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Analyzing Urban Drinking Water System Vulnerabilities and Locating Relief Points for Urban Drinking Water Emergencies

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Abstract
Urban water is known as a critical sector of urban environments which significantly impacts the life quality and wellbeing of reinstates. In the context of developing sustainable urban drinking system it is critical to analyze network events and develop sufficient systems of water supply. To the best of our knowledge, fewer studies have examined the potential of automated-based approaches such as deep learning convolutional neural network (DL-CNN) for analyzing urban water network events and identifying the optimal location of urban drinking water relief posts. Therefore, the current study aims to propose an efficient approach for Geospatial based urban water network events analyze and determine the optimal location of urban drinking water relief posts in Zanjan. For this goal, first, we prepared and preprocessed various predisposing variables for analyzing the urban water network events and determining the optimal location of urban drinking water relief posts. We then applied an integrated approach of analytical network process (ANP) and DL-CNN methods to locate the best location of urban drinking water relief posts. Finally, intersection over union and accuracy assessment were employed to evaluate the performance of the results. Our findings show that the DL-CNN performed well with an accuracy of 0.942 compared to the ANP (0.895) for determining the optimal location of urban drinking water relief posts. According to the results, the best place to build a relief post is in the city center, and the surrounding areas may not be suitable, which is in accordance with field work analysis. The results of the study also reveal that areas 5 and 3 are at high risk from the number of urban water network events perspective, which requires the construction of urban water relief stations.

Keywords Urban water network events · A novel approach · Geospatial analysis · Water relief posts · Zanjan city

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1 Introduction

Water consumption has significantly increased over the past few decades as a result of climate change and global warming, advancing technology and industry, and a growing population around the globe (Fang and Chen 2015; Flörke et al. 2018; Gopika et al. 2021; Feizizadeh et al. 2021a). The ever-increasing growth of urbanization leads to population density and the subsequent increase in the size of the urban water network (United National World Water Assessment Programme 2016; Lamm et al. 2018). A growing population, in combination with factors such as building density and worn-out water transmission networks, has led to water leakage in urban water distribution systems (Polsky et al. 2014; Han et al. 2022). It wastes large amounts of purified water, thus it is important to pay attention to incidents that endanger this resource. The occurrence of accidents and the inefficiency of drinking water network infrastructure is a serious threat to the sustainability of drinking water resources in the long term (Warner et al. 2015, 2016; Pan et al. 2021). In water distribution, leaks and broken pipes cause water losses. Some types of leaks can be considered cost items for urban networks and facilities (Fang and Chen 2017).

Leakage in networks depends on the amount of water pressure in the network, the diameter of the pipe, the number and type of connections, and the type of pipes (Pratap 2020; Ali et al. 2022). It is common for main lines, branches, fire valves, tanks, flare valves, and other related accessories to break and leak for a variety of reasons (Hu et al. 2022). The problems caused by the age of urban networks and the wear and tear of the components of the networks are part of the increasing problems of water and sewage companies (Liu et al. 2021; Rathore et al. 2022). A large number of events can result in breakdowns, traffic, and decreased water pressure in urban water distribution networks, along with water loss (Xiong et al. 2020; Molinos-Senante et al. 2022). Water and sewage companies are affected by this issue in a way that results in losses rather than profits (Macías Ávila et al. 2022).

It is well known that leaks in distribution networks waste a significant amount of water (Zhou et al. 2022). To deal with these issues, such events can, however, be controlled in such a way that losses are minimized and within an acceptable economic range. This can be done with proper management and implementation of appropriate solutions (Lamm et al. 2016). This issue is especially turned to be more critical due to the problems of the water crisis and the high percentage of water loss in urban water distribution networks in the country (Takai Eddine et al. 2023). Sufficient and detailed information regarding the map of a city's water supply network and the factors that cause accidents in the network (e.g., the density of piping, the population concentration, the number of connections, etc.) is of great importance for urban water management (Deng et al. 2018; Dinar et al. 2019; Zhong et al. 2023). In this context, advances in the field of detailed studies of urban services and the use of remote sensing and geographic information systems (GIS) lead to identifying impacting factors and indicators to provide optimal solutions (Attwa and Zamzama 2020).

Water and sewage networks have benefitted from the use of GIS in recent decades (Wang et al. 2020; Fang et al. 2020; Lam et al. 2021; Conicelli et al. 2021; Calle et al. 2021; Chen et al. 2022a, 2022b), supporting managers, planners, and designers to investigate, analyze, and monitor events. The use of GIS in advanced societies has assisted in improving the state of sewerage infrastructures and in controlling events using reducing human and financial losses caused by dangers (Tsihrintzis et al. 1996). Applying novel technologies such as GIS in concert with multi-criteria decision-analysis(MCDA), leads to considering a sufficient sewerage network before a crisis occurs by recognizing, analyzing, and planning to reduce factors that lead to events (Lam et al. 2021; Fernandes et al. 2021).

