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Rana Azizi

University of Tehran

Ali M. Rajabi

[amrajabi@ut.ac.ir](mailto:amrajabi@ut.ac.ir)

University of Tehran

Ali Manafiazar

Tarbiat Modares University

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## Research Article

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# Linking Groundwater Depletion to Land Subsidence; An Integrated Approach Using D-InSAR, Fuzzy Logic, and Machine Learning in the Isfahan-Borkhar Plain, Central Iran

Rana Azizi<sup>1</sup>, Ali M. Rajabi<sup>2\*</sup>, Ali Manafiazar<sup>3</sup>

1. Engineering Geology Department, School of Geology, College of Science, University of Tehran, Tehran, Iran; Email: rana.azizi@ut.ac.ir; <https://orcid.org/0009-0008-1619-562X>
2. Engineering Geology Department, School of Geology, College of Science, University of Tehran, Tehran, Iran; Email: amrajabi@ut.ac.ir; <https://orcid.org/0000-0003-4588-2185>
3. PhD Candidate, Engineering Geology Department, School of Geology, College of Science, Tarbiat Modares University, Tehran, Iran; Email: ali.manafiazar@modares.ac.ir; <https://orcid.org/0009-0001-4914-7850>

## Abstract

The Isfahan-Borkhar plain, located within the Sanandaj-Sirjan structural zone and mainly composed of fine-grained sediments, has experienced significant land subsidence in recent years. This study evaluates land subsidence potential by integrating conventional weighting methods, fuzzy logic models, and artificial intelligence techniques. Seven conditioning factors were considered: aquifer media, land use, groundwater pumping rate, recharge, alluvium thickness, distance from faults, and groundwater table decline. An initial land subsidence potential (LSP) map was generated using the simple additive weighting framework (SAWF), followed by an AHP-based LSP map using previously reported analytic hierarchy process (AHP) weights. To improve the assessment, three fuzzy logic models, including Sugeno fuzzy logic (SFL), Mamdani fuzzy logic (MFL), and Larsen fuzzy logic (LFL), as well as artificial neural network (ANN) and support vector machine (SVM) models, were applied. Interferometric synthetic aperture radar (D-InSAR) analysis of Sentinel-1 images acquired between April 2023 and April 2024 were integrated with the initial land subsidence potential index (LSPI) to generate the conditioned land subsidence potential index (CLSPI) as target/reference data; D-InSAR-derived displacement values were used for validation. Fuzzy logic and machine-learning models improved the agreement between generated maps and the observed subsidence pattern. SFL performed best among fuzzy models ( $R^2 = 0.82$ ), whereas SVM achieved the highest overall agreement ( $R^2 = 0.93$ ). High-potential zones were mainly identified in the southwestern part of the Borkhar plain, northern Isfahan, southeastern Shahin-Shahr, and the eastern part of Shahid Beheshti Airport. These findings can support groundwater-resource management and land-subsidence hazard mitigation in the region.

**Keywords:** Land subsidence, Isfahan-Borkhar plain, SAWF, AHP, FL, AI, D-InSAR

## 1. Introduction

Land subsidence refers to the gradual downward displacement of the Earth's surface. It is mainly related to changes in the effective stress of subsurface materials and the consolidation of fine-grained sediments, especially aquitards, due to drainage, loading, or groundwater withdrawal. Other processes, such as dissolution of subsurface layers, including salts and carbonates, lateral flow, mechanical erosion, and tectonic activity, may also contribute to subsidence. In some areas, subsidence may be accompanied by minor horizontal ground displacement (Galloway & Burbey, 2011; Ma et al., 2018; Poland, 1984; Terzaghi, 1925; Baum et al., 2008; Adiyaman, 2012). Increasing groundwater extraction is widely regarded as one of the main causes of land subsidence. This problem has become more serious in arid and semi-arid regions, where agricultural, industrial, and urban development has increased the demand for groundwater resources (Motagh et al., 2008).

The effects of land subsidence can be both direct and indirect. They include degradation and salinization of aquifers, saline water intrusion, formation of ground fissures, and damage to infrastructure such as roads, railways, bridges, and sewage networks. Subsidence can also change channel gradients, disturb natural river flow, reduce aquifer storage capacity and flood-control capability, and damage agricultural and urban areas (Amini et al., 2024; Li et al., 2006; Arabameri, 2020).

Land subsidence is a widespread geohazard and has been reported in many parts of the world, including China, Mexico, Indonesia, Australia, Italy, Spain, Greece, the United States, Iran, Afghanistan, and several European countries (Kakar et al., 2025; Cigna et al., 2025; Tzampoglou et al., 2023; Liu et al., 2017; Hu et al., 2004; Baum et al., 2008; Bagheri-Gavkosh et al., 2021; Dinar et al., 2018). In Iran, because of arid to semi-arid climatic conditions and intensive groundwater withdrawal, land subsidence has become a major environmental and geotechnical concern (Jahangir et al., 2021). Previous studies have reported land subsidence in several regions of the country, including Isfahan (Sorkhabi et al., 2022; Azizi et al., 2026; Shahhosseini et al., 2025), Arak (Rajabi & Ghorbani, 2016; Jahangir et al., 2021), Tehran (Manafiazar et al., 2024; Rajabi et al., 2026; Manafiazar et al., 2025; Taravatrouy et al., 2018; Dehghani et al., 2013a; Dehghani et al., 2013b), Semnan (Mohammady, 2024; Arabameri et al., 2020), Qom (Rajabi et al., 2024; Jafari et al., 2015; Rajabi, 2018), Khorasan Razavi (Kariminejad et al., 2024; Rahmati et al., 2019), and Yazd (Amighpey & Arabi, 2016; Amighpey et al., 2010).

Identifying the factors that control land subsidence is important for developing management and mitigation strategies suited to local conditions (Azarm et al., 2023; Galloway & Burbey, 2011). Different methods have been used to monitor and measure subsidence at local and regional scales (Galloway et al., 1999). Among them, interferometric synthetic aperture radar (InSAR) has become one of the most effective and widely used techniques. InSAR allows subsidence to be mapped over large areas with high spatial and temporal resolution and provides a cost-effective alternative to conventional surveying methods such as global positioning system (GPS) measurements and precise leveling (Crosetto et al., 2002; Fruneau & Sarti, 2000; Galloway et al., 1998; Hung et al., 2012; Luo et al., 2013). Among InSAR methods, differential interferometric synthetic aperture radar (D-InSAR) has been widely used in geological and geodetic studies because of its capability to detect and quantify large-scale surface displacement (Tomás et al., 2014).

The simple additive weighting framework (SAWF) and the analytic hierarchy process (AHP) are commonly used multi-criteria decision-making methods for land subsidence potential (LSP) assessment and for estimating the relative importance of conditioning factors. These methods determine factor weights using decision matrices and pairwise comparisons, respectively (Hwang & Yoon, 2012; Saaty, 1980; Roszkowska, 2013; Muslihudin & Gumanti, 2017; Muslihudin et al., 2017; Hidayat et al., 2017; Nadiri et al., 2018; Manafiazar et al., 2025). Because they can combine quantitative and qualitative information, SAWF and AHP have been applied in environmental assessment, resource management, urban planning, and engineering studies (Saaty, 1980; Kakavand et al., 2025; Haghiri et al., 2024). Several studies in Iran and elsewhere have shown the usefulness of SAWF and AHP for land subsidence potential and hazard assessment (Deros et al., 2022; Arabameri et al., 2021; Moghaddam et al., 2020; Manafiazar et al., 2019; Nadiri et al., 2018).

Fuzzy logic (FL) was introduced by Lotfi A. Zadeh in 1965 through the theory of fuzzy sets (Zadeh, 1965). Fuzzy models are used to describe the relationship between input and output variables when uncertainty and gradual transitions exist in the data. Each fuzzy set is defined by a membership function selected according to the characteristics of the input data (Ross, 2010). Fuzzy systems generally include fuzzification, rule-based inference, and defuzzification. Sugeno fuzzy logic (SFL), Mamdani fuzzy logic (MFL), and Larsen fuzzy logic (LFL) are among the most widely used fuzzy inference models. Their main differences are related to the structure of output membership functions and the operators used during inference (Sugeno, 1985; Mamdani, 1976; Larsen, 1980). Because fuzzy models can represent

uncertainty and nonlinear relationships among controlling factors, they have been widely applied in geoscience, environmental modeling, groundwater studies, and land subsidence potential assessment (Ghorbanzadeh, 2018; Park et al., 2012; Gholami, 2022).

In recent years, the use of artificial intelligence-based machine-learning algorithms for spatial analysis and for identifying relationships between geological factors and land subsidence has increased. Among these methods, artificial neural network (ANN) and support vector machine (SVM) models have been widely used (Banerjee et al., 2011). These models can capture complex patterns and nonlinear relationships in datasets and have shown good performance in areas with spatially variable conditions (Oh & Lee, 2010; Lee et al., 2012; Blachowski, 2016; Lee & Park, 2013). Although SVM was first developed for classification, it has also been extended to regression problems (Roy & Chakraborty, 2023). ANN models have also been useful for modeling geological phenomena, especially where datasets are limited or incomplete (Daliakopoulos et al., 2005).

Isfahan is located in the central Iranian Plateau within the Sanandaj-Sirjan structural zone (Aghanabati, 2004). The Zayandeh-Rud River has played an important role in the development of Quaternary deposits in the region (Mohammadi et al., 2020). The area has a mainly arid climate, although local topography affects spatial variations in temperature and precipitation (Geological Survey of Iran, 2014). Geotechnical studies show that fine-grained and clayey sediments form the dominant deposits of the Isfahan plain (Amini et al., 2024). These geological and hydroclimatic conditions, together with intensive groundwater extraction, have made the region highly prone to land subsidence.

The Isfahan-Borkhar plain was selected for this study because it includes several important urban, industrial, and engineering facilities, such as Shahid Beheshti Airport, power plants, industrial zones, residential areas, and major transportation corridors. The presence of this infrastructure increases the need for reliable land subsidence potential (LSP) assessment to support land subsidence management and mitigation. Therefore, this study aims to evaluate and improve LSP mapping in the Isfahan-Borkhar plain using an integrated framework that combines D-InSAR-derived displacement data, conventional weighting methods, fuzzy logic models, and machine-learning techniques. Seven conditioning factors, including aquifer media, land use, groundwater pumping rate, recharge, alluvium thickness, distance from faults, and groundwater-level decline, were used to generate the initial land subsidence potential index (LSPI). The LSPI was then integrated with D-InSAR-derived displacement values to produce the conditioned land subsidence potential index (CLSPI) as target/reference data for model

development, while the original D-InSAR-derived displacement values were used for validation. The main contribution of this study is the sequential integration of conventional weighting, fuzzy inference, and machine-learning models within a unified LSP mapping framework.

## 2. Materials and Methods

In this study, land subsidence potential (LSP) mapping was performed using the SAWF method, and the modeling procedure was organized within a three-level hierarchical framework. First, the conditioning-factor layers were integrated in a GIS environment based on the SAWF weighting scheme to generate the initial LSP map. At Level 1, previously derived AHP weights were applied to the same conditioning factors, and an AHP-based LSP map was produced. At Level 2, three independent fuzzy inference systems, namely SFL, MFL, and LFL, were applied to refine the initial LSP results. In this stage, the seven conditioning factors used in the SAWF model, together with the initial SAWF-derived index and the AHP-based LSP output, were used as model inputs. The target/reference data were generated by conditioning the initial SAWF-derived index using D-InSAR-derived LS displacement values. At Level 3, the initial SAWF-derived index, the AHP-based LSP output, and the outputs generated by the SFL, MFL, and LFL models were used as input variables in the artificial intelligence-based modeling (AIMM) framework. In this stage, ANN and SVM were trained using the conditioned target/reference data to generate the ANN- and SVM-based LSP maps. Finally, all generated LSP maps were compared with the D-InSAR-derived LS displacement values to evaluate the performance of the applied methods. The overall workflow of the proposed methodology is presented in Fig. 1.

The performance of the developed LSP models was evaluated by comparing the generated LSP maps with D-InSAR-derived LS displacement values using three statistical indicators: the pearson correlation coefficient ( $r$ ) (Eq. 1), the coefficient of determination ( $R^2$ ) (Eq. 2), and the root mean square error ( $RMSE$ ) (Eq. 3). Since LSP is a dimensionless index, whereas LS displacement represents ground displacement, all variables used for model development and validation were normalized before analysis. Accordingly,  $RMSE$  was calculated using normalized values rather than the original displacement units. The  $r$  and  $R^2$  values were used to assess the agreement between the model-derived LSP values and the reference LS displacement values, whereas  $RMSE$  quantified the average deviation between them. Higher  $r$  and  $R^2$  values and lower  $RMSE$  values indicate better model performance.

$$r = \frac{\sum(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum(y_i - \bar{y})^2 \times \sum(\hat{y}_i - \bar{\hat{y}})^2}} \quad (1)$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{n}} \quad (3)$$

where  $y_i$  represents the normalized reference LS displacement value derived from D-InSAR analysis,  $\hat{y}_i$  denotes the corresponding normalized model-derived LSP value,  $\bar{y}$  is the mean of the reference LS displacement values,  $\bar{\hat{y}}$  is the mean of the model-derived LSP values, and  $n$  denotes the total number of observations.

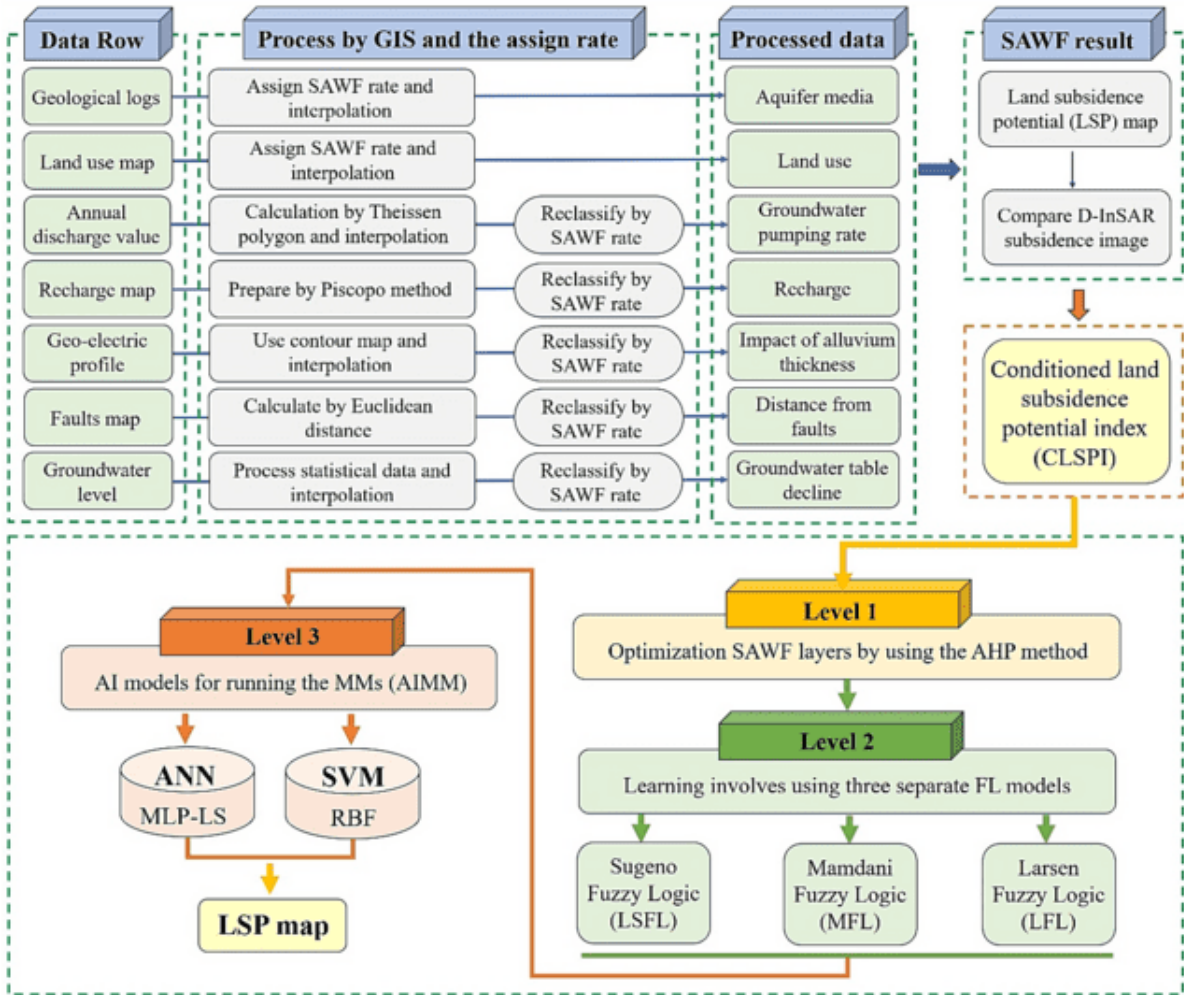


**Fig. 1.** Flowchart of the research methodology, including the SAWF framework and AI-based modeling methods (ANN and SVM).

## 2.1.SAWF

Simple additive weighting framework (SAWF) approach used in this study is based on the integration of multiple subsidence-related factors to evaluate LSP within the aquifer-plain system. Seven thematic layers were considered as independent conditioning factors, including aquifer media (A), land use (L), groundwater pumping rate (P), recharge (R), alluvium thickness (I), distance from faults (F), and groundwater table decline (T). These factors constitute the ALPRIFT framework proposed by Nadiri et al. (2018), which forms the basis of the SAWF methodology.

Although the relative contribution of these factors may vary among different regions, they can generally be grouped into three categories. Aquifer media (A) represents the environmental conditions influencing subsidence occurrence; land use (L) and groundwater pumping rate (P) correspond to anthropogenic drivers; and recharge (R), alluvium thickness (I), distance from faults (F), and groundwater table decline (T) represent intrinsic indicators associated with LSP. The characteristics of each factor and their corresponding weights are provided in Table 1, while the assigned rating values are presented in Table 2.

