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Collaborative spatial decision making empowering urban flood governance toward city resilience

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Urban flood management increasingly relies on adaptive and integrated systems alongside conventional structural measures. Rapid urbanization has escalated the complexity of managing floods. This paper proposes a novel, integrated spatial decision-making approach to enhance flood governance. The study emphasizes the collaborative engagement of stakeholders, including municipal authorities, water agencies, and local communities, within a GIS-based multi-criteria decision analysis (MCDA) framework. A toolbox developed in ArcGIS incorporates the analytic hierarchy process (AHP). While previous studies often treat spatial analysis and stakeholder participation separately, our model integrates these within a spatial planning support system (SPSS). Results from a case study in Tehran, Iran, demonstrate the model's practical effectiveness in supporting urban flood governance. A final flood hazard map classified the study area into six distinct risk levels: approximately 6% of the area fell into the very-high-risk category, mainly in low-slope, high-density zones with limited drainage capacity, whereas 43% represented moderate-to-high risk and 42% low risk. Least cost path (LCP) analysis, informed by land use, slope, and geology criteria, was applied to delineate optimal urban runoff collection routes, minimizing construction costs by leveraging existing channels and natural gradients. Overall, the proposed model advances data-driven and participatory flood governance by providing a transparent, reproducible, and governance-oriented framework that supports resilient infrastructure planning and policy decision-making in complex urban environments.

Keywords Flood governance, Collaborative planning, GIS, Multi-criteria decision analysis, Urban resilience

Urban flooding has become an escalating global concern, threatening human safety, critical infrastructure, and economic stability. Rapid urbanization, unplanned land development, and climate variability have amplified flood risk, particularly in dense metropolitan areas where governance fragmentation often undermines effective response. Addressing such challenges requires a shift from purely technical approaches toward integrative, adaptive, and collaborative governance systems. In this context, collaborative spatial decision-making (CSDM) has emerged as a promising paradigm, linking geographic information systems (GIS), participatory planning, and real-time spatial analytics.

Despite significant advances in flood risk modeling, existing frameworks often remain technocratic and poorly connected to governance dynamics and stakeholder perspectives. Studies reveal that data analytics and spatial modeling have been widely used to map hazard exposure, yet institutional coordination, community participation, and integrative governance remain underexplored dimensions of urban flood management[1,2]. Accordingly, there is a growing recognition that effective flood governance must incorporate not only hydrological and spatial data but also collaborative mechanisms enabling public agencies, planners, and communities to co-design resilient urban systems. Recent literature underscores four interconnected domains shaping contemporary flood governance:

Policy and institutional frameworks

Floods have caused severe impacts on infrastructure, economies, and communities, intensified by deforestation and urban expansion. Consequently, flood risk management has evolved toward integrated and risk-based approaches emphasizing coordinated engineering, land-use planning, public awareness, and stakeholder collaboration[3].

Comparative analyses across the Netherlands, Germany, the UK, and Australia show diverse multi-level governance models, from centralized to decentralized systems for flood risk reduction[4]. In the UK, the 2016 flood-reinsurance scheme promotes affordable coverage while transitioning toward risk-based pricing, highlighting the need for broader stakeholder engagement under climate stress[5].

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Evaluations of national and regional policies underscore the importance of clear guidance and adaptive planning tools enabling risk-based management[6]. Studies in Scotland and Austria reveal governance gaps, including coordination challenges and disconnects between theory and implementation, which require transformative governance frameworks[7,8]. In Ghana, proactive institutional measures such as training, spatial planning, and early-warning systems strengthen local resilience[9].

Japan's experience demonstrates the necessity of integrating local knowledge within governance systems otherwise hindered by insufficient institutional cohesion[10]. Similarly, research on urban areas identifies inadequate infrastructure and governance weakness as major barriers to flood resilience[11]. Analytical approaches such as serious games also highlight evolving local decision archetypes under uncertainty[12].

From Kenya to Germany and Ghana, recent cases show that community participation remains critical though often constrained by limited resources and coordination[13–15]. Participatory co-adaptation methods, including dotmocracy and stakeholder roundtables in Malaysia, offer promising tools for inclusive flood governance[16]. Studies in the Vietnamese Mekong Delta and post-disaster China further demonstrate how adaptive and power-responsive governance systems shape long-term environmental and institutional transformation[17,18].

Stakeholder involvement and risk co-management

A growing body of research emphasizes social learning, trust-building, and inclusive governance across heterogeneous institutional contexts[19–21].

The hydro-social contract (HSC) framework has been applied to explore how societal dynamics shape flood risk management in the Isere river basin, France[22]. Studies across diverse contexts consistently emphasize that stakeholder engagement and cross-sector collaboration enhance governance effectiveness. In Ghana's Wa West district, effective governance is achieved through training, participatory mechanisms, and local capacity building[23].

In the Netherlands, pilot projects in multilevel flood safety fostered collaboration and trust among fragmented authorities, identifying key enablers and barriers[24]. Similarly, Finland's watershed vision studies developed an evaluation tool to strengthen collaborative governance under uncertainty[19]. Evidence from Germany's 2021 floods exposed coordination gaps and infrastructure interdependencies that constrained effective disaster response[25]. Participatory mapping in Lusaka, Zambia, demonstrated that narrative-based flood maps can merge local knowledge with scientific data to improve resilience planning[26].

Urban and regional studies further reveal institutional and behavioral challenges. In China, the Sponge city program exposed multilevel governance barriers and the need for stronger community participation[27]. In eastern Pennsylvania (USA), a meta-analysis identified weak governance structures, policy misalignment, and insufficient public education as barriers to implementing stormwater green infrastructure[28]. Integrating surface-water drainage design within urban planning was found essential for improving collective response capacity and managing flood-related risks[29]. Finally, flood insurance serves as a vital risk-transfer mechanism, supported by a proposed municipal-level data platform enabling public–private collaboration for managing high-risk properties[30].

Multi-criteria decision-making (MCDM) methodologies

MCDM techniques offer a structured means of evaluating physical, environmental, and socio-economic factors affecting flood vulnerability[31,32]. They provide a quantitative foundation for comparing diverse spatial parameters under complex uncertainty conditions.

Tools and technology integration

Advances in GIS-based modeling, hydrological simulations, and decision-support systems have enabled transparent, data-driven planning processes[33–35]. Integrating these technologies promotes accountability and facilitates evidence-based policy formulation.

Nevertheless, despite these achievements, a critical research gap persists in linking spatially explicit analytical models to collaborative governance processes that recognize institutional complexity and stakeholder diversity, particularly within developing urban contexts.

To address this gap, the present study introduces a collaborative spatial decision-making model (CSDM) that integrates the analytic hierarchy process (AHP), artificial neural networks (ANN), and least-cost path (LCP) analysis within a participatory and governance-oriented framework. In this model, stakeholder integration is operationalized through two complementary phases:

1. the AHP elicitation phase, where stakeholders, including municipal engineers, planners, community representatives, and academics, participated in pairwise weighting of criteria; and
2. a validation workshop aimed at refining the interpretive outputs and aligning technical results with policy and community priorities.

This dual mechanism ensures that the model remains both scientifically robust and socially grounded, transforming stakeholder insight into measurable spatial decisions and actionable governance tools. Such methodological synthesis remains rare in developing settings and directly responds to recent calls for co-produced, actionable frameworks for flood governance[4,36].

To demonstrate the applicability of the proposed approach, the research focuses on Tehran City, an illustrative case characterized by complex topography, rapid urban growth, and recurrent flood incidents. The city's multi-agency governance structure, marked by overlapping institutional responsibilities, offers a relevant testing ground for assessing the coordination potential of a collaborative, data-driven framework.

Accordingly, this study pursues the following objectives:

1. To develop an integrated spatial multi-criteria decision-making (SMCDM) framework for assessing urban flood vulnerability by systematically incorporating physical, environmental, and infrastructural parameters.
2. To validate the model using neural-network analysis, thereby enhancing the reliability and robustness of vulnerability assessments.
3. To operationalize the framework through a custom GIS-based toolbox, enabling planners and policymakers to perform transparent and replicable flood analyses.
4. To optimize runoff collection routes using least-cost path (LCP) analysis, providing actionable spatial insights for infrastructure planning and resource allocation.

Collectively, these contributions advance the field of urban flood governance by offering a replicable, collaboratively developed, and technically validated methodology that bridges analytical modeling with participatory decision-making, thereby strengthening the link between science, policy, and practice.