Although GIS has high and unique spatial capabilities, it requires techniques to optimize location decisions. The spatial multi-criteria decision problem also involves evaluating a number of locations based on several criteria (Vojtek et al. 2021). Over the last few decades, machine learning methods have been used to optimize decision-making in many other sciences (Santos et al. 2017; Teixeira and Secchi 2019; Stapleton et al. 2019; Lee et al. 2019; Roy et al. 2023; Shakeel and Shakeel 2022; Zhang et al. 2023). In this regard, deep learning (DL) as one of the most popular machine learning methods , employs a nonlinear relationships between high-dimensional inputs which indicates multi-linearity, resulting in better accuracy for estimation (Kazemi Garajeh et al. 2021; Sun et al. 2023). State-of-the-art machine learning algorithms, particularly deep learning (DL), excel in capturing complex nonlinear relationships by utilizing multilayered stacks that enhance representation complexity and abstraction (Fu et al. 2022). The water network system is one of the fields in which DL can increase efficiency and reduce errors in decision-making positioning and routing activities (Kazemi Garajeh et al. 2022a). The integration of DL in the field of positioning with GIS will greatly increase the efficiency of this system, which is the most important challenge facing experts and analysts in solving complex problems in decision-making (Wai et al. 2022; Leite de Melo et al. 2022). A brief review of the research literature indicates high efficiency of integrated DL, MCDA techniques and GIS for modeling and monitoring the earth's features. This framework can contribute to identifying the most appropriate sites for urban drinking water post reliefs, which can fix the defects in the urban water supply systems and provide an effective way to enhance the effectiveness of urban water and sewage services against the reduction of waste, pollution, and possible hazards to the flow of urban water. To the best of our knowledge, fewer studies have examined the potential of automated-based approaches such as DL for analyzing urban water network events and identifying the optimal location of urban drinking water relief posts. An element of novelty of this study can be seen in the fact that comparison of the presented approaches for identifying the most suitable spots for urban drinking water relief posts lacks in literature. In addition, these approaches are applied for the first time in Iran when applying for identifying the most suitable spots for urban drinking water relief posts at regional spatial scale. Therefore, the main objective of this research are; a) to analyze events, which include leakage and water cut in the urban water network through statistical methods b) to propose a deep learning convolutional neural network (DL-CNN) based framework to identify the optimal location of urban drinking water relief posts, which can work as a supportive platform for urban water management, and c) to compare the performance of DL-CNN technique with analytical network process for identifying the most suitable spots for urban drinking water relief posts.

2 Study Area

Zanjan with a population of 386,851, is located in northwest Iran (Fig. 1). The area has experienced a semi-arid climate condition, which has limited the availability of water resources. Approximately 70% of the city's drinking water is derived from underground water resources, which contribute to the supply of drinking water and agriculture. In the province, surface water makes up 25% and underground water makes up 75% of the total water resources. Surface water resources in the province are exploited at a rate of 10%, while underground water resources are exploited at a rate of 78% (these ratios are equivalent to 47% and 88% in the entire country). This sector, particularly the surface water

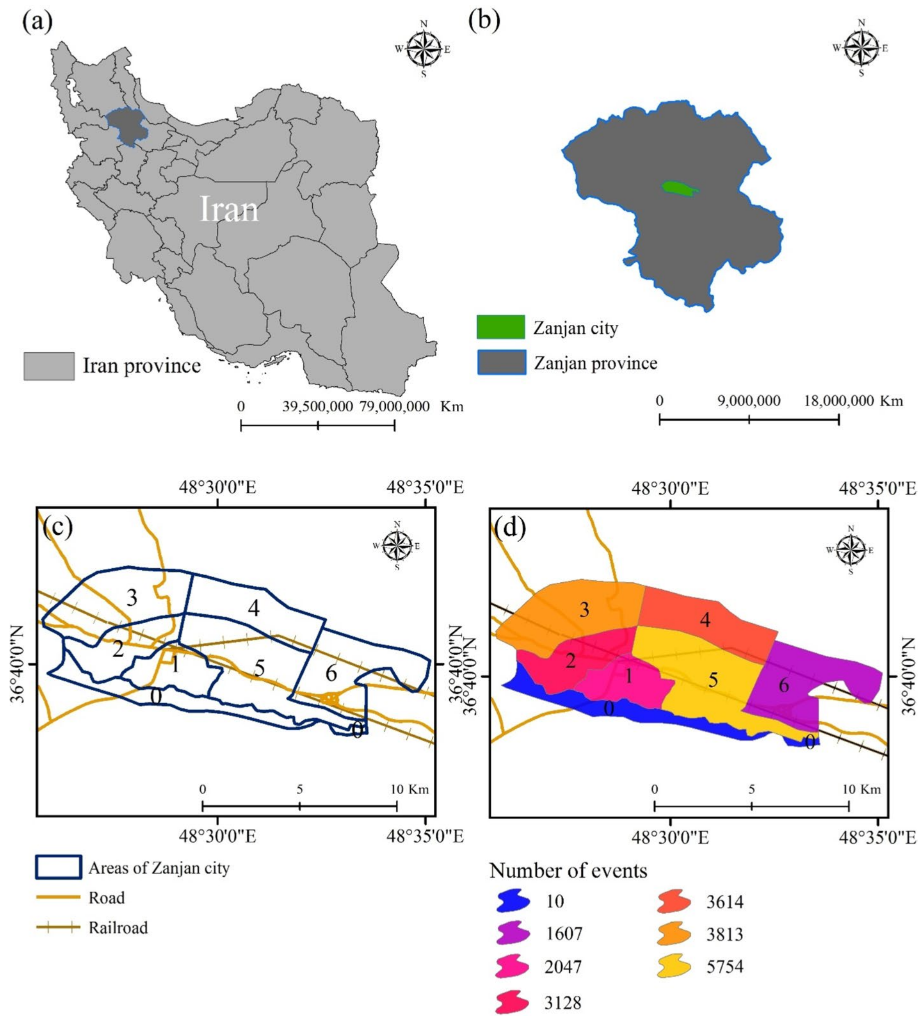

Fig. 1 Location of the study area; **a**) in Iran, **b**) in Zanjan Province, **c**) areas of Zanjan city, and **d**) distribution of urban water network events in different areas (Water and Sewerage Organization of Zanjan)

resources, can be developed to a large extent. If the unused capacities of the province's water resources are utilized, the agricultural, animal husbandry, and industry sectors will benefit. In this province, there are 264,000 water subscribers, and 154,000 m^3 of water are consumed every day, more than three times the international standard.

