Journal of Agricultural Science and Technology (JAST), 29(3)
In Press, Pre-Proof Version

Dual-scale assessment of managerial-institutional flood resilience potential: A virtual benchmarking-enhanced MADM framework for socio-hydrological systems

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Abstract

This study proposes an innovative framework for mapping absolute flood resilience potential in socio-hydrological units of the Sang Sefid region, Iran, by integrating theoretical benchmark alternatives into a TOPSIS-based assessment. Using a dual-scale approach (relative and absolute), managerial-institutional flood resilience was assessed through 16 expert-validated indicators across five dimensions: institutional collaboration, education and awareness, performance and public satisfaction, prevention and reconstruction, and participatory planning. Data were collected via Likert-scale surveys from 663 household heads, with questionnaire reliability confirmed (α = 0.768). Resilience was quantified using TOPSIS with hypothetical minimum/maximum scenarios as benchmarks. Results revealed significant spatial variability: relative resilience ranged from very low (S-int3, R=0.00) to very high (S9, R=0.99), while absolute resilience ranged from very low (S-int3, R=0.05) to high (S9, R=0.75) with no "very high" category, highlighting critical distinctions between the two approaches. Model validation through Receiver Operating Characteristic (ROC) curve analysis (AUC = 0.917) and Cronbach's alpha (α = 0.857) confirmed outstanding performance and reliability. This framework enables systematic intra- and inter-regional resilience comparisons and temporal monitoring, serving as a replicable tool for multi-scale mapping to enhance adaptive governance and sustainable flood management in socio-hydrological systems.

Keywords: Absolute resilience assessment, Expert-based validation, Managerial-institutional resilience, Socio-hydrological systems, Theoretical benchmark alternatives, TOPSIS-based assessment.

1. Introduction

In Iran, flood events, driven by unsustainable development, human interventions (Belvasi *et al.*, 2020), and climate change impacts (Irani *et al.*, 2025), have become increasingly severe in recent

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decades, affecting both urban and rural areas (Ghadbeygi *et al.*, 2024). These floods have caused extensive social, economic, and environmental damages across the country's watersheds (Foroudi Sefat *et al.*, 2024). Notable examples include the July 2015 floods in the Kan and Sijan watersheds in Tehran Province (Ranjbar and Moradi, 2020), the April 2018 floods in Lorestan (Doroudi, 2019), and the 2018 floods in Golestan Province (Rajabizadeh *et al.*, 2019). Accordingly, mapping flood susceptibility in watersheds , assessing various dimensions of urban and rural community resilience to flood risks , and identifying flood causes while formulating strategies to enhance flood resilience represent critical steps toward effective flood management, particularly within the framework of integrated watershed management (Mosaffaie *et al.*, 2019). In this study, the assessment of the institutional-managerial resilience potential of local communities against flooding within socio-hydrological units is examined. While infrastructural and environmental adaptations are essential, the role of managerial-institutional resilience remains a pivotal yet underexplored dimension. This refers to the capacity of local governance systems, organizational structures, and decision-making processes to anticipate, absorb, adapt, and recover from flood-related disruptions.

The concept of resilience was first introduced in physics, emphasizing a system's ability to recover from imposed stress (Cao *et al.*, 2023). Subsequently, in 1973, it was adopted by Canadian biologist Holling to describe the characteristics of a stable ecosystem in the field of ecology (Holling, 1973). Over time, the concept of resilience has been applied across various disciplines to urban and rural areas and ecosystems facing diverse natural hazards, including urban resilience to flooding , drought , and earthquakes , as well as rural resilience to flooding , drought , landslides , and earthquakes (Zhang *et al.*, 2022). Accordingly, various definitions of resilience have been proposed based on the context of study (Prashar *et al.*, 2023; Mesbah *et al.*, 2024). Broadly, resilience refers to a system's enhanced capacity to anticipate, absorb, or recover from a shock and successfully adapt to such conditions to ensure future improvement and security (Cutter, 2016). In other words, resilience denotes a system's ability to absorb and recover from the impacts of disruptive events without fundamental changes to its function or structure (Proag, 2014).