According to the workflow shown in Fig. 1, the generation of the initial LSP map using the SAWF approach consisted of two main stages. First, each thematic layer was converted into a raster dataset in ArcGIS, and pixel values were assigned according to the rating system presented in Table 2. Second, the raster layers were weighted and integrated using the Raster Calculator tool based on Eq. 4, resulting in the SAWF-based LSP map.

$$LSPI = A_r A_w + L_r L_w + P_r P_w + R_r R_w + I_r I_w + F_r F_w + T_r T_w \quad (4)$$

where  $A$ ,  $L$ ,  $P$ ,  $R$ ,  $I$ ,  $F$ , and  $T$  denote the thematic layers of the SAWF model. The subscripts  $r$  and  $w$  represent the assigned rating and weighting values, respectively. In the initial SAWF implementation, the weighting and rating values followed the adopted ALPRIFT-based classification structure summarized in Tables 1 and 2. Based on the adopted weighting and rating structure, the theoretical land subsidence potential index (LSPI) ranges from 24 to 240, with higher values indicating greater LSP.

After the initial SAWF-based LSP map was generated, the LSPI was calculated for each cell. Since the initial LSPI was derived only from the conditioning factors and their assigned weights, D-InSAR-derived LS displacement values were used to condition this index. Accordingly, the Conditioned Land Subsidence Potential Index (CLSPI) was calculated as:

$$CLSPI_i = \left( \frac{LSPI_{max}}{LS_{max}} \right) \times LS_i \quad (5)$$

where  $CLSPI_i$  is the conditioned index for cell  $i$ ,  $LSPI_{max}$  is the maximum LSPI value obtained in the study area,  $LS_{max}$  is the maximum D-InSAR-derived LS displacement value, and  $LS_i$  is the D-InSAR-derived LS displacement value for cell  $i$ . In this study, and  $LS_{max}$  and  $LSPI_{max}$  were 0.0852137 m and 155, respectively. The resulting CLSPI was used as the target/reference data for the fuzzy logic and machine-learning models, while the original D-InSAR-derived displacement values were used for validation.

In the subsequent analytic hierarchy process (AHP) stage, the weights derived from the pairwise comparisons reported by Helataei et al. (2025) were applied to the same conditioning factors, and an AHP-based LSP map was produced.

**Table 1.** Description of the SAWF thematic layers and their assigned weights.

| Data layers                         | Description                                                                                                                                                                                                                                                                                                                                                                | Weight |
|-------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------|
| <b>A:</b> Aquifer media             | The influence of aquifer media on LSP is classified according to soil texture. Clay and silt deposits have the greatest influence due to their compressibility and plastic behavior. Gravel-to-silt materials generally exhibit more elastic behavior and commonly act as groundwater-bearing units, whereas coarser deposits have a limited influence on land subsidence. | 5      |
| <b>L:</b> Land use                  | Land use reflects anthropogenic activities that modify subsurface conditions and influence land subsidence, including groundwater withdrawal, surface loading, and agricultural or urban development.                                                                                                                                                                      | 4      |
| <b>P:</b> Groundwater pumping rate  | Groundwater extraction for agricultural, domestic, and industrial purposes lowers groundwater levels and increases effective stress, potentially leading to land subsidence.                                                                                                                                                                                               | 4      |
| <b>R:</b> Recharge                  | Recharge entering the aquifer through precipitation and surface-water infiltration tends to mitigate land subsidence.                                                                                                                                                                                                                                                      | 3      |
| <b>I:</b> Alluvium thickness        | Alluvium thickness reflects the intrinsic potential of subsurface materials for land subsidence; therefore, thicker alluvial deposits generally correspond to higher subsidence potential.                                                                                                                                                                                 | 2      |
| <b>F:</b> Distance from faults      | Faults can influence land subsidence by affecting ground deformation patterns and subsurface hydrogeological conditions.                                                                                                                                                                                                                                                   | 1      |
| <b>T:</b> Groundwater table decline | Groundwater table decline reduces pore-water pressure and increases effective stress, thereby promoting land subsidence.                                                                                                                                                                                                                                                   | 5      |

216 **Table 2.** Classification ranges and corresponding ratings of the SAWF data layers (Nadiri et al. 2018).

| Aquifer media (A)      |      | Land use (L)                 |      | Groundwater pumping rate (P) |      | Recharge (R)    |      | Alluvium thickness (I) |      | Distance from faults (F) |      | Groundwater table decline (T) |      |
|------------------------|------|------------------------------|------|------------------------------|------|-----------------|------|------------------------|------|--------------------------|------|-------------------------------|------|
| Range                  | Rate | Range                        | Rate | Range (cm/year)              | Rate | Range (cm/year) | Rate | Range (m)              | Rate | Range (km)               | Rate | Range (m/year)                | Rate |
| Clay                   | 9-10 | Mining/ resources extraction | 9-10 | $<0.0001$                    | 1    | $0 < r < 4$     | 10   | $0 < r < 25$           | 1    | $0 < r < 1$              | 10   | $0 < r < 0.2$                 | 1    |
| Silt                   | 8-9  | Irrigated farming            | 7-9  | $0.0001 < r < 0.005$         | 2    | $4 < r < 9$     | 9    | $25 < r < 55$          | 2    | $1 < r < 2$              | 8    | $0.2 < r < 0.5$               | 2    |
| Karstic sediments      | 6-8  | Dam construction             | 6-7  | $0.005 < r < 0.01$           | 3    | $9 < r < 14$    | 7    | $55 < r < 90$          | 3    | $2 < r < 3$              | 6    | $0.5 < r < 0.9$               | 3    |
| Sand                   | 3-5  | Built-up (residential)       | 4-6  | $0.01 < r < 0.5$             | 4    | $14 < r < 19$   | 5    | $90 < r < 130$         | 4    | $0 < r < 4$              | 4    | $0.9 < r < 1.4$               | 4    |
| Gravel                 | 2-3  | Transportation               | 3-4  | $0.5 < r < 1$                | 5    | $19 < r < 24$   | 3    | $130 < r < 175$        | 5    | $4 < r < 5$              | 2    | $1.4 < r < 2$                 | 5    |
| Rock type              | 1-2  | Dry farming/ grassland       | 2-3  | $1 < r < 5$                  | 6    | $< 24$          | 1    | $175 < r < 225$        | 6    | $> 5$                    | 1    | $2 < r < 2.7$                 | 6    |
| Oxidized organic soils | 8-10 | Barren land                  | 1    | $5 < r < 20$                 | 7    |                 |      | $225 < r < 280$        | 7    |                          |      | $2.7 < r < 3.5$               | 7    |
|                        |      |                              |      | $20 < r < 40$                | 8    |                 |      | $280 < r < 340$        | 8    |                          |      | $3.5 < r < 4.4$               | 8    |
|                        |      |                              |      | $40 < r < 65$                | 9    |                 |      | $340 < r < 405$        | 9    |                          |      | $4.4 < r < 5.4$               | 9    |
|                        |      |                              |      | $> 65$                       | 10   |                 |      | $> 405$                | 10   |                          |      | $> 5.4$                       | 10   |

Note 1: if each data layer scores a rate of 1, the minimum SAWF LSP value is 24 ( $=1 \times 5 + 4 \times 1 + 4 \times 1 + 3 \times 1 + 2 \times 1 + 1 \times 1 + 5 \times 1$ ).

Note 2: if each data layer scores a rate of 10, the maximum SAWF LSP value is 240 ( $=5 \times 10 + 4 \times 10 + 4 \times 10 + 3 \times 10 + 2 \times 10 + 1 \times 10 + 5 \times 10$ ).

## 217 2.2. D-InSAR

218 In this study, two Sentinel-1A images acquired on April 11, 2023 and April 5, 2024 were  
 219 utilized. The Sentinel-1A datasets were obtained in Single Look Complex (SLC) format from  
 220 the Alaska Satellite Facility Distributed Active Archive Center (ASF DAAC) archive (ASF,  
 221 2024). The datasets correspond to path 28 and frame 102 and were acquired along a descending  
 222 orbit. D-InSAR processing was performed using SARscape and ENVI software (SARscape,  
 223 2018). Initially, the SLC images and their corresponding precise orbit files were imported into  
 224 SARscape. The image pair was then processed to generate a differential interferogram  
 225 containing surface displacement information in phase form. During interferogram generation,  
 226 phase components associated with orbital inaccuracies and topographic effects were removed  
 227 using precise orbit files and the Shuttle Radar Topography Mission (SRTM) digital elevation  
 228 model (DEM) with a spatial resolution of  $30 \text{ m} \times 30 \text{ m}$ .

229 Subsequently, adaptive interferogram filtering and coherence analysis were applied to  
 230 reduce noise and improve interferogram quality. Phase unwrapping was performed in

SARscape using the Minimum Cost Flow (MCF) algorithm to convert the wrapped interferometric phase into a continuous phase field. During this step, an unwrapping coherence threshold of 0.2 was applied; therefore, pixels with coherence values lower than 0.2 were excluded from the unwrapping and displacement extraction process because of their high noise level and low phase reliability. Finally, geocoding was performed to transform radar coordinates into geographic coordinates, enabling the extraction of spatial displacement information. Since D-InSAR initially measures displacement along the satellite line of sight (LOS), the LOS displacement values were converted into vertical land subsidence (LS) displacement values. These values were then used to condition the initial land subsidence potential index (LSPI) for generating the conditioned land subsidence potential index (CLSPI) and to validate the performance of the developed LSP models. A summary of the D-InSAR processing workflow is presented in Fig. 2.

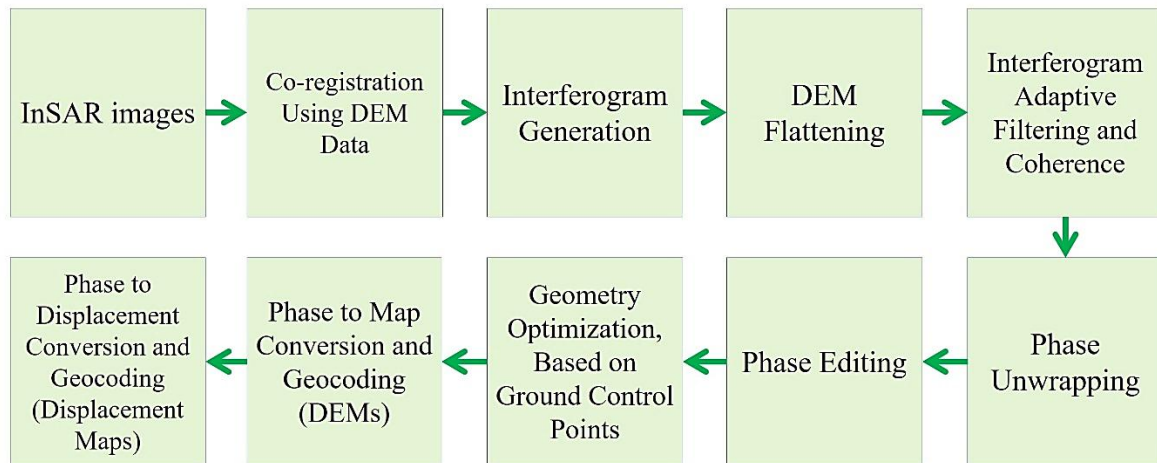


**Fig. 2.** Workflow of D-InSAR image processing.

### 2.3. Three fuzzy logic-based models

Three fuzzy logic (FL)-based models were developed in this study to refine the SAWF-derived LSP results rather than relying solely on the predefined weighting and rating structure of the SAWF method. These models are based on fuzzy set theory and are designed to establish relationships between input and output variables under uncertainty. Each fuzzy set is characterized by a membership function (MF), which may take different forms, including S-shaped, Gaussian, triangular, sigmoid, trapezoidal, generalized bell-shaped (gbellmf), and Z-shaped functions. The selection of an appropriate MF is generally performed through a trial-and-error procedure. Fuzzy sets allow partial membership, with membership grades ranging

from 0 to 1. In this study, Gaussian membership functions were used in the SFL model, whereas generalized bell-shaped membership functions were adopted in the MFL and LFL models.

Unlike conventional FL models that rely mainly on predefined rule-based structures, data-driven fuzzy modeling can use clustering techniques to identify data structures and derive fuzzy rules (Asadi et al., 2014). Numerous clustering algorithms have been proposed for identifying clusters and determining their optimal number. Among them, subtractive clustering (SC) (Li et al., 2018) and fuzzy C-means (FCM) (Bezdek, 1981) are widely recognized as effective approaches. In this study, the seven normalized conditioning factors and the normalized LSPI were used as input variables, while the normalized CLSPI was used as the target/reference data for calibrating the SFL, MFL, and LFL models.

The SFL model employs either constant or linear consequent functions, corresponding to zero-order and first-order Sugeno structures, respectively (Sugeno, 1985), and uses subtractive clustering (SC) to extract fuzzy if-then rules (Fijani et al., 2013; Moazamnia et al., 2020). In SC-based approaches, the number of clusters corresponds to the number of fuzzy rules and is controlled by the clustering radius, which ranges from 0 to 1. The MFL model uses fuzzy output membership functions (MFs) and the “MIN” operator for fuzzy implication (Mamdani, 1976), with fuzzy rules generated using the fuzzy C-means (FCM) clustering algorithm (Lee, 2005). The LFL model follows a structure similar to that of MFL but employs the “PRODUCT” operator for implication operations (Larsen, 1980).

## **2.4.ANN**

Artificial neural networks (ANNs) are parallel distributed information-processing systems inspired by the structure and functioning of biological neural networks (Hopfield, 1982). An ANN consists of interconnected processing units, or neurons, linked through weighted connections that control information transfer within the network. Its architecture generally includes an input layer, one or more hidden layers, and an output layer. The input layer receives the input variables, the hidden layer(s) perform nonlinear transformations of the data, and the output layer generates the model-derived output. The number of hidden-layer neurons is typically determined through a trial-and-error procedure. Owing to their capability to model complex nonlinear relationships, ANNs have been widely applied in pattern recognition, modeling, optimization, and system control problems. In multilayer ANNs, processing nodes are organized in successive layers and interconnected through weighted links, analogous to synapses in biological neural systems (Coppola et al., 2003).

In this study, the ANN model was developed using the outputs of the fuzzy models as input variables, while the normalized Conditioned Land Subsidence Potential Index (CLSPI) was used as the target variable. The mathematical formulation of the three-layer ANN used in this study is expressed as follows:

$$O_j = f_1(b_j + \sum_i w_{ji} x_i) \quad (6)$$

$$\hat{y} = f_2(b_k + \sum_i w_{kj} O_j) \quad (7)$$

where  $x_i$  denotes the  $i$ th normalized input variable,  $O_j$  represents the  $j$ th hidden-layer output, and  $\hat{y}$  denotes the normalized ANN-derived LSP output. The functions  $f_1$  and  $f_2$  correspond to the activation functions of the hidden and output layers, respectively. The parameters  $w_{ji}$  and  $w_{kj}$  are the connection weights between successive layers, whereas  $b_j$  and  $b_k$  represent the associated bias terms. In ANN applications, the hidden-layer transfer function is commonly nonlinear, while the output-layer transfer function is generally linear. In this study, the TANSIG and PURELIN functions were selected as the hidden- and output-layer transfer functions, respectively. During network training, the Levenberg-Marquardt supervised learning algorithm was employed to estimate the connection weights and bias terms. The trained ANN output was subsequently used to generate the ANN-based LSP map.

## 2.5.SVM

Support Vector Machine (SVM) was introduced by Cortes and Vapnik (1995). It is a supervised machine-learning technique derived from statistical learning theory and has been widely applied to both classification and regression problems. In classification, SVM aims to identify an optimal separating hyperplane that maximizes the margin between classes, whereas in regression problems, it seeks to construct an optimal function with high generalization capability (Lee et al., 2012). Several SVM variants have been developed, including Least-Squares Support Vector Machine (LS-SVM), Linear Programming Support Vector Machine, Support Vector Regression (SVR), and Nu-Support Vector Machine ( $\nu$ -SVM) (Raghavendra et al., 2015). In this study, the LS-SVM approach, introduced by Suykens (2001), was adopted because of its computational efficiency and suitability for regression-based modeling.

Consider a training dataset  $\{x_i, y_i\}_{i=1}^N$ , where  $x_i \in R_m$  represents the normalized input variables, including the outputs generated by SFL, MFL, and LFL, and  $y_i \in R$  denotes the normalized Conditioned Land Subsidence Potential Index (CLSPI) used as the target variable. The LS-SVM regression function is defined as:

$$y(x) = w^T \cdot \varphi(x) + b \quad (8)$$

where  $\varphi(x)$  is a nonlinear mapping function that projects the input data into a high-dimensional feature space,  $w$  denotes the weight vector, and  $b$  is the bias term. For function approximation, the LS-SVM optimization problem can be formulated as follows (Suykens, 2001):

$$\begin{aligned} \text{Minimize: } R(w, e) &= \frac{1}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^N e_i^2 \\ \text{subject to: } y_i &= w^T \varphi(x_i) + b + e_i \end{aligned} \quad (9)$$

where  $e_i$  represents the regression error and  $\gamma$  is the regularization parameter controlling the trade-off between model complexity and fitting accuracy. The LS-SVM regression model can subsequently be expressed as:

$$y(x) = \sum_{i=1}^N \alpha_i K(x_i, x) + b \quad (10)$$

where  $\alpha_i$  and  $b$  are obtained from the solution of the corresponding linear system, and  $K(x_i, x)$  denotes the kernel function. In this study, the radial basis function (RBF) kernel was employed:

$$K(x_i, x_j) = \exp\left(\frac{-\|x_i - x_j\|^2}{\sigma^2}\right) \quad (11)$$

where  $\sigma$  is the kernel parameter. The performance of the LS-SVM model strongly depends on the appropriate selection of the kernel parameter  $\sigma$  and the regularization parameter  $\gamma$ . Therefore, both parameters were determined through a trial-and-error procedure. The trained LS-SVM output was subsequently used to generate the SVM-based LSP map.

### 3. Study Area

The study area is the Isfahan-Borkhar plain, covering approximately 1244 km<sup>2</sup> in Isfahan Province. Geographically, it is located between 51°28'E and 51°57'E longitude and between 32°36'N and 32°51'N latitude. The plain is situated near the center of Iran, within the central part of the Sanandaj-Sirjan structural zone and the middle sector of the Gavkhuni drainage basin. Its sedimentary sequence is mainly composed of clay, silt, and alluvial deposits derived from the surrounding highlands (Aghanabati, 2004; Malmir & Delbari, 2015; Goorabi et al., 2020). These materials were transported and deposited in alluvial plains, river terraces, and other geomorphic units under the combined influence of climatic fluctuations and tectonic processes (Goorabi et al., 2020). Extensive alluvial plains are mainly distributed across the eastern, northern, and northeastern parts of the study area (Geological Survey and Mineral Explorations of Iran, 2014).

