QGIS are used to delineate catchments, determine flow directions, analyze land cover and map areas with high flood susceptibility. Abedin and Stephen (2019) developed a GIS workflow for spatiotemporal flood mapping on a university campus in Las Vegas; calibrating the DEM resolution, the temporal resolution of rainfall and a clogging factor of the inlets, they obtained the best agreement with a 5 m DEM and a clogging factor of 0.83, with an error of 24% between estimated and observed flood depth. Jahangiri (2019) combined ArcHydro and LiDAR data to delineate the drainage areas of green stormwater infrastructure (GSI) automatically and highlighted the influence of DEM quality on the results.

DEM resolution therefore plays a decisive role in identifying catchment boundaries, flow directions and water-accumulation zones. Low-resolution DEMs may fail to represent urban microrelief, curbs, buildings and artificial barriers, whereas high-resolution LiDAR data can refine drainage areas and correctly incorporate GSI/LID elements into a model (Jahangiri, 2019; Guo et al., 2021). As shown in Figure 3, the drainage area delineated for the same GSI site increased several-fold – by up to about an order of magnitude – when the 1–2 ft (0.3–0.6 m) LiDAR DEM was replaced by DEMs with 3.2 ft (about 1 m) and 5–10 ft (1.5–3 m) resolution.

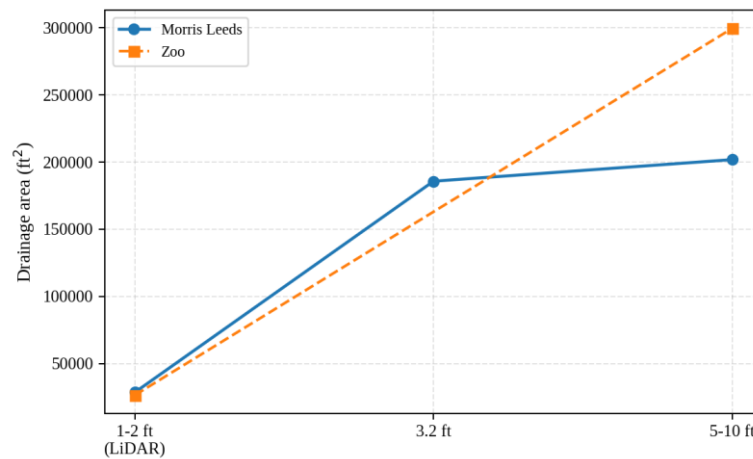


Figure 3. Effect of DEM resolution on the drainage area delineated for two green stormwater infrastructure sites ("Morris Leeds" and "Zoo") analysed by Jahangiri (2019); DEM resolution 1–2 ft = 0.3–0.6 m (LiDAR), 3.2 ft $\approx$ 1 m, 5–10 ft = 1.5–3 m; drainage area in ft² (1 ft² = 0.0929 m²)
Source: adapted from Jahangiri (2019).

3.3 Application of SWMM, StormCAD and HEC-RAS

EPA SWMM is the most frequently used tool in the corpus. It is a dynamic rainfall–runoff and routing model that simulates the transformation of rainfall into surface runoff, the hydraulic regime of sewer and channel networks and the effect of LID controls over time (Rossman, 2015). Palaka et al. (2021) used SWMM and GIS to analyze and redesign the stormwater drains of the central zone of Narsapur town (India), checking channel capacity with Manning's equation. Under data scarcity, Ahmad et al. (2024) generated design hyetographs for Lahore (Pakistan) with the log-Pearson type III distribution and the alternating block method; in a 2.71 km² community, a 2-year storm inundated about 60% of the area, showing that the existing system designed for a 2-year return period was inadequate. In Handan (China), Liu et al. (2022) showed that the increase in impervious surfaces from 32.44% to 76.57% between 1987 and 2017 raised the simulated flood volume from 7.89×10^4 to 3.85×10^5 m³, whereas expansion of the drainage network alone reduced it by 27.56%; the model was checked against 11 flooding locations reported on social media. Ahmed et al. (2026) calibrated a 1D–2D SWMM model for Udon Thani (Thailand) and found the curve number and imperviousness to be the most influential parameters, followed by sub-catchment width and slope. Other applications in the corpus combine SWMM and GIS for campus-scale drainage assessment (Patel et al., 2024), apply large-scale GIS-based urban flood modelling in Ouagadougou (Bouvier et al., 2018) or use remote sensing and GIS to assess flood damage by land-use type (Al Faisal et al., 2018).