In the context of flooding, the concept of resilience has been particularly defined for the resilience of urban environments against floods (Prashar *et al.*, 2023). Urban flood resilience is characterized as the capacity of a city's natural conditions, economic structure, social development, and infrastructure to adapt to floods and recover effectively through the rapid deployment of resources

(Cao *et al.*, 2023). To fully capture the multifaceted nature of resilience, it is often categorized into several dimensions, including social-cultural, economic, managerial-institutional, and physical dimensions (Meerow *et al.*, 2016; Mesbah *et al.*, 2024). These dimensions collectively contribute to a system's capacity to withstand and adapt to disruptions. Among these, managerial-institutional resilience is particularly critical in socio-hydrological systems, as it encompasses the governance structures, policies, and decision-making processes that enable effective preparation, response, and recovery from flood-related disturbances (Adger *et al.*, 2005). Specifically, managerial-institutional resilience refers to the ability of institutions and management frameworks to coordinate resources, implement adaptive strategies, and foster collaboration among stakeholders to mitigate the impacts of floods and enhance system recovery (Pahl-Wostl *et al.*, 2013). This dimension is particularly relevant for developing robust frameworks, such as multi-criteria decision-making models, to assess and enhance flood resilience in complex socio-hydrological contexts.

A range of indicators contribute to the assessment of managerial-institutional resilience in local communities facing flood risks (Cao *et al.*, 2023). These indicators can be categorized into different groups, including (1) institutional collaboration , (2) education and awareness , (3) performance and public satisfaction , (4) prevention and reconstruction , and (5) participatory planning . This classification highlights key dimensions of flood management, from governance to community engagement and risk mitigation. Furthermore, the literature review indicates that the assessment of resilience is typically based on the identification of relevant indicators, the use of Likert-scale surveys (González-Quintero and Avila-Foucat, 2019), and the application of various statistical tests, such as one-way analysis of variance (Nahid *et al.*, 2021). Furthermore, the integration of indicators based on multi-attribute decision-making (MADM) methods (Miao *et al.*, 2025) or developed indices (Md Munjurul Haque et al. 2022) can also be applied to assess resilience. In contrast to statistical methods, which solely rely on the values of obtained indicators for prioritizing rural environments or other alternatives, MADM methods incorporate both the values and the relative importance of indicators in the prioritization process. This approach enables the determination of resilience potential in rural settings (Mabrouk and Haoying, 2023; Miao *et al.*, 2025). In this regard, the TOPSIS method employed in this study is among the widely used MADM methods, applied for prioritizing and assessing the potential of events (Pandey *et al.*, 2023).

Despite the growing body of research on flood resilience assessment, existing frameworks suffer from a fundamental limitation: they predominantly rely on relative rankings that only permit intra-regional comparisons and fail to provide a universal baseline for evaluating whether a system's resilience is intrinsically sufficient (Pandey *et al.*, 2023; Salehpour Jam *et al.*, 2023; Miao *et al.*, 2025). This methodological gap is particularly critical for managerial-institutional resilience, where governance structures and institutional capacities vary significantly across regions, yet no standardized benchmark exists to distinguish between contextually adequate and fundamentally insufficient resilience. Consequently, a community classified as "highly resilient" in a relatively vulnerable region may, in absolute terms, still fall short of minimum resilience thresholds necessary for effective flood adaptation. To address this gap, the present study introduces a novel framework for the dual-scale assessment of managerial-institutional flood resilience in socio-hydrological units by integrating theoretical benchmark alternatives (min/max resilience scenarios) into a TOPSIS-based multi-attribute decision-making approach. It is important to emphasize that the term "absolute resilience" in this study refers to a benchmark-based quantification using hypothetical minimum and maximum resilience scenarios (mean scores of 1 and 5 on the Likert scale). This does not imply an objectively "true" or universal measure of resilience, but rather a standardized reference framework that enables consistent comparisons across units and regions, while acknowledging that the results remain dependent on the selected indicators, expert weights, and perceptual survey data. Unlike conventional approaches, this method enables both relative and absolute resilience potential mapping, allowing for meaningful intra- and inter-regional comparisons as well as temporal monitoring. Furthermore, the study employs expert-based model validation through a combination of Likert-scale expert surveys and Receiver Operating Characteristic (ROC) curve analysis, enhanced by Cronbach's alpha for questionnaire reliability, to ensure the robustness of the proposed model (Richardson *et al.*, 2024). This approach is proposed as a replicable tool for assessing both relative and absolute flood resilience potential in other socio-hydrological units, enabling the evaluation of absolute resilience potential and the generation of integrated regional and national maps.

