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Sustainable dam site selection using artificial intelligence-based graph neural networks with MCDM

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Abstract

Identification of suitable location for construction of dam/reservoir is important for the sustainable development and flood control. This paper introduces a novel application between Artificial Intelligence (AI) and multi-criteria decision making (MCDM) for the enhancement of dam site suitability evaluation. In this research, Graph Neural Networks (GNNs) were introduced to automatically discriminate the MIF weights and substituted the weight schemes used in previous MCDM methods. A total of 12 climatic, geophysical, and accessibility indices working under a Geographic Information System (GIS) were considered. The GNN-weights were used in weighted overlay analysis to create a dam suitability map, and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was applied for ranking possible dam locations. The results show that the GNN-based weights can significantly improve model accuracy, with the AUC value increasing from 0.806 to 0.826 after incorporating them into consideration. The top-ranked site was the same as previous reports, indicating that the method we used is robust. This AI-enhanced framework has greatly advanced the objectivity and predictability of dam site selection strategies, thereby enhancing the moderator's ability to make informed decisions when choosing sites for sustainable water infrastructures.

Keywords: Artificial intelligence, Graph neural networks, GNN, Dam site selection, Multi-criteria decision making, Sensitivity analysis.

1. Introduction

Water resources are a major global concern due to the demands of climate change, population increase, and urbanization [1-2]. Droughts in dry seasons and floods during wet seasons put many areas at risk. Dams are key to addressing these challenges in terms of capturing water, controlling river discharge and providing an assured supply for irrigation, drinking and hydroelectric power [3]. Dams can contribute to water security and socio-economic development if planned properly as they manage floods and droughts, which means that renewable energy production may be possible. Nevertheless, obtaining these benefits is greatly conditioned by sustainable location of the dams, as the wrong localization can prove to have social, environmental and economic complications. Choosing the best location for a dam is not straightforward and depends on multiple criteria, ranging from technical and economic parameters to social, environmental, and even political factors [4-6]. The optimization, among these not necessarily compatible requirements is necessary in order to impact that the dam be safe, have an economic justification and contribute to a sustainable development socially accepted.

The dam site selection is actually one of multi-criteria decision-making (MCDM) problems because of several number of factors and stakeholders associated [7]. Conventional methods have used expertise-based MCDM techniques integrated with geographic information system (GIS) applications to assess the favorableness of alternative sites [8-13]. In MCDM, decision makers establish a set of criteria (hydrology, geology, ecology, cost and community impact) along with associated weights based on their relative importance and rate the performance of each alternative relative to these criteria. Many MCDM methods like AHP (Analytic Hierarchy Process), WLC (Weighted Linear Combination), TOPSIS (Technique of Order Preference Similarity to Ideal Solution) and different fuzzy logic approaches are commonly employed in dam site selection studies. For example, AHP was commonly used to derive weights by conducting pairwise comparisons of criteria and incorporating expert knowledge in dam suitability mapping [14-18]. A large number of case studies all over the world, such as locating small dam site in arid region and reservoir planning have used AHP base GIS efficiently to generate dam suitability maps ranging from low to very high suitability. One benefit of such MCDM methods is they offer a structured, transparent process for combining multiple criteria to assist decision makers in selecting areas that fulfill several different needs [19-21]. Although traditional MCDM methods are widespread and have been shown in many studies to be very useful, they also possess some significant drawbacks. They usually involve a great deal of expert judgment, and therefore they can be subjective and biased. Whilst in fact many of the environmental and geotechnical parameters (say slope, elevation) are interdependent, methods such as AHP assume independence of criteria [14]. This can impact the ranking results themselves. What is more, classical GIS-MCDM usually oversimplifies complicated phenomena: such as for accessibility when may consider only a single distance-to-road metric to estimate how good a site connect to communities or ecosystems.

More recently, sophisticated AI and machine-learning methods have been introduced to optimize the selection of sites [22-27]. There have been attempts to merge evolutionary algorithm techniques such as genetic algorithms (GA) and ant colony optimization (ACO) with GIS for optimising multi-criteria site selection. These methods can explore huge solution space to find out the best, or near-optimal site combination under different constraints. Fuzzy extensions of MCDM (such as fuzzy AHP, fuzzy TOPSIS) have been proposed for dealing with the uncertainty on criteria weighting and ranking in making more robust or ambiguity approaching decisions. For instance, group fuzzy-TOPSIS models have been applied to consider multiple experts' opinions in ranking dam site alternatives [19,28-29]. In this context, the availability of more data through a growing amount of geospatial information and new computational power has fostered an increasing number of data-driven approaches such as machine learning models for suitability prediction. These models operate not only on user-defined expert weights, but also learn patterns from past data if any is available of dam locations or suitability measures. Types of classification and ensemble learning methods such as Random Forests (RF) and Support Vector Machines (SVM) have been used to classify sites for suitability or unsuitability using a training set of environmental and physical attributes. Neural network models have been studied for better predictive mapping of site suitability [30]. For example, sophisticated neural network structures (i.e., including deep learning models) were applied for check dam site selection in a sub-tropical river basin and it can identify complex nonlinear relationships among hydro-geological factors. Compared to conventional weighted overlays, these AI methods often provide substantial improvement by exploiting large datasets (e.g., remote sensing layers and hydrological features) and complex feature interactions so that dam site evaluations can be performed with higher objectivity and more powerful predictability. Yet, many current machine learning models continue to consider each location as an independent sample with no consideration for how the suitability of one site might inform the suitability of another, a concern when dealing with connected networks in river systems.

To model spatial interactions and networks in the site selection problem, Graph Neural Networks (GNNs) are emerging as a state of-the-art AI approach [31-33]. GNNs are meant to process data with graph structure or, abstractly, graphs as we could think of it: nodes for entities (e.g., places) and edges indicating relationships or flows between them [6,34-37]. Unlike classical neural networks, GNNs can learn representations that consider the relationships of sites, a characteristic critical to environmental planning and infrastructure planning. In the framework of dam site selection, for example, a GNN could similarly model A river basin to capture interactions between sites (e.g., by means of edges representing hydrological or environmental connections) as A network (graph). This network-aware modeling might help the AI learn how the suitability of one site is dependent on or affects other sites in the watershed, how building a dam at one location would affect flood control or water availability elsewhere. The combination of these graph-based interests with MCDM, would mark a substantial step forward for sustainable dam site location, not just in terms of satisfying multiple criteria at the selected site, but with respect to considering whole system implications. Table 1 shows the literature on dam site selection techniques and their applications.