Method

Case study

Tehran, the capital of Iran, was selected as the urban case study (Fig. 1). Geographically, the city is bounded by the Alborz mountain foothills to the north, the Varamin plain and Kahrizak highlands to the south, the Sorkheh-Hesar basin to the east, and the Kan river basin to the west. The hydrological system of the Tehran basin comprises three major drainage subsystems:

1. Rivers and streams flowing southeast,
2. Rivers flowing southwest, and
3. A network of artificial and natural channels within the central and southern zones.

The third subsystem collects surface runoff, rainfall, and municipal or industrial wastewater, while the Jajroud river (northeast) and Karaj river (northwest) converge with these urban flow systems across the agricultural lands of southern Tehran.

Building on the geographic and hydrological characteristics introduced above, the next section presents the methodological framework developed to model and analyze urban flood governance in Tehran. By linking the spatial context to the modeling design, this transition ensures continuity between the case-specific conditions and the applied analytical procedures. It also situates the proposed models (AHP, ANN, and LCP) within the broader governance-based decision-making framework.

Methodological framework

The methodological framework integrates spatial multi-criteria analysis within a GIS-supported decision environment (Fig. 2). It follows a three-stage sequence:

1. Spatial Multi-Criteria Decision-Making (SMCDM): generation of a flood-hazard map.
2. Artificial Neural Network (ANN) validation: assessment of model accuracy.
3. Least-Cost Path (LCP) analysis: identification of optimal storm-water collection routes.

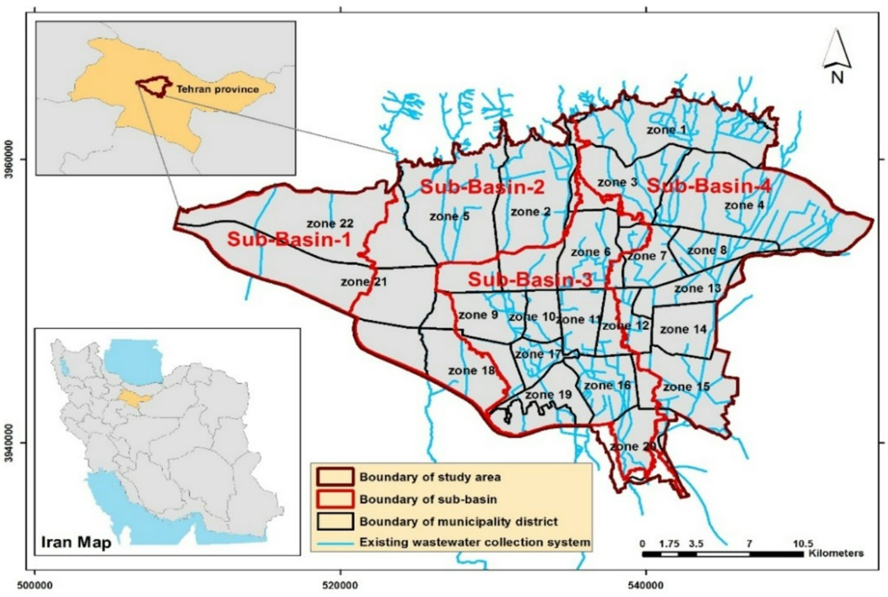

Fig. 1. Geographic location of the study area (Tehran city in Tehran province, Iran). (Figure created in ArcGIS 10.8 ESRI, http://www.esri. com).

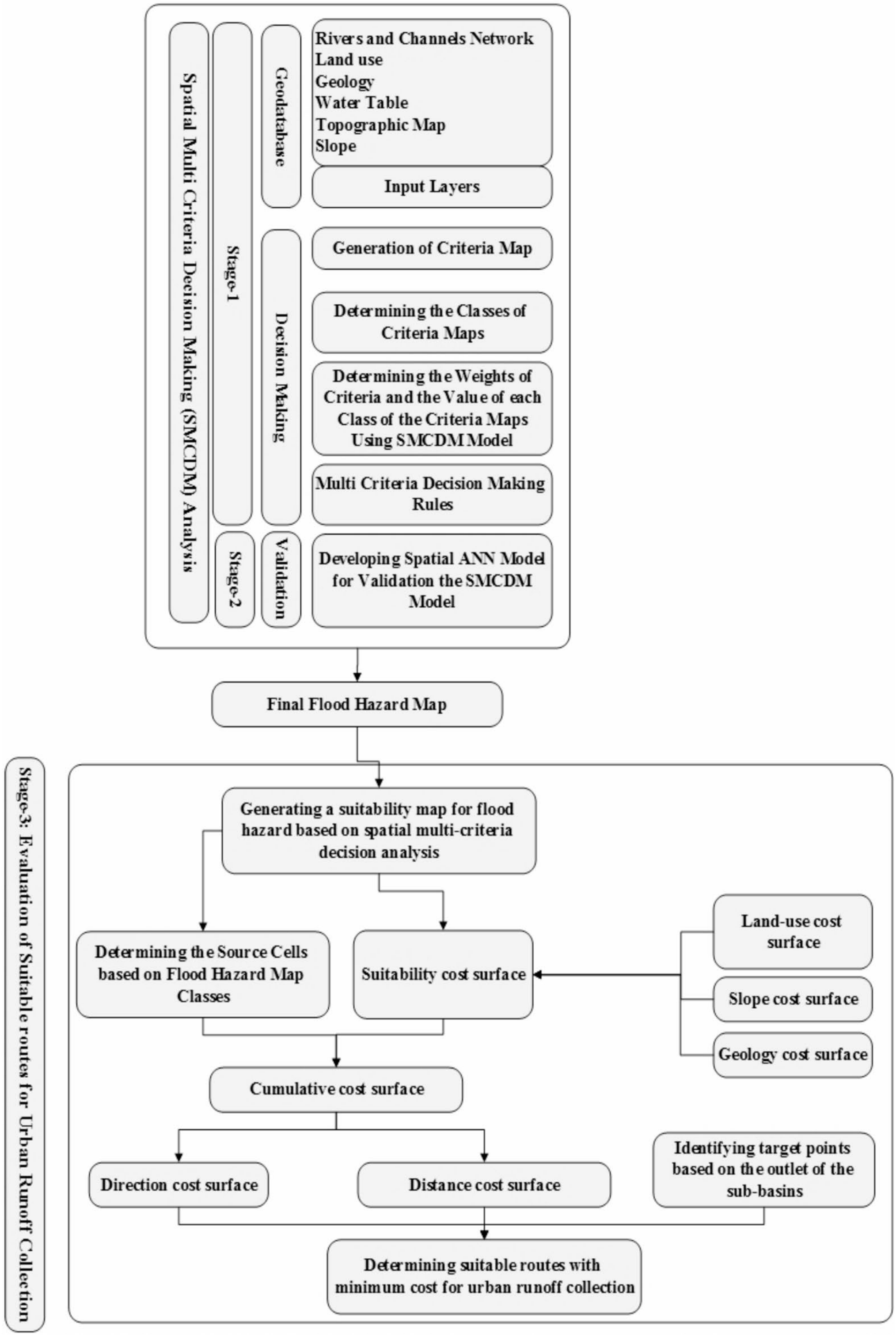

Fig. 2. The process of the research.

The effective implementation of integrated flood management policies is rare, resulting in a gap between policy development and practical execution[37]. This work aims to help bridge that gap. The process is implemented through a custom GIS toolbox, enabling integrated analysis of spatial indicators such as land use, slope, and drainage density. The ANN ensures model accuracy and minimizes bias, while the LCP defines optimal drainage corridors based on terrain and infrastructure conditions. A built-in decision-support system (DSS) provides a user-friendly interface linking technical modeling with policy practice, supporting data input, parameter setup, and visualization. This integrated workflow bridges the persistent gap between flood-management planning and implementation.

Collaborative framework and stakeholder engagement

To ensure transparency and legitimacy, a structured collaborative governance framework was established for active stakeholder engagement in spatial decision-making. Key stakeholders were purposefully identified through a stakeholder mapping exercise based on their roles, responsibilities, and expertise in flood risk and urban water management. These included municipal urban planners, officials from water and wastewater management authorities, environmental protection agencies and academic researchers with specialization in hydrology, GIS, and spatial planning.

Engagement occurred in two participatory phases: first, semi-structured discussions defined the flood-risk context and jointly selected spatial indicators and assessment criteria; second, participants performed AHP pairwise comparisons to quantify the relative importance of each criterion, with facilitators guiding consensus to ensure balanced weighting.