2. Materials and Methods

2.1. Study area

The Sang Sefid study area (13481.1 ha) is located northeast of Ilam city within Chardavol County, Ilam Province, in western Iran. This region is also located between 46° 39' 6" to 46° 52' 2" east longitude and 33° 36' 45" to 33° 45' 10" north latitude. The study area receives a mean annual precipitation of 678 mm (GDNRWM, 2019c). Primary access is via the Ilam-Sarabaleh road, which traverses the southern boundary of the region. The region's altitude ranges between a minimum of 741 m and a maximum of 1789 m above sea level (Fig. 1). It contains 4919.54 hectares of agricultural land (both rainfed and irrigated systems) and orchards, predominantly cultivated with wheat, barley, rice, lentils, and grape vineyards (GDNRWM, 2019a). According to online data from Iran's 2016 National Population and Housing Census (SCI, 2016), the watershed comprises 18 villages with a total population of 2984 inhabitants, showing the highest settlement density in the southern sector of the region (Fig. 1). Peak flood discharges for 10-, 25-, 50-, and 100-year return periods in the watershed were estimated at 35.2, 40.8, 43.7, and 45.7 m^3/s, respectively, using the SCS method (GDNRWM, 2019b). Recurrent destructive flood events in recent decades have caused significant economic damage across the region, particularly to agricultural lands, transportation routes, and pastoral infrastructure. Notable recent events include the May 2016 and March 2023 floods, which severely impacted built structures, road networks, transhumance pathways, and cultivated areas, including orchards.

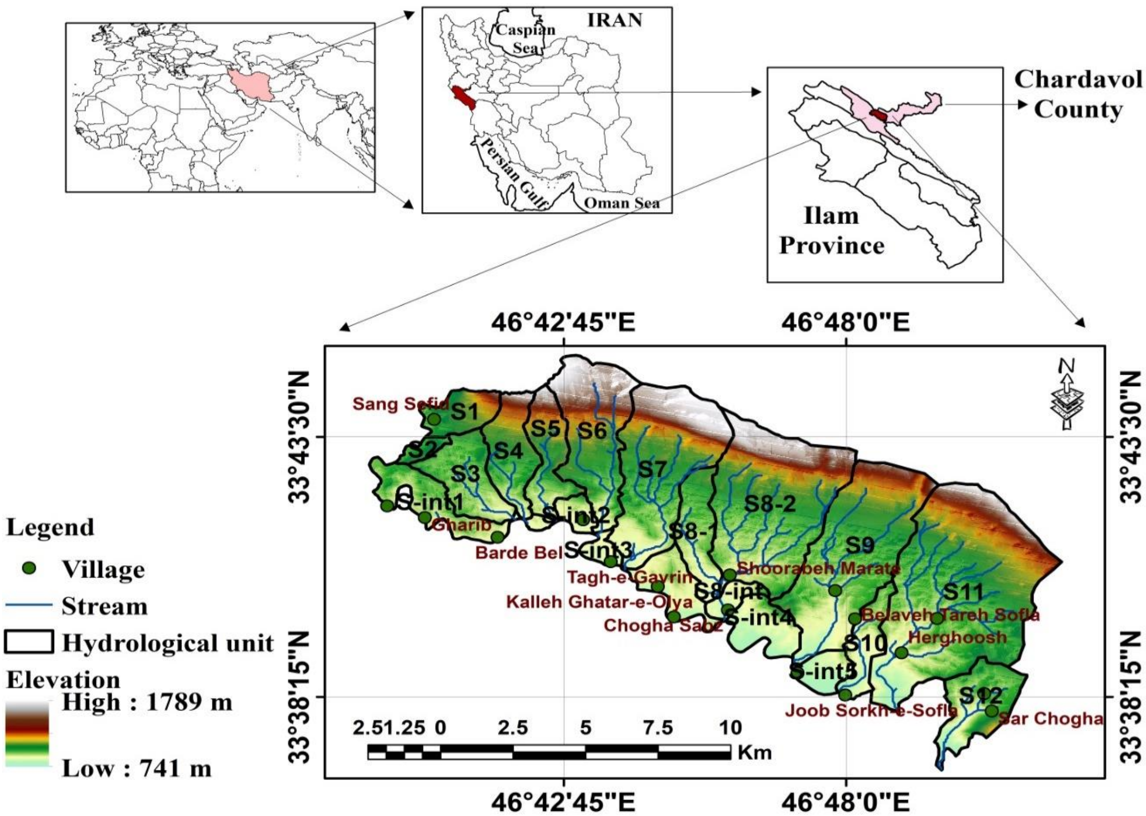

Fig. 1 Location of the Sang Sefid study area within Chardavol County, Ilam Province, western Iran.