Table 1. Summary of dam site selection techniques and their applications

References	Technique	Application (case and data)	Validation /main outcome
[38]	GIS + AHP + ML overlay	Dam suitability mapping (Sharjah, UAE) using 9 layers (rainfall, slope, geology, lineaments, CN, etc.)	Produced DSSM and ranked dam sites
[39]	GIS + MIF–TOPSIS	Potential dam site screening with 12 climatic/geophysical/accessibility factors	ROC–AUC = 0.806; low-cost decision aid
[40]	Fuzzy logic + exploratory regression	GIS-based reclassification (geology, LULC, slope, rainfall, soils) with fuzzy memberships	Data-driven fuzzy weights; improved interpretability
[41]	FAHP → ANFIS (two-phase)	Double assessment for sustainable siting (HWSP case); includes reservoir volume, sediment, cost	Sequential FAHP→ANFIS refined choice (Zmkan-B)
[42]	GIS–MCDA (AHP/FAHP)	Basin-scale suitability (Bagmati River, Nepal); 9+ criteria	FAHP slightly outperformed crisp AHP
[43]	AHP vs TOPSIS (comparative)	GIS-based dam siting (geology, erosion, slope, groundwater, discharge, water quality)	Reported consistency & rank differences
[44]	RF & SVM (supervised ML)	Predict suitability from terrain/hydro factors; data-driven classifiers	Demonstrated ML feasibility for dam siting
[45]	BRT/MARS/MDA/RF/SVM	Check-dam siting optimization; 5-model comparison	RF/SVM competitive; multi-model ensemble insight
[46]	Group MCDA for SHP planning	Small hydropower site decision support with group preferences	Structured group decisions for plant siting
[47]	FAHP + VIKOR	Earth-dam alternative ranking (18 criteria)	Integrated fuzzy weights + compromise ranking
[48]	Binary / nadir compromise programming	Formal dam site selection problem (DSSP) under certainty & uncertainty	Optimized multi-objective site choice
[49]	Deep learning + spatial analysis	Detecting unknown dams from high-res RS to feed candidate extraction	Broad-area detection pipeline
[50]	YOLOv5s-ViT-BiFPN	Automatic dam extraction; RSDams dataset	Precision ≈ 88.2% after transfer learning
[51]	RF + spatial constraints	Candidate-region identification for large dams (5 countries)	Reduced search to < 1.06% of area
[52]	Geographic knowledge + DL	Verify dam locations in open datasets (SE Asia) to build reliable inventories	End-to-end verification framework
[53]	Hybrid RF + DL	Large-area dam detection with geographic factor analysis (Sindh, Pakistan)	Faster, scalable database enrichment
[54]	GIS–MCDA + ML	Dam siting (Nigeria): integrated geospatial/ML map with stream proximity & rainfall effects	Identified optimal sites KA1/KA2
[55]	RS–GIS pre-screen (flow/valley)	Hydropower dam siting from flow accumulation & valley algorithms	Workflow for initial site narrowing

The aim of this research is to develop a sustainable dam site selection framework using an artificial intelligence-based Graph Neural Network (GNN) integrated with multi-criteria decision-making (MCDM) techniques. There are a number of key contributions from this study to the field of knowledge. First, it applies a graph neural network to the dam site selection problem domain, thus linking modern deep learning with classical multi-criteria analysis for spatial decision support. Second, it is a deep analysis on the past methodologies (MCDM, fuzzy systems, evolutionary algorithms, machine learning) for sustainable dam planning which achieves an overview of literature for researchers as well as practicing engineers. Third, the proposed model offers in-depth insight into how to blend AI with sustainability constraints and provides a decision support indexed which is based on data but achieves good alignment for scheduling some values of an expert opinion versus computational speed, an important tradeoff when addressing sustainable infrastructure. The work is a pioneering one towards the next generation of intelligent decision systems for water resources engineering, which has significant implications in making dam construction more sustainable and successful around the globe.

2. Methodology

Study Area

This study was carried out in the basin of the Ulhas River, Western Maharashtra, India (Fig. 1). This catchment area is about 4,390 km² in extent and lies across parts of Thane, Raigad and Pune districts [56]. The Ulhas River is the main river which flows from the eastern side of the city, beginning in Rajmachi and flowing eventually into the sea. The river is joined by the Kalu and the Bhatsa rivers in the basin, which increases its flow. The topography of the basin can be categorised into three main geomorphologic zones: a western coastal lowland plain, a central pediment zone and an eastern highland or escarpment area. These variables create a semi-circular catchment with dendritic drainage, and the latter can cause concentrated water to flow towards the lower part of the basin. The climate in the Ulhas basin is tropical monsoon. Annual precipitation is generally about 3,000 mm, most of this precipitates during the June–September monsoon [56-58]. Heavy rains during this time can cause significant runoff. The heaviest rainfall occurs along the eastern highlands, which are drained by a network of streams flowing to join downstream rivers. Average temperatures are about 15°C in winter and 35°C in summer, but the climate is moderate between the monsoons. The Deccan Traps basalt which covers most of the study area [56]. The basin is underlain geologically by Late Cretaceous Deccan Traps and hard volcanic surface rock that form the highest levels. Alluvial deposits and marine sediments lie on top of the basalt near the coast and along river valleys, leaving areas of less rocky soil. Soil types range from coarse alluvium in the coastal plains to shallow stony soils in the uplands.

The Ulhas River basin is heavily populated, with human settlement and development. Portions of the basin fall under the Bombay Metropolitan Region (covers towns like Kalyan, Dombivli, Badlapur, Navi Mumbai) and are depended upon for water supply directly using Ulhas River along with its tributaries. Water demand has increased over recent decades due to rapid urbanisation, population growth and further changes in land uses in the basin. This region is subject to flooding during heavy monsoon rains, and (i) lack of adequate upstream storage or containment facilities, has caused downstream areas to experience major floods, such as the Mumbai floods in 2005. On the other hand, during drier months some areas in the basin suffer from water shortage for agriculture and human consumption. All these factors underline the need for sustainable dam site selection in the Ulhas basin. Reservoirs are designed to be strategically located, the goal is to capture extra monsoon runoff to prevent flooding and save water for drought periods, with minimal socio-environmental effects. Hence, this study from Ulhas basin is a case in point to illustrate an improved decision framework for dam site selection utilizing state-of-the-art AI and MCDM approaches.