StormCAD relies on the Rational Method ($Q = CiA$) and IDF curves for the engineering design of pipe networks. For three developing zones near Dammam (Saudi Arabia), Abd-Elhamid et al. (2020) reported that increasing the runoff coefficient C from 0.2 to 0.6 increased peak discharge 3–7 times and increasing it to 0.8 increased it 4–9 times, depending on the return period, while construction costs rose up to 3.5 times. The 12-fold increase reported in that study refers to the combined worst case in which C increases from 0.2 to 1.0 and the design return period from 5 to 100 years. Because peak discharge is linear in C under the Rational Method, ratios exceeding the ratio of the C values reflect the simultaneous increase in design rainfall intensity with the return period. HEC-RAS, in turn, is suited to 1D/2D modelling of open channels and floodplains: Ertan and Celik (2021) combined a 1D HEC-RAS model, GIS and the Rational Method for a 1,653 ha urban section of the Kağıthane Stream in Istanbul to compare urbanization and GI scenarios.

Table 4 summarizes the main tools. In addition to the tools used in the included studies, it lists widely used 1D/2D packages (MIKE URBAN/MIKE+, InfoWorks ICM, TUFLOW and LISFLOOD-FP) that are discussed in model reviews (Teng et al., 2017; Guo et al., 2021).

Table 4. Main tools used for urban flood modelling

Tool	Model type	Application area	Advantages	Limitations
EPA SWMM	1D hydrological-hydraulic	Urban sewer systems, stormwater runoff, LID scenarios	Dynamic simulation; LID module; free and open source	Requires reliable rainfall and network data for calibration; no 2D surface flow
StormCAD	1D engineering design	Pipe-network design	Rapid peak-discharge estimation with the Rational Method and IDF curves	Steady-state design; does not represent 2D surface inundation
HEC-RAS	1D/2D hydraulic	Open channels, rivers, floodplains	Free; detailed channel and floodplain hydraulics	Requires high-quality geometric data; limited pipe-network representation
PCSWMM 2D	Coupled 1D/2D	Urban flooding and LID scenarios	Couples pipe networks with 2D surface runoff	Commercial; computational demand and calibration effort
MIKE URBAN / MIKE+	Coupled 1D/2D	Urban drainage and surface flooding	Integrated network and surface modelling; widely used by utilities	Commercial licence; high data requirements
InfoWorks ICM	Coupled 1D/2D	Integrated catchment modelling	Combined sewer, river and surface flow in one model	Commercial licence; high data requirements
TUFLOW	1D/2D hydrodynamic	Overland and urban flooding	Detailed 2D solution on high-resolution grids	Commercial licence; computational cost at fine resolution
LISFLOOD-FP	2D raster-based	Large-area inundation	Computationally efficient; suitable for large domains (Bates & De Roo, 2000)	Simplified physics; usually no explicit pipe network
GIS + machine learning	Spatial-statistical	Flood susceptibility mapping	Uses many conditioning factors; does not need a drainage network	Depends on flood inventory quality; no hydraulic process representation

Source: compiled by the authors based on Rossman (2015), Teng et al. (2017), Guo et al. (2021) and the included studies.

3.4 Effectiveness of green infrastructure and LID/SUDS

GI/LID/SUDS elements are designed to retain stormwater at the source, increase infiltration, slow surface runoff and reduce the peak load on drainage networks. They include rain gardens, bioretention cells, permeable pavements, infiltration trenches, green roofs and detention ponds (Greco & Larsen, 2014; Porse, 2018; Skrygan et al., 2018). The quantitative results of the included GI studies are summarized in Table 5. They differ not only in magnitude but also in what is measured: runoff volume, peak discharge, flooded area or channel conveyance.