In Zanjan, 21.8% of the water has wasted per day. Table 1 shows the number of water network events from 2012–2018. Figure 2 also reveals several examples of the most common urban water network events. There have been 5754 events related to water networks in area 5 of Zanjan, according to Table 1. Additionally, it has 35,145 water subscribers. In the second category, there are 3813 water network events in area 3, and the lowest number of water network events is in area 6, with 1607 events (Studies of Water and Wastewater Company of Zanjan 2016). In this regard, a new framework is necessary to manage water resources for reaching an optimal strategy.

Table 1 Number of water network events recorded from 2012–2018 per area (Water and Sewerage Organization of Zanajn)

Area	Number of subscribers	Number of events
1	14,402	2047
2	18,661	3128
3	23,483	3813
4	18,317	3614
5	35,145	5754
6	10,226	1607

Fig. 2 Several examples of the most common urban water network events in Zanjan city (Water and Sewerage Organization of Zanjan)

3 Materials and Methodology

3.1 Materials

There are two main categories of data used in this study. Descriptive data is the first category of recorded data. These data and information related to 19,963 events recorded in the city's sewer network from 2012 to 2018 obtained from Zanjan Water and Sewerage Organization (ZW-SO). The second category is spatial data, which was obtained from the deputy municipality and governorate of Zanjan province (Fig. 3). Various predisposing variables and their resources are listed in Table 2 for analyzing urban water network events and determining the optimal location of urban drinking water relief posts. Training and validation of machine learning-based models and image classification algorithms require valid

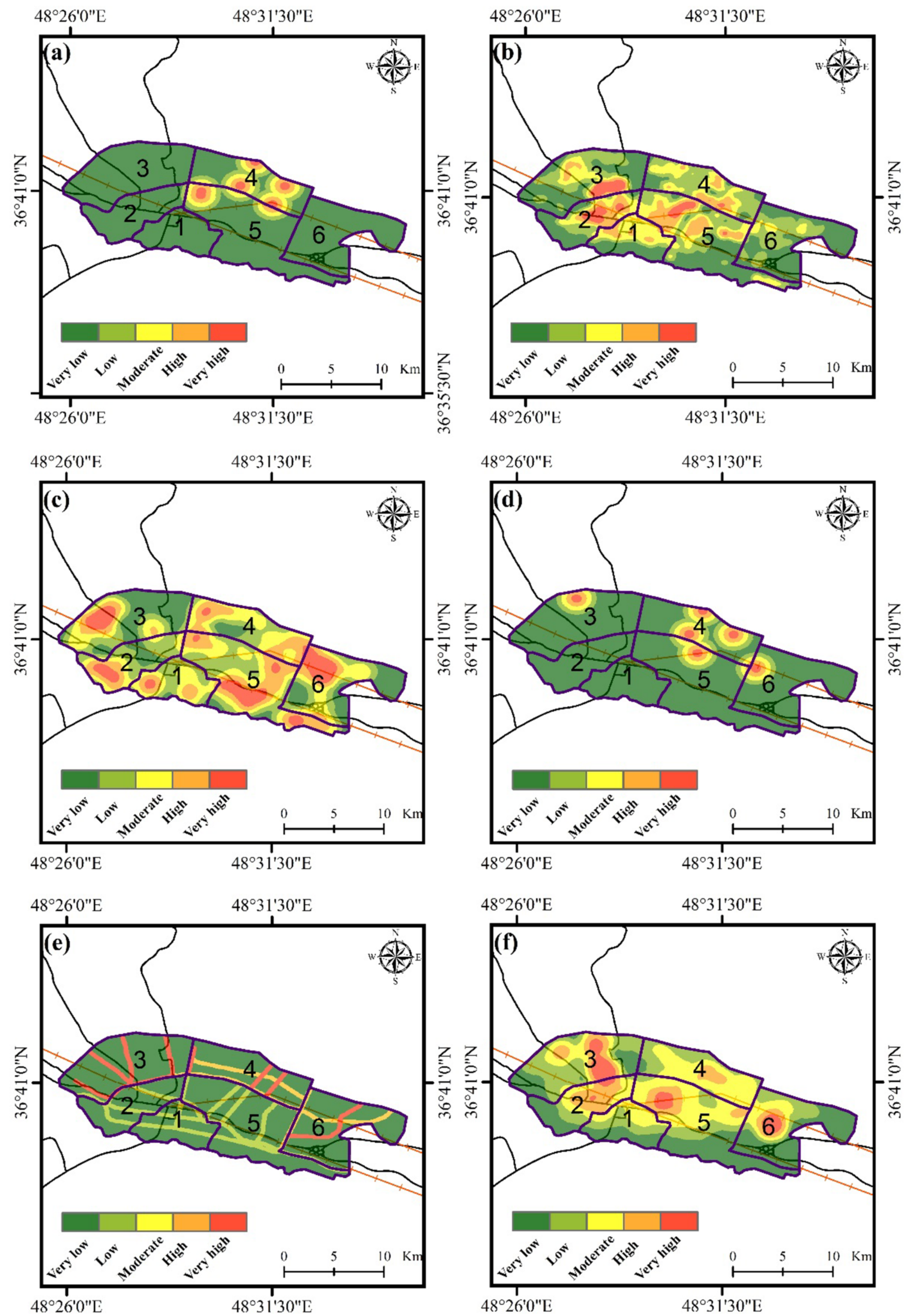

Fig. 3 Various predisposing variables to analyze urban water network events and locate the optimal location of urban drinking water relief posts, **a**) distance from water storage sources, **b**) accident-prone areas, **c**) areas with high water pressure, **d**) distance from pump stations, **e**) traffic density, **f**) population density, **g**) road networks, **h**) landuse, and i) slope