A custom GIS-based decision-support toolbox enabled real-time scenario testing, visualization of hazard maps, and integration of expert knowledge, supporting transparency and reproducibility. Embedding stakeholder input into criteria selection and weighting enhanced shared ownership, institutional trust, and policy applicability. Overall, the collaborative process bridged technical modeling with practical urban governance, exemplifying the co-production of knowledge in flood-risk management.

Spatial multi-criteria analysis and flood-hazard mapping

Flood hazards were assessed by analyzing variables governing surface run-off beyond drainage capacity. The workflow comprised five streamlined steps:

1. Data collection and preprocessing.
2. Selection and standardization of evaluation criteria in GIS.
3. Weight derivation via the AHP.
4. Weighted linear combination (WLC) of spatial layers.
5. Generation of the final hazard-intensity map.

The selection of evaluation criteria followed a structured, multi-stage procedure to ensure both scientific validity and contextual relevance. First, a comprehensive literature screening was performed to identify commonly used parameters in flood hazard assessment, referencing seminal works[31,36] and recent governance-oriented studies.

Subsequently, a group of senior experts specializing in urban hydrology, watershed management, and GIS applications were consulted to verify the technical and practical adequacy of the proposed variables. Their input guided the refinement of preliminary indicators related to vulnerability, hydraulic performance, and environmental sensitivity. Finally, the proposed list was reviewed during a stakeholder workshop involving municipal and academic participants, where consensus was reached on criteria based on data reliability, policy relevance, and local applicability.

<u>Evaluation criteria</u> Flood-hazard assessment was based on three main categories of criteria: vulnerability, hydraulic, and environmental.

- *Vulnerability criteria*: urban land use, distance from channels, and drainage-network density.
- *Hydraulic criteria*: elevation and slope.
- *Environmental criteria*: geology and groundwater level.

In a study on forest conservation planning, water and soil conservation were considered as key criteria, with flood management as a sub-criterion, including factors such as slope, annual rainfall, soil depth, geology, and topography[38].

All spatial layers were converted to raster format and classified into hazard levels, where lower class numbers indicate higher flood potential. Urban land use was divided into five classes (streets to open spaces), distance-from-channels into seven, drainage-density into six, slope and elevation each into nine, geology into five, and groundwater level into six classes.

The criteria were selected based on literature review and available data, focusing primarily on vulnerability to flooding. Geological structures of the study area (A, Bn, Bs, C, D) were further categorized by formation permeability, reflecting their influence on flood susceptibility.

<u>Analytic hierarchy process (AHP)</u> The Analytic Hierarchy Process (AHP) is a widely applied multi-criteria decision-making method[39]. In this study, twelve stakeholders participated in the weighting process, including four municipal engineers, three policy planners, three academics, and two NGO representatives, who were selected through a purposive sampling approach. Their roles involved providing pairwise comparisons and validating the weighted layers to ensure both technical accuracy and governance relevance. This method is based on pairwise comparisons, allowing managers and decision makers to evaluate different scenarios.

The AHP procedure comprises three main steps:

1. Constructing the hierarchical structure of the problem.
2. Forming pairwise comparison matrices and calculating criteria weights, and
3. Performing a consistency check.

Preferences (Verbal judgment)	Numerical value
Completely preferred, significantly more important, or highly desirable	9
Very strong preference, importance, or desirability	7
Strong preference, importance, or desirability	5
Slightly preferred, somewhat more important, or slightly more desirable	3
Equal preference, importance, or desirability	1
Intermediate preferences between the above values	8, 6, 4, 2

Table 1. Numerical values of preferences in pairwise comparisons.

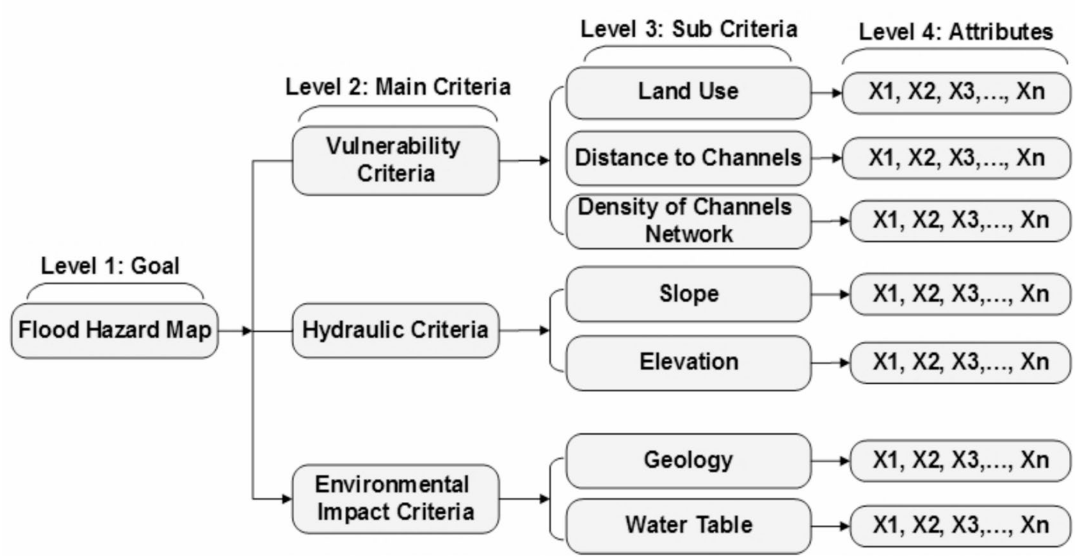

Fig. 3. Hierarchical structure of urban flood management.

Preference values used in pairwise comparisons follow Saaty's scale (Table 1[39]. The hierarchical framework for urban flood management is presented in Fig. 3, where the first level represents the overall goal, the second level the main criteria, the third level the sub-criteria, and the fourth level the corresponding classes for each sub-criterion.

Toolbox development and GIS integration A custom GIS toolbox was created in ESRI ArcMap to automate the spatial decision-making process (Fig. 4). It includes three main modules:

1. Data preprocessing (vector-to-raster conversion and alignment),
2. Criteria weighting (importing AHP-derived weights), and
3. Map overlay and hazard classification using the weighted linear combination (WLC) method.

The toolbox operates as a GIS extension executing the AHP process, where input layers are converted to raster format, criteria weights are calculated via pairwise comparisons, and the final flood-hazard map is produced through WLC integration. With its user-friendly and replicable design, the toolbox supports participatory decision-making and can be applied to other urban flood management contexts.

Model evaluation via artificial neural networks (ANN)

Because recorded flood-event maps were unavailable, an ANN-based spatial validation was employed to test the internal coherence of the SMCDM results. Rasterized inputs representing decision criteria served as training data for the ANN model developed within the GIS environment.

The network was trained to predict hazard classes based on the weighted criteria maps. Convergence between ANN predictions and the SMCDM-derived hazard categories verified model stability and minimized classification bias. Dimensional reduction was achieved using cluster analysis (nearest-neighbor method) to prevent overfitting and accelerate computation within the large spatial matrix (1125 × 962 cells). This hybrid integration of spatial multi-criteria decision-making and artificial neural network validation strengthened confidence in the spatial-governance model by combining expert-driven weighting with data-driven learning.