Table 5. Reported effects of GI/LID/SUDS measures in the included studies

Study, city	Approach	Metric	Reported effect	Calibration / validation
Al Amin et al. (2024), Palembang, Indonesia	PCSWMM 2D; five LID types on 9.81% of an 18.37 km ² catchment; 2- to 25-year storms	Runoff volume; peak discharge	Volume -21.0 to -35.4%; peak -11.3 to -37.7%	Calibrated against the December 2021 flood (NSE = 0.948; r = 0.987)
Sehrawat & Shekhar (2025), Gurugram, India	SWMM + GIS; green roofs, permeable pavements, rain barrels in eight high-runoff sub-catchments; 2- to 10-year storms	Runoff volume; peak discharge	Green roofs about -41% volume; combined LID up to -72.31% volume and -54.05% peak	Compared with Rational Method estimates (NSE, RMSE), not with observed floods
Ertan & Celik (2021), Istanbul, Turkey	1D HEC-RAS + GIS + Rational Method; six urbanization/GI scenarios	Flooded area (flood mitigation rate)	Combined GI scenario -36.94%; green roofs + permeable pavements -18.93%; full urbanization without GI +86.89%	No calibration described
Greco & Larsen (2014), Sacramento River, USA	Channel-width and roughness scenarios for flood-control channels	Conveyance (Manning's n allowed)	Wider channel allowed nearly four times higher roughness (riparian vegetation) while keeping 100-200-year protection	Scenario analysis
Porse (2018), Los Angeles, USA	GIS and open data; statistical analysis of sewer locations and sociodemographic indicators	Spatial priority	Watersheds suitable for multi-benefit, equity-oriented GI projects identified	Not applicable
Jahangiri (2019), USA	ArchHydro + LiDAR; automated GSI drainage-area delineation	Drainage area	Delineated area strongly dependent on DEM resolution (Figure 3)	Agreement with design drainage areas reported

Source: compiled by the authors.

3.5 Flood risk, uncertainty and machine learning

Urban flood risk assessment combines the components of hazard, vulnerability and exposure. Apel et al. (2004), Tsakiris (2014) and Merz et al. (2014) emphasize the need to assess flood risk probabilistically, to account for uncertainty and to model scenarios under climate change. Monte Carlo methods, return periods and IDF curves are important for testing the reliability of drainage infrastructure. For Almaty, Mukhanbet et al. (2026) analyzed annual maximum precipitation at five stations for 2000–2023, found the generalized extreme value distribution to fit best at most stations and derived design rainfall for 10-, 50- and 100-year return periods. At the regional scale, Ceresa et al. (2025) built a probabilistic riverine flood risk model for the five Central Asian countries using the TOPKAPI-X hydrological model (1 km grid) and the CA2D inundation model (about 90 m), validated against discharge observations, satellite flood extents and historical losses.

Machine learning methods are increasingly combined with GIS layers to map flood susceptibility. Algorithms such as random forest, gradient boosting, GARP and QUEST can analyze topography, impervious surfaces, rainfall, drainage density and land use together (Mosavi et al., 2018; Darabi et al., 2019). Linh et al. (2026) applied random forest, XGBoost and AdaBoost with SHAP-based explanation to map flood susceptibility in Jalal-Abad, Osh and Tokmok (Kyrgyzstan), using a Sentinel-1 flood inventory; success and prediction rates exceeded 84%. Darabi et al. (2019) mapped urban flood risk in Sari (Iran) from 113 flooded locations, with AUC-ROC values of 93.5% for GARP and 89.2% for QUEST. These models do not require a digitized drainage network, which makes them attractive under data scarcity, but they depend on the quality of historical flood inventories, require independent validation and do not represent hydraulic processes.