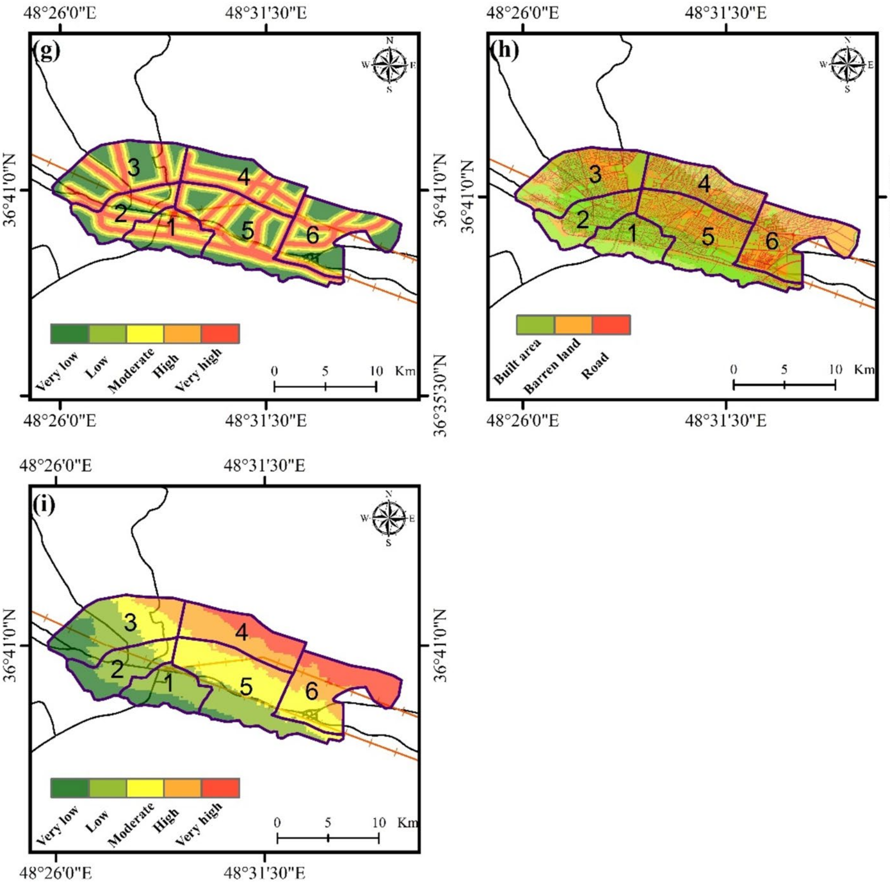

Fig. 3 (continued)

Table 2 Predisposing variables obtained from different sources to analyze urban water network events and identify the optimal location of urban drinking water relief posts

Data types	Name	Source
Descriptive	Water storage sources	Water and Sewerage Organization
	Accident-prone areas	Water and Sewerage Organization
	Areas with higher water pressure	Water and Sewerage Organization
	Pump stations	Water and Sewerage Organization
	Traffic density	Municipality of Zanjan
	Population density	Governorate of Zanjan Province
Spatial	Road network in the scale of 1/2000	Municipality of Zanjan
	Land use in the scale of 1/2000	Governorate of Zanjan Province
	Slope	Topographical map in scale of 1/2000

inventory data (Tavakkoli Piralilou et al. 2019). Thus, 354 ground control points (GCPs) were collected using GPS from the study area where most water network events occurred. As rule, we employed about 70% of the ground control points (GCPs) as training data, and the rest 30% was used as validation data (Fig. 4).

3.2 Methodology

An overview of the methodology for analyzing urban water network events and determining the optimal location of urban drinking water relief posts is shown in Fig. 5.

3.2.1 Implementation of Analytical Network Process

Modeling analysis extensively employs analytical networks, and GIS-MCDA is the most common context in which they are utilized (Musakwa et al. 2017; Kausika et al. 2017; Achu et al. 2020; Shao et al. 2020; Fernandes et al. 2021; Feizizadeh et al. 2021b). Analytical Network Process (ANP) is more efficient because it identifies possible dependencies among the selected criteria (Saaty 1980). The decision-making process of an ANP model is elucidated through clusters and nodes. Beyond offering a systematic approach to handling dependencies, ANP models excel in resolving intricate problems involving interdependent relationships. We can use the pairwise comparison matrix from Table 3 to create a new matrix and evaluate factors on a scale ranging from 1 to 9 (Saaty 1980). ANP involves constructing a network by organizing elements and potential substitutes into clusters. These elements can be interconnected in various ways within the network, with feedback and interdependence connections present both within and between clusters (Saaty and Ozdemir 2021). The formula for the component of the super-matrix is as follows:

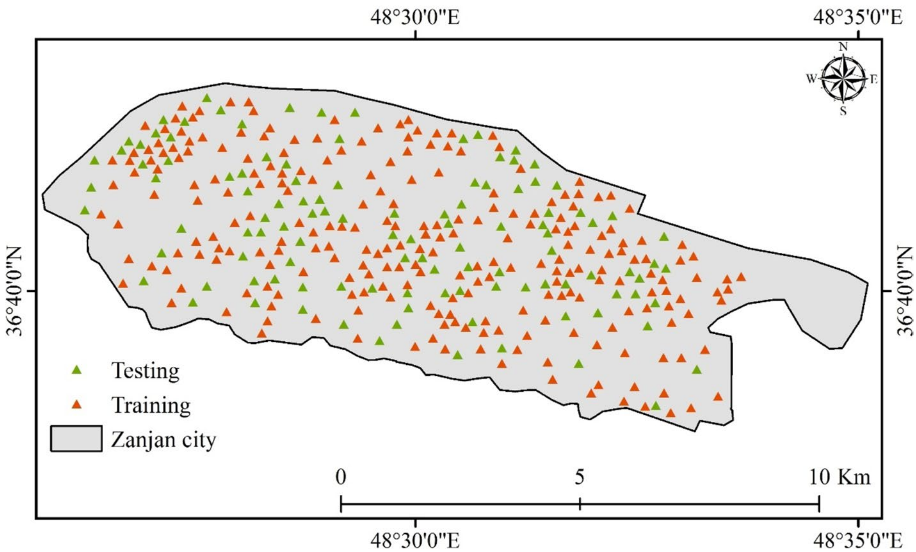

Fig. 4 Distribution of training and testing datasets over the study area

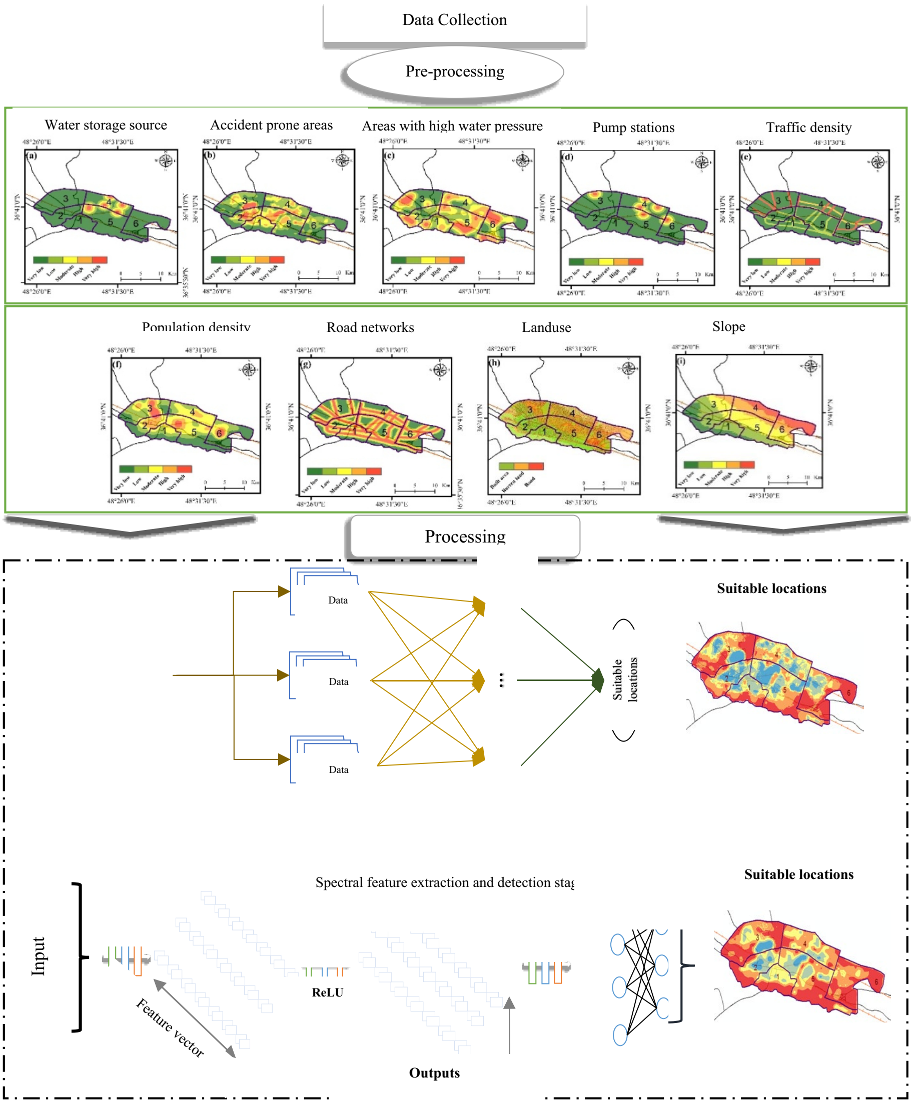

Fig. 5 An overview of the present study's methodology

$$W = \begin{bmatrix} W_{i1}^{(j1)} W_{i1}^{(j2)} \dots W_{i1}^{(jn_j)} \\ W_{i2}^{(j1)} W_{i2}^{(j2)} \dots W_{i2}^{(jn_j)} \\ \vdots \ \vdots \vdots \vdots \\ W_{in_i}^{(j1)} W_{in_i}^{(j2)} \dots W_{in_i}^{(jn_j)} \end{bmatrix} \tag{1}$$

where the *ij* element in the matrix is the ratio of the priorities of W_i and W_j of the *i* and *j* alternatives. *n* also is the number of variables.

Table 3 Various predisposing variables for determining the optimal location of urban drinking water relief posts and their weights using the ANP

Rank	criteria	Weight obtained by ANP	Importance level	Ranking scale in ANP framework
1	Accident-prone areas	0.251	Equally important	1
2	Road networks	0.177	Equally crucial to slightly more important	2
3	Land use	0.158	Slightly more important	3
4	Traffic density	0.105	Slightly more important to much more important	4
5	Areas with higher water pressure	0.090	Much more important	5
6	Subscribers	0.075	Much more critical to very much more important	6
7	Population density	0.067	Very much more important	7
8	Water storage sources	0.038	Very much more important to extremely importance	8
9	Pump stations	0.035	Extremely importance	9

The priority for each pairwise comparison matrix is computed independently. Subsequently, the outcomes of all pairwise comparison matrices are amalgamated into a super-matrix, facilitating the determination of the final weighting for the elements (Saaty 1980). In the network, the super-matrix W represents the influence of one element on another, depicting interrelationships between elements. Clusters in the ANP are formed by organizing matrices of criteria and 11 potential substitutes, arranged from small to large. The network can incorporate various substitutes or alternatives, intertwining them with interdependencies and feedback mechanisms between clusters (Saaty 2004). In the ANP model, pairwise comparisons use a foundational scale with values ranging from 1 to 9, providing a framework for expert evaluations. Table 3 provides this ranking. Table 3 also shows the cluster matrix based on the ANP for determining the optimal location of urban drinking water relief posts. Accident-prone areas, Road networks, and Land use were prioritized as the first, second and third variables with weights of 0.25158, 0.17748, and 0.15859, respectively for determining the optimal location of urban drinking water relief posts, as shown in Table 3.