The dominant geological units in the study area belong to the Quaternary succession and include the Qft2 and Qcf units (Fig. 3). The youngest alluvial deposits (Qcf) are mainly clay-rich and occur adjacent to the older Qft2 unit, which consists mostly of alluvial fan deposits and fluvial terrace sediments. The locations of geological borehole logs and four geological cross-sections (A-A', B-B', C-C', and D-D') are shown in Fig. 4.

The climate of the area is controlled by the combined influence of the Dasht-e Kavir to the east and southeast and the surrounding mountainous regions to the west. Based on regional climatic classifications, three major climate types are recognized in the broader area: cold semi-humid, desert, and semi-desert conditions. Nevertheless, the study area is generally characterized by an arid climate (Geological Survey and Mineral Explorations of Iran, 2014).

The Zayandeh-Rud River, the largest river in the Central Iranian Plateau, is the principal drainage system of the region and passes through the city of Isfahan. However, upstream water withdrawal, dam construction, and prolonged drought conditions have substantially reduced river discharge, causing some reaches to become seasonal or completely dry (Geological Survey and Mineral Explorations of Iran, 2014; Goorabi et al., 2020). Reduced river flow has decreased aquifer recharge, while intensive groundwater abstraction has further accelerated groundwater-level decline (Zhou et al., 2013). These conditions have reduced pore-water pressure and increased effective stress within compressible sediments, thereby intensifying land subsidence across the plain (Goorabi et al., 2020). A section of the Zayandeh-Rud River flows through the Borkhar Basin, highlighting its hydrological significance within the study area (Malmir & Delbari, 2015).

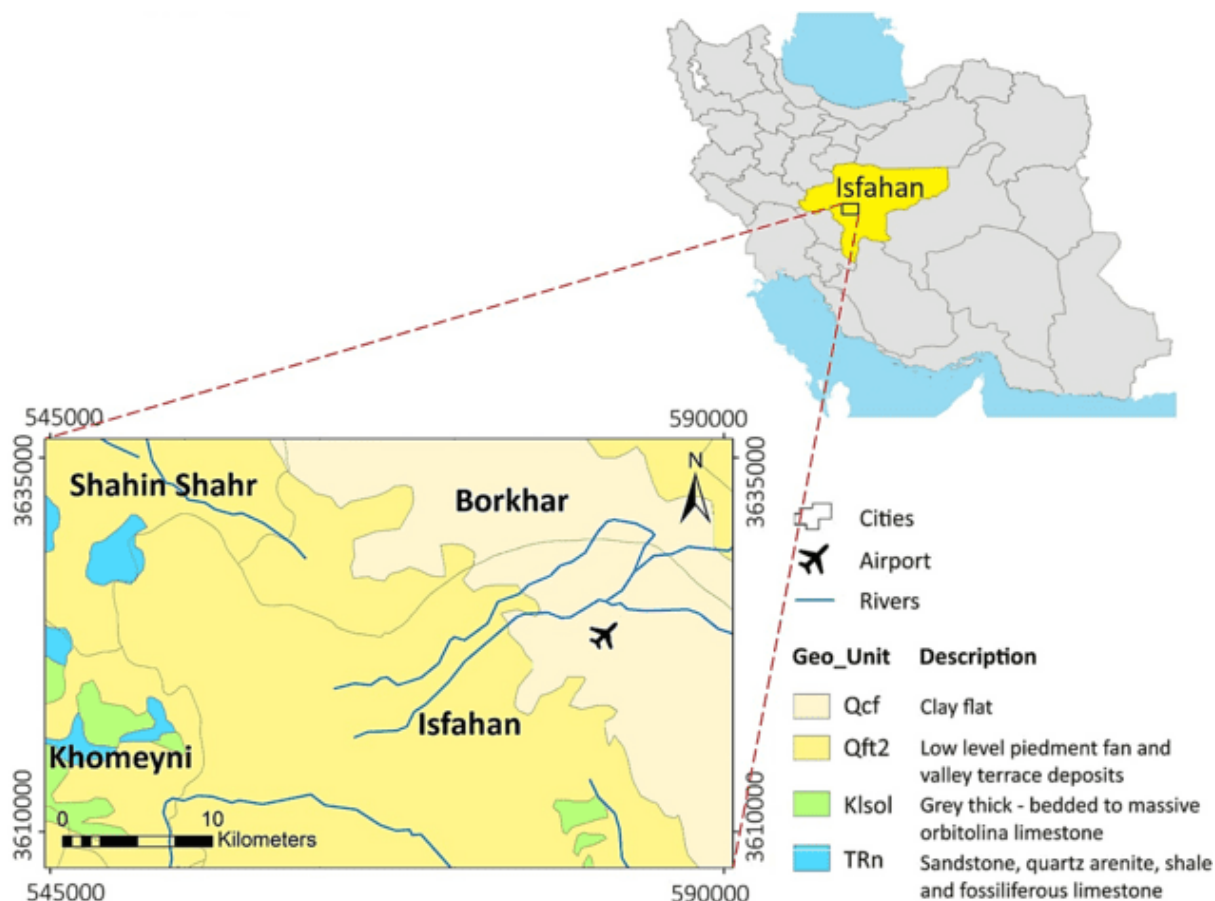
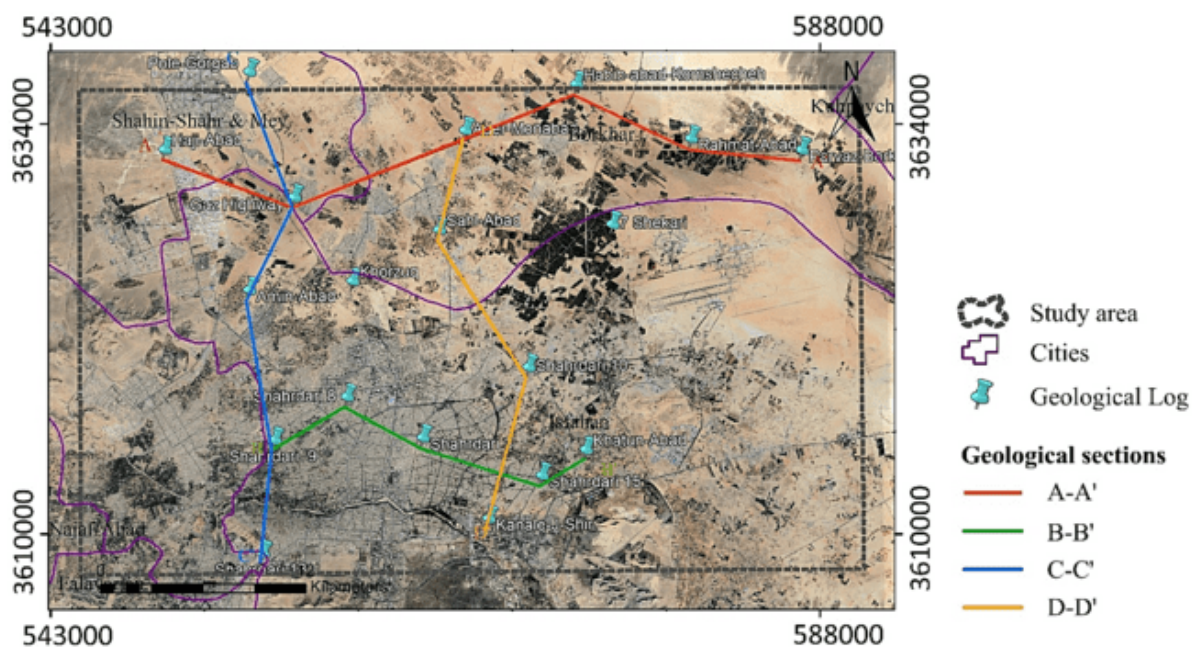


Fig. 3. Geological map of the Isfahan-Borkhar plain, central Iran.



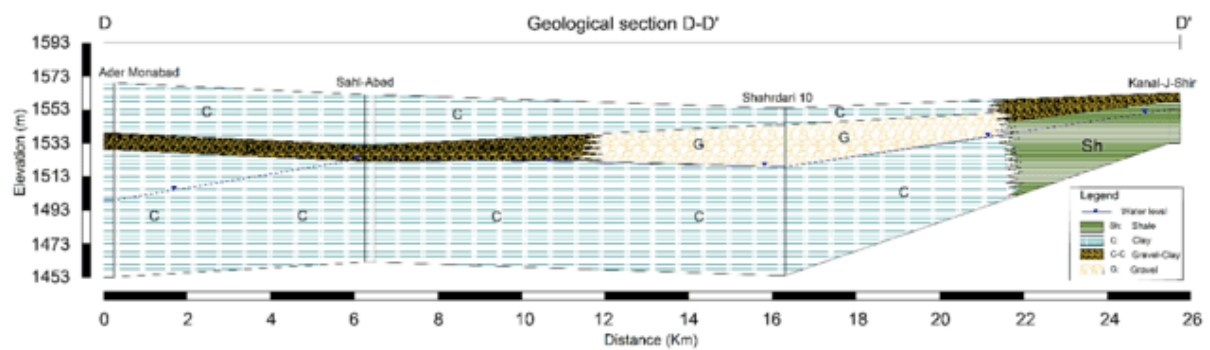
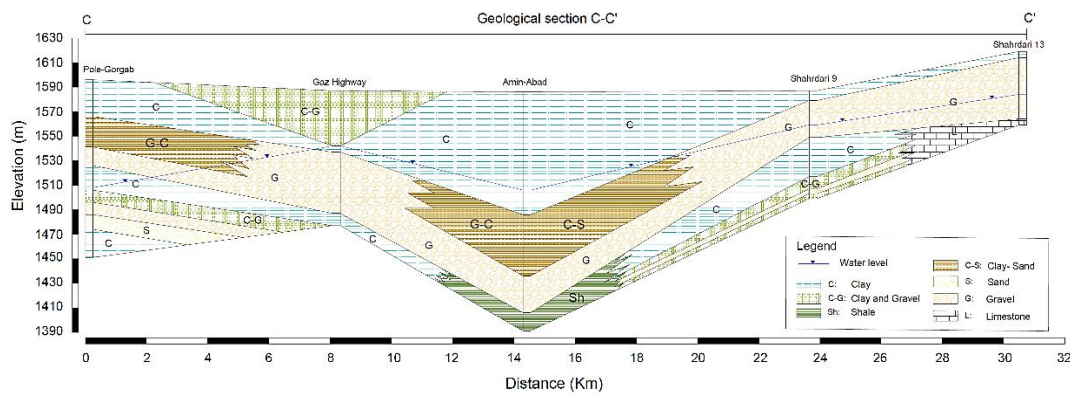
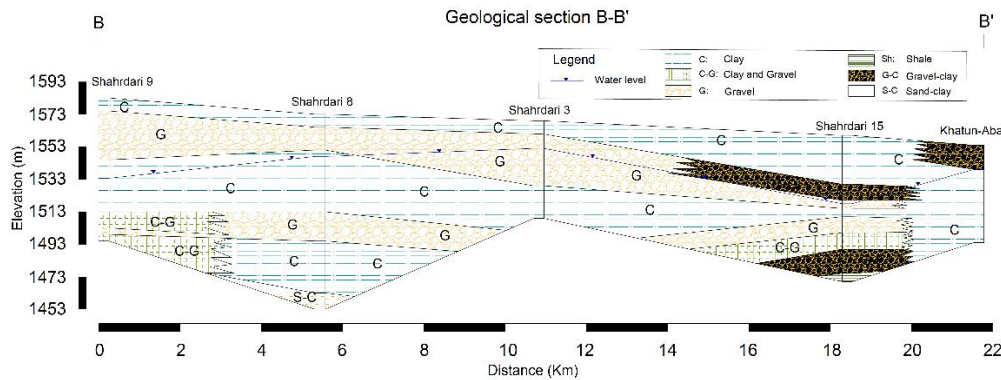
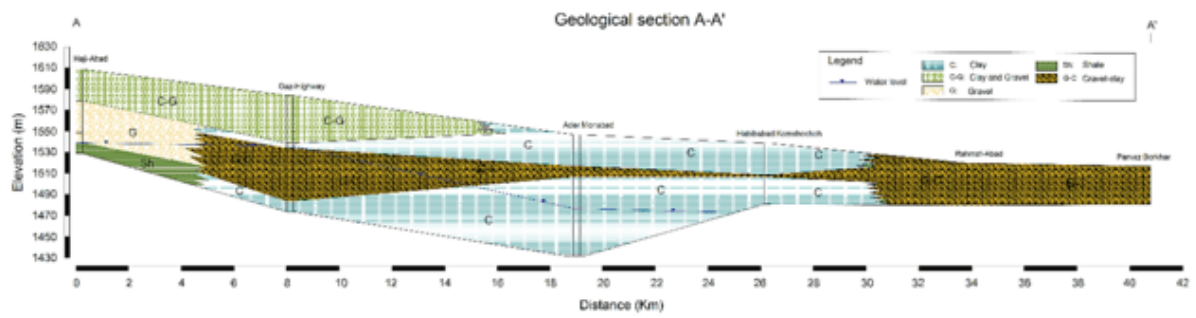


**Fig. 4.** Location of geological borehole logs and four geological cross-sections (A-A', B-B', C-C', and D-D').

#### 4. Preparation of the Dataset

The study area was discretized into  $150 \times 150$  m grid cells, resulting in approximately 55,289 raster cells. Fig. 5 shows the spatial distribution of groundwater abstraction wells and piezometers, together with the digital elevation model (DEM) and major faults in the Isfahan-Borkhar plain. To prepare the spatial database, data from 32 piezometric wells were used to derive the groundwater-level decline layer, 6,246 groundwater abstraction wells were used to construct the groundwater pumping-rate layer, and 23 geological logs were used to characterize the aquifer media and alluvium thickness. In addition, the land-use layer was derived from a land-use map, the distance-to-fault layer was generated from the fault map, and the recharge layer was prepared using rainfall data, surface-soil permeability, and DEM-derived slope information.

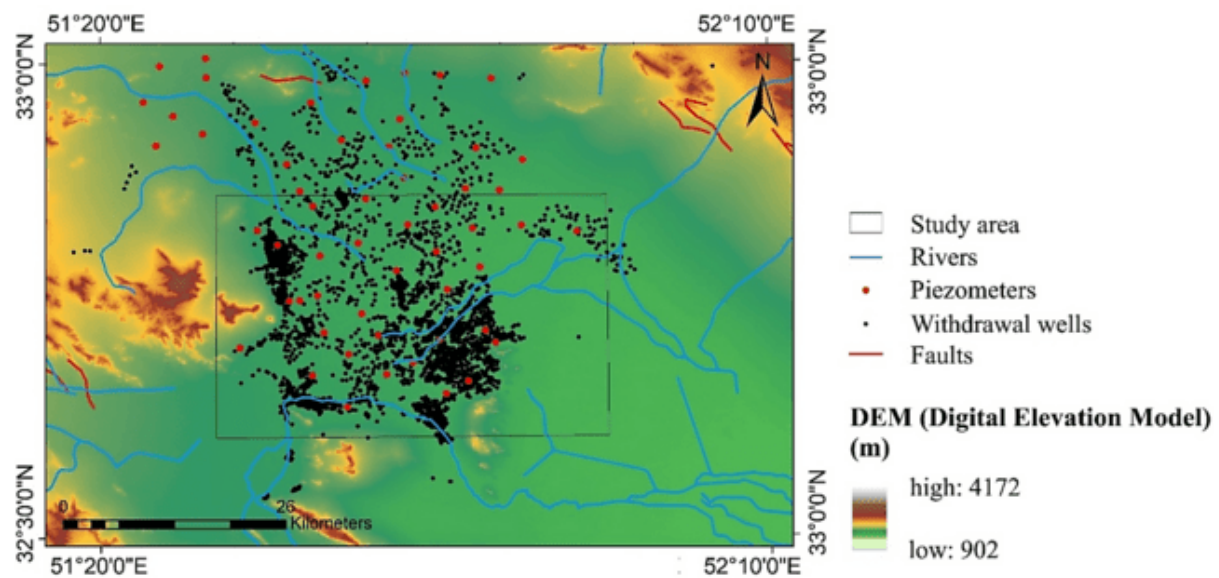


**Fig. 5.** Spatial distribution of pumping wells and piezometers, together with the DEM and major fault systems, in the Isfahan-Borkhar plain.

##### 4.1. Layers of input data

- *Aquifer media (A)*: The aquifer media layer represents the lithological characteristics of subsurface materials. The preparation procedure consisted of four steps: (1) subsurface lithology, including the thicknesses of clay, silt, sand, gravel, and rock units, was determined from 23 geological logs distributed across the study area; (2) a rating value was assigned to each lithological unit according to Table 2; (3) weighted average ratings were calculated using Eq. 12; and (4) the resulting values were spatially interpolated across the study area using the Kriging method in GIS. The rating values assigned to the A layer range

from 1 to 10. Fig. 6a illustrates the ranked aquifer media classes and their corresponding percentages.