2.2. Methodology

In this study, the managerial-institutional resilience of socio-hydrological units exposed to flood risk is evaluated using a novel TOPSIS-based framework enhanced with virtual benchmarking, following a structured multi-step process (Fig. 2). The methodology integrates theoretical benchmark alternatives (minimum and maximum resilience scenarios) to enable both relative and absolute resilience assessments. The process begins with the identification and quantification of resilience indicators using expert-derived data. Subsequently, a weighted decision matrix is constructed, incorporating the relative importance of these indicators. The TOPSIS method is then applied to compute resilience indices, followed by validation through expert-based analysis. This approach ensures a comprehensive assessment of resilience potential across flood-vulnerable units.

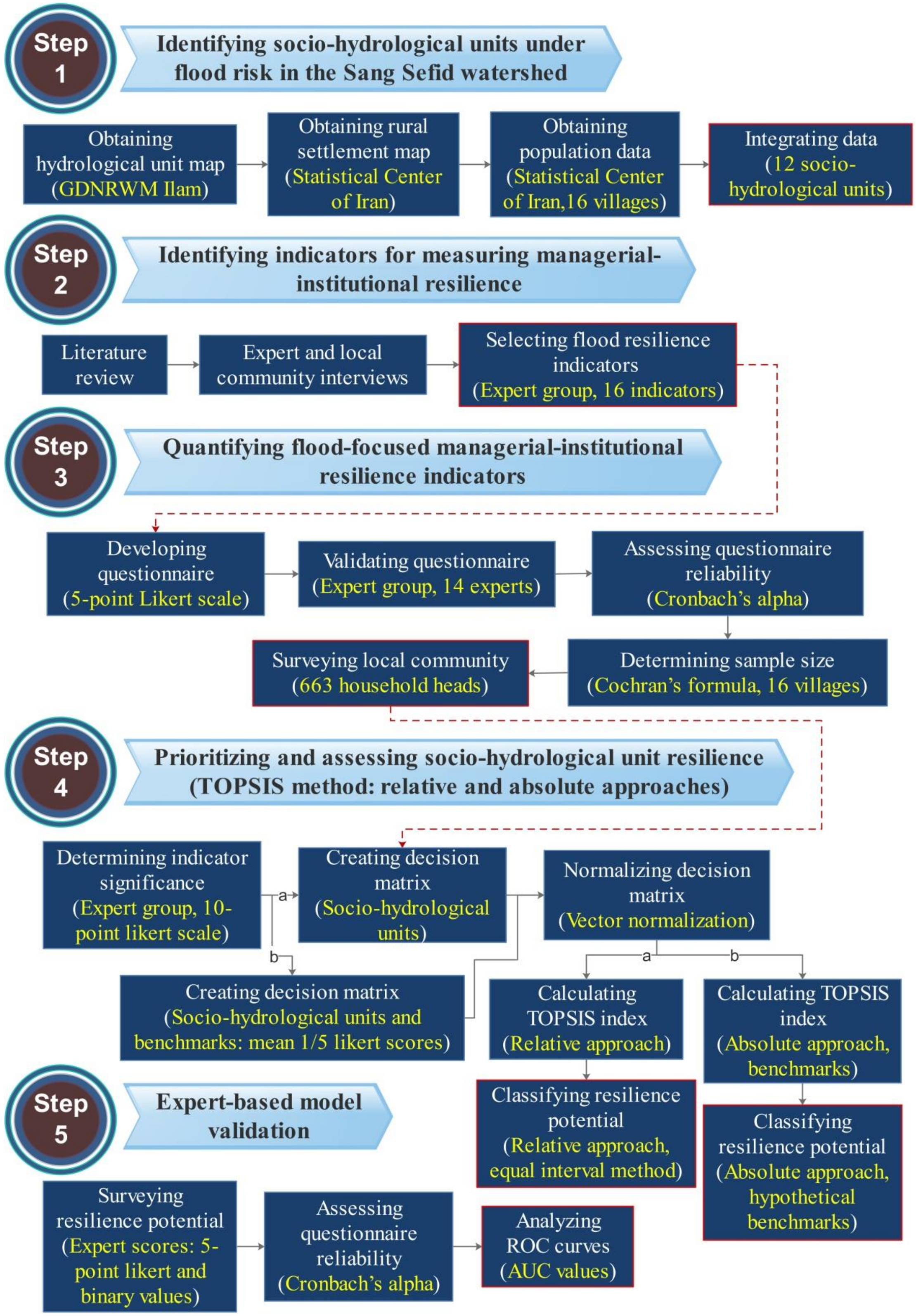

Fig. 2. Flowchart of methodology for assessing and validating socio-hydrological unit flood resilience using TOPSIS and expert-based validation.

2.2.1 Study Scope Definition

This study employed a systematic approach to delineate socio-hydrological units through the integration of hydrological boundaries and a settlement distribution map. First, hydrological units within the Sang Sefid region were identified using GIS-based maps provided by GDNRWM (2019d). These hydrological units were officially delineated by the General Department of Natural Resources and Watershed Management of Ilam Province and form the basis for watershed management activities in the area. Concurrently, a spatial overlay analysis was performed between the hydrological map and settlement distribution map of the Sang Sefid region using ArcGIS 10.8. Accordingly, 12 socio-hydrological units were determined in the study area (Table 2).

2.2.1.1 Identifying indicators for measuring managerial-institutional resilience

In this study, indicators for measuring managerial-institutional resilience were identified through a literature review and interviews with experts and local communities (Table 3). Ultimately, 16 indicators were selected by the expert group. The expert group consisted of 14 experts from different centers, including 4 experts from the Soil Conservation and Watershed Management Research Institute, 2 experts from the Agricultural and Natural Resources Research and Education Center of Ilam Province, 4 experts from Ilam University, and 4 experts from the General Department of Natural Resources and Watershed Management of Ilam Province. All experts possessed