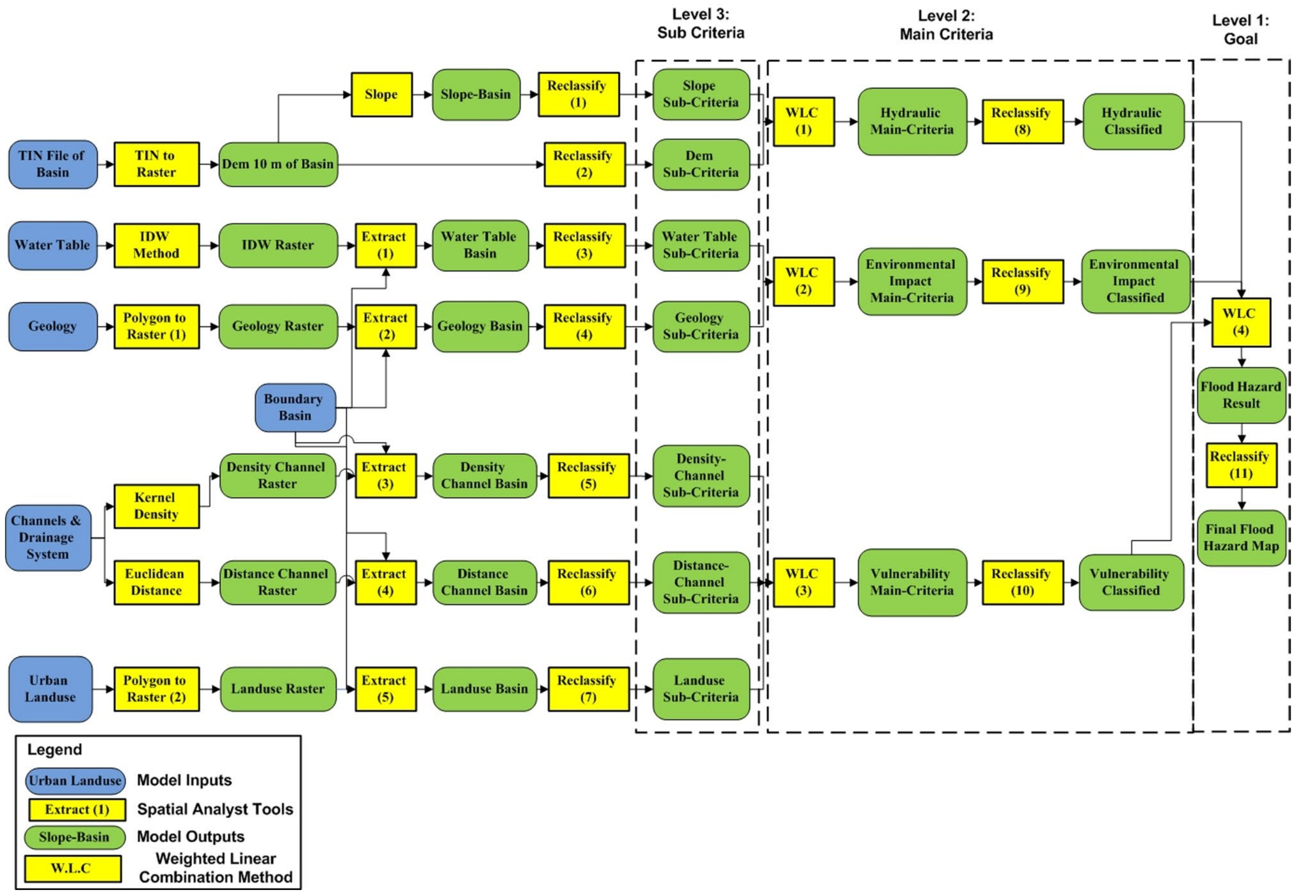

Fig. 4. The process of spatial modeling in the toolbox developed within the GIS environment.

Identifying optimal urban runoff routes

Following validation, flood-prone cells were delineated as runoff source points for simulation of collection pathways. Using least-cost path (LCP) analysis, the model identified routes minimizing cumulative cost in both distance and time between source and outlet cells.

Four computational steps were implemented:

1. Define source and target cells;
2. Generate and weight the suitability (cost) surfaces;
3. Compute cumulative-cost rasters;
4. Extract least-cost polylines as optimal routing paths.

The LCP algorithm integrates weighted maps for land use, slope, and geology, offering realistic pathways for storm-water conveyance compatible with existing infrastructure. The outputs directly inform municipal decision-making by prioritizing feasible drainage corridors within a GIS-based DSS platform.

Results

This section presents the outcomes of the flood hazard mapping, model validation, and least-cost path analysis conducted for urban runoff planning.

Criteria weighting and model validation

The analytical hierarchy process (AHP) was employed to derive the relative weights of the flood-related criteria after structuring the hierarchical framework of the study. Based on Saaty's pairwise comparison scale (Table 1), the comparison matrices were calculated, and their inconsistency ratios (IR) were verified to be below the acceptable threshold ($IR < 0.1$). Thus, the derived weights were considered valid for subsequent spatial modeling.

To operationalize this process, a customized GIS-based decision-support toolbox was developed within ArcGIS 10.8 (ESRI), integrating data preprocessing, AHP weight computation, and weighted linear combination (WLC) for flood hazard assessment. The relevant datasets (Table 2) were prepared in raster format (30 m cell size) and standardized to ensure comparability across thematic layers. Three main criteria, namely Vulnerability (V), Hydraulic (H), and Environmental Impacts (EI), and their respective sub-criteria were mapped and weighted according to Table 3.

No.	Type of data	Source	Data format
1	Topographic map	Ministry of Energy - Iran's Water Resources Management Company	.dwg
2	Land use map	Ministry of Energy - Iran's Water Resources Management Company	.dwg
3	Geological map	Ministry of Energy - Iran's Water Resources Management Company	.dwg
4	Groundwater table levels from observational wells	Ministry of Energy - Iran's Water Resources Management Company	.xls

Table 2. Data used in the research. * It should be noted that the data received in .dwg format were digitized and converted into shapefile format to generate the required spatial layers.

The final criteria weights (Table 3) indicate that Vulnerability (0.635) has the greatest influence, followed by Hydraulic (0.287) and Environmental Impacts (0.078). Among sub-criteria, urban land use and distance from drains yielded the highest relative impacts. The suitability index for each cell was computed using Eq. (1), integrating weighted raster values under all criteria. The composite hazard maps were produced through the weighted integration of sub-criteria according to Eqs. (2)–(4), and finally combined into the overall hazard index (Eq. 5).

The final hazard index (Eq. 5) integrates all weighted factors from vulnerable, hydraulic, and environmental components. The spatial distribution of the resulting flood hazard zones is shown in Fig. 5, where lower numeric classes correspond to higher flood potential. Approximately 6% of the region falls in the very-high-hazard class (Class 1), 43% in medium-to-high classes (2–3), 42% in moderate class (4), and about 9% in low-hazard classes (5–6). The southeastern lowlands (slope < 2%) appear as the most flood-prone zones due to defective stormwater drainage, whereas western sectors exhibit minimal risk.

$$F_i = \sum_{j=1}^{n} W_j \ X_{ij} \tag{1}$$

F_i:
The index related to the flood hazard of area i
W_j:
The relative weight of criterion j ($\sum W_j = 1$)
X_{ij}:
The standardized values of area i under criterion j, and n represents the total number of criteria.

$$Vulnerability\_Map = Map\_Landuse \times 0.571 + Map\_Distance\_Channel \times 0.286 + Map\_Density\_Channel \times 0.143 \tag{2}$$

$$Hydraulic\_Map = Map\_Dem \times 0.5 + Map\_Slope \times 0.5 \tag{3}$$

$$Environmental\_Impact\_Map = Map\_Geology \times 0.643 + Map\_Water\_Table \times 0.357 \tag{4}$$

$$\begin{aligned} F = & \left[V \times \left(\sum_i (W_{V1} \times W_{Vi1}) + \sum_i (W_{V2} \times W_{Vi2}) + \sum_i (W_{V3} \times W_{Vi3}) \right) \right] \\ & + \left[H \times \left(\sum_i (W_{H1} \times W_{Hi1}) + \sum_i (W_{H2} \times W_{Hi2}) \right) \right] \\ & + \left[EI \times \left(\sum_i (W_{EI1} \times W_{EIi1}) + \sum_i (W_{EI2} \times W_{EIi2}) \right) \right] \end{aligned} \tag{5}$$

In Eq. (5), F represents the index associated with the output map (flood hazard). Additionally, V is the main vulnerability criterion, and W_{V1}, W_{V2} and W_{V3} denote the weights related to the sub-criteria of land use, distance from channels and drains, and channel network density, respectively. Similarly W_{Vi1}, W_{Vi2} and W_{Vi3} represent the weights related to the classes of each sub-criterion of vulnerability. The H index represents the main hydraulic criterion, W_{H1} and W_{H2} as the weights related to the sub-criteria of elevation and slope, W_{Hi1} and W_{Hi2}, as the weights related to the classes of each hydraulic sub-criterion. The EI index represents the main environmental impact criterion, W_{EI1} and W_{EI2} as the weights related to the sub-criteria of geology and groundwater level, W_{EIi1} and W_{EIi2}, as the weights related to the classes of each environmental impact sub-criterion.

To verify the robustness of the SMCDM output, an artificial neural network (ANN) model was developed for validation. The ANN architecture consisted of 7 input neurons (criteria layers), two hidden layers with 4 neurons each, and one output neuron representing the final hazard index (Fig. 6). The dataset matrix (962 × 1125 cells) was clustered (126 × 150) to ensure computational efficiency and sufficient sample size exceeding the minimum constraint (30 × Ni × (Ni + 1), where Ni represents the number of input variables[40].

After training the network using the hazard map from AHP-WLC as target data, testing was conducted by modifying the vulnerability weights and generating predictive hazard maps. Conversion to ASCII raster format enabled spatial comparison between the AHP-based and ANN-predicted flood hazard layers (Figs. 7 and 8).