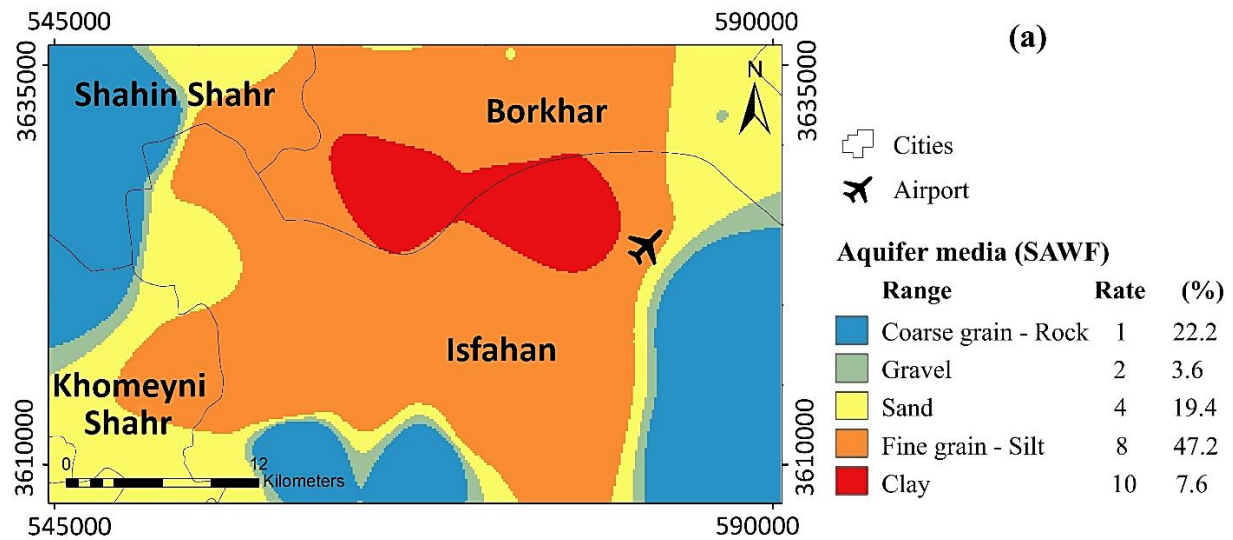
$$Aquifer\ media = \frac{\sum_{n=1}^n layer\ thickness \times rate}{Total\ thickness} \quad (12)$$

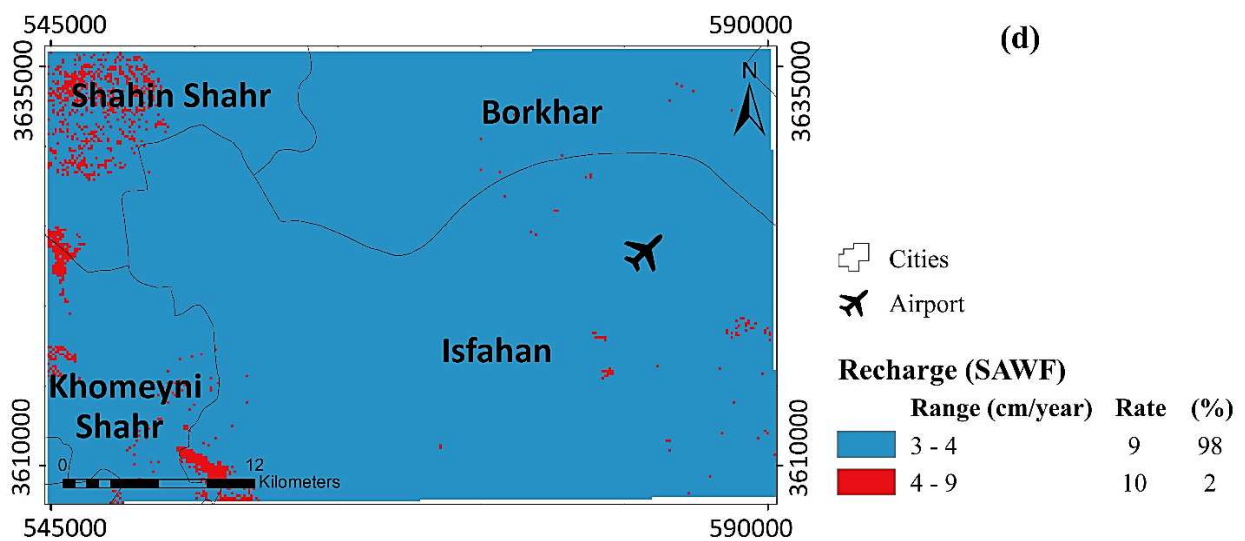
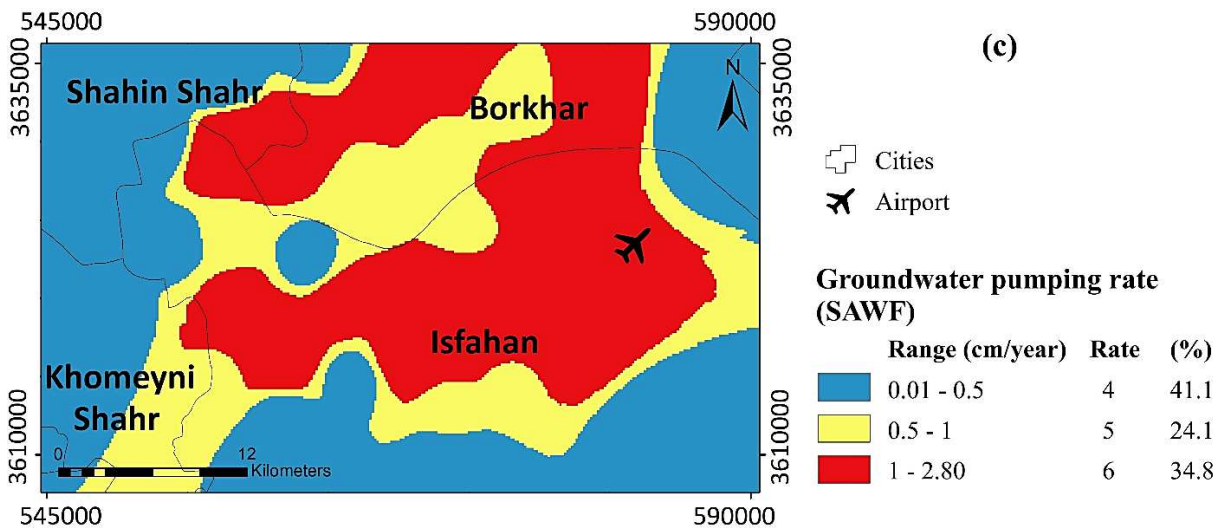
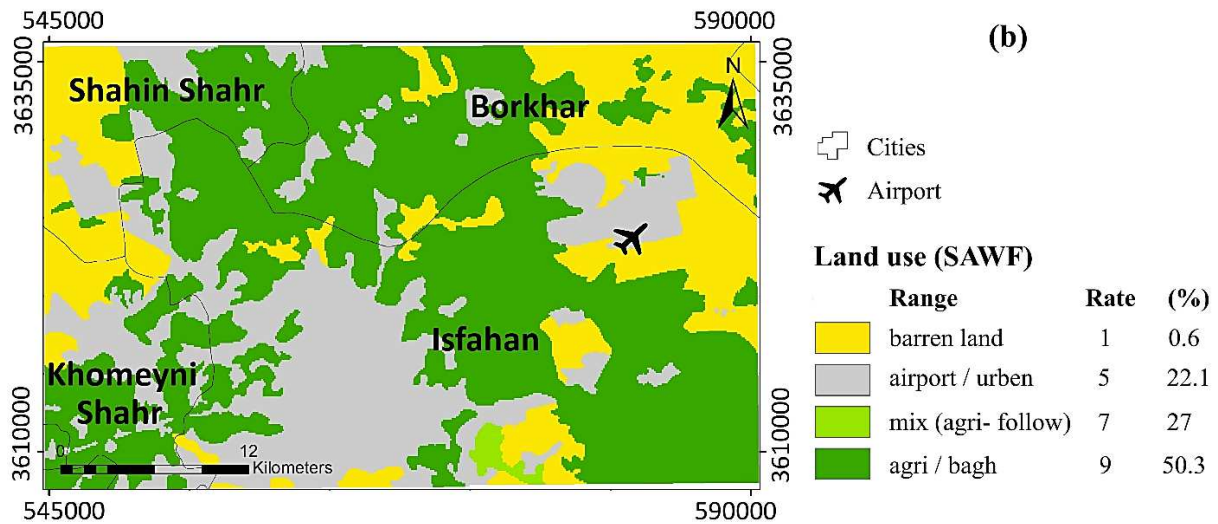
- *Land use (L)*: The land-use layer was prepared in two steps: (1) agricultural lands, residential areas, and barren lands were identified using Google Earth imagery; and (2) a raster land-use layer was generated, and rating values were assigned to each class according to Table 2. Fig. 6b presents the ranked land-use classes and their corresponding percentages.
- *Groundwater pumping rate (P)*: Groundwater abstraction data from pumping wells for the 2023-2024 period were obtained from the Isfahan Regional Water Authority (IRWA, 2024) and used to construct the P layer. The preparation procedure included: (1) subdivision of the study area into 31 Thiessen polygons based on the spatial distribution of the piezometers; (2) calculation of the total or average groundwater abstraction rate for pumping wells located within each polygon; (3) assignment of rating values according to the classification ranges presented in Table 2; and (4) spatial interpolation of the resulting polygon-based values using the Kriging method. Fig. 6c shows the ranked classes of the P layer and their associated percentages.
- *Recharge (R)*: The recharge layer was prepared using the method proposed by Piscopo (2001) (Table 3), which integrates three thematic layers: (1) rainfall data recorded at the Isfahan-Borkhar plain meteorological station between April 2023 and April 2024, indicating a total annual precipitation of 98.11 mm; (2) slope values derived from the DEM, ranging from 0 to 288% across the study area; and (3) soil permeability data obtained from the Isfahan Regional Water Authority (IRWA, 2024), classified from low to very high permeability. The recharge map was generated by integrating these three layers according to the Piscopo (2001) rating scheme. Fig. 6d presents the final recharge layer.

**Table 3.** Recharge classification ranges and corresponding ratings based on the Piscopo method (Piscopo, 2001).

| Slope (%) |      | Rainfall (mm) |      | Permeability |      | Recharge |      |
|-----------|------|---------------|------|--------------|------|----------|------|
| Range     | Rate | Range         | Rate | Range        | Rate | Range    | Rate |
| < 2       | 4    | > 850         | 4    | High         | 5    | 11-13    | 10   |
| 2-10      | 3    | 700-850       | 3    | Medium-high  | 4    | 9-11     | 8    |
| 10-33     | 2    | 500-700       | 2    | Medium       | 3    | 7-9      | 5    |
| > 33      | 1    | < 500         | 1    | Low          | 2    | 5-7      | 3    |
|           |      |               |      | Very low     | 1    | 3-5      | 1    |

- *Alluvium thickness (I)*: The alluvium thickness layer was derived from drilling-log data obtained from the Isfahan Regional Water Authority (IRWA, 2024). Based on these records, alluvium thickness across the Isfahan-Borkhar plain ranges from 3 to 249 m. Fig. 6e shows the spatial distribution of alluvium thickness within the study area.
- *Distance from faults (F)*: The fault-distance layer was generated by identifying the active faults surrounding the study area and calculating the distance of each grid cell from the mapped fault network using the Euclidean distance method in GIS. The resulting distances were subsequently classified and assigned rating values according to the ranges presented in Table 2. As no active faults occur within the study area and all calculated distances fall within the >5 km class, a rating value of 1 was assigned to the entire layer. Fig. 6f presents the ranked fault-distance classes and their corresponding percentages.
- *Groundwater table decline (T)*: The groundwater table decline layer was prepared using water-level measurements from 31 piezometric wells collected between April 2023 and April 2024. The recorded groundwater-level changes were spatially interpolated across the study area using the Kriging method. The resulting surface was subsequently classified according to the rating values provided in Table 2. The final groundwater table decline map is presented in Fig. 6g.





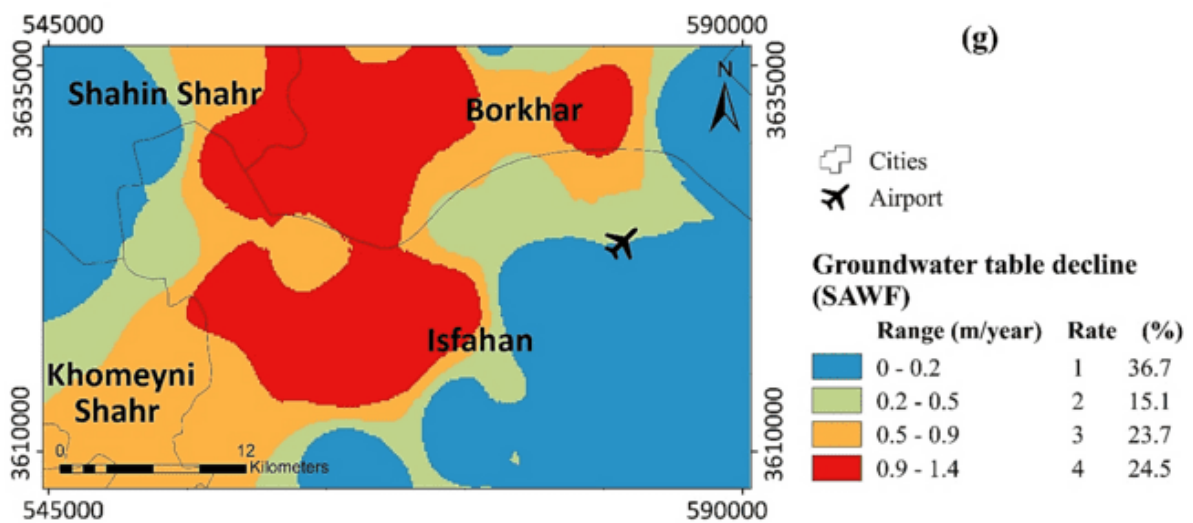
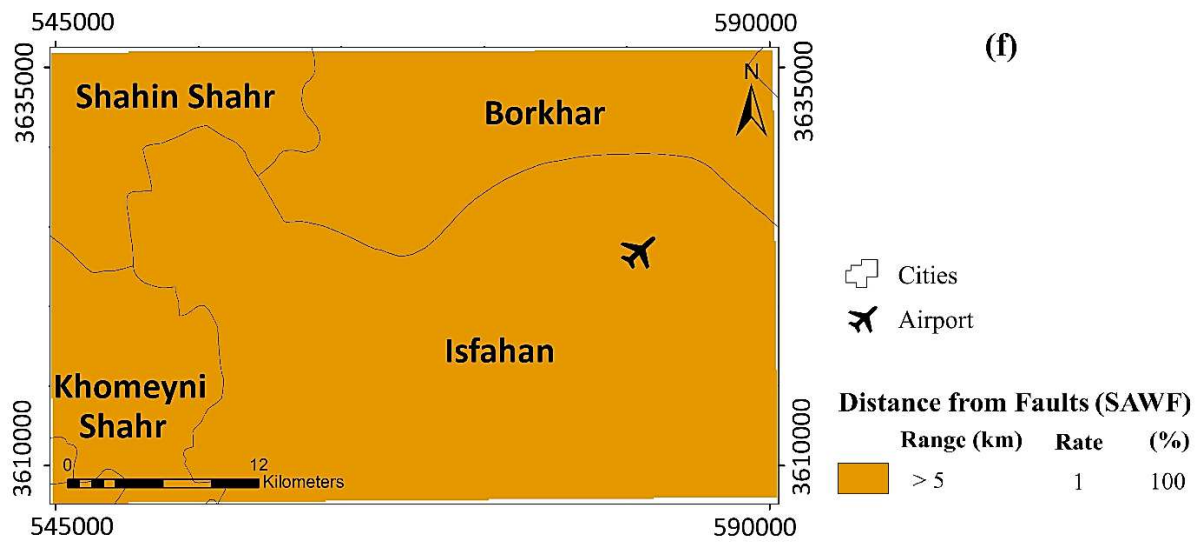
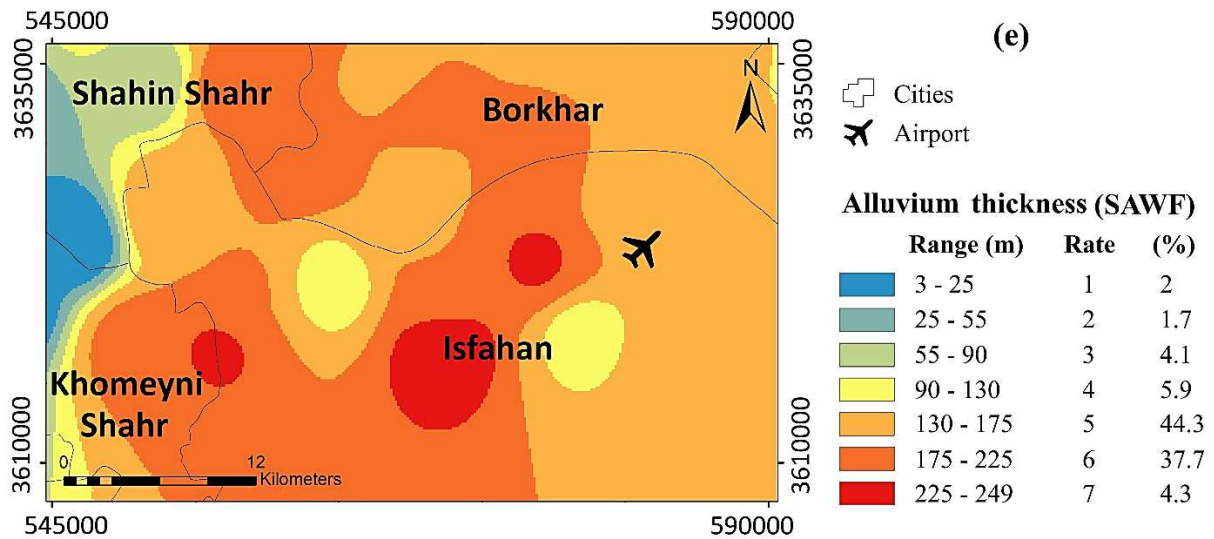


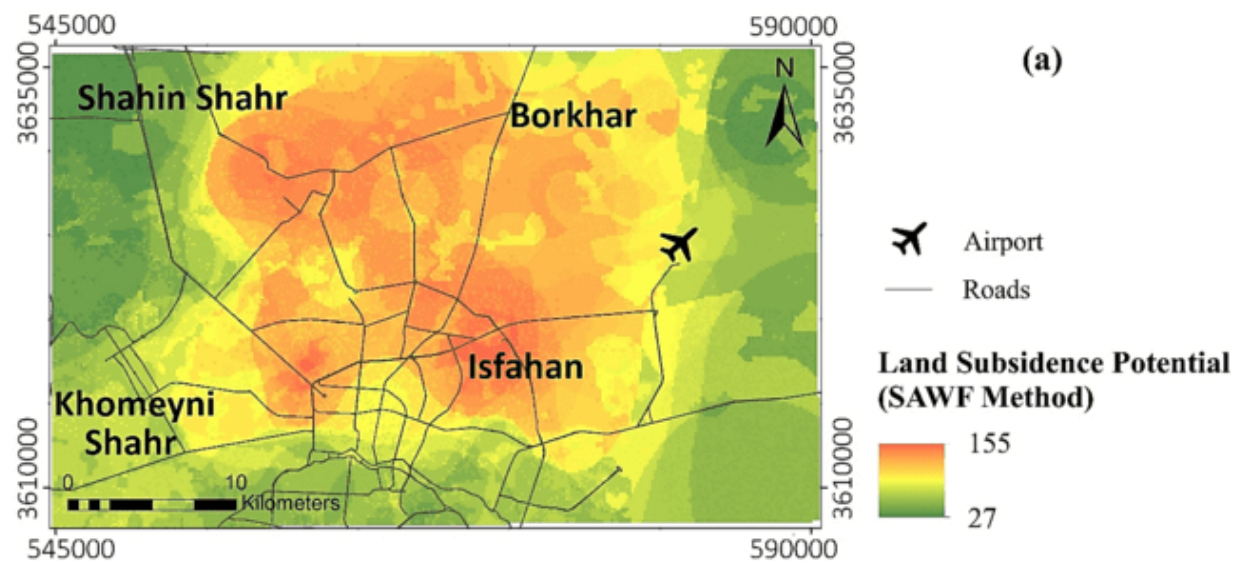
**Fig. 6.** Raster-based SAWF thematic layers: (a) aquifer media, (b) land use, (c) groundwater pumping rate, (d) recharge, (e) alluvium thickness, (f) distance from faults, (g) groundwater table decline (April 2023-April 2024), and the locations of cities within the study area.