3.2.2 Implementation of Deep Learning Convolutional Neural Network

Training Phase Neural networks commonly consist of input layers, hidden layers, and output layers, which work together to process and produce desired outputs (Li et al. 2021). Depth in a neural network is determined by the number of hidden layers and the output layer. Apart from the input layer, these layers consist of neurons (Kazemi Garajeh et al. 2022b). Hidden layers in a neural network depict processed factors, where each neuron functions as a convolutional layer. Typically, each convolutional layer integrates various elements, such as a pooling operation, multiple weights, and an activation function (Zhang et al. 2020). Pooling in neural networks entails reducing feature vectors by consolidating the results of an $N \times 1$ patch from the previous convolutional layer into a single value at the next layer. Among the various pooling layers, max-pooling is the most commonly employed, retaining only the maximum values from the feature maps. In CNN, max-pooling is widely regarded as a fundamental operation (Sun et al. 2019; Zhu et al. 2020), which is defined by Eq. (2).

$$O^l = P(\sigma\left(O^{l-1} \times W^l + b^l\right)) \tag{2}$$

where O^{l-1} is the output feature from the earlier layer of the l th layer, W^l and b^l are the weights and biases of the layer, respectively, which convolve O^{l-1} by the linear convolution, and σ is the non-linearity function outside the convolutional layer.

In the quest to identify optimal locations for urban drinking water relief posts, this study employed a nine-layer CNN structure. The CNN was trained independently, using an input window size of 128×128. In the process of feeding the CNN with nine layers, the input sample patch consisted of $b \times b \times 9$ units, where b represents 128. Multiple convolutions were applied to the input, each utilizing a distinct 2×2 filter, resulting in different feature maps. These feature maps were then stacked together to form the ultimate output of the convolutional layer. For this study, nine different filters (one per convolutional layer) were employed, generating nine feature maps each of size $128 \times 128 \times 1$. The final output of the convolutional layers, representing the locations for urban drinking water relief posts, was produced by stacking all features along the depth dimension, resulting in a volume of $128 \times 128 \times 9$.

Activation Function Activation functions are placed at the end or within neural networks to determine whether a neuron will activate or not (Dewa and Afiahayati 2018). Generally, three activation functions are used namely sigmoid, hyperbolic tangent (tanh), and Rectified Linear Unit (ReLU). The most commonly used activation function in neural networks is currently the ReLU. (Dewa et al. 2018). Unlike alternative activation functions, ReLU transforms all negative inputs to zero and selectively activates neurons instead of doing so simultaneously. This efficiency arises from the fact that only a few neurons are activated at any given time (Dahanayaka et al. 2022). Thus, we used the ReLu to train the water relief posts model. In Eq. (3), the ReLU parameters are defined as follows:

$$ReLu(x) = \max(x, 0) \tag{3}$$

where x is the input vector from neuron that will be activated.

Loss/cost Function Loss functions play a pivotal role in neural networks, serving as one of the most crucial components, along with optimization functions, responsible for fitting the model to the provided training data (Xie et al. 2021). The loss function evaluates the fidelity of a neural network's representation of the training data by comparing predicted and target output values. The objective during training is to minimize the disparity between the predicted and actual outputs (Pezzano et al. 2021; Fu et al. 2022). Cross-entropy was used in this study to measure the performance of a classification model. Loss functions based on binary cross-entropy are widely favored for binary classification tasks (Yin et al. 2021). It is defined by the following equation:

$$L(y, \hat{y}) = -\frac{1}{N} \sum_{i=1}^{N} \left(y_i \log\left(\hat{y}_i\right)\right) + \left(1 - y_i\right) \log(1 - \hat{y}_i)) \tag{4}$$

where N is the number of sample datasets, y_i is the actual output of ample i, which is equals to 0 or 1, $\hat{y}_i$ is the forecasted possibility sample i having output 1, and $y_i, \hat{y}_i$ are the vectors of actual outputs and forecasted possibilities.

Optimization Function Algorithms or strategies used for optimization reduce losses and ensure accurate results (Kim et al. 2021). Optimization algorithms commonly used for this purpose include SGD (Stochastic Gradient Descent), Adam (Adaptive Moment Optimization), RMSProp (Root Mean Square Propagation), SGD + Momentum, Adagrad and Adadelta. In this study, we employed ADAM to optimize the performance of a classification model. ADAM operates with first and second-order momentums to enhance the optimization process (Hamdi et al. 2019; Bai et al. 2021). The rationale behind Adam is to gradually decrease velocity during optimization, promoting a more meticulous search rather than rapidly traversing potential minima. Adam maintains both an exponentially decaying average of past gradients and an exponentially decaying average of past squared gradients, similar to AdaDelta. This approach contributes to adaptive learning rates and efficient optimization (Kim and Cho 2021). Equations (5) and (6) are defined as the ADAM optimizer:

$$m_t^{(j)} = \beta_1 m_{t-1}^{(j)} + (1 - \beta_1) g_t^{(j)} \tag{5}$$

$$v_t^{(j)} = \beta_2 v_{t-1}^{(j)} + (1 - \beta_2)(g_t^{(j)})^2 \tag{6}$$

where β_1 and β_2 are new introduced hyper-parameters of the algorithm, which are commonly chosen to be 0.9 and 0.999, respectively. m and v are moving averages, and g is gradient on current mini-batch. The first and second moments are then bias-corrected:

$$\widehat{m}_t^{(j)} = \frac{m_t^{(j)}}{1-\beta_1^t}, \widehat{v}_t^{(j)} = \frac{v_t^{(j)}}{1-\beta_2^t} \tag{7}$$

And used to weight the update:

$$w_{t+1}^{(j)} = w_t^{(j)} - \frac{\alpha}{\sqrt{\widehat{v}_t^{(j)}} + \varepsilon}\widehat{m}_t^{(j)} \tag{8}$$

where w is model weights and α is the initial learning rate, which the default value for it is 0.001.