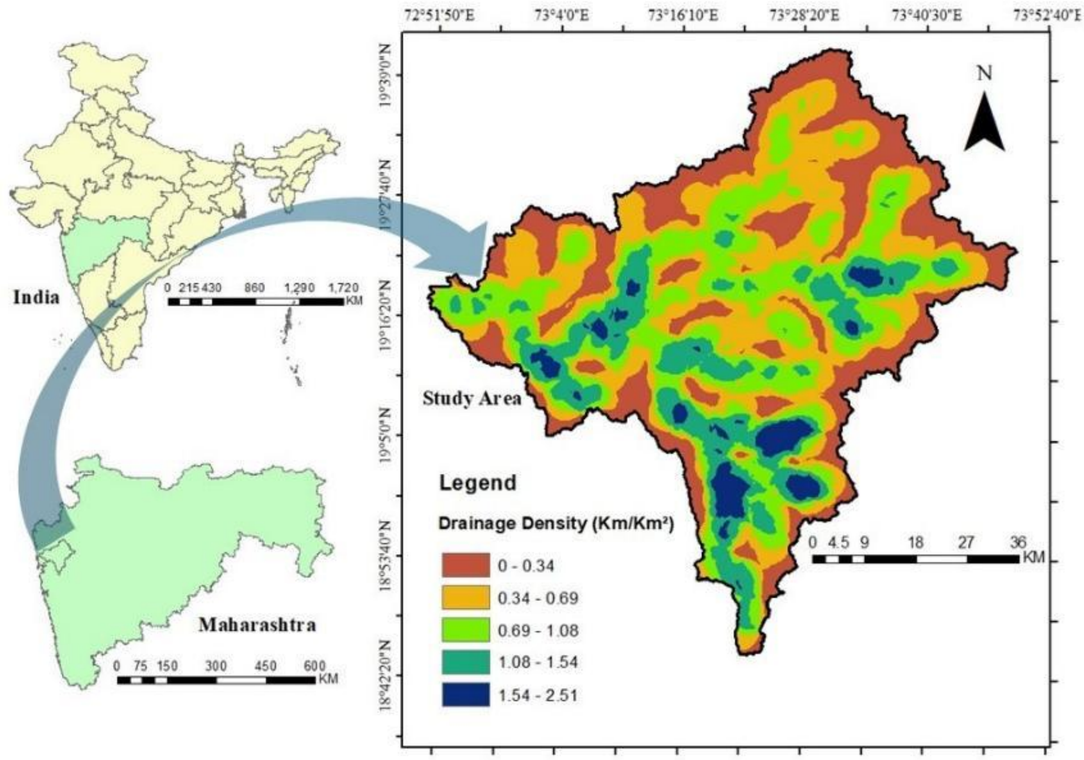


Fig. 1 Location of the study area

GIS–MIF–TOPSIS framework

We utilized a GIS-based multi-criteria decision-making methodology that extends the traditional GIS–MCDM–TOPSIS approach. In such a framework various thematic criteria are integrated through GIS to produce a dam site suitability index, which is in turn utilized for selecting dam sites. These candidates are refined by application of an MCDM technique and prioritized for final decision. The major steps of the GIS-based technique include (i) Acquisition of data and preprocessing in GIS for relevant criteria layers (ii) Weighting and aggregation of criteria to produce a suitability map using multi-influence factor analysis model; (iii) Application of Graph Neural Network model to obtain multidimensional influence factor weights. It replaces subjective or heuristic weighting of influence factors process;(v) Priority ranking top candidate using Technique for Order Preference by Similarity to Ideal Solution (TOPSIS); (vi) Conduct sensitivity analysis to verify the robustness of influence factors and, lastly, validate results use Receiver Operating Characteristic-Area Under Curve analysis with existing dam's information. All spatial analysis was performed in a GIS environment, and the process followed the standard workflow, with exception of inclusion of a GNN-based weighting technique.

Data Acquisition and Criteria Preparation

An integrated approach should be adopted for dam site suitability assessment taking into account environmental, hydrological and socio-economic aspects [59-63]. We used literature and guidelines to find out 12 factors that affect decision-making of the site for dam construction. These in the form of weather, geophysics and accessibility. The following criteria are used; 1) CN - Curve; 2) Slope; 3) Drainage density; 4) Geology; 5) Geomorphology; 6) Soil type; 7) Land Use/Land Cover (LULC); 8) Rainfall; 9) Elevation; 10) Distance to rivers; 11-Distance to roads; and 12-Distance from fault lines. These twelve criteria summarize the most important topographic, hydrological and access conditions that can influence a site's appropriateness for damming. A GIS was used for the collection and processing of data on space-variable approaches to each criterion. The elevation and slope were based on digital elevation data from USGS (30 m resolution). The DEM was also processed with classical hydrological tools, flow direction, accumulation and by generating the drainage density which shows how packed river channels are in each sub-area. Geological and fault map shapefiles were procured from the Geological Survey of India (GSI) who is responsible for supplying Geology layers, and Fault zones as vector datasets. Land use/land cover was derived from Landsat 8 OLI satellite imagery (30 m) through supervised classification methods. Rainfall data were obtained from India Meteorological Department and adjusted for the spatial extent of precipitation over basin. For accessibility reasons, we generated distance to roads, distance to rivers, and distance to settlements by Euclidean distance on point and line layers derived from Survey of India topographic maps. All of the vector data were converted to raster format with a common resolution (30 m) to match the resolution of DEM and remote sensing layers. All the criterion layers were then standardized, transferred to a common suitability scale, reclassified into five classes that ranged from very low to very high, based on methods such as Jenks natural breaks or important value ranges indicated by domain knowledge. These 12 raster layers were used as the input factors for the MIF model.

Multi-Influencing Factor (MIF) model and weighted overlay

We fused these discrete criteria and used the weighted overlay technique. In the MIF method influence is given to each criterion according to its relative importance and the contributions of all criteria are added up for arriving at suitability index for every site [2,64-66]. In the baseline methodology, this weight was typically obtained through expert judgment or straightforward heuristic rules. For instance, some works categorized criteria into 'major' and 'minor' influential levels, giving a weight of 1.0 to major ones and 0.5 to minor ones followed by normalization for obtaining final weights [67-70]. However, such manual weighting may bring subjectivity and could fail to reflect the complicated inter-criteria connections. Instead of doing these manual operations, we propose using a GNN framework for learning the best weights in MIF method. The MIF remains the aggregation mechanism and its criteria weights are entirely determined by the GNN. When the GNN is trained, it modifies its internal weights in order to minimize the error in predicting which sites qualify or not for a dam. In this learning process, the model learns to give different relevance scores for each input feature to produce a proper prediction. In effect, GNN figures out on its own which factors are important or not-so-important when it comes to appropriate dam sites by looking at patterns in the data putting a pulse weight on such features. This evidence-driven weighting method minimizes the man-made bias and customizes the impacts on the features of the study area. Fig. 2. Shows the spatial distribution maps.

Following is the implemented methodology in which a Graph Neural Network (GNN) is used to compute criterion weights for the Multi-Influencing Factor (MIF).

Step 1: Inputs and preprocessing

Twelve climatic, geophysical and accessibility criteria were prepared as raster layers (30 m) and reclassified to five suitability classes: Distance to river, distance from fault line, soil type, elevation, proximity to roads, drainage density, rainfall, geomorphology, Curve Number (CN), slope, geology, and LULC.

Step 2: Baseline MIF influence

Each criterion was assigned major and minor interrelations against the rest (major = 1.0; minor = 0.5) [15,71-72]. For criterion i, the relative effect is

$$r_i = M_i + 0.5\, m_i \tag{1}$$

The MIF weight (percent) used in the baseline model is

$$w_i^{\mathrm{MIF}} = \frac{100\, r_i}{\sum_{j=1}^{n} r_j} = \kappa\, r_i, \quad \kappa = \frac{100}{\sum_j r_j} \left(= 4.878 \text{ for } \sum r_j = 20.5\right) \tag{2}$$

Step 3 – Factor graph construction

We represented the interdependent criteria as a 12-node undirected graph $G = (V, E)$, one node per criterion. Because the manuscript reports aggregated major/minor totals rather than a full pair list, we encoded co-influence and co-sensitivity with a dense, symmetric similarity matrix Scombining relative effect and sensitivity:

$$S_{ij} = \frac{r_i r_j}{\sum_k r_k^2} + \frac{VI_i\, VI_j}{\sum_k VI_k^2} \tag{3}$$

Self-loops were added to stabilize propagation: $A = S + I$. The normalized adjacency is

$$\hat{A} = D^{-1/2} A D^{-1/2}, \quad D = \text{diag}\left(\sum_j A_{ij}\right) \tag{4}$$

Step 5: Node features

Each node $i$carries a 2-vector $x_i = [\, r_i,\, VI_i\,]$. Stacking gives $X \in \mathrm{R}^{12\times 2}$.

Step 6: One-layer GCN for weight scoring

We used a single linear graph convolution to obtain a scalar score $h_i$per criterion:

$$h = \hat{A}\, X\, \Theta, \qquad \Theta = \begin{pmatrix} 1 \\ 1 \end{pmatrix} \tag{5}$$

with identity activation. This choice restricts the GNN's role to weight computation only and avoids overfitting given limited labels.