over 10 years of professional experience in watershed management, natural resources, or related fields, and were selected based on their direct familiarity with the Sang Sefid region and the watershed management operations implemented in the area. This combination of technical expertise and local knowledge ensured that the indicator validation and weighting reflected both scientific rigor and practical relevance (Table 1).

Table 1. Expert panel composition and professional background.

Expertise Area	Affiliation	Number of Experts	Years of Experience (range)
Watershed Management	Soil Conservation and Watershed Management Research Institute	4	18–32
Watershed Management	Agricultural and Natural Resources Research and Education Center of Ilam Province	2	14–29
Watershed Management & Hydrology	Ilam University	4	19–24
Watershed Management & Executive Operations	General Department of Natural Resources and Watershed Management of Ilam Province	4	12–28

2.2.1.2 Quantifying indicators of measuring managerial-institutional resilience in socio-hydrological units

In this study, the questionnaire variables were considered as qualitative ordinal variables and matched with the five-point Likert scale (very low (1), low (2), moderate (3), high (4), and very high (5)). Therefore, based on the multiple-response coding method, a survey of local communities was conducted after assessing the validity and reliability of the questionnaire. In this study, the validity of the questionnaire as a measurement tool was confirmed by an expert group. Also, the reliability of the measurement tool was determined based on the calculation of Cronbach's alpha in IBM SPSS Statistics 22. In this regard, Cronbach's alpha value was calculated using IBM SPSS Statistics 22 based on equation 1 (Cronbach, 1951):

$$\alpha = \frac{k}{k-1}\left(1-\frac{\sum_{i=1}^{k} S_i^2}{S_t^2}\right) \qquad (1)$$

Where: K is the number of items, S_i^2 is the variance of scores on each item, and S_t^2 is the variance of the sum scores.

In this study, the rural household was considered as the sample unit. Cochran's formula (Cochran, 1977) was used to calculate the sample size (Equation 2) based on the number of rural households located in hydrological units (Table 2).

$$n = \frac{\frac{z^2pq}{d^2}}{1+\frac{1}{N}\left(\frac{z^2pq}{d^2}-1\right)} \qquad (2)$$

Where: n is the sample size, N is the population size (number of rural households), Z is the standard value of 1.96 for the 95% confidence level, d is the allowable error of 0.05, p is the estimated proportion of 0.5, and q is 0.5 (q=1-p).