3.6 Calibration and data availability in the primary studies

The extraction (Appendix A) shows large differences in the evidence base of the primary studies. Calibration or validation against observed flood data was reported explicitly by Abedin and Stephen (2019; flood depth from photographs), Liu et al. (2022; social-media reports), Al Amin et al. (2024; NSE = 0.948) and Ceresa et al. (2025; discharge, satellite extents and losses), and machine learning studies validated their susceptibility maps against flood inventories. In contrast, Vahida and Sahoo (2022) and Ertan and Celik (2021) did not report calibration, and Dieme et al. (2025) state explicitly that the necessary data for validating their Dakar model could not be obtained. Several studies replaced missing observations with proxies: design hyetographs derived from daily rainfall (Ahmad et al., 2024; Ali & Mawlood, 2023), satellite rainfall and DEM products (Sehrawat & Shekhar, 2025) or crowdsourced flood reports (Liu et al., 2022).

4 Discussion

4.1 Why reported effects of green infrastructure differ between cities

The reported GI/LID effects range from about 11% to more than 70% (Table 5), but these numbers cannot be combined into a single range. First, they refer to different metrics: runoff volume and peak discharge (Al Amin et al., 2024; Sehrawat & Shekhar, 2025) respond differently from the flooded area (Ertan & Celik, 2021), and a reduction in runoff volume does not translate proportionally into a reduction in flood extent. Second, the effect depends on the design storm: in Palembang the reductions span 21.0–35.4% for volume and 11.3–37.7% for peak discharge across 2- to 25-year storms, consistent with reviews showing that LID performance generally declines as storm size increases (Ahiablame et al., 2012; Eckart et al., 2017). Third, the implementation area and placement differ: 9.81% of the catchment in Palembang versus eight selected high-runoff sub-catchments in Gurugram. Fourth, soil infiltration capacity, baseline imperviousness and maintenance condition all modify performance (Eckart et al., 2017). Finally, the evidence differs in strength: only the Palembang model was calibrated against an observed flood, whereas the Gurugram model was compared with Rational Method estimates and the Istanbul model was not calibrated. GI effectiveness should therefore be reported together with the metric, design storm,

implementation area and calibration status, and verified through local modelling rather than transferred as a universal percentage.

4.2 Common data limitations and model combinations under data scarcity

The most common limitations are incomplete or undigitized drainage-network data, rainfall records available only at daily resolution, coarse DEMs that do not resolve urban microrelief, and the absence of observed flood depths or extents for calibration. The studies suggest several practical combinations for such conditions. Where network data exist but rainfall data are short, SWMM can be driven by design hyetographs derived from frequency analysis and the alternating block method (Ahmad et al., 2024). Where calibration data are scarce, sensitivity analysis helps to concentrate the calibration effort on the most influential parameters, such as the curve number and imperviousness (Ahmed et al., 2026). Crowdsourced reports and photographs can provide qualitative validation (Abedin & Stephen, 2019; Liu et al., 2022). Where no network data exist, GIS-based simplified routing (Dieme et al., 2025) or machine-learning susceptibility maps (Darabi et al., 2019; Linh et al., 2026) can be used for screening, followed by detailed 1D/2D modelling in priority areas. Reliance on a single model is therefore insufficient: GIS integrates spatial data, SWMM simulates rainfall–runoff and network dynamics, StormCAD supports pipe design, HEC-RAS represents open-channel flow and machine learning assesses multi-factor susceptibility.

4.3 Implications for Central Asian cities and aryk-drainage systems

Peer-reviewed evidence on urban drainage in Central Asian cities remains limited, but the available studies outline the main conditions. In Almaty, extreme rainfall shows strong spatial variability across stations and is best described by the generalized extreme value distribution (Mukhanbet et al., 2026), and urbanization-related groundwater flooding has been documented in the Akbulak micro-district in the north of the city, where reduced infiltration and the clogging of a Karasu-type stream concentrated runoff that then recharged a shallow aquifer (Mirlas et al., 2025). Regional risk modelling covers riverine floods at a resolution of about 90 m (Ceresa et al., 2025), which is too coarse for street-scale pluvial flooding, and machine learning has been applied to flood susceptibility in three Kyrgyz cities (Linh et al., 2026). Grey literature documents the reconstruction of aryk networks and storm sewers in eastern Almaty (Zhumabekov, 2021) and the influence of the urban landscape on rainfall flood hazard (Myagkov et al., 2021).