Main criteria	Weight	IR	Sub-criteria	Weight	IR	Sub-criteria classes	Weight	IR	Final weight
Vulnerability	0.635	0.09	Urban land use	0.571	0.001	Street	0.439	0.04	0.159
						Commercial-Business	0.289		0.105
						Industrial	0.149		0.054
						Residential	0.074		0.027
						Open Space	0.049		0.018
			Distance from channels and drains	0.286		0–100	0.353	0.03	0.064
						100–200	0.239		0.043
						200–300	0.158		0.029
						300–400	0.104		0.019
						400–500	0.067		0.012
						500–1000	0.049		0.009
						> 1000	0.03		0.005
			Drain network density	0.143		0–0.64	0.428	0.07	0.039
						0.64–1.3	0.255		0.023
						1.3–1.93	0.15		0.014
						1.93–2.57	0.088		0.008
						2.57–3.22	0.047		0.004
						3.22–3.86	0.033		0.003
Hydraulic	0.287		Elevation	0.5	0	> 1100	0.273	0.01	0.039
						1100–1200	0.203		0.029
						1200–1300	0.152		0.022
						1300–1400	0.112		0.016
						1400–1500	0.082		0.012
						1500–1600	0.059		0.008
						1600–1700	0.076		0.011
						1700–1800	0.043		0.006
						< 1800	0.033		0.005
			Slope	0.5		< 2%	0.312	0.03	0.045
						2–5%	0.222		0.032
						5–8%	0.155		0.022
						8–10%	0.108		0.015
						10–12%	0.074		0.011
						12–15%	0.051		0.007
						15–20%	0.035		0.005
						20–30%	0.025		0.004
						> 30%	0.018		0.003
Environmental impacts	0.078		Geology	0.643	0	A	0.473	0.06	0.024
						Bs, R	0.263		0.013
						D1	0.144		0.007
						D2	0.072		0.004
						Bn, C	0.048		0.002
			Groundwater table	0.357		< 12	0.434	0.26	0.012
						12–15	0.281		0.008
						15–20	0.151		0.004
						20–25	0.063		0.002
						25–30	0.042		0.001
						> 30	0.03		0.001

Table 3. Suitability classes of criteria, sub-criteria, and their respective weights for urban flood management.

Validation metrics (Table 4) demonstrate a high level of concordance between observed (SMCDM) and predicted (ANN) results: correlation coefficients of 0.87, 0.82, and 0.76, and low RMSE values of 0.190–0.276 across training, validation, and testing stages, confirming the high predictive reliability of the hybrid model.

Flood hazard mapping and LCP optimization

Following flood hazard mapping and ANN validation, least-cost path (LCP) analysis was conducted to identify the most cost-efficient routes for urban runoff collection. For this purpose, a cost surface layer was generated to

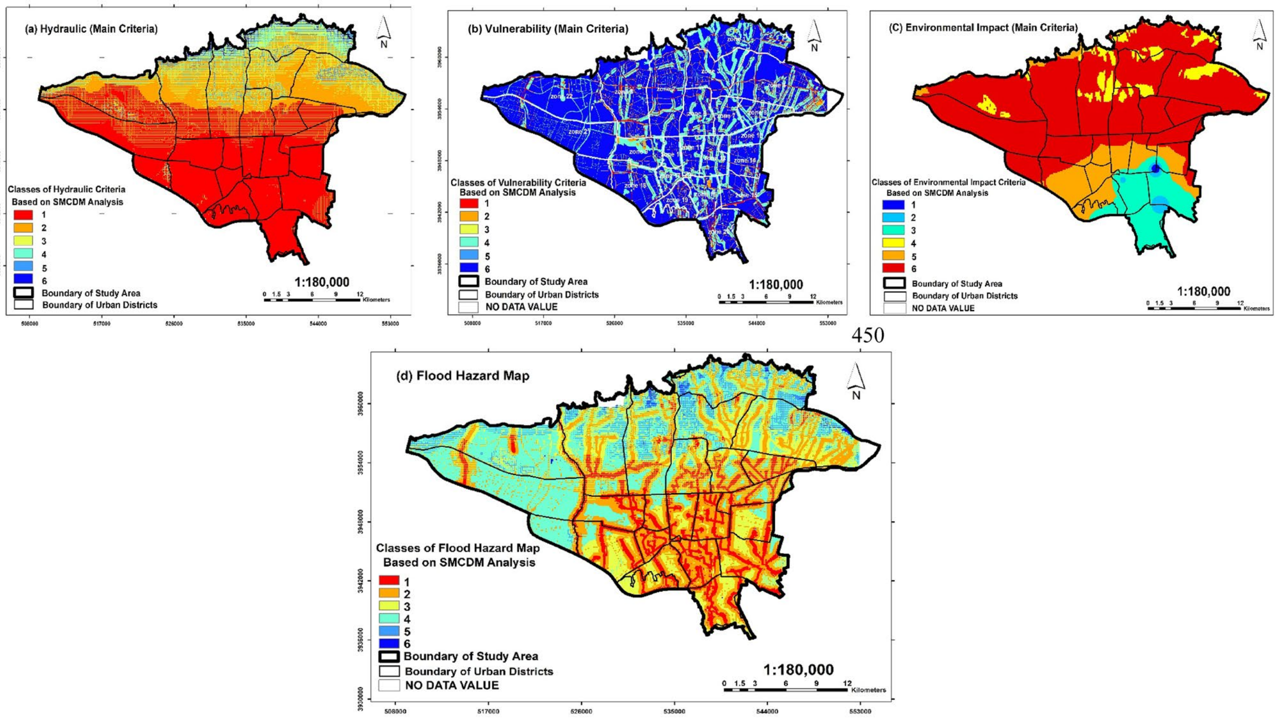

Fig. 5. Flood hazard mapping results for the study area. (**a**) Hydraulic component; (**b**) Vulnerability component; (**c**) Environmental-impact component; (**d**) Final integrated flood hazard map (Figures created in ArcGIS 10.8 ESRI, http://www.esri. com).

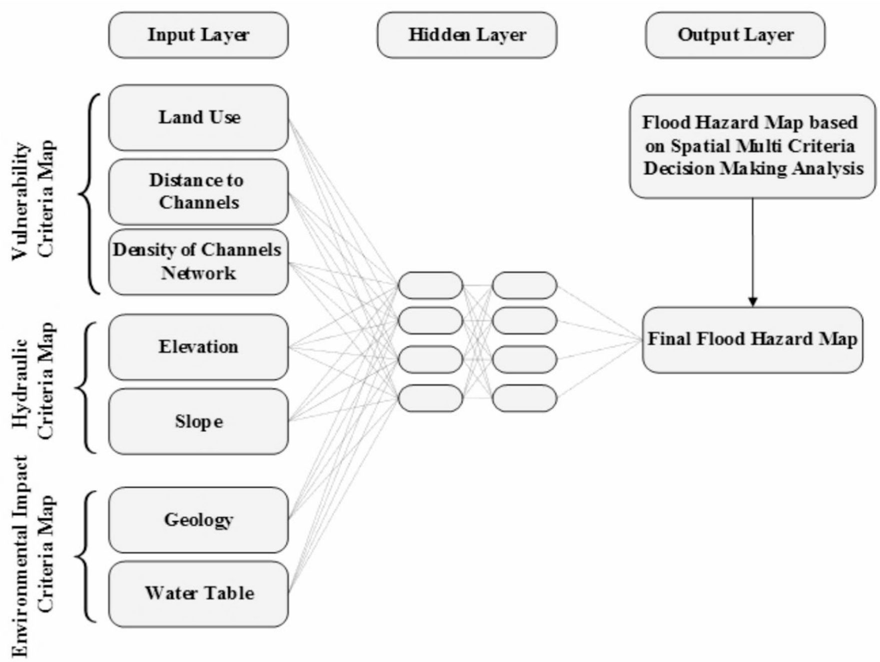

Fig. 6. Neural network structure of the research.

quantify the cumulative movement cost through each cell within the study area. The cost values of all decision-making criteria were normalized on a scale of 1–10, where 1 indicates the lowest cost (highest suitability) and 10 the highest cost (lowest suitability). Optimal drainage paths correspond to the least-cost routes calculated over this composite surface.