2.2.1.3 Determining the significance of indicators based on experts' perspectives

In this stage, the significance of each resilience assessment indicator was determined based on the average scores provided by experts using a ten-point Likert scale (1: least important, 10: most important). It should be noted that in this study, a survey was conducted among 14 experts (4 experts from the Soil Conservation and Watershed Management Research Institute, 2 experts from the Agricultural and Natural Resources Research and Education Center of Ilam Province, 4 experts from Ilam University, and 4 experts from the General Department of Natural Resources and

Watershed Management of Ilam Province) to assess validity and determine the significance of resilience measurement indicators.

2.2.1.4 Prioritization and determination of the resilience potential of socio-hydrological units using the TOPSIS method

In this stage, the prioritization and determination of the resilience potential of socio-hydrological units were carried out using the TOPSIS method, based on relative and absolute approaches, respectively. In this regard, the following steps were undertaken (Hwang and Yoon, 1981).

2.2.1.4.1 Creating a decision matrix

This matrix (A) includes the quantity of each identified managerial-institutional resilience assessment indicator for each selected socio-hydrological unit in the study area, based on the perspectives of the local community (section 2.2.2) (Equation 3). In this matrix, the value of each indicator in each unit is the arithmetic mean of the scores given by household heads, based on the sample size calculated using Cochran's formula for each unit (Table 2).

$$A = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mn} \end{bmatrix} \qquad (3)$$

2.2.1.4.2 Creating a weighted normalized matrix

Normalization by making the data dimensionless enables an analysis of heterogeneous indicators (Papathanasiou and Ploskas, 2018). In this study, the vector normalization method (Equation 4) was implemented to normalize the dataset.

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \qquad (4)$$

Where, n_{ij} are the normalized value (dimensionless) and X_{ij} is the value of indicator j for alternative i.

After creating the normalized matrix, the weighted normalized matrix was created based on Equation 5.

$$v_{ij} = w_j n_{ij} \qquad (5)$$

Where, V_{ij} is the weighted normalized value, W_j is the weight of the indicator j, and n_i is the normalized value of the indicator j for alternative i.

2.2.1.4.3 Calculating the TOPSIS index

The prerequisite for calculating the TOPSIS index at this stage involves determining the positive ideal solution (A^+) and the negative ideal solution (A^-) (Equations 6 and 7) and computing the relative closeness to the A^+ (d^+) and A^- (d^-) based on the Euclidean distance of the values (Equations 8 and 9).

$$A^+ = \{(v_1^+, v_2^+, \cdots, v_n^+)\} = \{(\max_i v_{ij} | j \in S_B), (\min_i v_{ij} | j \in S_C)\} \quad (6)$$

$$A^- = \{(v_1^-, v_2^-, \cdots, v_n^-)\} = \{(\min_i v_{ij} | j \in S_B), (\max_i v_{ij} | j \in S_C)\} \quad (7)$$

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, \forall i \in I. \quad (8)$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}, \forall i \in I. \quad (9)$$

Finally, the TOPSIS index (R_i) was calculated based on Equation 10. Based on this index, the relative prioritization of managerial-institutional resilience of socio-hydrological units was conducted (Table 4). In this regard, the minimum and maximum values of this index represent the lowest and highest levels of managerial-institutional resilience among the units, respectively.

$$R_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad (10)$$

2.2.1.4.4 Relative and absolute classification of managerial-institutional resilience of socio-hydrological units exposed to flood risk

In this stage, the relative potential of managerial-institutional resilience of socio-hydrological units exposed to the flood was classified based on the TOPSIS index obtained from the previous stage (Table 4) and the Equal Interval classification method.

This study investigates the innovative incorporation of two hypothetical reference alternatives (minimum and maximum flood resilience potentials) to enable absolute resilience potential quantification within a MADM method. This innovative approach was enabled by (1) the measurable nature of resilience indicators (quantified using 5-point Likert scales), and (2) the precise definition of minimum/maximum scoring thresholds in the proposed virtual benchmarks.