Aryk networks differ from the pipe systems for which most tools were developed. They are open, often irregular channels that combine irrigation and stormwater functions, are prone to clogging by sediment and debris, and run down steep foothill gradients. In SWMM they can be represented as open conduits with irregular cross-sections, and in HEC-RAS as channels coupled with 2D overland flow; however, both require surveyed cross-sections, inverts and connections that are usually not digitized. A clogging factor, as used by Abedin and Stephen (2019) for inlets, may also be relevant for aryk inlets and culverts. At the same time, aryks offer an opportunity for GI: vegetated aryk corridors and adjacent tree strips could function as bioswales and infiltration trenches if their capacity and maintenance are ensured.

4.4 Limitations of this review

This review has several limitations. It is a narrative review with a PRISMA-informed selection procedure rather than a registered systematic review, and no meta-analysis was performed because of the heterogeneity of metrics and models. The corpus is small (33 sources) and includes five grey-literature sources (two theses or conference papers and three Russian-language reports), which were retained to represent under-studied regions but were not used for quantitative comparison. The numbers of records at the identification and screening stages were not recorded, which limits the reproducibility of the search. Some information in Appendix A could not be extracted because it was not reported in the original studies.

Finally, the search was limited to English, Russian and Kazakh sources, so studies in other languages (e.g., Chinese) may be under-represented.

5 Conclusion

This critical review synthesized GIS, SWMM, StormCAD, HEC-RAS, GI/LID/SUDS and machine learning approaches to urban flood management on the basis of 33 sources, 26 of which are primary case or modelling studies. GIS platforms play a central role in the spatial analysis of urban drainage, whereas SWMM, StormCAD and HEC-RAS have complementary functions in evaluating rainfall–runoff dynamics, pipe design and open-channel flood propagation. High-resolution DEM/LiDAR data substantially change the delineated drainage areas and therefore the model results.

Reported GI/LID effects are context-specific: depending on the metric, design storm, implementation area and calibration status, they range from about 11% to more than 70% and should not be generalized as a single percentage. Calibration against observed flood data was reported in only some of the primary studies, which limits the comparability of the results.

For Central Asian cities, and for the aryk-drainage system of Almaty in particular, the following practical steps are recommended: (1) digitize the aryk and storm-sewer network, including cross-sections, inverts, culverts and connections, using GNSS and UAV/LiDAR surveys; (2) derive design hyetographs from local extreme-rainfall statistics (Mukhanbet et al., 2026); (3) represent aryks as open channels in a coupled 1D/2D model and calibrate it with observed flooding locations, including crowdsourced reports; and (4) test GI options such as vegetated aryk corridors, bioswales and permeable pavements in priority sub-catchments, together with maintenance scenarios.

Future research should prioritize (i) observed flood-depth and extent datasets for calibrating models in Central Asian cities; (ii) comparative studies of the hydraulic, ecological and economic effectiveness of GI under local soil and climate conditions; (iii) the joint modelling of pluvial and groundwater flooding, as indicated for northern Almaty; and (iv) near-real-time monitoring systems that integrate GIS, SWMM/HEC-RAS, IoT sensors and machine learning.