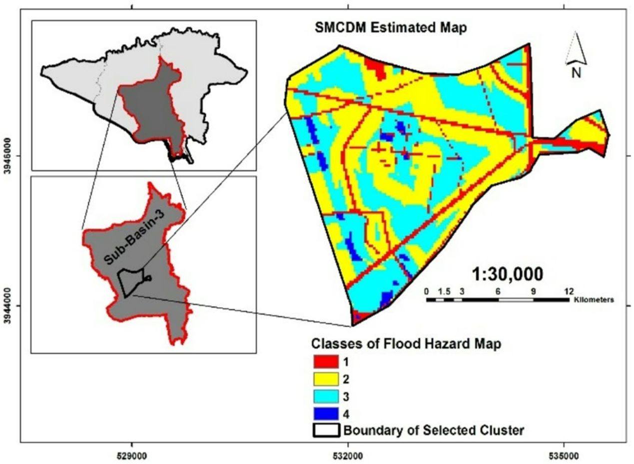

Fig. 7. Generated flood hazard map by the spatial multi-criteria decision-making model for the selected cluster (Figure created in ArcGIS 10.8 ESRI, http://www.esri. com).

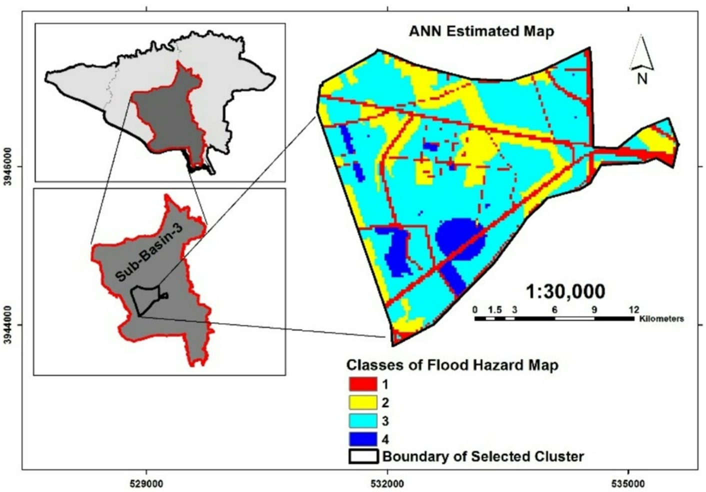

Fig. 8. Estimated map of the neural network model for the selected cluster (Figure created in ArcGIS 10.8 ESRI, http://www.esri. com).

Efficiency indices	CORR	RMSE	VE (%)
Training	0.87	0.190	0.38
Validation	0.82	0.231	0.33
Testing	0.76	0.276	0.32

Table 4. Efficiency indices values for different stages of training, validation, and testing.

Cost surface development
Three cost-based criteria were selected: urban land use, slope, and geology, each influencing the construction and operational costs of the proposed runoff collection system (see Supplementary Tables S1–S3 for full classification).

Identification of source cells
Source cells, representing the starting points of the drainage network, were determined using the flood hazard map generated previously. Two categories of source cells were defined:

(1) Cells within Class 1 (very high hazard) zones, and
(2) Cells within Class 2 (high hazard) zones.

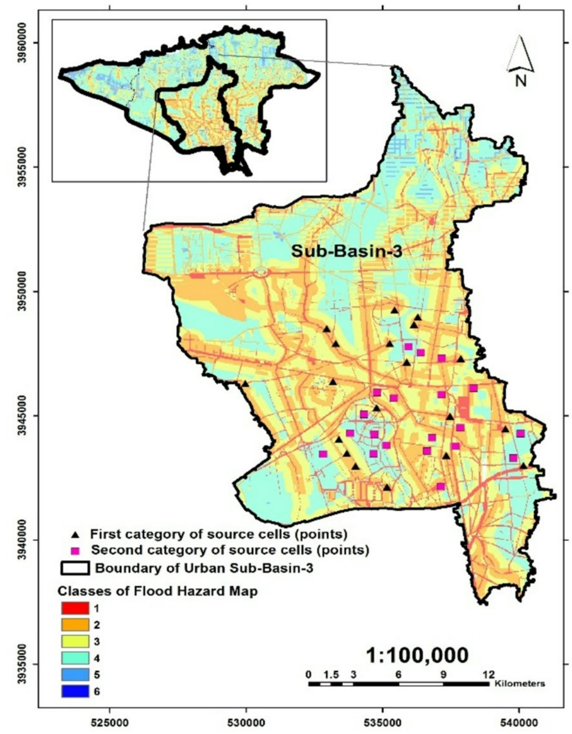

Fig. 9. Location of source cells based on flood hazard classes in urban sub-basin-3. (Figure created in ArcGIS 10.8 ESRI, http://www.esri. com).

Cost surfaces	Land use	Slope	Geology	Criteria weight
Land use	1	2	7	0.582
Slope	-	1	6	0.348
Geology	-	-	1	0.069

Table 5. Pairwise comparison matrix of cost surfaces for decision-making criteria. Inconsistency ratio (IR): 0.03.

A total of 39 source cells (19 primary and 20 secondary) were identified and introduced into the GIS model as shapefile inputs (.shp). Figure 9 displays their spatial distribution in urban sub-basin 3, which was selected based on its priority for flood-control planning.

Computation of the suitability cost surface
Each cost criterion was assigned a weight using the Analytic Hierarchy Process (AHP). The overall suitability cost surface was then produced by the Weighted Linear Combination (WLC) method (Eq. 6):

$$\text{Suitability cost surface} = \sum \left[Cost\ Surface\ (C_n) \times Weight\,(W_n)\right] \tag{6}$$

- Cost surface: The cost surface related to each decision-making criteria.
- W_n: The weights of the cost surfaces for the decision-making criteria, which is derived using the AHP method.

The pairwise comparison matrix and weights are reported in Table 5, with an inconsistency ratio of 0.03, confirming high consistency (see Supplementary Table S4 for full classification and weighting details).

Determination of least-cost paths
The least-cost routes between each identified source cell and the outlet of its respective sub-basin were determined using the cost-weighted distance and direction maps implemented via the developed GIS toolbox. The resulting routes in sub-basin 3 (Figs. 10 and 11) align with areas of minimal cumulative cost and converge toward existing drainage channels classified as Class 1 (lowest cost).

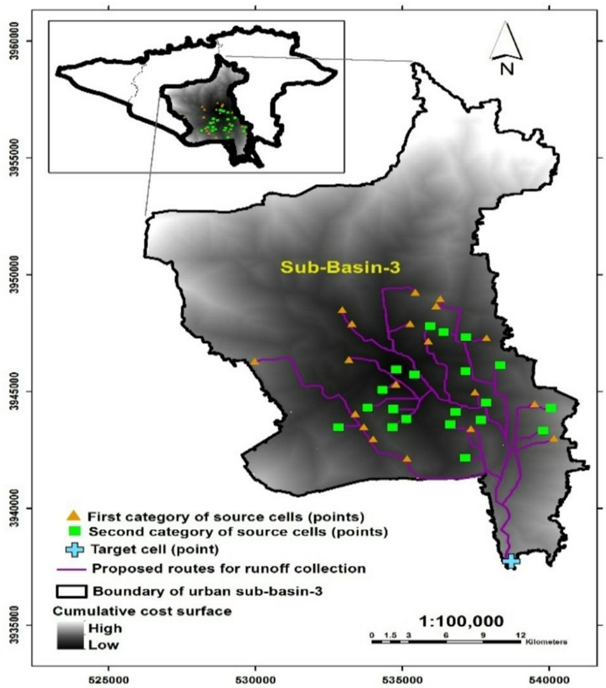

Fig. 10. Proposed routes for runoff collection in urban sub-basin-3. (Figure created in ArcGIS 10.8 ESRI, http://www.esri. com).

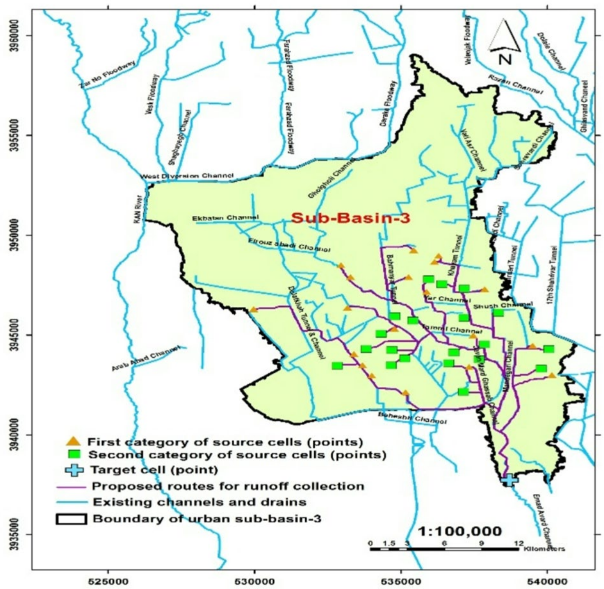

Fig. 11. Comparison of the proposed routes with the existing channels and drains in urban sub-basin-3 (Figure created in ArcGIS 10.8 ESRI, http://www.esri. com).