In other words, each indicator in the hypothetical reference alternatives—representing minimum and maximum resilience potentials—is assigned mean scores of 1 and 5, respectively (Table 5). It should be noted that the term "absolute" is used here in a relative-to-benchmark sense (minimum/maximum benchmarks), not as an objectively true or universal value. The resulting absolute resilience scores are contingent upon the chosen indicators, expert-derived weights, and the perceptual nature of the survey data, and should be interpreted as a standardized reference for comparison rather than an absolute physical or social reality.

The incorporation of these hypothetical alternatives achieves three critical outcomes: (1) Following Equations (5) and (6), their values in the weighted standardized decision matrix were considered as positive and negative ideal solutions; (2) As per Equations (7) and (8), relative closeness to ideals is computed based on weighted standardized values of the benchmark alternatives; (3) The TOPSIS index extremes (0 and 1) correspond to the resilience potential extremes of the benchmark alternatives (Table 5). Accordingly, absolute flood resilience potential mapping of hydrological units was implemented using the TOPSIS index by incorporating two hypothetical alternatives as benchmarks for minimum and maximum resilience potential values.

2.2.1.5 Model validation

This study implements an expert-based approach to validate the resilience potential model outputs, incorporating both questionnaire reliability analysis and the Area Under the Curve (AUC) values of the Receiver Operating Characteristic (ROC) curves method. The rationale for using expert-derived classifications as the reference dataset in ROC analysis is rooted in the inherent lack of directly observable "ground truth" data for resilience, a well-documented challenge in resilience research (Berkes and Ross, 2013; Quinlan *et al.*, 2016). In the absence of systematic observational data, expert knowledge serves as a reliable and widely accepted proxy for validating multidimensional constructs such as institutional-managerial resilience (Hochrainer-Stigler *et al.*, 2025). This approach assumes that collective expert judgment, when aggregated across a diverse panel of specialists, provides a sufficiently accurate representation of the actual resilience status of each socio-hydrological unit (Colson Abigail and Cooke Roger, 2018).

In this regard, an expert survey (n=14) was implemented to evaluate managerial-institutional resilience potential using a 5-point Likert scale across socio-hydrological units within the study area. All experts possessed over 10 years of professional experience in watershed management, natural resources, or related fields, and were selected based on their direct familiarity with the Sang Sefid region and the watershed management operations implemented in the area (Table 1). This ensured that the expert classifications were grounded in both technical expertise and local contextual knowledge. Additionally, questionnaire reliability was examined using Cronbach's alpha method (Equation 1).

Subsequently, binary values of 0 (non-resilient) and 1 (resilient) were assigned based on expert opinion averages ≤ 3 and >3, respectively, for each unit. Finally, the TOPSIS model was validated through ROC curve analysis, where AUC values were computed by plotting false positive rate (FPR) against true positive rate (TPR) using IBM SPSS Statistics software (version 22) (Richardson *et al.*, 2024).

3. Results and Discussion

This study assesses the managerial-institutional resilience of flood-exposed rural communities within socio-hydrological units of the Sang Sefid watershed. In this regard, Table 2 presents the population and household counts for each village within the study area's hydrological units, based on the 2016 national census data from the Statistical Center of Iran. The sample size for each unit was calculated using Cochran's formula, with households as the sampling unit, and is presented in Table 2. Accordingly, the total calculated sample size for the study area comprised 663 household heads, as detailed in Table 2. The variation in sampling fractions across units (71.6% to 100%) reflects the application of Cochran's formula to populations of different sizes; for smaller populations, the calculated sample size often approaches or equals the total population, while for larger populations, the proportion is lower.

Table 2. Demographic characteristics and sampling framework of villages in the Sang Sefid region.

Row	Socio-hydrological unit	Village name	Population	Households	Sample size (Households)	Sampling Fraction(%)
1	S1	Sang Sefid	460	135	100	74.1
2	S-int1	Cham Kabud	56	14	83	78.3
3		Gharib	136	38		
4		Barde Bel	208	54		
5	S-int2	Sang Shelen	46	12	12	100.0
6	S-int3	Tagh-e-Gavrin	511	155	111	71.6
7	S-int4	Kalleh Ghatar-e-Sofla	85	25	33	91.7
8		Kalleh Ghatar-e-Olya	41	11		
9	S8-int	Chogha Sabz	112	28	26	92.9
10	S-int5	Joob Boor	65	15	15	100.0
11	S8-2	Shoorabeh Marate	186	55	48	87.3
12	S9	Belaveh Tareh Olya	81	23	102	73.9
13		Belaveh Tareh Sofla	405	115		
14	S10	Joob Sorkh-e-Sofla	71	17	16	94.1
15	S11	Belaveh Khoshkeh	237	66	81	79.4
16		Herghoosh	134	36		
17	S12	Helt	106	27	36	92.3
18		Sar Chogha	44	12		