Validation Validation is a crucial aspect of spatial modeling, aiming to assess the reliability and accuracy of the obtained results (Lyons et al. 2018). The results of ANP and a nine-layer CNN were assessed using intersection over union (IOU) and accuracy (ACC), which are defined by Eqs. (9) and (10), respectively. Table 4 shows the results of ANP and a nine-layer CNN. According to Table 4, DL-CNN performed well with an ACC of 0.942 for determining the optimal location of urban drinking water relief posts compared to ANP (ACC of 0.895).

$$IOU = \frac{AO \bigcap EO}{AO \bigcup EO} = \frac{TP}{TP + FP + FN} \tag{9}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{10}$$

Where AO is actual output; EO is on behalf of expected result; TP, FP, FN, and TN are true positive, false positive, false negative, and true negative, respectively.

4 Results and Discussion

4.1 General Information

The urban water network is one of the critical factors of urban life. Existing published works usually adopt specific learning-based techniques for water quality assessment (Wai et al. 2022), mitigating urban water hazards (Allen-Dumas et al. 2021) and water deficits (Melo et al. 2022). Hence, there is a huge demand for advanced technologies to monitor urban water

Table 4 Results of accuracy assessment for a nine-layer CNN using IOU and ACC indexes

Accuracy assessment	ANP	CNN
IOU	0.805	0.837
ACC	0.895	0.942

network behavior and assess its defects. Previous studies have examined the potential of automated approaches, such as DL, for analyzing events in urban water networks and identifying optimal locations for urban drinking water relief posts. A novel aspect of this study can be observed in the lack of a comparison of the presented approaches for identifying the most suitable spots for urban drinking water relief posts in the existing literature. Additionally, these approaches are being applied for the first time in Iran to identify the most suitable locations for urban drinking water relief posts at a regional spatial scale.

In this study, we proposed and developed a novel framework for analyzing urban water network events and determining the optimal location of urban drinking water relief posts. Results show that the automated DL-CNN approach outperforms the ANP with an ACC of 0.942 (Table 4). Figure 6 also reveals the results of ANP and the DL-CNN for determining the optimal location of urban drinking water relief posts. As shown in Fig. 6, the central parts of the city were determined as the most appropriate place for constructing urban drinking water relief posts. According to data analysis and descriptive statistics, Zanjan city's Islamabad, Farhang, and Bisim neighborhoods have more events. Upon reviewing the areas of Zanjan city, it found that areas 5, 3 and 4 are at high risk. By establishing a positive correlation between events in the water network and variables such as population density, water pressure, and water subscribers, it can be demonstrated that these variables are related. Based on results obtained from the ANP and DL-CNN, it is obvious that the most suitable places for building a relief post are in the center of the city and surrounding areas are not suitable due to barren lands and sparse population. Area 5 is the urgent district for the construction of an urban water relief station, and areas 3 and 4 are the next priorities.

The Relationship between Predisposing Variables and Urban Water Network Incidents

By examining the population of Zanjan city, it was found that urban area 5 has the largest population (109480) and urban area 1 has the lowest population (30028) (Tables 1 and 5). Islamabad neighborhood also has the most population in terms of

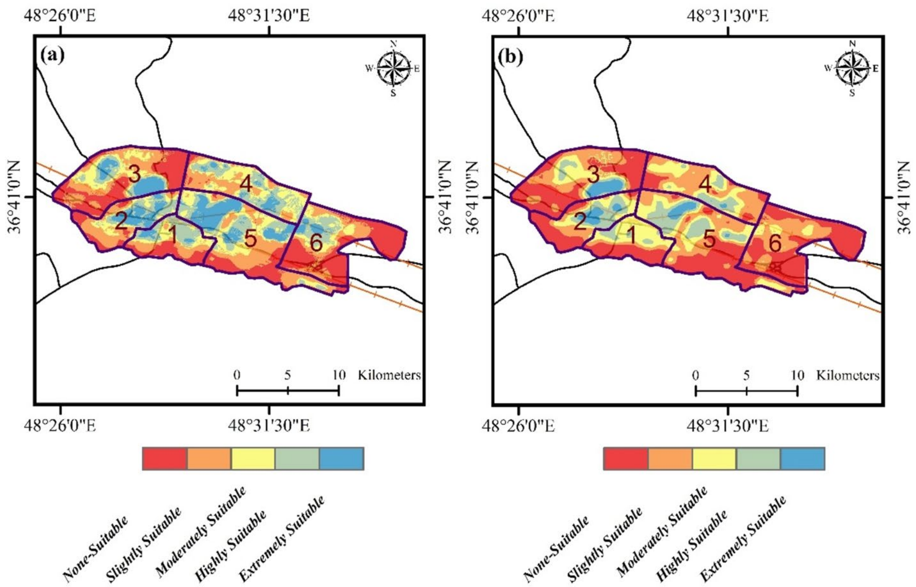

Fig. 6 Determined areas for locating urban drinking water relief posts; **a**) using the ANP, and **b**) using the DL-CNN