Evaluation and benefits of proposed routes

The optimized LCP routes offer clear technical and economic advantages relative to the existing drainage network:

- Starting points were systematically defined using flood hazard classes derived from previous multi-criteria analyses.
- Cost attributes were quantified across three domains (urban land use, geology, slope), enabling explicit incorporation of physical and economic constraints.

- The proposed routes follow the lowest cumulative-cost corridors, ensuring minimal excavation and structural requirements.
- Although the current drainage transfer capacity was not explicitly modeled due to insufficient data, it is recommended for inclusion in future optimization frameworks.

Cost analysis of proposed routes
To quantify route-specific costs, each proposed path was intersected with the cost-criteria layers, and the total cost was computed for multiple model iterations. Figure 12 illustrates the four resulting routes (Routes 1–4), generated for one selected source point by varying the cost value of the "urban channels and drains" class (1, 4, 7, and 10, respectively) (see Supplementary Tables S5–S8 for full details and classification). Analysis reveals that land-use cost accounts for the largest share of total costs, followed by geology and slope (Fig. 13).

Figure 14 compares decision-criteria costs across the four proposed routes, whereas Fig. 15 summarizes their total costs. Among them, Route 1, corresponding to the lowest class cost value ($C=1$), demonstrated the minimum overall cost and is therefore recommended as the optimal alignment for the urban runoff collection system.

Discussion

The integrative framework developed in this study, which combines the analytic hierarchy process (AHP), artificial neural networks (ANN), and least-cost path (LCP) analysis within a collaborative spatial decision-making (CSDM) structure, proved effective for bridging expert-driven prioritization with data-validated modelling in urban flood risk management[36]. Multi-stakeholder weights, derived from the inputs of engineers, policy planners, academics, and NGOs, were not only consistent with hydrological indicators but, after ANN validation, yielded improved spatial discrimination of flood-susceptibility zones[41]. Incorporating LCP analysis generated implementable, low-cost pathway alternatives for stormwater conveyance through Tehran's complex urban fabric, linking risk assessment with actionable design.

Our findings align with recent research advocating hybrid MCDA–machine-learning frameworks for hazard mapping[42,43]. Integrated Bayesian networks with GIS have demonstrated enhanced causal representation and uncertainty quantification for urban flood disaster assessment[42]. Coupled 1D–2D bidirectional hydrodynamic models have similarly improved the representation of pluvial-flooding mechanisms, providing validation support for structural alternatives identified by spatial optimization[44]. From a susceptibility-mapping perspective,

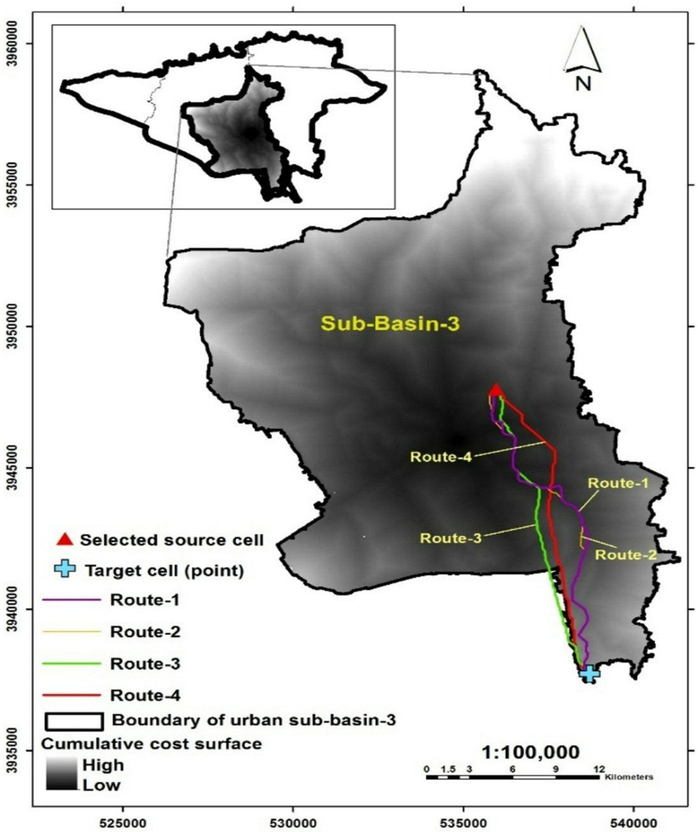

Fig. 12. Proposed routes for urban runoff collection system for the selected starting cell (point) (Figure created in ArcGIS 10.8 ESRI, http://www.esri. com).

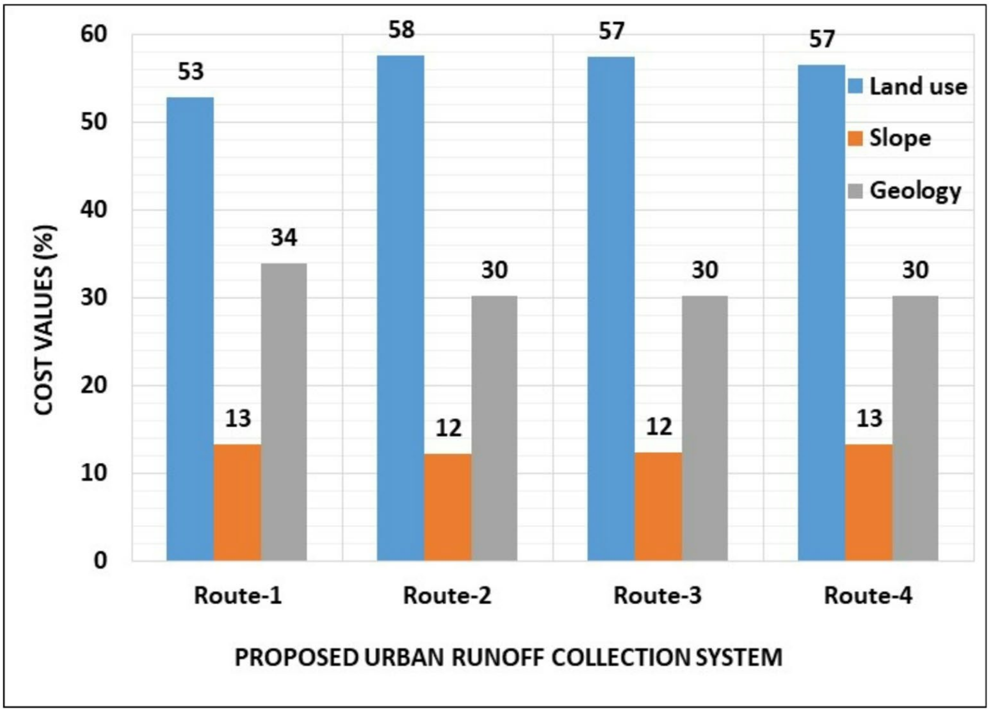

Fig. 13. Percentage of cost for each decision-making cost criteria for the proposed urban runoff collection system.