Appendix A. Data extraction for the primary studies (n = 26)

Table A1. Data extraction for the primary studies included in the review

Study	Location	Tools / model	Main input data	Calibration / validation	Main quantitative result
Apel et al. (2004)	Rhine reaches downstream of Cologne, Germany	Stochastic flood-risk model of simplified process components in a two-layer Monte Carlo framework	Parameters derived from deterministic DFNK process models (rainfall to damage)	Not applicable (uncertainty analysis)	Epistemic uncertainty significantly altered risk estimates obtained from aleatory uncertainty alone
Greco & Larsen (2014)	Sacramento River flood-control system, USA	Channel-width and Manning's n scenarios	Channel geometry, design floods	Scenario analysis	Wider main channel allowed nearly four times higher roughness while keeping 100–200-year protection
Bouvier et al. (2018)	Ouagadougou, Burkina Faso (whole agglomeration)	GIS-based model: SCS runoff, lag-and-route, kinematic wave in streets and channels	10 m DTM, urban blocks, drainage axes, soils; 1,057 catchments	No validation reported	Flood mapping for the whole city with fast computation, suitable for decision support
Al Faisal et al. (2018)	Naogaon District, Bangladesh	Remote sensing + GIS (ERDAS Imagine)	Landsat TM/OLI images, 2004–2017	Not applicable	Flood-related land-use losses by year (built-up and agricultural land)

Table A1. (Continued)

Study	Location	Tools / model	Main input data	Calibration / validation	Main quantitative result
Porse (2018)	Los Angeles County, USA	GIS, open data, statistical analysis	Sewer locations, design parameters, sociodemographic data	Not applicable	Watersheds suitable for multi-benefit GI identified
Abedin & Stephen (2019)	UNLV campus, Las Vegas, USA	GIS workflow: delineation, runoff hydrographs, inundation mapping	DEM (best 5 m), rainfall, inlet clogging factor	News reports and photographs	24% error in flood depth (66 vs 86 cm) with clogging factor 0.83
Jahangiri (2019) [thesis]	Two GSI sites, USA	ArcHydro + LiDAR	LiDAR DEM (1–2 ft) and coarser DEMs	Agreement with design drainage areas reported	Drainage area increased several-fold with coarser DEMs (Figure 3)
Darabi et al. (2019)	Sari, Iran	GARP and QUEST machine learning + GIS; fuzzy ANP for vulnerability	113 flooded locations; 8 hazard and 5 vulnerability factors	AUC-ROC and kappa	GARP: AUC 93.5%, $\kappa = 0.86$; QUEST: AUC 89.2%, $\kappa = 0.79$
Abd-Elhamid et al. (2020)	Three zones near Dammam, Saudi Arabia (0.4–0.7 km ²)	StormCAD, Hyfran, GIS	Rainfall series, C = 0.2–1.0, return periods 5–100 years	Design scenarios; no calibration reported	Peak discharge $\times 3$ –7 (C 0.6) and $\times 4$ –9 (C 0.8); $\times 12$ in combined worst case; cost up to $\times 3.5$
Ertan & Celik (2021)	Kağıthane Stream, Istanbul, Turkey (1,653 ha)	1D HEC-RAS + ArcGIS + Rational Method	DEM, 1:1000 base maps, cross-sections, stormwater network	No calibration described	Flooded area $\sim 36.94\%$ (combined GI); $+86.89\%$ under full urbanization
Palaka et al. (2021)	Narsapur town, Telangana, India	SWMM + GIS	Road and drain network survey, elevations	Capacity check with Manning's equation	Redesigned drains to convey peak discharge without inundation
Zhumabekov (2021) [project report]	Eastern Almaty, Kazakhstan	Engineering design and environmental impact assessment of aryk and storm-sewer reconstruction	Project design documentation	Not applicable	Qualitative assessment of planned reconstruction and its environmental impacts
Myagkov et al. (2021) [report]	Uzbekistan	Analysis of urban landscape factors of rainfall flood hazard	Report not available online	Not applicable	Qualitative assessment of the influence of urban landscape on rainfall flood hazard
Vahida & Sahoo (2022) [conference paper]	Saheed Nagar, Bhubaneswar, India (1.47 km ²)	SWMM	Rainfall, sub-catchments, drainage network	None reported	Peak runoff and flow volume at outfalls estimated
Liu et al. (2022)	Handan, China	SWMM + ArcGIS; control-variable scenarios	1 m imagery, drainage database, DEM, 1987–2017	11 flooding points from social media (July 2016)	Flood volume $7.89 \times 10^4 \rightarrow 3.85 \times 10^5$ m ³ with imperviousness $32.44 \rightarrow 76.57\%$; network expansion -27.56%
Ali & Mawlood (2023)	Erbil, Iraq (23 sub-catchments)	SWMM (dynamic wave, Horton infiltration)	Daily maximum rainfall 1992–2022 converted to hourly (IMD method)	None reported	10–14 flooded nodes per event; network capacity insufficient
Ahmad et al. (2024)	Lahore, Pakistan (2.71 km ²)	GIS-SWMM with LPT-III and alternating block design hyetographs	Rainfall frequency analysis, drainage network	Design-storm scenarios	2-year storm: about 60% of the area inundated
Al Amin et al. (2024)	Bendung watershed, Palembang, Indonesia (18.37 km ²)	PCSWMM 2D + five LID types (9.81% of area)	Observed December 2021 flood, design storms 2–25 years	NSE = 0.948; r = 0.987	Runoff volume ~ 21.0 to -35.4% ; peak ~ 11.3 to -37.7%