Step 7: Softmax mapping to GNN weights

Scores were converted to percentage weights with a temperature-controlled softmax:

$$w_i^{\text{GNN}} = 100 \cdot \frac{\exp(h_i/\tau)}{\sum_{\text{l}=1}^{n} \exp(h_{\text{l}}/\tau)}, \qquad \tau = 50 \tag{6}$$

Step 8: Suitability index (weighted overlay)

The dam-site suitability index (DSSI) at pixel $p$was computed exactly as in the manuscript, replacing $w_i^{\text{MIF}}$by $w_i^{\text{GNN}}$when using the GNN variant:

$$\text{DSSI}(p) = \sum_{i=1}^{n} W_i\ R_i(p), \qquad W_i \in \{w_i^{\text{MIF}},\, w_i^{\text{GNN}}\} \tag{7}$$

where $R_i(p)$is the reclassified rank (1–5) of criterion $i$at pixel p.

After receiving the GNN-inferred weights, these were input to a weighted overlay analysis to derive the dam site suitability map. The standardization of the individual criterion layers was applied to obtain the suitability index in each grid cell by multiplying each standardized layer by its weight and summing all layers together.

TOPSIS for final site prioritization

Based on the suitability mapping, we selected highest ranking sites for detailed inspection. The best fit zones from MIF-GNN analysis were searched with field knowledges and practical issues to identify a group of preliminary dam sites. Finally, these potential sites were evaluated through TOPSIS analysis in order to obtain the preference ranking. We adapted the classical multi-criteria analysis tool TOPSIS for ranking of alternatives based on the distance to an ideal solution [6,73-77]. From the viewpoint of this study, each candidate dam site is assumed as an alternative and the criteria for decision-making by TOPSIS are those upon signs and parameters on design and feasibility in terms of building dams at these sites.

Sensitivity analysis of criteria weights

We conducted a sensitivity analysis to examine the reliability of the MIF-GNN model and the impact of each criterion on suitability result. The objective was to assess the sensitivity of suitable site selection on varying criteria weights or data. To explore different ways to address this, one of the methods we used was a leave-one-out approach whereby we iteratively removed out each criterion one by one and then re-ran the suitability mapping again to see how that change influenced the outcome [6,78-81]. When leaving out a criterion results in big differences for the high-suitability areas, we say that criterion has high impact on outputs; otherwise, it is less important. We also tested the sensitivity condition by taking the trained GNN model and perturbing the weights with small amounts to see if this changes which sites are selected. The sensitivity analysis therefore identifies which input layers the model is most sensitive to and can inform future data collection and model development efforts. It also gives confidence that the top ranked sites continue to be detected across small perturbations, suggesting a robust decision-making mechanism.

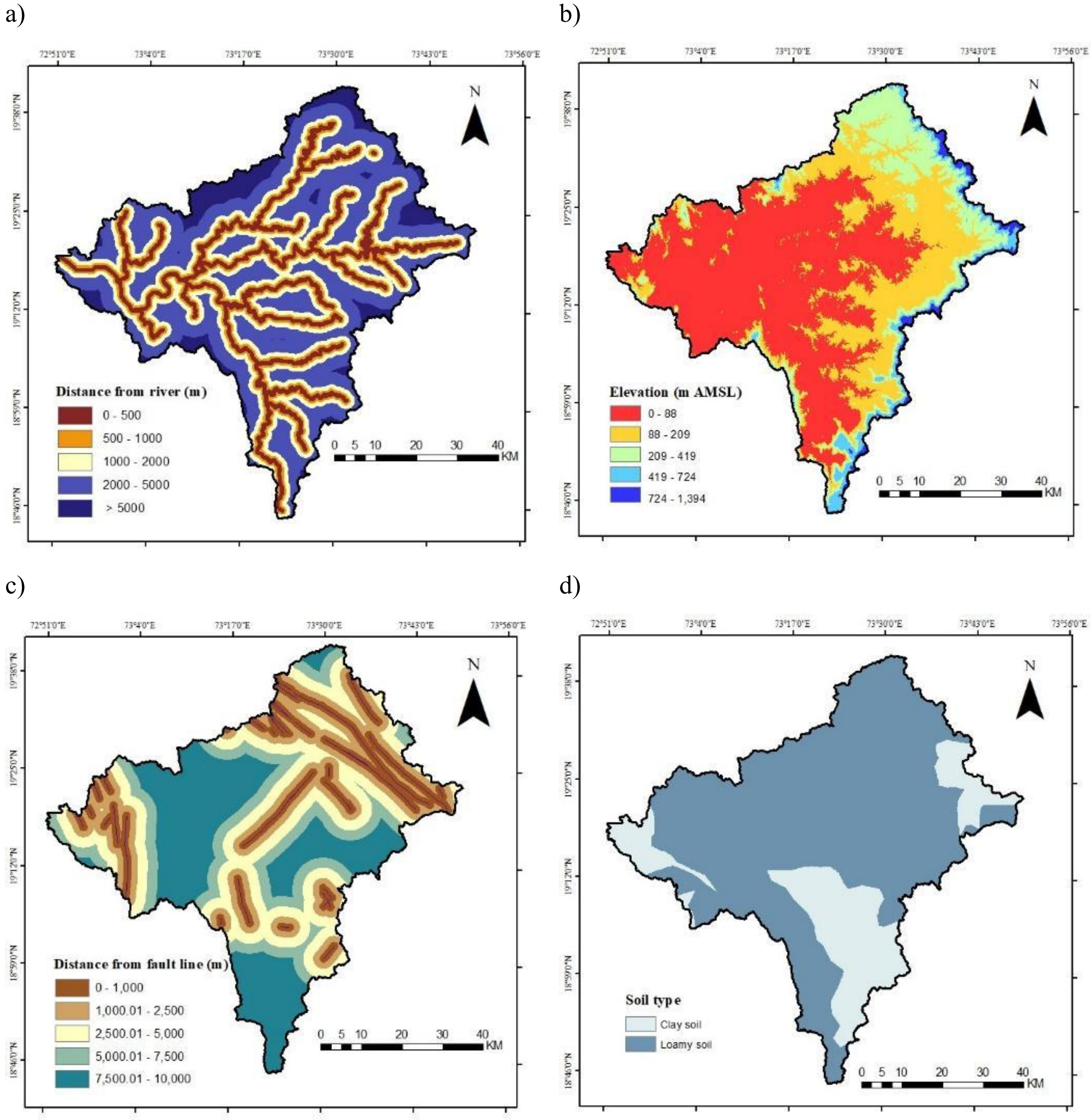
Model validation using ROC-AUC

We further compared the predicted suitability with independent indications of the actual site suitability as validation effort. This was achieved by overlaying the locations of known dams and of suitable dam sites in the area on existing dams to determine whether or not the model predicted these well-established dams. We considered the suitability map to be a kind of dam suitability classifier, using an ROC-based method. Existing dam locations were employed as validation points, a true positive would be an existing dam within a high-suitability cell, and a false positive would be one such without an existing dam. By converting the suitability index to a response at different frequencies and checking how many of the dam points were caught as positives we generated ROC curves that depict true positive rate against false positive rate. The Area Under the Curve (AUC) was finally calculated as an overall prediction measure [82,83]. An AUC value that peaks toward 1 represents good agreement between the model and actual dam site outcomes, while a value about midway (0.5) would indicate no better than random performance. This validation provides confidence that the AI weighting and overall framework can distinguish between good and low suitability dam sites. In addition, the validation exercise is a chance to further refine the model, if some known dam sites were ranked badly, it raises questions about whether certain criteria or weights ought to be changed, and/or there were factors not captured by the model.