Table 5 Events of Zanjan urban water network in different urban areas

Area name	Population	Number of neighborhood	Number of events
1	30,028	16	2047
2	56,320	19	3128
3	100,384	24	3813
4	76,265	21	3614
5	109,480	28	5754
6	52,577	12	1607

Table 6 Incidents of Zanjan urban water network in different urban neighborhoods

Rank	Neighborhood name	Population	Number of events
1	Islamabad	24,464	1643
2	Bisim	18,406	998
3	Farhang	15,531	880
4	Paein Kooh	12,939	830
5	Foroudgah	12,671	667
6	Ziba shahr	7794	665
7	Ansarieh	7722	656
8	Trans	10,527	480
9	Masjed shohada	6819	393
10	Meshki	7094	376
11	Bitol Moghadas	43	328
12	Shahed	36	564
13	Yeri Bala	33	235
14	Gholestan	30	26
15	Goljik Abad	21	610
16	Rah Ahan	21	631
17	Zafaranieh	19	264
18	Daneshgah	5	362
19	Ghabrestan Bala	2	65
20	Amadghah	2	1023

neighborhoods, which is located in area 5 (Tables 6). By examining and analyzing the relationship between events and population density, a positive relationship was found (coefficient correlation of 0.90%) between these two variables in most localities. The survey of urban neighborhoods shows that in the neighborhoods of Islamabad, Bisim, Farhang, Paein Kooh, and Foroudgah, there is a very high and strong relationship between urban water network events and population density. In other words, with the increase in population, the number of events in the urban water network increase. This means that growing populations are putting enormous pressure on the water net-work by consuming huge amounts of water and as a result increasing water network events. Table 6 also shows a low relationship between urban water network events and population density in Daneshgah, Ghabrestan Bala, and Amadghah neighborhoods.

According to the study, there is a positive correlation between water pressure and event density. A comparison between the pressure of night and day and the density of events in the localities reveals that the relationship between the two variables is greater at night (coefficient correlation of 0.16%) than during the day (coefficient correlation of 0.04%). The results of the study show a significant correlation between the density of events in the neighborhoods of Islamabad, Bisim, Paein Kooh and the pressure of night and day. Analyzing the relationship between subscriber numbers and urban water network events reveals a positive correlation (correlation coefficient of 0.76%). Thus, as subscribers increase, events also increase. The most common urban water network event involves water leakage from water pipes and related branches. Water leakage from the water meter and related branches is recognized as the most common urban water network event. According to the correlation coefficient between the independent variable (slope) and the dependent variable (urban water network events), the two variables have a lower correlation (Correlation Coefficient of 0.05%). In Zanjan, the majority of the terrain is flat with a low slope, so the relationship between events and the slope is not significant.

4.2 Vulnerable Water Transmission Networks in Terms of Events

Upon investigating and analyzing the events in the urban drinking water network, it was determined that the Islamabad neighborhood water network had the most events. This issue in the Islamabad neighborhood is primarily caused by wear and tear, improper implementation of water, low-quality pipes and consumables, improper use of the network, and excavations done by other organizations. According to this study, 19.31% of the events are caused by leaks of the main branch, which are the most common occurrences in this neighborhood, followed by fractures with 17.44%, and the lowest type of accidents in this neighborhood is related to land subsidence. It was determined from investigating and analyzing the events occurring in the urban neighborhoods of Zanjan that Islamabad, Farhang, and Bisim are among the neighbor-hoods with high vulnerability, while Ghabrestan Bala and Gholestan are among the neighborhoods with low vulnerability. Additionally, areas 5 and 3 accounted for the majority of events in urban areas.

4.3 Analysis the Efficiency of the Applied Methods for Analyzing Events in Urban Water Networks

Analyzing network events and establishing robust water supply systems are crucial aspects when it comes to developing a sustainable urban drinking water system. Applying an automated approach, such as DL in conjunction with GIS, can significantly enhance the efficiency of urban water network management. The methodology introduced in this study also serves as an early warning system for stakeholders and decision-makers in the domain of water hazard events. With this information, locating optimized sites for promptly constructing relief posts to respond immediately to water network events becomes much easier and faster. Despite the efficiency of the applied method, having a large number of input datasets is crucial to constructing the DL models. The effectiveness of this work proves useful for analyzing urban water events in big cities around the world with the most complicated water networks. By employing learning-based approaches, such as DL, stakeholders can analyze vast amounts of data and gain insights that were previously impossible to obtain. DL can be used to predict water demand and optimize water supply throughout the day, assisting water utilities in reducing water waste and ensuring effective fulfillment of water demand. Additionally, it is employed to predict and mitigate potential risks associated with the water cycle.

5 Conclusion

This study proposed and developed an innovative approach of ANP and DL-CNN for analyzing urban water network events and determining the optimal location of urban drinking water relief posts in Zanjan city, Iran. The results show that the central parts of Zanjan are more suitable for constructing water relief posts. Our findings demonstrate the highest efficiency of an automated DL-CNN with an ACC of 0.942 compared to the ANP with an ACC of 0.895. The findings of this study also indicate a positive relationship between population density and water network events. The results of this research demonstrate the highest efficiency of computer-based approaches such as DL-CNN for determining the optimal location of urban drinking water relief posts. In sum, the findings of this research provide a deeper understanding of the spatial spreading of urban water network events and their affected areas. The efficiency of this study can help urban planners and decision-makers in the Water and Sewage Organization and Ministry of Power to understand the complex mechanism of water flow and simulate its prone areas for damage.

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Data Availability The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request.

Declarations

Ethics Approval The authors confirm that this article is original research and has not been published or presented previously in any journal or conference in any language (in whole or in part).

Consent to Participate and Consent to Publish The authors declared that they approved on the submission of the final manuscript.

Conflicts of Interest The authors declare no conflict of interest.

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