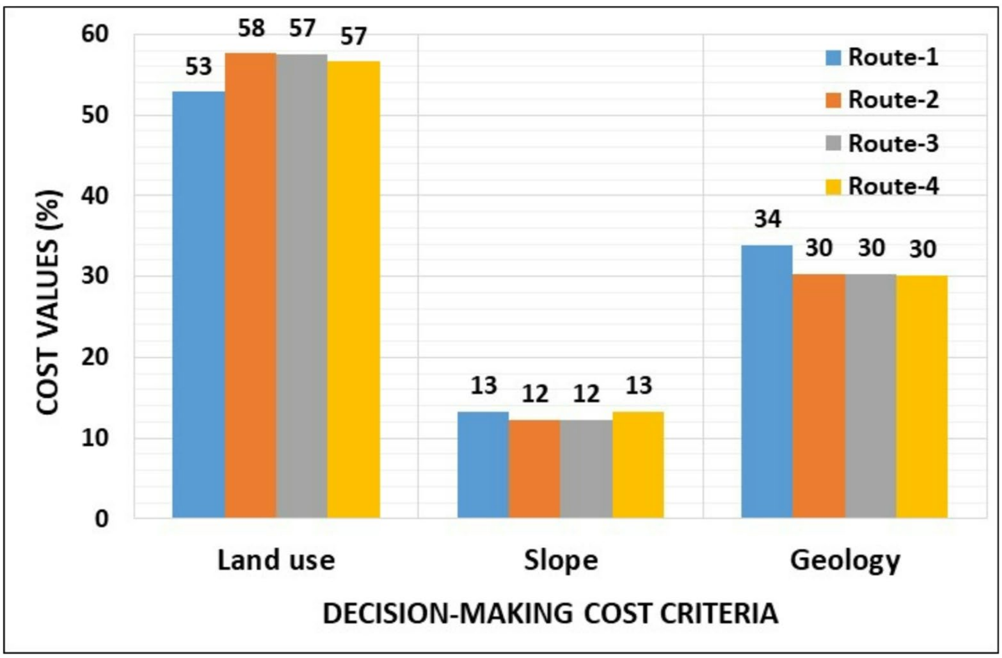

Fig. 14. Comparison of the proposed runoff collection routes based on each decision-making cost criterion.

systematic reviews underline the role of high-resolution remote-sensing datasets and key parameter selection in shaping robust flood-prediction models[45].

Furthermore, deep-learning architectures such as deep abstract network (DANet) have shown superior capacity to capture non-linear spatial relationships in dense urban contexts, as validated in recent case studies of Iranian cities[46]. The prominence of land-use and slope as leading criteria indicates a strong alignment between experiential local knowledge and hydrological science, affirming the value of participatory calibration in spatial

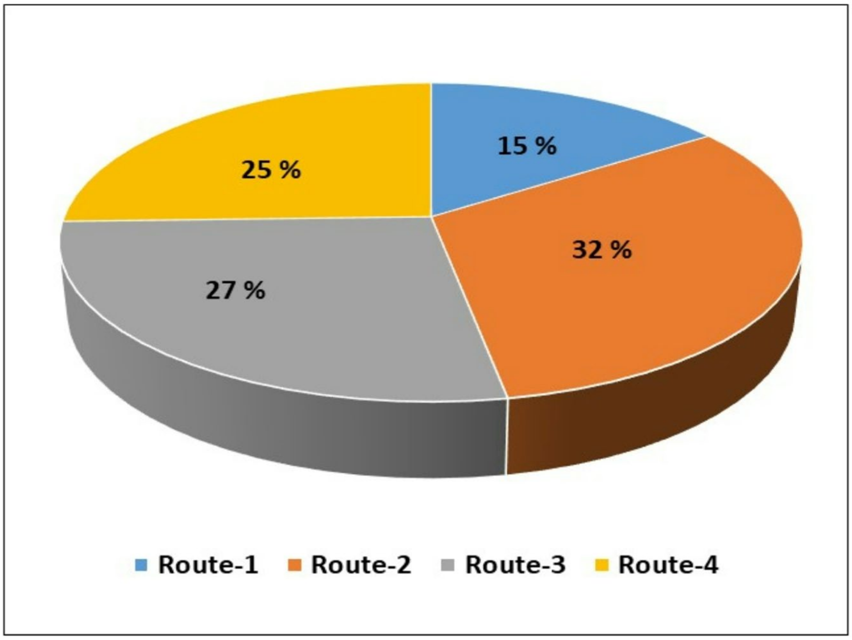

Fig. 15. Total cost comparison among the proposed routes.

models. This alignment reinforces both methodological robustness and governance credibility, as municipal stakeholders directly recognize their empirical knowledge in model outcomes.

New scenario-driven frameworks have explicitly combined climate-change and land-use projections within susceptibility assessment, emphasizing the resilience advantages of hybrid methods over static approaches[47]. Parallel advances in drainage-network generation using Gibbs-model random trees enable simulation-ready designs that can be readily matched to LCP outputs[48]. Green–grey–blue-system (GGBS) optimizations reported in 2024 highlight that nature-based solutions, when harmonized with conventional engineering measures, outperform single-infrastructure strategies in stormwater management[49].

Technically, the LCP analysis produced optimized runoff collection routes that function as decentralized and adaptive complements to conventional drainage systems, which are consistent with recent evidence on Sustainable Urban Drainage Systems (SUDS) and nature-based solutions (NBS) for resilient cities[33,19]. By embedding LCP within a GIS-based workflow, this study illustrates how adaptive storm-water design can be spatially optimized using data-driven yet governance-responsive models. From a governance perspective, the model provides a decision support toolbox that unifies expert knowledge, stakeholder insight, and spatial analytics, thereby facilitating institutional coordination, which is particularly evident as a challenge in cities with fragmented governance systems such as Tehran[3,1].

Compared with those governance-focused models, the current approach emphasizes operational applicability and practitioner usability, narrowing the persistent gap between modelling theory and policy implementation.

Relative to current trends, the novelty of our work lies in three aspects: (i) reducing the expert-data gap by using ANN to validate the weights derived from AHP; (ii) operationalizing LCP to identify feasible, low-cost interventions directly linked to physical topography, drainage capacity, and urban constraints; and (iii) institutionalizing stakeholder collaboration within the decision-making workflow, in line with emerging evidence that participatory governance enhances policy adoption and long-term resilience[41].

Nonetheless, certain limitations remain. Our current models rely partly on static layers (land use, imperviousness) without embedding dynamic climate scenarios into the weighting and validation cycle. Drainage-network representation is simplified and could be strengthened via graph-reconstruction models for incomplete infrastructure datasets[50].

Uncertainty quantification, though implicitly addressed through ANN validation, could be expanded via formal Bayesian sensitivity analysis[42]. Future research should integrate multi-objective optimization linking LCP with drainage-topology design, scenario-based climate and land-use change, and coupling hydrodynamic simulations for event-based performance testing.

Ultimately, by combining stakeholder-derived priorities with machine-learning validation and spatial optimization, this study contributes to the evolving discourse on collaborative flood governance. It demonstrates that scientifically rigorous, participatory models can generate both hydrological insight and institutional engagement, delivering a reproducible framework adaptable to other data-scarce and institutionally complex urban contexts worldwide.

Concluding remarks

This study presents a comprehensive, collaborative spatial model for urban flood governance. The integration of GIS, MCDA and stakeholder engagement within a single platform demonstrates high utility in planning and prioritization. A flood hazard map serves as a valuable tool for enhancing urban runoff collection infrastructure and can assist policymakers and designers in this field. The finalized map categorizes flood hazard into six distinct classes. Classes one through five indicate hazard levels ranging from very high, moderate to high, moderate, low, to very low, respectively, while class six represents the minimal hazard level. Accordingly, about 6% of the study area falls under hazard class one, while approximately 43% belong to classes two and three. Around 42% are classified as class four, and nearly 9% fall within hazard classes five and six. The map reveals that areas near primary runoff collection systems are vulnerable to flooding. High-hazard zones are characterized by a dense network of channels, low-lying topography, and mild slopes of less than 2%.

To identify the optimal routes for urban runoff collection, the flood hazard map generated using a spatial multi-criteria decision-making model was utilized. Optimal routes were determined by applying a suitable algorithm while considering reasonable assumptions. In this process, informational layers representing decision-making cost criteria (decision-making cost surfaces) were created, incorporating factors such as land use, slope, and geology. Source cells, representing the starting points of the runoff collection system, were established based on the flood hazard map and its classifications. Additionally, urban sub-basin outlets were designated as target points, allowing for the identification of the optimal runoff collection routes.

It is important to emphasize that the developed model is intended for preliminary studies on flood control in urban basins. More detailed models require more precise information on rainfall and peak discharge within the study area. Using the analytical method presented in this study, which combines suitability analysis (preparing the flood hazard map) and the minimum-cost path model, the results of this research can serve as an initial guideline for future urban planning.

The findings of this study demonstrate that utilizing multi-criteria decision-making techniques within a geographic information system (GIS) is a highly effective method for generating accurate flood hazard maps. Given that a fundamental aspect of management is identifying priorities, this model and its outcomes can provide a suitable approach to flood governance in urban basins. Future work should extend validation using real flood data and expand criteria (e.g., economic losses, infrastructure capacity).

Data availability

All relevant data are included in the paper.

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A.R. First author, Corresponding author, Data curation; Investigation; Formal analysis; Resources; Conceptualization; Funding acquisition; Methodology; Project administration; Supervision; Validation; Visualization; Roles/Writing—original draft, review and editing.

Declarations

Competing interests
The authors declare no competing interests.

Additional information

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