3. Results and discussions

GNN-derived criterion weights vs. manual MCDM weights

The adoption of a GNN in criterion weight derivation led to new weights of the dam construction site selection criteria, compared with these expert weighed MCDM. In MCDM, weights were assigned based on expert opinions and literature in the original model, and with regards to current knowledge of each factor's importance. This manual MIF technique includes by definition subjective assessment because it relies on weight assignment by humans, which can alter the outcome of final suitability. As a result, these expert-derived weights tended to assign greatest importance to certain criteria, and as less important others. With GNN this optimized weight was the learned weight of a model that has been trained to match examples in the data. The weights that are derived by GNN are quite different from the manual ones. Many of the criteria received an adjusted important level, some items with major importance at experts' level have been downweighed while others gained higher weight, reflecting a data-driven re-evaluation. For example, if the original MIF method had overweighted a factor such as distance from roads, then this may have been underweighted by the GNN in favor of hydrological or geomorphological factors more strongly correlating with suitable dams in the data. Conversely, those factors that may have been underweighted through manual methods e.g. geological stability or catchment characteristics could receive higher weights if the model identified that these had consistent impacts on successful dam site decisions based on known successes in applying this GNN scheme to new areas.



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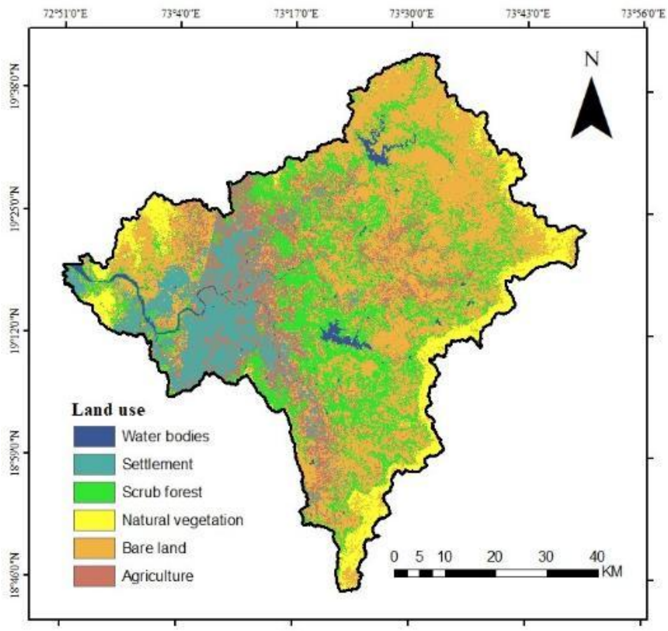
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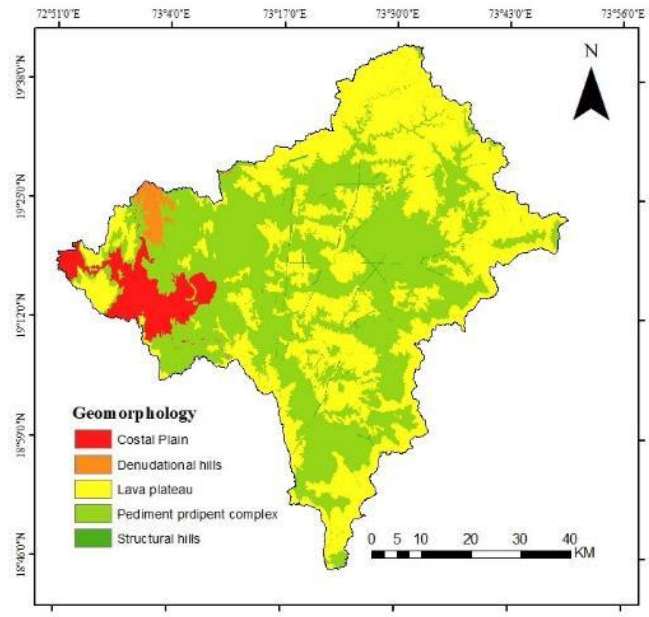
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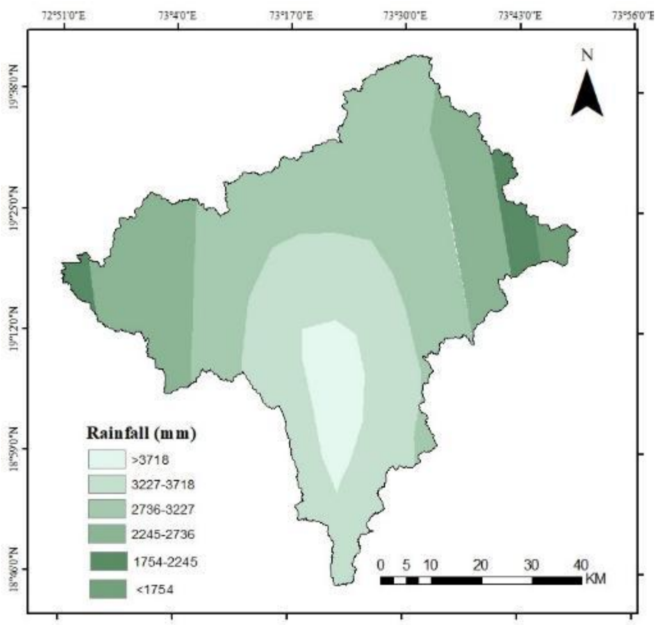
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Rainfall (mm)
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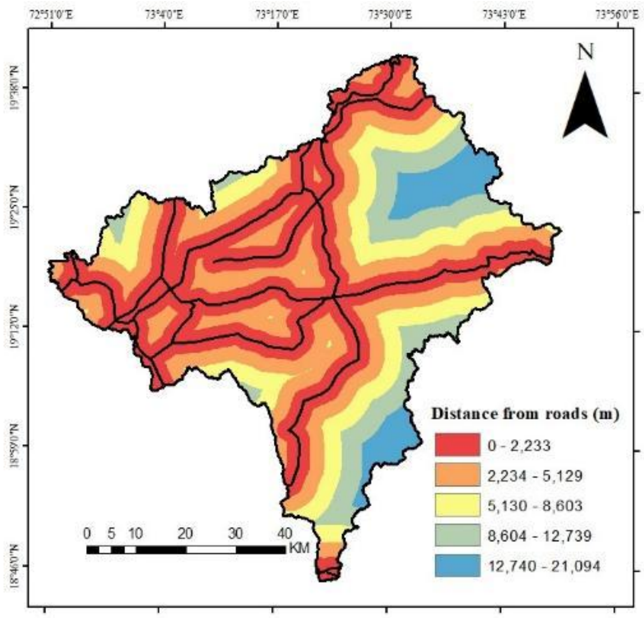
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Distance from roads (m)
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2,234 - 5,129
5,130 - 8,603
8,604 - 12,739
12,740 - 21,094
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KM