## 5. Results

### 5.1. SAWF LSP

To estimate the LSP of the study area, the thematic layers generated using the SAWF method (Section 4.1) were integrated in ArcGIS using the Raster Calculator tool based on the weights assigned to each factor (Table 1) and Eq. (1). According to Table 2, the theoretical range of LSPI values varies from 24 to 240. The resulting SAWF-based LSP map (Fig. 7a) showed LSPI values ranging from 27 to 155.

The performance of the SAWF model in assessing land subsidence potential was evaluated using the  $r$  and the  $R^2$  by comparing the LSP map (Fig. 7a) with the land subsidence measurements derived from D-InSAR analysis (Fig. 7b). Although the two datasets show areas of agreement as well as local discrepancies, ...such differences are expected because the SAWF approach is primarily intended to identify relative spatial patterns of land subsidence potential rather than reproduce the magnitude of observed subsidence. The resulting  $r$  and  $R^2$  values were 0.72 and 0.52, respectively (Fig. 7c), indicating a moderate agreement between the SAWF-derived LSP map and the observed subsidence pattern.



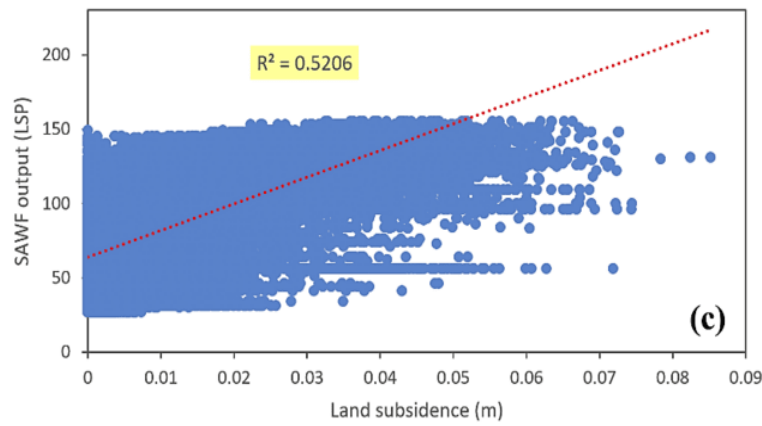
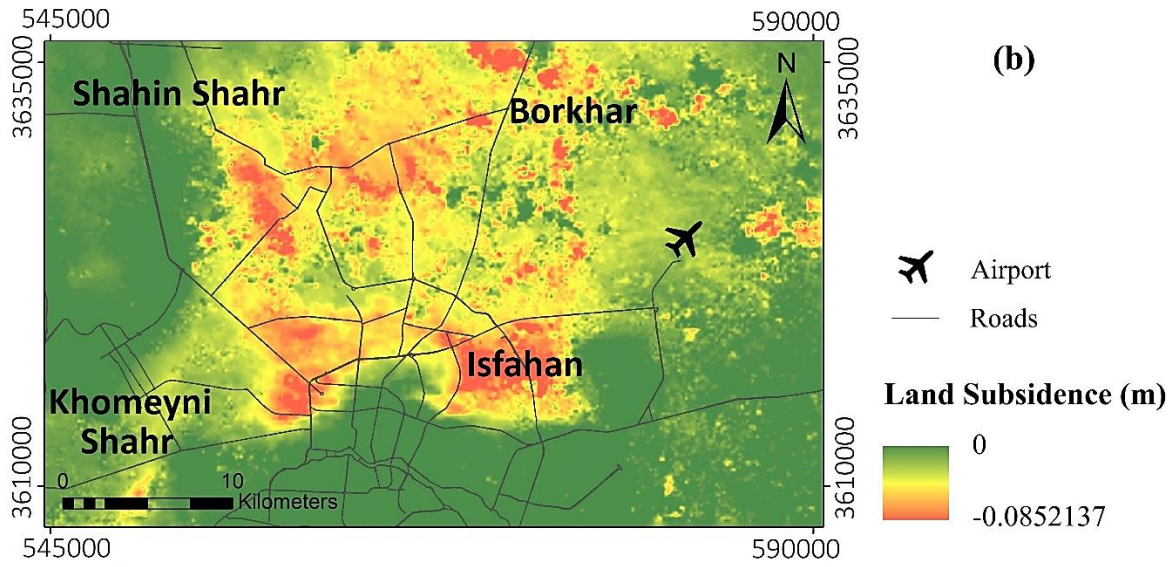


**Fig. 7.** LSP mapping for hotspot identification: (a) LSP map derived from the SAWF model; (b) land subsidence (LS) map derived from D-InSAR data (April 2023-April 2024); and (c)  $R^2$  values between the SAWF-LSP and D-InSAR LS results.

## 5.2. Level 1: AHP-based Optimization

To examine the effect of an expert-based weighting scheme on land subsidence potential mapping, the Analytic Hierarchy Process (AHP) weights reported by Halataei et al. (2025) were adopted. In their study, a pairwise comparison matrix was constructed, and the required information was collected through the collective judgment of experts to minimize individual bias. A questionnaire was distributed among specialists to evaluate the relative importance of each parameter based on their knowledge and professional experience.

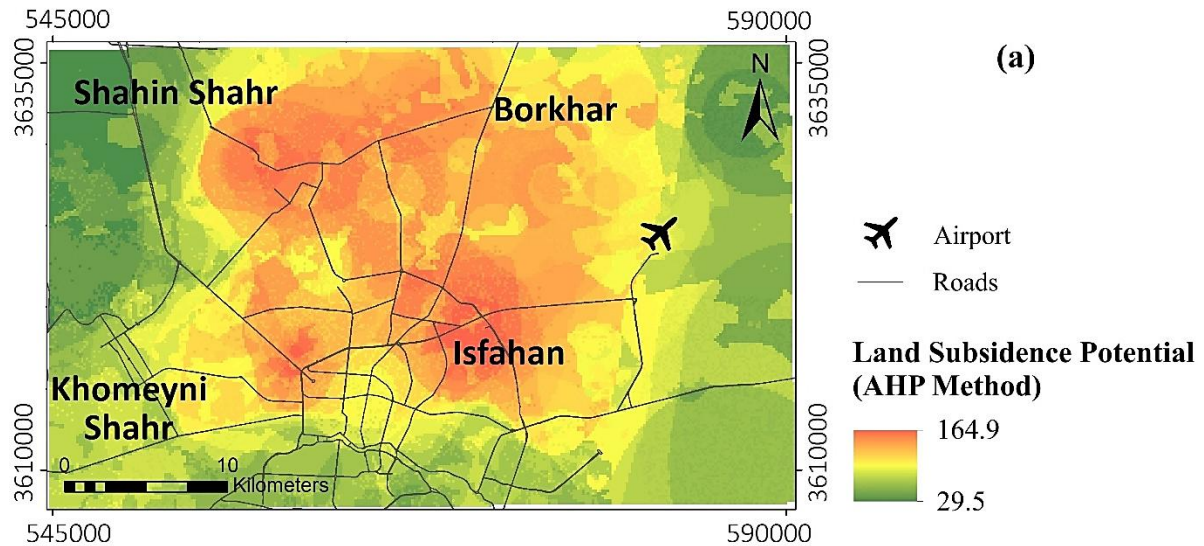
To assess expert qualifications, Halataei et al. (2025) employed the expert rating framework proposed by Renjith et al. (2010), which considers criteria such as education, work experience, age, and organizational position. After aggregating the expert judgments, the final weights of

the conditioning factors were obtained and are presented in Table 4. These weights were applied to the corresponding thematic layers to generate the AHP-based LSP map. The resulting AHP-based LSPI values ranged from 29.5 to 164.9. Fig. 8a illustrates the spatial distribution of LSP across the Isfahan-Borkhar plain derived from the AHP approach.

**Table 4.** Final weights assigned to the SAWF thematic layers using the elite score and the AHP method.

| Layers           | Aquifer media | Land use | Groundwater pumping rate | Recharge | Alluvium thickness | Distance from faults | Groundwater table decline |
|------------------|---------------|----------|--------------------------|----------|--------------------|----------------------|---------------------------|
| Weight           | 1.73          | 1.73     | 1.66                     | 1.08     | 0.96               | 0.95                 | 1.82                      |
| AHP final weight | 4.7           | 4.7      | 4.5                      | 3        | 2.6                | 2                    | 5                         |

The performance of the AHP-LSP model was evaluated using the  $r$  and the  $R^2$  by comparing the AHP-LSP map with the subsidence measurements derived from D-InSAR analysis. The resulting  $r$  and  $R^2$  values were 0.79 and 0.62, respectively, indicating a relatively strong agreement between the modeled land subsidence potential pattern and the observed land subsidence.



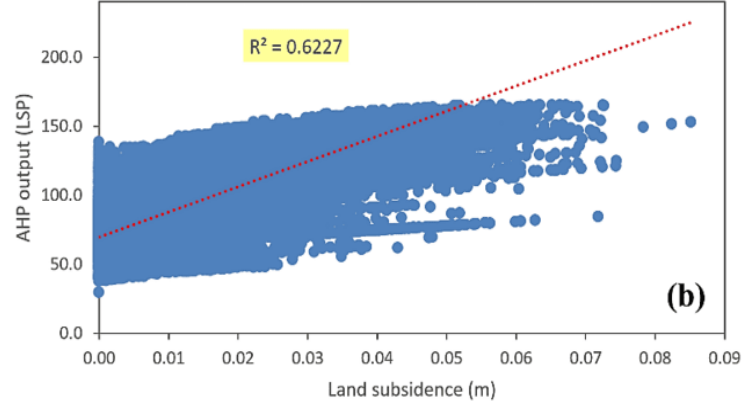


**Fig. 8.** LSP mapping for hotspot identification: (a) LSP map derived from the AHP-LSP model; (b)  $R^2$  values of the AHP-LSP results.

### 5.3. Level 2: Fuzzy logic-based Optimization

The input and target datasets used for implementing the SFL, MFL, and LFL models were divided into training and testing subsets, with 80% of the data randomly allocated to training and the remaining 20% reserved for testing.

The SFL model was developed to refine the initial LSP results and approximate the conditioned land subsidence potential index (CLSPI). The model inputs included the seven conditioning factors used in the SAWF model, the initial SAWF-derived index, and the AHP-based LSP output, while CLSPI was used as the target/reference data. The subtractive clustering (SC) algorithm was employed, with the clustering radius varying between 0 and 1. The optimal performance was achieved at a radius of 0.7, corresponding to the lowest RMSE and the highest correlation coefficient. Under this configuration, nine fuzzy if-then rules were generated and subsequently used for LSP mapping. Each fuzzy rule  $i$  can be expressed as:

$$\text{Rule } i: \text{If } \left( \begin{array}{l} A \text{ belongs to } MF_A^i \text{ and} \\ L \text{ belongs to } MF_L^i \text{ and} \\ P \text{ belongs to } MF_P^i \text{ and} \\ R \text{ belongs to } MF_R^i \text{ and} \\ I \text{ belongs to } MF_I^i \text{ and} \\ F \text{ belongs to } MF_F^i \text{ and} \\ T \text{ belongs to } MF_T^i \text{ and} \\ LSPI \text{ belongs to } MF_{LSPI}^i \text{ and} \\ AHP \text{ belongs to } MF_{AHP}^i \end{array} \right) \quad (13)$$

$$\text{Then: } LSP_i^{SFL} = m_i A + n_i L + o_i P + p_i R + q_i I + r_i F + s_i T + t_i LSPI + u_i AHP + v_i \quad (14)$$

510 where  $MF_A^i$  and  $MF_L^i$  denote the membership functions of the  $i$ th cluster for inputs  $A$  and  $L$ ,  
 511 respectively, while the remaining terms represent the corresponding membership functions of  
 512 the other input variables, including  $P, R, I, F, T, LSPI$  and  $AHP$ . The “and” operator combines  
 513 the membership functions within each rule.  $LSP_i^{SFL}$  denotes the output of rule  $i$ , formulated as  
 514 a linear function of the corresponding cluster, whereas  $m_i, n_i, o_i, p_i, q_i, r_i, s_i, t_i, u_i$  and  $v_i$  are  
 515 constant coefficients. The final SFL-LSP value is obtained as the weighted average of all rule  
 516 outputs:

$$517 \quad LSP^{SFL} = \frac{\sum w_i LSP_i^{SFL}}{\sum w_i} \quad (15)$$

518 where  $w_i$  represents the firing strength of rule  $i$ . Table 5 summarizes the performance of the  
 519 SFL model in terms of  $r, R^2$ , and  $RMSE$ . During training, the corresponding values were 0.95,  
 520 0.91, and 0.0629, respectively, whereas during testing they were 0.93, 0.87, and 0.0792. The  
 521 resulting SFL-LSP map is presented in Fig. 9a.

522 The MFL and LFL models were also implemented to refine the initial LSP results and  
 523 approximate the CLSPI values. The same input and target/reference datasets used for the SFL  
 524 model were employed for the MFL and LFL models. The fuzzy C-means (FCM) clustering  
 525 technique was used to derive the clusters and generate the fuzzy rules. Through a trial-and-  
 526 error procedure, the optimal number of rules was determined to be nine, corresponding to the  
 527 number of extracted clusters. Each fuzzy rule  $i$  for the MFL and LFL models is expressed as:

$$528 \quad \text{Rule } i: \text{If} \left( \begin{array}{l} A \text{ belongs to } MF_A^i \text{ and} \\ L \text{ belongs to } MF_L^i \text{ and} \\ P \text{ belongs to } MF_P^i \text{ and} \\ R \text{ belongs to } MF_R^i \text{ and} \\ I \text{ belongs to } MF_I^i \text{ and} \\ F \text{ belongs to } MF_F^i \text{ and} \\ T \text{ belongs to } MF_T^i \text{ and} \\ LSPI \text{ belongs to } MF_{LSPI}^i \text{ and} \\ AHP \text{ belongs to } MF_{AHP}^i \end{array} \right) \quad (15)$$

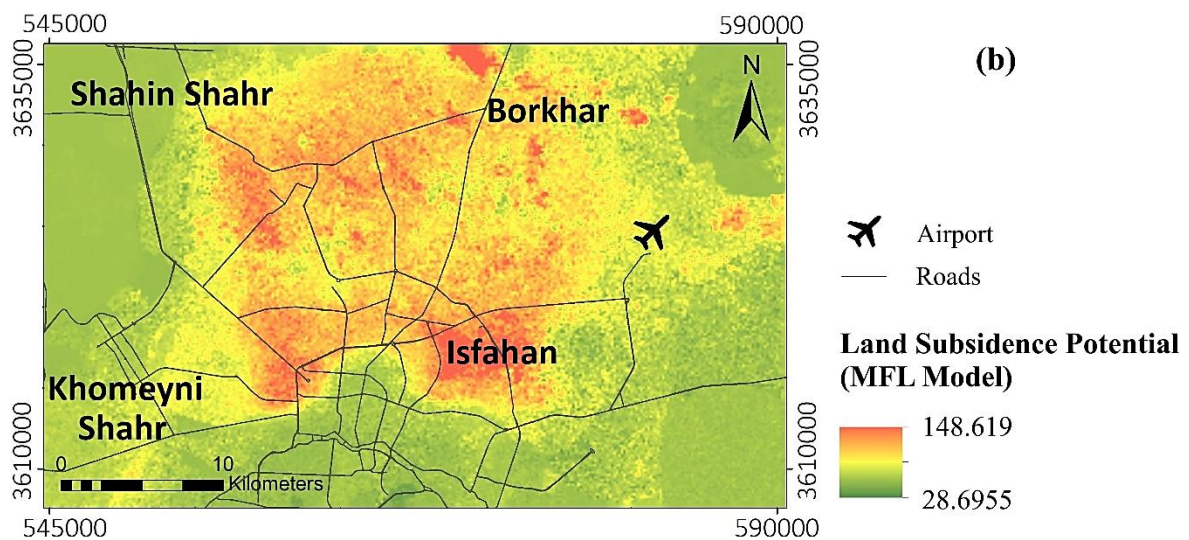
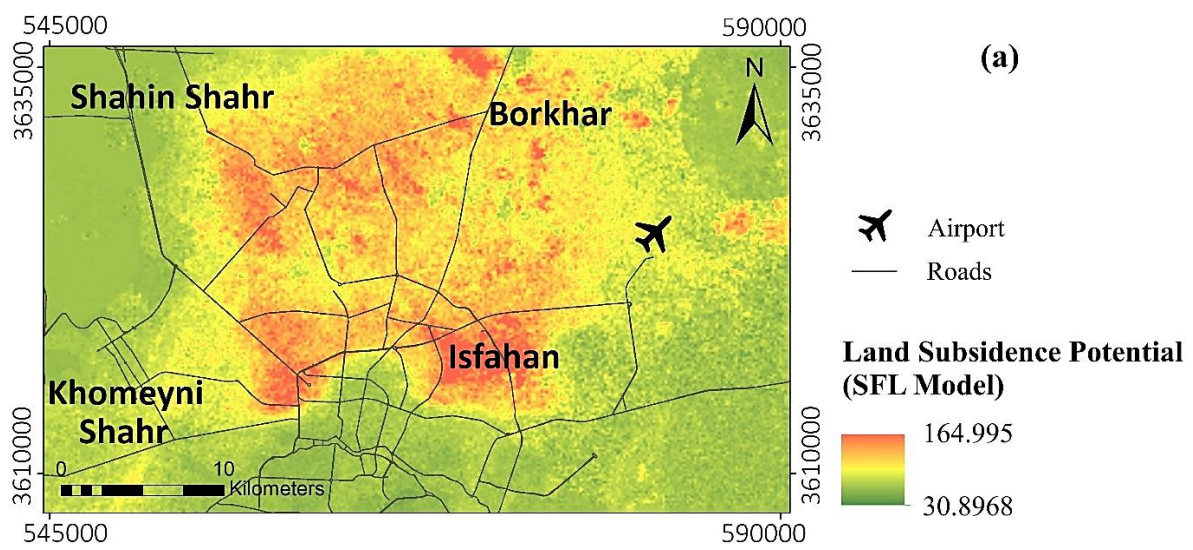
$$529 \quad \text{Then: } \widehat{CLSPI}_i \text{ belongs to } MF_{\widehat{CLSPI}}^i \quad (16)$$

530 where  $\widehat{CLSPI}_i$  represents the model-derived output and  $MF_{\widehat{CLSPI}}^i$  denotes the output  
 531 membership function associated with rule  $i$ . Table 5 reports the performance of the MFL and  
 532 LFL models using  $r, R^2$ , and  $RMSE$ . For the MFL model, the training values were 0.95, 0.90,  
 533 and 0.0661, respectively, while the testing values were 0.91, 0.83, and 0.0702. For the LFL  
 534 model, the corresponding training values were 0.93, 0.87, and 0.0769, whereas the testing

values were 0.88, 0.78, and 0.0997. The MFL-LSP and LFL-LSP maps are shown in Figs. 9b and 9c, respectively.