Table A1. (Continued)

Study	Location	Tools / model	Main input data	Calibration / validation	Main quantitative result
Patel et al. (2024)	MANIT campus, Bhopal, India	SWMM + ArcGIS	Campus drainage network, rainfall	Not specified	Runoff at outfall nodes analyzed; planning interventions proposed
Sehrawat & Shekhar (2025)	Gurugram, India (eight sub-catchments)	SWMM + GIS; green roofs, permeable pavements, rain barrels	Sentinel-2, ALOS PALSAR DEM, soil data, GPM IMERG 2000–2023	NSE/RMSE vs Rational Method	Combined LID up to –72.31% volume and –54.05% peak
Dieme et al. (2025)	Dakar periphery, Senegal (about 400 km ²)	GIS-based hydrological model + 1D network routing (25 m ² cells)	5 m DTM, building footprints, 297 channel sections, 106 basins, IDF curves	Not validated (no data available)	10-year storm: overflows of 1–18 m ³ /s at several sections
Mirlas et al. (2025)	Akbulak micro-district, northern Almaty, Kazakhstan	Visual MODFLOW groundwater flow model	Field survey of the water table (0.25–1.2 m below ground over 0.07 km ²)	Scenario simulation consistent with field observations	Runoff accumulation up to eight times the annual average precipitation; clogged Karasu-type stream concentrated runoff
Ceresa et al. (2025)	Five Central Asian countries	TOPKAPI-X (1 km) + CA2D (about 90 m) + CAPRA	ERA5-Land 1981–2020, exposure and vulnerability data	Discharge observations, satellite flood extent, historical losses	Highest relative average annual loss in Kazakhstan and Tajikistan (> 6%)
Ahmed et al. (2026)	Udon Thani, Thailand	1D–2D SWMM; one-factor-at-a-time sensitivity analysis	Design storm (5-year, 1-h), catchment data	Iterative calibration to design-storm performance	Curve number and imperviousness most influential
Mukhanbet et al. (2026)	Almaty, Kazakhstan (five stations)	Extreme value analysis (GEV, lognormal, gamma)	Annual maximum precipitation 2000–2023	Goodness-of-fit testing	GEV best fit; design rainfall for 10-, 50- and 100-year return periods
Linh et al. (2026)	Jalal-Abad, Osh and Tokmok, Kyrgyzstan	Random forest, XGBoost, AdaBoost + SHAP	Sentinel-1 flood inventory; flood-contributing factors	AUC-ROC, kappa and other metrics	Success and prediction rates > 84%; very high susceptibility class 8.44%, 12.01% and 37.8% of area

Note: [thesis], [conference paper], [report] – grey literature. NSE – Nash–Sutcliffe efficiency. Source: compiled by the authors.

Author contributions statement:

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Yerkin Kakimzhanov	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
Naci Yastikli	✓		✓		✓		✓		✓		✓			
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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

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