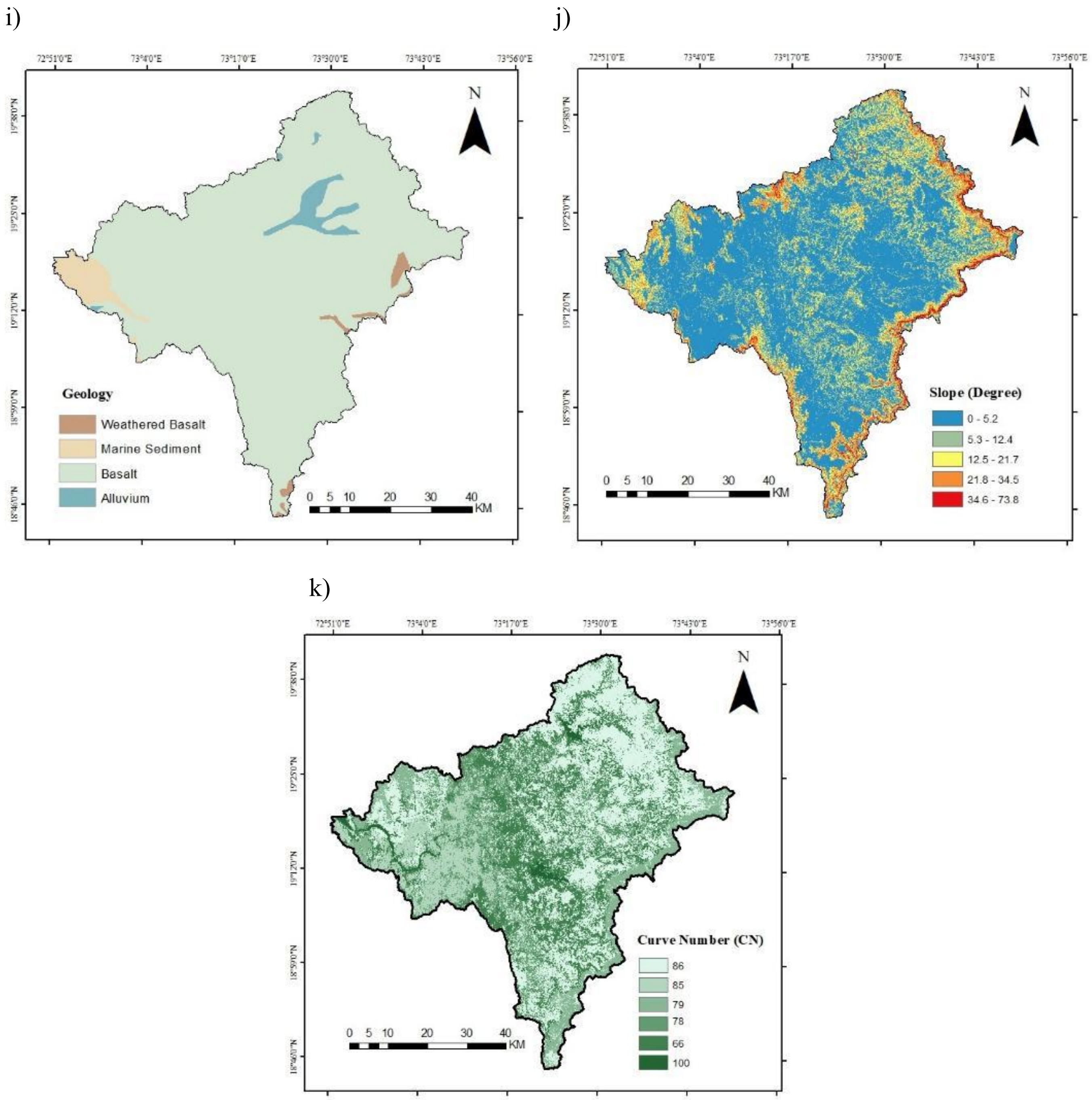

Fig. 2. Spatial distribution maps representing: a) distance to river, b) elevation, c) distance from fault lines, d) soil characteristics, e) land use and land cover (LULC), f) geomorphological features, g) rainfall pattern, h) road proximity, i) geological formations, j) slope, and k) Curve Number (CN).

The GNN has effectively learned naturally its own relative weight and mutual correlation among criteria without interference of human knowledge. Such data driven weight is more objective, as GNNs would optimize weights to increase predictive power rather than making any assumptions. Modified weights are interesting also to highlight this power of GNNs to encode complex relationships, for example, just by getting a model smart enough to recognize that moderate slope plus high rainfall and the proper geology together mean perfect conditions can raise some entire combination's implicit weight even if one of those things on its own was not top ranked. The result is a set of weights for the weights for criteria, that are more realistic and well reflect what factors ranked higher into deeming dam site suitable. Table 2 shows the weights calculated using the GNN.

In terms of quantitation, the importance of the 12 factors was redistributed in the generated weight vector by a GNN. The rank ordering of the most pressing factors was broadly in line with expert judgement, for example, both methods agree that hydrological and topographic attributes play a leading role. The GNN assigned most weight to a driver that was similarly highly weighted in the manual scheme showing suggestive evidence that some major determinants of suitability have been recognized correctly by experts. Although all of the other criteria did change, an attribute such as geological formation or distance to faults for example may have been assigned a greater weight by GNN than the manual MIF did. However, this also indicated that the model found stronger evidence regarding their important effects from the data. Conversely, variables such as land use/land cover or overall accessibility, which experts tend to weight based on subjective judgement, were sometimes accorded a lower relative weighting by the GNN, suggesting that these were less of an influence on successful dam placements than might have been guessed a priori. Such discrepancies suggest that the GNN was able to generalize from empirical spatial patterns, perhaps by recognizing that certain criteria trade off or substitute for one another. GNN-based weighting not only verified some of the expert-derived weight priorities but also improved the distribution way by considering inter-criterion influences that human may miss. This is a more elaborate basis for the multi-criteria decision analysis.

Table 2 Weights calculated using the GNN

Sr. No.	Factor	w_i^{GNN} (%)
1	Curve Number (CN)	3.604
2	Slope	9.193
3	Drainage Density	9.195
4	Geology	6.628
5	Proximity to roads	7.402
6	Rainfall	8.609
7	Geomorphology	5.703
8	LULC	8.497
9	Soil type	7.896
10	Distance from fault line	7.069
11	Elevation	17.373
12	Distance to river	8.832
Σ		100.000

Suitability mapping and validation

Table 3 shows the statistics of sustainable dam site suitability. The revised weight of the GNN was used in the GIS–MCDM (TOPSIS, overlay analysis) and new dam site suitability map was produced. The map is categorized into five suitability classes (very low, low, moderate, high, very high) used for easy comparison. Fig. 3 shows the delineated sustainable dam sites for dam. The spatial pattern of suitability within the study area in this map was consistent with that produced from previous investigations. Areas targeted as highly suitable by our previous approach tend to remain so in this new map and past low-suitability targets remain similarly low. This result is not surprising as the GIS layers used and TOPSIS ranking procedure remains unchanged. The percentage of the land in each class of suitability has changed slightly, however, because of the reweighted criteria. Remarkably, the GNN-weighted analysis tends to exhibit a better sense of extremes suitability identification. In the GNN-based result, this proportion has been modified to account for the improved weights, meaning that a number of locations characterized as being at the threshold between high and very high previously were re-categorized. A similar adaptation occurs for the other classes, the “high” class and the intermediate or “moderate”, with some areas transferring between them. In general, regions with multiple positive factors present are more likely to be reclassified into a higher class if they had otherwise fallen to places where just one attribute factor was strong, and the others were not as much. These reclassifications reflect the effect making use of data-driven weights, the GNN-based map arguably brings out truly optimal zones more clearly, filtering out some false positives that were too highly rated by manual weighting.