**Table 5.** Performance results of the three FL models during the training and testing phases.

| FL models  | Criteria |         |          |         |          |         |
|------------|----------|---------|----------|---------|----------|---------|
|            | $r$      |         | $R^2$    |         | $RMSE$   |         |
|            | Training | Testing | Training | Testing | Training | Testing |
| <b>SFL</b> | 0.95     | 0.93    | 0.91     | 0.87    | 0.0629   | 0.0792  |
| <b>MFL</b> | 0.95     | 0.91    | 0.90     | 0.83    | 0.0661   | 0.0702  |
| <b>LFL</b> | 0.93     | 0.88    | 0.87     | 0.78    | 0.0769   | 0.0997  |



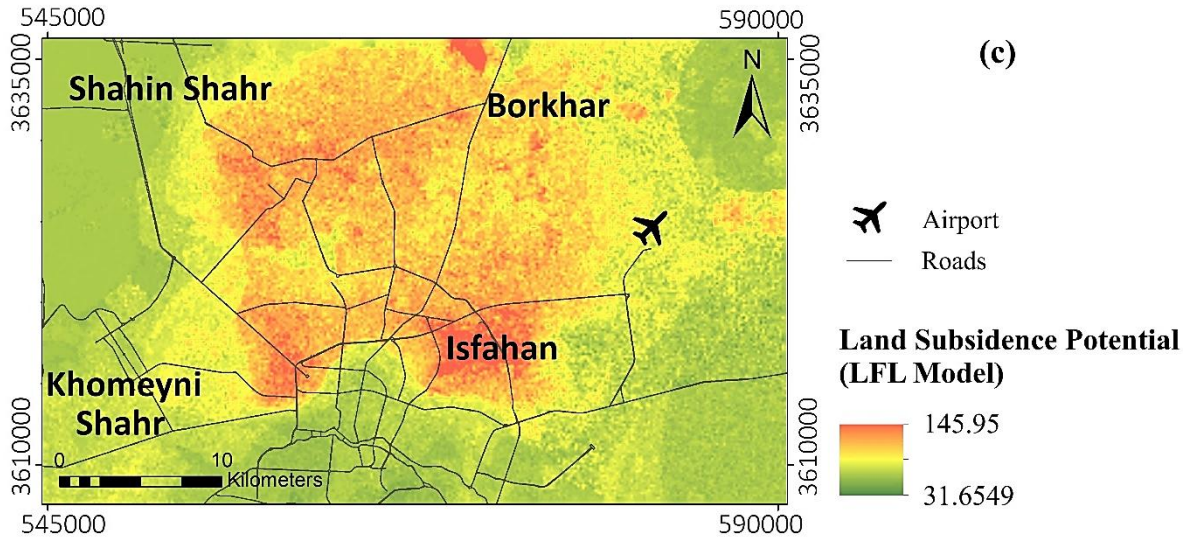


**Fig. 9.** LSP mapping for hotspot identification: (a) LSP map derived from the SFL-LSP model; (b) LSP map derived from the MFL-LSP model; and (c) LSP map derived from the LFL-LSP model.

#### 5.4. Level 3: Artificial intelligence-based Optimization

ANN and SVM were employed to implement the AIMM for LSP assessment. In this stage, LSPI, the outputs of the AHP method and fuzzy logic models were used as input variables for the AI-based models. The normalized CLSPI values served as the target/reference outputs.

For the ANN model, a multilayer perceptron (MLP) architecture coupled with the Levenberg-Marquardt (LM) training algorithm was implemented. The network consisted of an input layer with five neurons, corresponding to the normalized LSPI, the AHP-based LSP output, and the outputs of the SFL, MFL, and LFL models, a hidden layer containing nine neurons, and a single-neuron output layer (Fig. 10). The hidden layer employed the tangent sigmoid (TANSIG) transfer function, whereas the output layer used the linear PURELIN transfer function. After a maximum of 1000 training epochs, the ANN model achieved  $r$ ,  $R^2$ , and  $RMSE$  values of 0.96, 0.93, and 0.0570, respectively, for the training dataset, and 0.94, 0.89, and 0.0732, respectively, for the testing dataset (Table 6). The resulting ANN-based LSP map of the Isfahan-Borkhar plain is presented in Fig. 11a.

The SVM model was developed using the normalized LSPI, the AHP-based LSP output, and the outputs of the SFL, MFL, and LFL models as input variables, whereas the normalized CLSPI values were used as the target/reference outputs. Model optimization was performed using a radial basis function (RBF) kernel. The resulting SVM-based LSP model yielded  $r$ ,  $R^2$ , and  $RMSE$  values of 0.98, 0.96, and 0.0395, respectively, for the training dataset, and 0.97, 0.95, and 0.0504, respectively, for the testing dataset (Table 6). Fig. 11b presents the SVM-

based LSP map of the Isfahan-Borkhar plain. The higher correlation coefficients and lower RMSE values obtained for the SVM model indicate a stronger agreement between the model-derived LSP values and the CLSPI target/reference values compared with the ANN model.

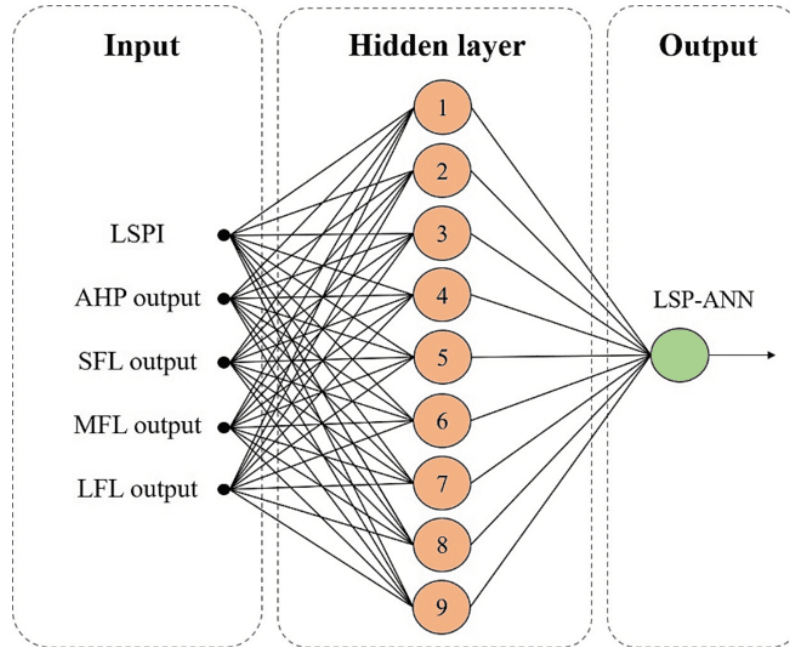
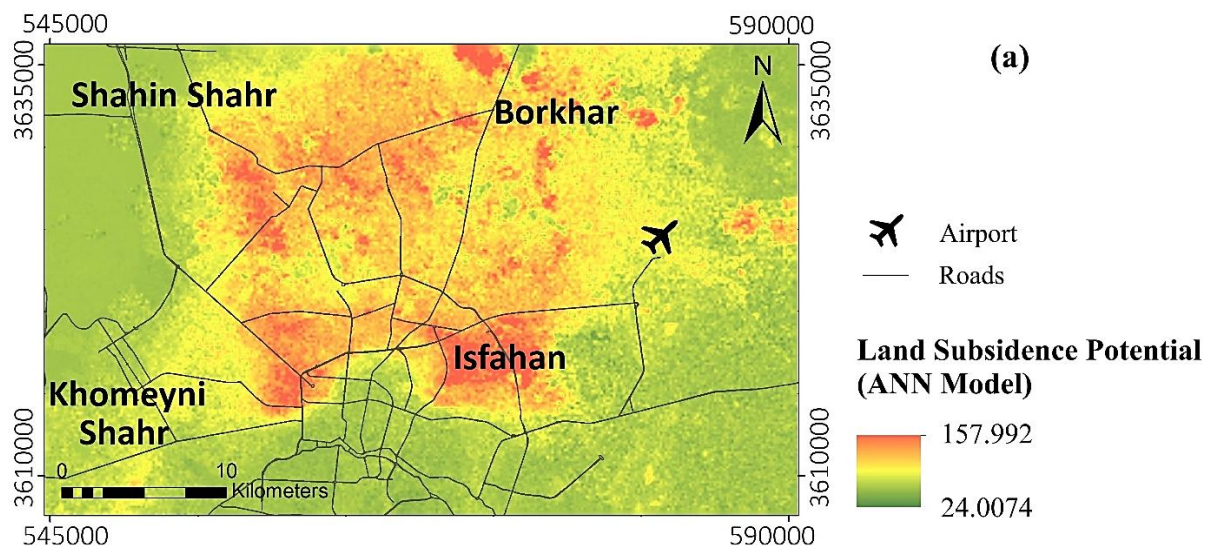


**Fig. 10.** Generalized ANN architecture for the LSP-ANN model.

**Table 6.** Results of the AIMM models (ANN and SVM) during the training and testing phases.

| AIMM<br>models | Criteria |         |          |         |          |         |
|----------------|----------|---------|----------|---------|----------|---------|
|                | $r$      |         | $R^2$    |         | $RMSE$   |         |
|                | Training | Testing | Training | Testing | Training | Testing |
| ANN            | 0.96     | 0.94    | 0.93     | 0.89    | 0.0570   | 0.0732  |
| SVM            | 0.98     | 0.97    | 0.96     | 0.95    | 0.0395   | 0.0504  |



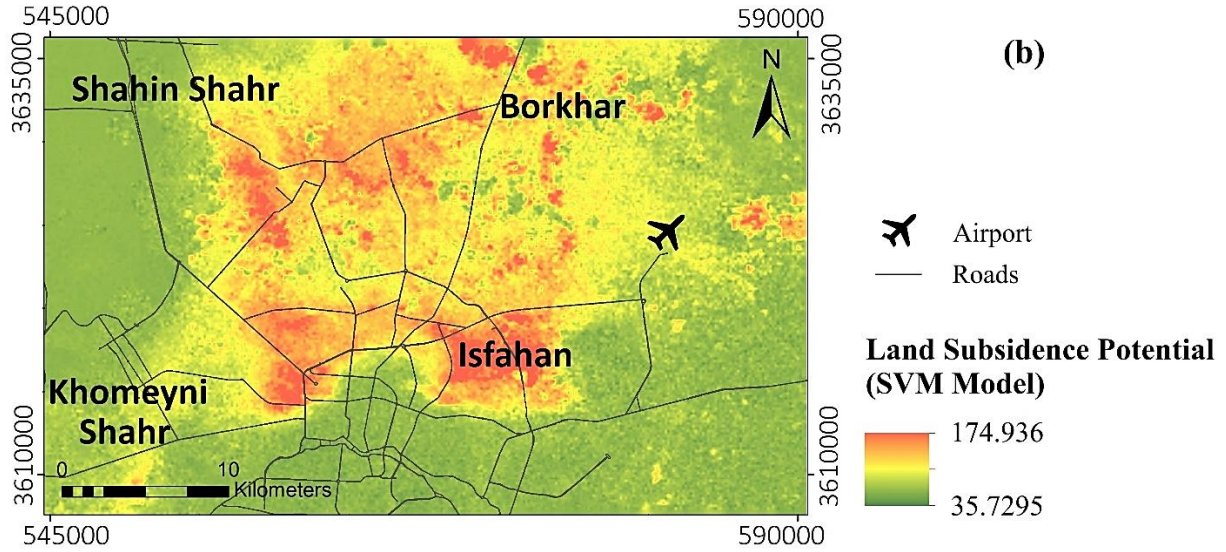


**Fig. 11.** LSP mapping for hotspot identification: (a) LSP map derived from the ANN-LSP model; and (b) LSP map derived from the SVM-LSP model.

### 5.5. Comparison of model performance

To validate the LSP maps generated by the Level 2 fuzzy logic models (SFL, MFL, and LFL) and the Level 3 AIMM models (ANN and SVM), the results were compared with ground deformation measurements derived from D-InSAR analysis. Fig. 12 presents the LS distribution between April 2023 and April 2024.

The validation results indicate that the AI-based models provide a closer agreement with the observed subsidence pattern than the conventional SAWF and AHP approaches. Fig. 13 illustrates the relationship between the model-derived LSPI values and the D-InSAR-derived LS measurements. As shown, the  $r$  increased from 0.72 for the SAWF model to 0.91, 0.89, and 0.86 for the SFL, MFL, and LFL models, respectively. Furthermore,  $r$  reached 0.92 and 0.96 for the ANN and SVM models, respectively.

Overall, the results demonstrate a progressive improvement in model performance from Level 1 to Level 3, indicating that the incorporation of fuzzy logic and machine-learning techniques enhances the capability of the models to reproduce the spatial pattern of observed land subsidence derived from D-InSAR analysis.

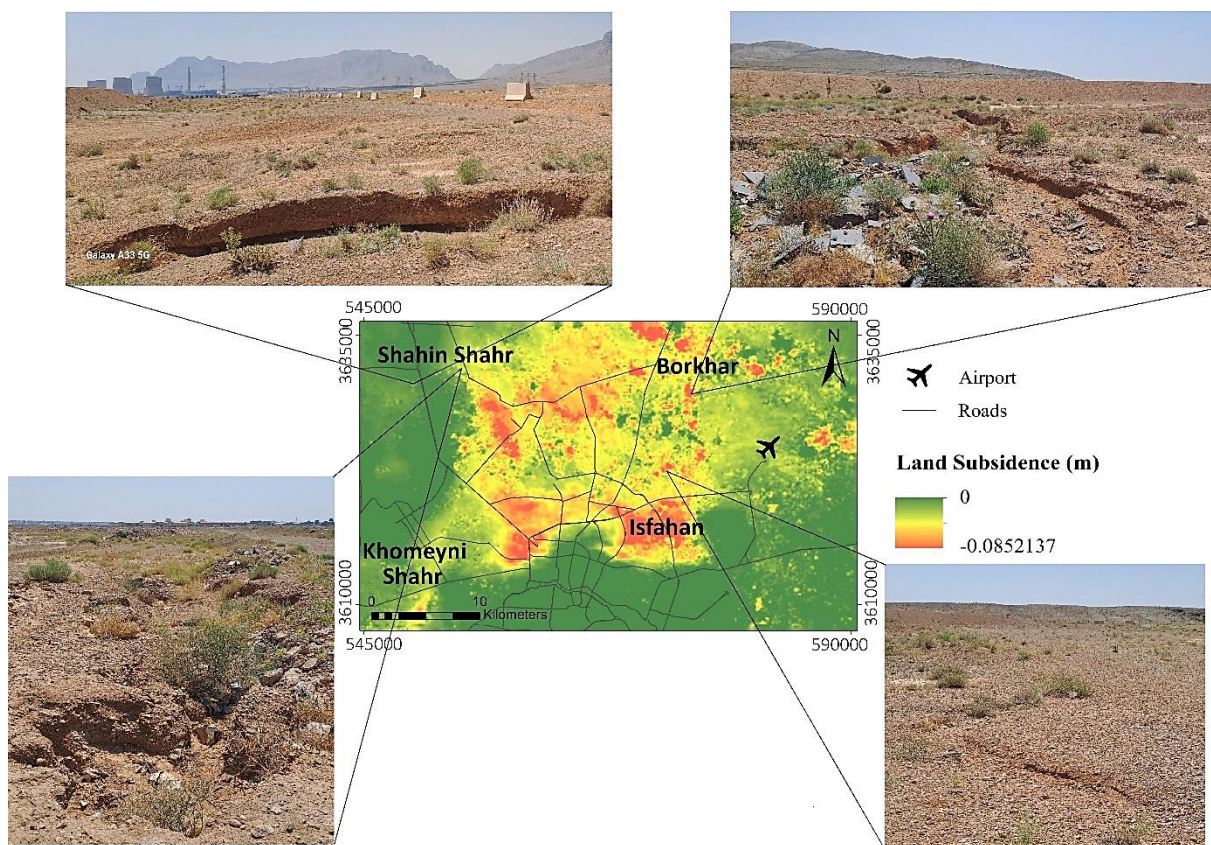
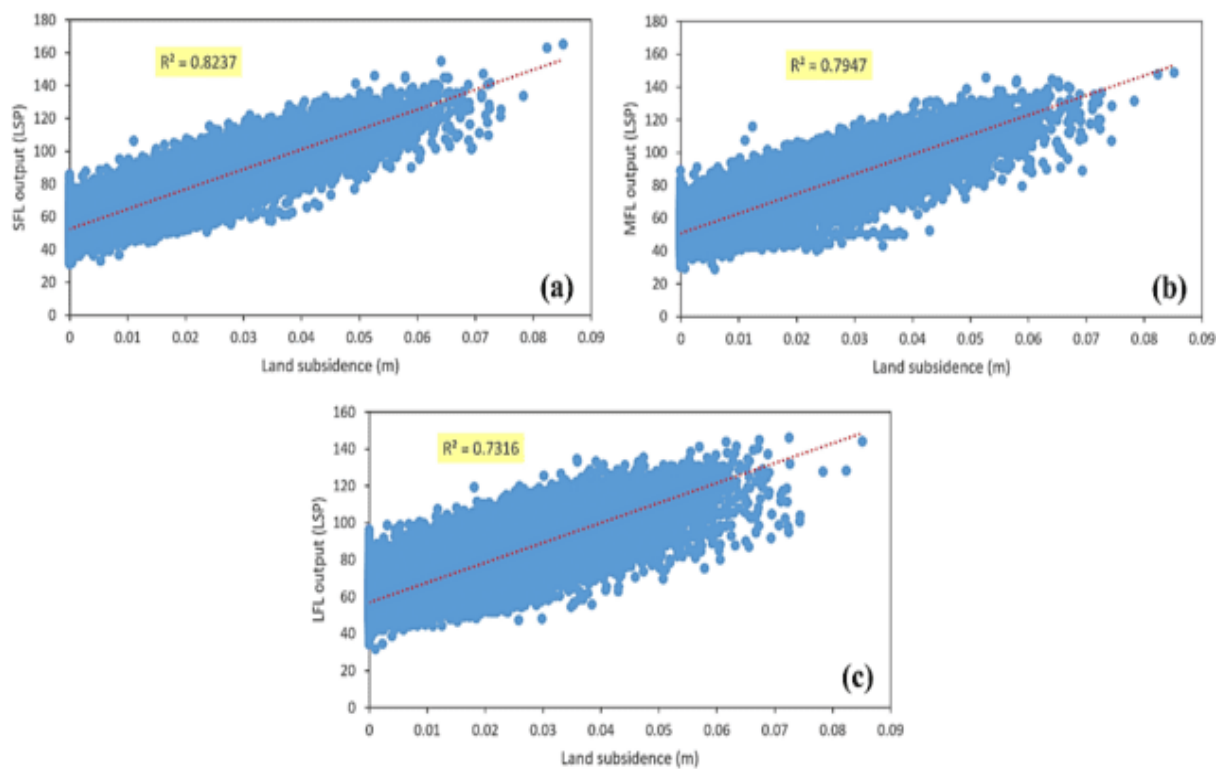


**Fig. 12.** D-InSAR-based land subsidence (LS) analysis from April 2023 to April 2024 and the spatial characteristics of LS in the study area.



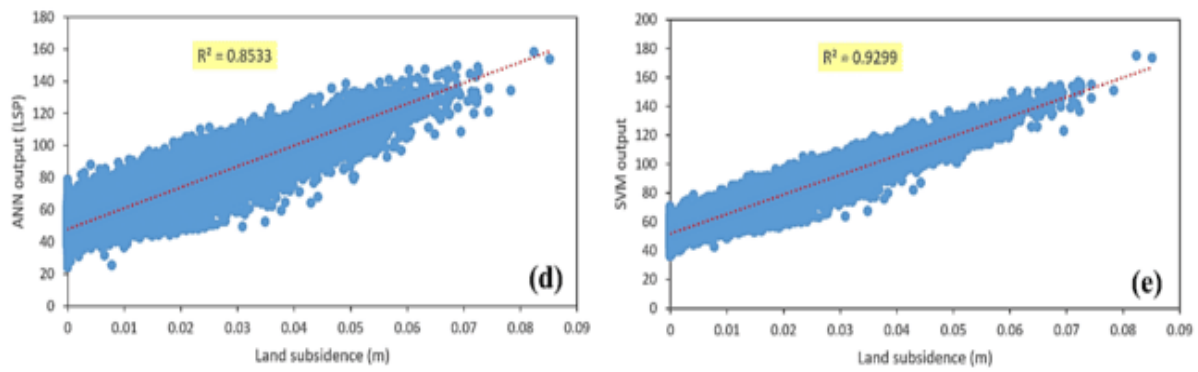


**Fig. 13.** Correlation between the LSP maps derived from (a) SFL, (b) MFL, (c) LFL, (d) ANN, and (e) SVM models and the land subsidence (LS) data obtained from D-InSAR.

## 6. Discussion

Land subsidence in the Isfahan-Borkhar plain is controlled by the combined effects of hydrogeological, geological, climatic, and anthropogenic factors. The region's arid climate, the influence of the Zayandeh-Rud River system, the dominance of fine-grained Quaternary deposits, and intensive groundwater abstraction have collectively created favorable conditions for land subsidence. At the same time, the presence of extensive urban and industrial development, important engineering infrastructure, valuable historical and cultural heritage sites, and several densely populated urban and peri-urban areas increases the need for reliable LSP mapping to identify zones more prone to ground deformation and to support subsidence-related management and mitigation strategies.

The comparison of the applied models shows that, although all approaches produced broadly comparable spatial patterns in delineating low-, moderate-, and high-potential zones, their agreement with D-InSAR-derived LS displacement values varied considerably. The conventional SAWF model provided a first-order representation of LSP distribution; however, its performance was limited because it relies on predefined factor weights and linear combination of conditioning factors. The AHP-based model improved the results to some extent by incorporating an expert-based weighting structure, but it was still unable to fully represent the nonlinear and spatially heterogeneous nature of land subsidence processes.

The incorporation of fuzzy logic models substantially improved model performance compared with the conventional weighting approaches. Among the fuzzy models, SFL achieved the best performance, with an  $R^2$  value of 0.87. This improvement can be attributed to the ability of fuzzy inference systems to represent uncertainty, gradual transitions between potential classes, and nonlinear interactions among conditioning factors. These characteristics

are particularly important in land subsidence studies, where hydrogeological, geological, and anthropogenic factors often interact in complex and spatially variable ways.

Among the artificial intelligence models, SVM showed the strongest agreement with the D-InSAR-derived LS displacement pattern, achieving the highest  $R^2$  value of 0.93 and outperforming the ANN model. The superior performance of SVM is likely related to its ability to capture complex nonlinear relationships while maintaining strong generalization capability, particularly when dealing with spatially heterogeneous datasets. This finding indicates that machine-learning approaches, especially SVM, can improve the representation of localized deformation patterns that may not be adequately captured by conventional index-based methods.

As shown in Fig. 13, the progressive integration of information through the AIMM framework resulted in increasingly consistent LSP estimates from Level 1 to Level 3. This improvement suggests that data-driven learning approaches can provide more representative model structures than predefined or expert-assigned weights alone. Overall, the results support the main concept of the proposed AIMM framework and demonstrate its potential for improving the practical applicability of conventional LSP assessment methods. From an applied perspective, the integration of D-InSAR observations with fuzzy logic and machine-learning techniques may also support the future operational use of LSP mapping frameworks for subsidence monitoring and mitigation planning.

## 7. Conclusion

This study evaluated and improved land subsidence potential (LSP) mapping in the Isfahan-Borkhar plain using a multi-level modeling framework that integrates SAWF, AHP, fuzzy logic models, and machine-learning techniques with Sentinel-1 D-InSAR-derived surface deformation observations. The results showed that the conventional SAWF model provides an initial approximation of LSP distribution, but its ability to delineate localized deformation-prone zones is limited. The incorporation of AHP improved the model performance moderately, while fuzzy logic and machine-learning approaches substantially increased the agreement between model-derived LSP maps and D-InSAR-derived LS displacement values.

Among the fuzzy logic models, SFL produced the best performance, indicating the effectiveness of fuzzy inference in representing uncertainty and nonlinear interactions among conditioning factors. Among all tested models, SVM achieved the highest agreement with the D-InSAR-derived deformation pattern, confirming its superior performance for LSP mapping

in the study area. High-potential zones were mainly concentrated in Gaz-e Borkhar, Dowlatabad, Baharan, Habibabad, Gavart, the eastern sector of Shahid Beheshti Airport, Khorzuq, and the northern districts of Isfahan, particularly municipal districts 8 and 10. These areas should therefore be considered priority zones for subsidence monitoring and mitigation planning.

Despite the improved performance of the proposed framework, uncertainties associated with groundwater data quality, temporal inconsistencies in auxiliary datasets, and inherent limitations of remote sensing observations remain. Therefore, the produced LSP maps should be interpreted as relative indicators of land subsidence potential rather than absolute predictions of future subsidence. For practical applications, the results should be complemented by field-based geotechnical investigations and continuous monitoring to support engineering decision-making, infrastructure protection, and cultural heritage preservation within the Isfahan metropolitan area.

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## References:

- 1) Adiyaman, I. B. (2012). Land subsidence and earth fissure due to groundwater pumping. *Doctoral dissertation, The University of Arizona*. USA, 199p.
- 2) Aghanabati, A. (2004). Geology of Iran. Geological survey of Iran. Geological Survey & Mineral Explorations of Iran.
- 3) Alaska Satellite Facility. (2024). \*ASF data search\*. <https://search.asf.alaska.edu/>

- 4) Amighpey, M., & Arabi, S. (2016). Studying land subsidence in Yazd province, Iran, by integration of InSAR and levelling measurements. *Remote Sensing Applications: Society and Environment*, 4, 1-8. <https://doi.org/10.1016/j.rsase.2016.04.001>
- 5) Amighpey, M., Arabi, S., & Talebi, A. (2010). Studying Yazd subsidence using InSAR and precise leveling. *Scientific Quarterly Journal of Geosciences*, 20(77), 157-164. <https://doi.org/10.22071/gsj.2010.55368>
- 6) Amini, D., Kafi, M., & Talebi, M. R. (2024). Assessment of the impacts of land subsidence on historical structures (District 3 of Isfahan). *Eighth International Conference on Technology Development in Materials Engineering, Mining and Geology papers*. <https://civilica.com/doc/2093696> (in Persian)
- 7) Arabameri, A., Pal, S.C., Rezaie, F., Chakraborty, R., Chowdhuri, I., Blaschke, T., & Ngo, P.T.T. (2021). Comparison of multi-criteria and artificial intelligence models for land-subsidence susceptibility zonation. *Journal of Environmental Management*, 284, 112067. <https://doi.org/10.1016/j.jenvman.2021.112067>
- 8) Arabameri, A., Saha, S., Roy, J., Tiefenbacher, J. P., Cerda, A., Biggs, T., ... & Collins, A. L. (2020). A novel ensemble computational intelligence approach for the spatial prediction of land subsidence susceptibility. *Science of the Total Environment*, 726, 138595. <https://doi.org/10.1016/j.scitotenv.2020.138595>
- 9) Asadi, S., Hassan, M., Nadiri, A.A., & Dylla, H. (2014). Artificial intelligence modeling to evaluate field performance of photocatalytic asphalt pavement for ambient air purification. *Environmental Science and Pollution Research*, 21(14), 8847-8857. <https://doi.org/10.1007/s11356-014-2821-z>
- 10) Azarm, Z., Mehrabi, H., & Nadi, S. (2023). Investigating the Relationship between Subsidence and Groundwater Level Changes using InSAR Time Series Analysis (Isfahan Study Area). *Journal of Geography and Environmental Hazards*, 11(4), 173-192. <https://doi.org/10.22067/geoh.2022.75774.1199> (in Persian)
- 11) Azizi, R., Rajabi, A. M., ManafiAzar, A. and Sayari, M. (2025). Assessment of Land Subsidence Hazard in the Isfahan-Borkhar Plain Using Simple Weighting and Factor Optimization through the Analytic Hierarchy Process (AHP). *Journal of Ecohydrology*, 13(2). <https://doi.org/10.22059/ije.2025.402822.1883>
- 12) Bagheri-Gavkosh, M., Hosseini, S. M., Ataie-Ashtiani, B., Sohani, Y., Ebrahimian, H., Morovat, F., & Ashrafi, S. (2021). Land subsidence: A global challenge. *Science of The Total Environment*, 778, 146193. <https://doi.org/10.1016/j.scitotenv.2021.146193>
- 13) Banerjee, P., Singh, V. S., Chattopadhyay, K., Chandra, P. C., & Singh, B. (2011). Artificial neural network model as a potential alternative for groundwater salinity forecasting. *Journal of Hydrology*, 398(3-4), 212-220. <https://doi.org/10.1016/j.jhydrol.2010.12.016>
- 14) Baum, R.L., Galloway, D.L., & Harp, E.L. (2008). Landslide and land subsidence hazards to pipelines. <https://doi.org/10.3133/OFR20081164>

- 15) Bezdek, J. C. (1981). Pattern recognition with fuzzy objective function algorithms. *Springer Science & Business Media*. <https://doi.org/10.1007/978-1-4757-0450-1>.
- 16) Blachowski, J. (2016). Application of GIS spatial regression methods in assessment of land subsidence in complicated mining conditions: case study of the Walbrzych coal mine (SW Poland). *Natural Hazards*, 84(2), 997-1014. <https://doi.org/10.1007/s11069-016-2470-2>
- 17) Cigna, F., Paranunzio, R., Bonì, R., & Teatini, P. (2025). Present-day land subsidence risk in the metropolitan cities of Italy. *Scientific reports*, 15(1), 34999. <https://doi.org/10.1038/s41598-025-18941-8>
- 18) Coppola Jr, E., Szidarovszky, F., Poulton, M., & Charles, E. (2003). Artificial neural network approach for predicting transient water levels in a multilayered groundwater system under variable state, pumping, and climate conditions. *Journal of hydrologic engineering*, 8(6), 348-360. [https://doi.org/10.1061/\(ASCE\)1084-0699\(2003\)8:6\(348\)](https://doi.org/10.1061/(ASCE)1084-0699(2003)8:6(348))
- 19) Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine learning*, 20(3), 273-297. <https://doi.org/10.1007/BF00994018>
- 20) Crosetto, M., Tscherning, C. C., Crippa, B., & Castillo, M. (2002). Subsidence monitoring using SAR interferometry: Reduction of the atmospheric effects using stochastic filtering. *Geophysical Research Letters*, 29(9), 26-1. <https://doi.org/10.1029/2001GL013544>
- 21) Daliakopoulos, I. N., Coulibaly, P., & Tsanis, I. K. (2005). Groundwater level forecasting using artificial neural networks. *Journal of hydrology*, 309(1-4), 229-240. <https://doi.org/10.1016/j.jhydrol.2004.12.001>
- 22) Dehghani, M., Zoj, M. J. V., & Entezam, I. (2013a). Neural network modelling of Tehran land subsidence measured by persistent scatterer interferometry. *Photogrammetrie-Fernerkundung-Geoinformation*, 5-17. <https://doi.org/10.1127/1432-8364/2013/0154>
- 23) Dehghani, M., Zoj, M. J. V., Hooper, A., Hanssen, R. F., Entezam, I., & Saatchi, S. (2013b). Hybrid conventional and persistent scatterer SAR interferometry for land subsidence monitoring in the Tehran Basin, Iran. *ISPRS journal of photogrammetry and remote sensing*, 79, 157-170. <https://doi.org/10.1016/j.isprsjprs.2013.02.012>
- 24) Deros, S.M., Din, N.M., Norzeli, S.M., Omar, R.C., Usman, F., & Hamim, S.A. (2022). Land subsidence susceptibility projection for Palembang slum area by complex MCDM-AHP technique. *J. Eng. Technol. Sci*, 54(1), 220104. <https://doi.org/10.5614/j.eng.technol.sci.2022.54.1.4>
- 25) Dinar, A., Esteban, E., Calvo, E., Herrera, G., Teatini, P., Tomás, R., ... & Albiac, J. (2020, January). Land subsidence: the forgotten enigma of groundwater (over-) extraction. *AERE/ASSA 2020 Allied Social Sciences Associations Annual Meeting, San Diego, CA*.
- 26) Fijani, E., Nadiri, A.A., Asghari Moghaddam, A., Tsai, F., Dixon, B. (2013). Optimization of DRASTIC method by supervised committee machine artificial intelligence to assess groundwater vulnerability for Maragheh-Bonab plain aquifer Iran. *Journal of hydrology*, 503, 89-100. <https://doi.org/10.1016/j.jhydrol.2013.08.038>.