For instance, a particular subregion in the eastern side of the basin that was labeled "high" in the original raster. If the high rating of that area before was conditioned on an expert-assigned weight on some moderately important factor, then recalibration of the GNN could be led to a reassignment of that area to “moderate” in case other crucial aspects weren't just as good. On the other hand, another region that was “moderate” could be promoted to “high”, because GNN identified a strong conjoint influence of multiple factors, which were suppressed by uniform MIF weighting. While such changes may be small at large spatial scales, they can be significant for individuals managing where to target their efforts. Significantly, the new suitability map still maps out a similar set of top potential dam locations as before confirming that the site selection framework is effective. Five highest ranked dam site alternatives resulted in old and new analyses. The lists of the previously recommended sites are mostly maintained at top with weights based on GNN. The reordering of the sites by TOPSIS score was not very pronounced i.e., a site that ranked second before might be ranked first now if, in the shift of attribution weights during GNN weight adjustment, the properties of this site were favored more. These small changes in the ranking indicate that all of the candidate sites were already in acceptable zones and that the GNN weight places only minor adjustments to their relative rankings. In general, decisionmakers would still be deciding among the same pool of possible locations, but there would be more confidence in the ranking because the process for weighting is now more objective.

The use of a validation process by means of an appropriate location, such as the location where known dams exist or ground truth data is available, has confirmed higher prediction performance. When applying the method of validation as in the previous study (ROC curve) it was observed that a AUC of 0.826 was obtained using GNN-weights, which is significantly better than using manual MIF weights, with an AUC=0.806. This better ROC-AUC value shows higher discrimination performances of the new model in classifying suitable vs. non-suitable sites. A difference in AUC of 0.826 vs 0.806 is modest but important for intensive landscape forecasting, it implies there will be fewer errors introduced by model predictions. The curve says that for the various threshold settings, given that you are now identifying a higher percentage of actual suitable dam sites than before, this is balanced by an even higher proportion of sites not actually suitable identified as suitable. This improvement can be related to GNN’s capability of adjusting weights in a manner that moves the model output closer to the reality, thus leading to better agreement with the real distribution of favorable dam sites. In the multi-criteria framework, an increase in AUC of 2% point suggests a more than non-trivial gain in trustworthiness. It would push the model’s capability yet closer to that of “good” prediction potential for sustainable site selection. Furthermore, the increased AUC is an indication of predictive ruggedness, that we made less reliance on a single factor could mean that this criterion less sensitive to noise in any one criterion due to the GNN-based weighting. The outcome is a dam site suitability map which can be more trusting of the stakeholders as it has now been quantitatively validated to better determine real suitable sites on the ground. The integration of GNN-produced weights has provided an equal or better configured suitability zoning and significantly increased the model’s ability to predict suitable dam locations.

Table 3 Statistics of sustainable dam site suitability

Site suitability	**Area (sq.km)**	**Area (%)**	**Index range**
Very low	402.6	9.2	6.5 - 160.8
Low	955.7	21.8	160.8 - 255.7
Moderate	1140.0	26.0	255.7 - 348.6
High	1280.8	29.2	348.6 - 420.6
Very high	611.2	13.9	420.6 - 548.67

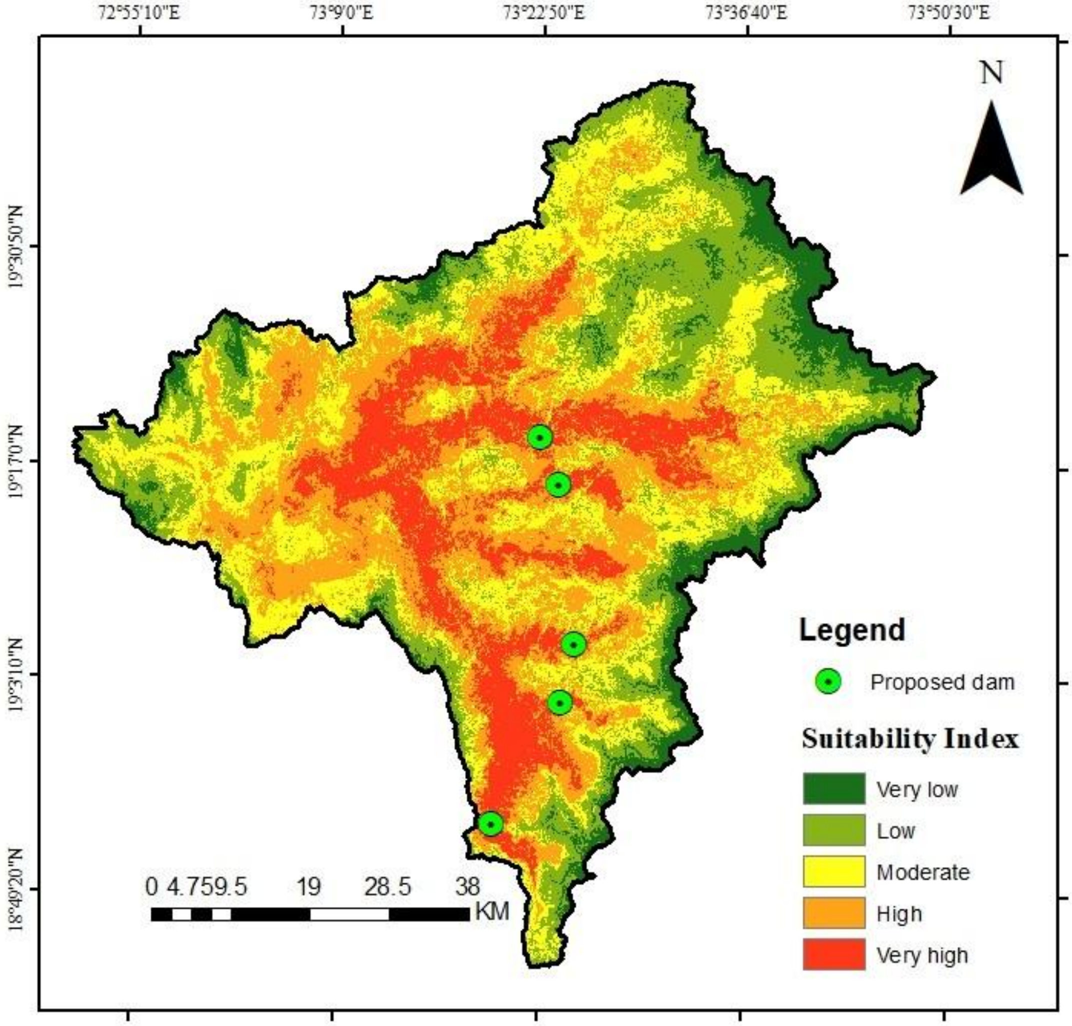

Fig. 3 Delineated sustainable dam sites for dam

Advantages of GNN-Based Weight Computation

The results emphasize a number of advantages in adopting a graph neural network to computing MCDM weights for dam site selection problem. First, the weighting process in GNN is highly objective. This is in contrast to manual MCDM weighting, which relies on human expertise leading to potential personal bias and discrepancy of judgment, while the GNN learns weights based on data patterns. This implies that the criterion weights are based on real relationships found in the study area rather than systems prior judgment. Because it reduces subjective bias, the GNN is designed to make the weight assignment reproducible and transparent; other human experts using the same training data would get exactly these weights, which cannot be said of a different expert assigning them. Such objectiveness is important in sustainable planning, which instills stakeholder confidence that the suitability analysis is an evidence-based one.