- 27) Fruneau, B., Sarti, F. (2000). Detection of ground subsidence in the city of Paris using radar interferometry: isolation of deformation from atmospheric artifacts using correlation. *Geophysical Research Letters*, 27(24), 3981-3984. <https://doi.org/10.1029/2000GL008489>
- 28) Galloway, D. L., Hudnut, K. W., Ingebristen, S. E., Phillips, S. P., Peltzer, G., Rogez, F., and Rosen, P. A. (1998). Detection of Aquifer System Compaction and Land Subsidence Using Interferometric Synthetic Aperture Radar. Antelope Valley, Mojave Desert. California. *Water Resources Research*, 34(10), 2573-2585. <https://doi.org/10.1029/98WR01285>
- 29) Galloway, D. L., Jones, D. R., & Ingebristen, S. E. (1999). Land Subsidence in the Unites States. *Geological Survey (USGS)*, 1182.
- 30) Galloway, D.L., Burbey, T.J. (2011). Regional land subsidence accompanying groundwater extraction. *Hydrogeology Journal*, 19(8), 1459-1486. <https://doi.org/10.1007/s10040-011-0775-5>.
- 31) Geological Survey and Mineral Exploration of Iran (2014). Geological Map Report of Esfahan, 1:25,000 Scale. <https://www.jiraeg.ir/> (in Persian)
- 32) Gholami, V. (2022). Spatial modeling of groundwater depth fluctuations using co-active neuro-fuzzy inference system (CANFIS) and geographic information system (GIS). *Applied Water Science*, 12(3), 24. <https://doi.org/10.1007/s13201-022-01572-z>
- 33) Ghorbanzadeh, O., Rostamzadeh, H., Blaschke, T., Gholaminia, K., & Aryal, J. (2018). A new GIS-based data mining technique using an adaptive neuro-fuzzy inference system (ANFIS) and k-fold cross-validation approach for land subsidence susceptibility mapping. *Natural Hazards*, 94(2), 497-517. <https://doi.org/10.1007/s11069-018-3449-y>
- 34) Goorabi, A., Karimi, M., Yamani, M., & Perissin, D. (2020). Land subsidence in Isfahan metropolitan and its relationship with geological and geomorphological settings revealed by Sentinel-1A InSAR observations, *Journal of Arid Environments*, 181, 104238. <https://doi.org/10.1016/j.jaridenv.2020.104238>
- 35) Haghiri, M., Raeisi, N., Azizi, R., Shabani, K., & Ghadiri, M. (2024). Evaluation of karst aquifer development and karst water resource potential using fuzzy logic model (FAHP) and analysis hierarchy process (AHP): a case study, North of Iran. *Carbonates and Evaporites*, 39(2), 11. <https://doi.org/10.1007/s13146-024-00925-w>
- 36) Halataei, M., Khamechian, M., Amighpey, M., & Manafiazar, A. (2025). Investigating the land subsidence potential of the Varamin Plain using a Simple Additive Weighting method and optimizing the weighting of affecting factors on land subsidence by Analytical Hierarchy Process. *Scientific Quarterly Journal of Iranian Association of Engineering Geology*, 17(4), 97-114. [https://www.jiraeg.ir/article\\_228132\\_en.html](https://www.jiraeg.ir/article_228132_en.html) (in Persian)
- 37) Hidayat, A., Muslihudin, M., & Utami, I.T. (2017). Sistem Pendukung Keputusan Menentukan Lokasi Cafe Baru Suncafe Sebagai Destinasi Wisata Kuliner Di Kabupaten Pringsewu Menggunakan Metode Simple Additive Weighting (SAW). *Jurnal TAM (Technology Acceptance Model)*, 6, 71-79. <https://doi.org/10.56327/jurnaltam.v6i0.64>

- 38) Hopfield, J.J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the national academy of sciences*, 79(8), 2554-2558. <https://doi.org/10.1073/pnas.79.8.2554>
- 39) Hu, R. L., Yue, Z. Q., Wang, L., & Wang, S. J. (2004). Review on current status and challenging issues of land subsidence in China. *Engineering Geology*, 74(1-2), 65-77. <https://doi.org/10.1016/j.enggeo.2004.06.006>
- 40) Hung, W. C., Hwang, J.C., Liou, J.C., Lin, Y.S., & Yang, H.L. (2012). Modeling aquifer-system compaction and predicting land subsidence in central Taiwan. *Engineering Geology*, 147, 78-90. <https://doi.org/10.1016/j.enggeo.2012.07.018>
- 41) Hwang, C.L., & Yoon, K. (2012). Multiple Attribute Decision Making, Methods and Applications a State-of-the-Art Survey, *Springer Science & Business Media*.
- 42) IRWA (2024). The data supplied by the Isfahan Regional Water Authority to the authors. (<https://www.esrw.ir/>)
- 43) Jafari, F., Javadi, S., & Karimi, N. (2015). Forecasting of subsidence due to groundwater over exploitation using MODFLOW and interferometry technique in Radar imagery. In *36th IAHR World Congress, Netherlands*.
- 44) Jahangir, M.H., Khosravi, Z., and Sarrafha, H. (2021). Modeling of land subsidence due to groundwater overexploitation using elastoplastic Mohr-Coulomb model in Arak plain, Iran. *Geopersia*, 11(1), 131-151. <https://doi.org/10.22059/geope.2020.294079.648519>
- 45) Kakar, N., Metzger, S., Schöne, T., Motagh, M., Waizy, H., Nasrat, N. A., Lazecký, M., Amelung, F., Bookhagen, B. (2025). Interferometric radar satellite and in-situ well time-series reveal groundwater extraction rate changes in urban and rural Afghanistan. *Water resources research*, 61(3), e2023WR036626. <https://doi.org/10.1029/2023WR036626>
- 46) Kakavand, M., Haghizadeh, A., & Soleimani-Motlagh, M. (2025). Spatio-temporal analysis of trend the hydro-climatic time series and identify factors affecting Flood Hazard. *Earth Science Informatics*, 18(1), 177. <https://doi.org/10.1007/s12145-024-01577-z>
- 47) Kariminejad, N., Sepehr, A., Garajeh, M. K., Ahmadi, A., & Gholamhosseinian, A. (2024). Deep learning-based predictive models of land subsidence and collapsed pipes in Razavi Khorasan Province, Iran. *Earth Science Informatics*, 17(4), 3529-3545. <https://doi.org/10.1007/s12145-024-01349-9>
- 48) Larsen, P.M. (1980). Industrial applications of fuzzy logic control. *International Journal of Man-Machine Studies*, 12(1), 3-10. [https://doi.org/10.1016/S0020-7373\(80\)80050-2](https://doi.org/10.1016/S0020-7373(80)80050-2)
- 49) Lee, K. H. (2005). First course on fuzzy theory and applications. *Springer Berlin Heidelberg*.
- 50) Lee, S., Park, I. (2013). Application of decision tree model for the ground subsidence hazard mapping near abandoned underground coal mines. *Journal of environmental management*, 127, 166-176. <https://doi.org/10.1016/j.jenvman.2013.04.010>

- 51) Lee, S., Park, I., & Choi, J.K. (2012). Spatial prediction of ground subsidence susceptibility using an artificial neural network. *Environmental management*. 49(2), 347-358. <https://doi.org/10.1007/s00267-011-9766-5>
- 52) Li, C., Tang, X., & Ma, T. (2006). Land subsidence caused by groundwater exploitation in the Hangzhou-Jiaxing-Huzhou Plain, China. *Hydrogeology Journal*. 14(8), 1652-1665. <https://doi.org/10.1007/s10040-006-0092-6>
- 53) Li, H., Chen, C. P., & Huang, H. P. (2018). Fuzzy neural intelligent systems: Mathematical foundation and the applications in engineering. *CRC Press*.
- 54) Liu, Y., Ma, T., & Du, Y. (2017). Compaction of muddy sediment and its significance to groundwater chemistry. *Procedia Earth and Planetary Science*. 17, 392-395. <https://doi.org/10.1016/j.proeps.2016.12.099>
- 55) Luo, Q., Perissin, D., Lin, H., Zhang, Y., & Wang, W. (2013). Subsidence Monitoring of Tianjin Suburbs by TerraSAR-X Persistent Scatterers Interferometry. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 7(5), 1642-1650. <https://doi.org/10.1109/JSTARS.2013.2271501>
- 56) Ma, T., Du, Y., Ma, R., Xiao, C., & Liu, Y. (2018). Water-rock interactions and related eco-environmental effects in typical land subsidence zones of China. *Hydrogeology Journal*. 26(5), 1339-1349. <https://doi.org/10.1007/s10040-017-1708-8>
- 57) Malmir, M., & Delbari, M. (2015). Investigating the spatial variability of groundwater table in barkhar plain, Esfahan *Journal of Water and Sustainable Development*, 1(3), 73-82. <https://doi.org/10.22067/jwsd.v1i3.48660> (in Persian)
- 58) Mamdani, E.H. (1976). Advances in the linguistic synthesis of fuzzy controllers. *International Journal of Man-Machine Studies*, 8(6), 669–678. [https://doi.org/10.1016/S0020-7373\(76\)80028-4](https://doi.org/10.1016/S0020-7373(76)80028-4)
- 59) Manafiazar, A., Khamechiyan, M., Nadiri, A.A., Sharifikia, M. (2024). Learning simple additive weighting parameters for subsidence vulnerability indices in Tehran plain (Iran) by artificial intelligence methods. *European Journal of Enviromental and Civil Engineering*, 28(1), 108-127. <https://doi.org/10.1080/19648189.2023.2205914>
- 60) Manafiazar, A., Khamechiyan, M., Nikudel, M.R., & Sharifikia, M. (2025). Prediction of groundwater level in the southwest plain of Tehran-Iran by Multiple Modelling (MM) and treating heterogeneity by self-organizing map (SOM). *Geopersia*, 15(1), 163-179. <https://doi.org/10.22059/geope.2024.381089.648773>
- 61) Manafiazar, A., Khamehchiyan, M., & Nadiri, A.A. (2019). Comparison of vulnerability of the Southwest Tehran Plain aquifer with simple weighting model (ALPRIFT Model) and Genetic Algorithm (GA). *Kharazmi Journal of Earth Sciences*, 4(2), 199-212. <http://dx.doi.org/10.29252/gnf.4.2.199> (in Persian)
- 62) Moazamnia, M., Hassanzadeh, Y., Nadiri, A.A., & Sadeghfam, S. (2020). Vulnerability indexing to saltwater intrusion from models at two levels using artificial intelligence multiple model (AIMM).

- 863 *Journal of environmental management*, 255, 109871.  
 864 <https://doi.org/10.1016/j.jenvman.2019.109871>
- 865 63) Moghaddam, S., Ahmadi, H., Zeynalzadeh, K., & Hessari, B. (2020). Potential location of  
 866 renewable groundwater in Urmia Lake basin by AHP analysis and spatial fuzzy technique (case  
 867 study: Urmia plain). *Hydrogeology*, 5(2), 142-153. <https://doi.org/10.22034/hydro.2020.11035> (in  
 868 Persian)
- 869 64) Mohammadi, M., Fatemi Aghda, S.M., Talkhablou, M., & Cheshomi, A. (2020). Introducing a  
 870 comprehensive geological and geotechnical classification for urban planning and design, a case  
 871 study in Isfahan (Iran). *Geotechnical and Geological Engineering*, 38(6), 6809-6826.  
 872 <https://doi.org/10.1007/s10706-020-01471-7>
- 873 65) Mohammady, M. (2024). Land Subsidence Susceptibility Assessment in Semnan plain. *Iranian*  
 874 *Journal of Watershed Management Science and Engineering*, 17(63), 84-90.  
 875 <http://dx.doi.org/https://doi.org/10.22034/17.63.84> (in Persian)
- 876 66) Motagh, M., Walter, T.R., Sharifi, M.A., Fielding, E., Schenk, A., Anderssohn, J., & Zschau, J.  
 877 (2008). Land subsidence in Iran caused by widespread water reservoir overexploitation.  
 878 *Geophysical Research Letters*. 35(16). <https://doi.org/10.1029/2008GL033814>
- 879 67) Muslihudin, M., & Gumanti, M. (2017). A System to Support Decision Makings in Selection of Aid  
 880 Receivers for Classroom Rehabilitation for Senior High Schools by Education Office of Pringsewu.  
 881 *IJISCS (International Journal of Information System and Computer Science)*, 1(2), 1-9.  
 882 <https://doi.org/10.56327/ijiscs.v1i2.495>
- 883 68) Muslihudin, M., Kurniawan, D., & Widyaningrum, I. (2017). Implementasi Model Fuzzy SAW  
 884 Dalam Penilaian Kinerja Penyuluh Agama (Studi Kasus: Kementerian Agama Kabupaten  
 885 Pringsewu). *Jurnal TAM (Technology Acceptance Model)*, 8(1), 39-44.  
 886 <https://doi.org/10.56327/jurnaltam.v8i1.85>
- 887 69) Nadiri, A.A., Taheri, Z., Khatibi, R., Barzegari, G., & Dideban, K. (2018). Introducing a new  
 888 framework for mapping subsidence vulnerability indices (SVIs), ALPRIFT. *Science of the Total*  
 889 *Environment*, 628, 1043-1057. <https://doi.org/10.1016/j.scitotenv.2018.02.031>
- 890 70) Nasa (2023). <https://www.earthdata.nasa.gov/topics/human-dimensions/land-subsidence>.
- 891 71) Oh, H.J., & Lee, S. (2010). Assessment of ground subsidence using GIS and the weights-of-  
 892 evidence model. *Engineering Geology*, 115(1-2), 36-48.  
 893 <https://doi.org/10.1016/j.enggeo.2010.06.015>
- 894 72) Park, I., Choi, J., Lee, M. J., & Lee, S. (2012). Application of an adaptive neuro-fuzzy inference  
 895 system to ground subsidence hazard mapping. *Computers & Geosciences*, 48, 228-238.  
 896 <https://doi.org/10.1016/j.cageo.2012.01.005>
- 897 73) Piscopo, G. (2001). Groundwater vulnerability map, explanatory notes-Castlereagh catchment.  
 898 NSW. *Parramatta NSW: Australia NSW Department of Land and Water Conservation*.

- 74) Poland, J.F. (1984). Guidebook to studies of land subsidence due to ground-water withdrawal. *In Studies and Reports in Hydrology (Unesco)*, 40, Paris.
- 75) Rahmati, O., Golkarian, A., Biggs, T., Keesstra, S., Mohammadi, F., & Daliakopoulos, I.N. (2019). Land subsidence hazard modeling: Machine learning to identify predictors and the role of human activities. *Journal of Environmental Management*, 236, 446-480. <https://doi.org/10.1016/j.jenvman.2019.02.020>
- 76) Rajabi, A. M., Salehi, M., & Sohrabi Bidar, A. (2026). Groundwater over-exploitation and land subsidence in Tehran, Iran: A comprehensive assessment of causes and impacts. *Journal of Mountain Science*, 23(4), 1476-1492. <https://doi.org/10.1007/s11629-025-9595-2>
- 77) Rajabi, A.M. (2018). A numerical study on land subsidence due to extensive overexploitation of groundwater in Aliabad plain, Qom-Iran. *Natural Hazards*, 93(2), 1085-1103. <https://doi.org/10.1007/s11069-018-3448-z>
- 78) Rajabi, A.M., & Ghorbani. E. (2016). Land subsidence due to groundwater withdrawal in Arak plain, Markazi province, Iran. *Arabian Journal of Geosciences*, 9(20), 738. <https://doi.org/10.1007/s12517-016-2753-7>
- 79) Rajabi, A.M., Edalat, A., Abolghasemi, Y., & Khodaparast, M. (2024). Using neural network modeling to improve the detection accuracy of land subsidence due to groundwater withdrawal. *Journal of Mountain Science*, 21(7), 2320-2333. <https://doi.org/10.1007/s11629-023-8470-2>
- 80) Renjith, V.R., Madhu, G., Nayagam, V.L.G., & Bhasi, A.B. (2010). Two-dimensional fuzzy fault tree analysis for chlorine release from a chlor-alkali industry using expert elicitation. *Journal of hazardous materials*, 183(1-3), 103-110. <https://doi.org/10.1016/j.jhazmat.2010.06.116>
- 81) Ross, T. J. (2010). Fuzzy logic with engineering applications (3rd ed.).
- 82) Roszkowska, E. (2013). Rank ordering criteria weighting methods: A comparative overview. *Optimum. Studia Ekonomiczne*, 5(65), 14-33. <https://doi.org/10.15290/ose.2013.05.65.02>
- 83) Roy, A., & Chakraborty, S. (2023). Support vector machine in structural reliability analysis: A review. *Reliability Engineering and System Safety*, 233, 109126. <https://doi.org/10.1016/j.ress.2023.109126>
- 84) Saaty, T.L. (1980). The analytical hierarchy process. pinning priority, resource allocation. *RWS Publication*, USA.
- 85) SARscap (2018). <https://www.sarmap.ch/index.php/software/sarscape/>.
- 86) Shahhosseini, G., Fatemi, E., Gheidi, S., Sartipi Isfahani, M., Esmailpour Zanjani, N., & Matin, N.M. (2025). Machine Learning-Driven Urban Development Based on Land Subsidence: Isfahan, Iran. *International Conference on Innovation in Urban and Regional Planning. Springer Nature Switzerland*, 255-265. [https://doi.org/10.1007/978-3-032-18818-2\\_21](https://doi.org/10.1007/978-3-032-18818-2_21)

- 87) Sorkhabi, O.M., Nejad, A.S., Khajehzadeh, M. (2022). Evaluation of Isfahan City subsidence rate using InSAR and artificial intelligence. *KSCE Journal of Civil Engineering*, 26(6), 2901-2908. <https://doi.org/10.1007/s12205-022-2013-1>
- 88) Sugeno, M. (1985). Industrial application of fuzzy control. Elsevier Science Inc.
- 89) Sujay Raghavendra, N., & Deka, P.C., Shukla, S. (2015). Forecasting monthly groundwater level fluctuations in coastal aquifers using hybrid Wavelet Packet-Support vector regression. *Cogent Engineering*, 2(1), 999414. <https://doi.org/10.1080/23311916.2014.999414>
- 90) Suykens, J.A. (2001). Support vector machines: A nonlinear modelling and control perspective. *European journal of control*, 7(2-3), 311-327. <https://doi.org/10.3166/ejc.7.311-327>
- 91) Taravatrooy, N., Nikoo, M. R., Sadegh, M., & Parvinnia, M. (2018). A hybrid clustering-fusion methodology for land subsidence estimation. *Natural Hazards*, 94(2), 905-926. <https://doi.org/10.1007/s11069-018-3431-8v>
- 92) Terzaghi, K. (1925). Principals of Soil Mechanics, Settlement and consolidation of Clay. *Engineering News-Record*. 874-878.
- 93) Tomás, R., Romero, R., Mulas, J., Marturià, J.J., Mallorquí, J.J., Lopez-Sanchez, J.M., Herrera, G., Gutiérrez, F., González, P.J., Fernández, J., Duque, S., Concha-Dimas, A., Cocksley, G., Castañeda, C., Carrasco, D., & Blanco, P. (2014). Radar interferometry techniques for the study of ground subsidence phenomena: A review of practical issues through cases in Spain. *Environmental Earth Sciences*, 7(1), 163-181. <https://doi.org/10.1007/s12665-013-2422-z>
- 94) Tzampoglou, P., Ilia, I., Karalis, K., Tsangaratos, P., Zhao, X., & Chen, W. (2023). Selected worldwide cases of land subsidence due to groundwater withdrawal. *Water*, 15(6), 1094. <https://doi.org/10.3390/w15061094>
- 95) Zadeh, L.A. (1965). Fuzzy sets. *Information and Control*, 8(3), 338-353. [https://doi.org/10.1016/S0019-9958\(65\)90241-X](https://doi.org/10.1016/S0019-9958(65)90241-X)
- 96) Zhou, Y., Dong, D., Liu, J., Li, W. (2013). Upgrading a regional groundwater level monitoring network for Beijing Plain. China. *Geoscience Frontiers*, 4(1), 127-138. <https://doi.org/10.1016/j.gsf.2012.03.008>

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