Second, it avoids non-linear entanglement among the factors and thus can learn from interdependences and complicated relationships of them. Classic MCDM weight assignment presumes that the influence of every criterion is essentially independent or can be replaced by linear combinations. In fact, environmental and geophysical processes are interconnected, slope of terrain might affect both soil depth and runoff together or rainfall effect may vary depending on land cover and geo-science. The GNN can capture such interconnected effects due to its architecture. It essentially works on a graph where spatial units or category interactions are defined, and influences can be propagated through the links. It has been shown that graph neural networks are effective at capturing relationships between geographical entities and utilise contextual information. This capability to encode dependencies also allows the resulting suitability layer to take conditional influence into account. This results in a more holistic weighting scheme. The GNN does not only ask “how important is factor X on average”, but rather “how important is factor X if it gets triangulated with Y and Z in a way that represents their position relative to each other.

Third, the employment of a GNN for weights calculation reduces possible human bias and error. Since human-derived weights are potentially biased by an expert’s finite local experience or stale assumptions, this benefit is problematic as well. By fitting the GNN to data we are permitting the model to update its estimate of the importance of criteria in light of evidence. This avoids the potential of overlooking factors which may be subtle, but crucial. It also eliminates the prejudices of “expert consensus,” in which multiple experts may subconsciously support each other’s views. Instead, the “opinion” of the GNN is that which emerges as patterns in data, which might show, for instance, that a factor traditionally weighed low actually usually correlates with unsuccessful dam sites and hence should be weighted higher to steer one away from low suitability areas. The AI-driven methodology effectively democratizes the weighting, it is not biased by any individual’s outlook but influences a much wider set of training relationships and examples.

Moreover, the GNN approach has practical advantages in terms of elasticity. With the model architecture and training process in place, updating weights is simple, adding new data to be worked on is often all that needs to be done. The GNN modifies the weights to reflect new patterns or changes, which would be a manual task of assembling experts and repeating pairwise comparisons or influence evaluations in an MIF/AHP process. This flexibility makes the framework future proof to some degree, as long as dam site selection continues to be calibrated according to the same conditions. It is important to note that use of AI-driven weighting leads to more consistent and quantifiable rationale behind the decisions. Applying GNNs into MIF weight calculation makes objectivity, learning complex bilateral factor interactions, treatment on weakening or even eliminating human factors and universalization of dam site selection process possible and the rationale is coherent.

Future directions for artificial intelligence in dam site selection

Recently developed deep learning architectures, such as convolutional neural networks (CNNs) to retrieve spatial features from remote sensing measurements [84,85], recurrent neural networks (RNNs) to capture temporal patterns in hydrological processes and autoencoders for reducing dimensionality are able to represent the nonlinear relationships among geological, hydrological, and environmental variables more accurately than conventional techniques. These techniques can lead to increased accuracy with respect to the discovery of suitable dam locations by being able to learn complex spatial temporal patterns on which site sustainability is based. Ensemble learning algorithms (e.g., random forests, gradient boosting) improve predictive models by providing a combination of several models. For example, studies have produced high classification accuracy of site suitability classes over various regions with these ensembles. Reinforcement Learning (RL) represents an evolutionary optimization framework by which an agent learns optimal locations to place or operate dams through trial-and-error in simulated environments [86,87]. Most interestingly, RL-based algorithms have achieved much better performance than human-engineered policies in challenging water operations such as multi-reservoir systems, suggesting their capabilities to optimize strategic site selection under uncertainties. New approaches to spatiotemporal modeling now allow time-series data (e.g., climate projections and seasonal runoff trends) to be incorporated with GIS-based spatial analyses, thus allowing planning decisions to be based on both current conditions as well as projected changes. The emergence of explainable AI (XAI) methods such as SHAP or LIME can be employed with these black-box models to determine which factors most influenced an AI’s advice, rendering results interpretable to decision-makers [88,89]. This traceability consequently leads to transparency and trust, a pre-requisite of long-term infrastructure planning. Emerging paradigms such as generative AI show promise. By simulating new data scenarios, generative models (e.g., GANs or diffusion networks) may generate synthetic environmental data to evaluate dam performance in extreme conditions that would help support resilient planning. Similarly, transfer learning allows adapting models trained with data-rich or related regions to other basins with little data, making cross-regional model generalization better. Active learning methods may include human experts in the loop, with possible iterations to force the model to concentrate on more informative spots or data points, making training more efficient and AI outputs consistent with expert knowledge. Compared with the central learning, federated learning is more collaborative. In federation learning multiple regions or agencies train a shared model on their own hardware using their own data without sharing privacy-sensitive raw data with one another, thus can be potentially generalized well to broader datasets and better ensures privacy. Hybrid AI-MCDM multi-criteria decision-making systems are also increasingly employed to combine data driven AI with proven decision analysis approaches. For instance, the GIS-based multi-criteria analysis of machine learning algorithms (e.g., analytical hierchy process and fuzzy logic) used to make dam site suitability maps. These hybrid models involve AI for sophisticated pattern recognition while applying MCDM to absorb experts´ criteria, thus obtaining a transparent and science driven selection procedure. These advanced AI-based methods can have the potential to greatly enhance dam siting decision-making as they increase methodological prediction capability and efficiency, improve interpretability of model outputs, and ready itself for a seamless integration within GIS data and multi-criteria evaluation frameworks.

4. Conclusions

This study demonstrates that the inclusion of AI-based GNN weightings within dam site selection can significantly improve the accuracy and reliability of MCDM analyses. Due to the automatic learning process of weights for multiple environmental and topographic factor, the subjective weight assignment is excluded in the GNN model, and multi-factor coupling complexity can be fully considered. The enhanced validation performance, including an elevated AUC of 0.826 suggests a more stable predictive model that is closer to real world applicability as compared with the previous manual-weighting model (AUC 0.806). The high-suitability zones and top-ranked dam sites in the study area, which were identified, not only complied with the known preferential locations (e.g. upper basin's narrow valleys), but also gained much confidence due to data-driven weighting. This AI incorporation has therefore increased the level of trust of the improved decision-making tool for planners and engineers, who can now be more confident that proposed dam sites have been vetted through sound, dispassionate analysis.

Significantly, the successful implementation of GNN-based MIF weighting in this case study demonstrates the wider applicability of AI and GIS-MCDM integration in water resource planning. The proposed approach is cost-effective, repeatable and can be applied over different sites at different scales to serve as a useful decision-support system for both dam location selection and beyond. This method can be used by planners in many situations such as reservoir site selection, planning of flood control structures, and other infrastructure location problems with conflicting objectives.

Author Contributions

AM: Conceptualization, study design, data collection, software, writing original draft, and writing review and editing. NLR: Data collection, methodology, software, visualization, writing original draft, and writing review and editing. JR: Data collection, methodology, software, resources, visualization, writing original draft, writing review and editing, and supervision.

Conflict of interest

The authors declare no conflicts of interest.

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