Table 3 presents the managerial-institutional flood resilience assessment indicators developed through literature review and expert consultations (26 watershed and water resource management specialists). Sixteen core indicators were identified as essential metrics for assessing flood resilience in rural communities, with their validity confirmed through expert review (Table 3). The results demonstrate that these indicators can be systematically classified into five categories: (1) institutional collaboration (V_1, V_2, V_7, V_{11}), (2) education and awareness (V_3, V_4, V_5, V_{16}), (3) performance and public satisfaction (V_8, V_9, V_{10}), (4) prevention and reconstruction (V_{12}, V_{13}, V_{14}), and (5) participatory planning (V_6, V_{15}) . This classification highlights essential facets of flood management, spanning governance, community participation, and risk mitigation efforts.

Table 3. Managerial-institutional flood resilience assessment indicators in socio-hydrological units of the study area.

Index	Indicator	Reference (s)
V_1	Degree of interaction between flood-related governmental institutions and local communities	(Nahid *et al.*, 2021)
V_2	The collaboration level of related NGOs (Non-Governmental Organizations) in the watershed	(Chowdhooree and Islam, 2018)
V_3	Development of flood early warning systems and risk awareness in the watershed	(Qasim *et al.*, 2016)
V_4	Number of training programs for local communities on flood management	(Ghasemzadeh *et al.*, 2021)
V_5	Production of flood management educational content for the watershed	(Ghasemzadeh *et al.*, 2021)
V_6	Expansion of social networks	(Karunarathne and Lee, 2022)
V_7	The level of responsibility among flood management institutions	(Ali and George, 2022)
V_8	Public satisfaction with the performance of responsible institutions	(Hataminejad *et al.*, 2021)
V_9	Effectiveness of local institutions in flood crisis management	(Batica and Gourbesville, 2011)
V_{10}	Effectiveness of external institutions in flood crisis management	(Batica and Gourbesville, 2011)
V_{11}	Coordination between internal and external institutions in flood management	(Ghasemzadeh *et al.*, 2021)
V_{12}	The extent of implemented preventive measures in the watershed	(Cao *et al.*, 2023)
V_{13}	The level of monitoring over the reconstruction process in affected areas	(Ghasemzadeh *et al.*, 2021)
V_{14}	The extent of flood insurance development in the watershed	(Ghasemzadeh *et al.*, 2021)
V_{15}	The degree of attention given to participatory planning in flood crisis management	(Laeni *et al.*, 2021)
V_{16}	The frequency of flood preparedness drills conducted	(Atreya *et al.*, 2017)

The Cronbach's alpha coefficient was calculated to be 0.768, indicating acceptable reliability of the measurement instrument. In other words, given that the Cronbach's alpha statistic exceeds the threshold of 0.7, the measurement instrument demonstrates high reliability (Streiner, 2003). This indicates that the included items possess strong internal consistency (George and Mallery, 2003). Accordingly, based on the calculated sample size, a survey of local communities was conducted, and resilience assessment was performed using the TOPSIS method.

Table 4 presents the importance values of indicators (W_i) along with the weighted normalized values of the indicators for calculating the relative potential of managerial-institutional resilience. In this regard, Table 4 displays the relative closeness to both positive ideal solution (di^+) and negative ideal solution (di^-), as well as the TOPSIS index values (R_i). Furthermore, Table 5 presents the values of di^+, di^-, and R_i, to calculate the absolute potential of managerial-institutional resilience in socio-hydrological units exposed to the flood.

Table 4. The weighted normalized decision matrix and computational parameters of the TOPSIS method for calculating the relative potential of managerial-institutional resilience in flood-prone socio-hydrological units.

Attribute/ Parameter	W_i	S1	S-int1	S-int2	S-int3	S-int4	S8-int	S-int5	S8-2	S9	S10	S11	S12
V_1	8.57	2.20	2.89	1.43	0.94	2.28	2.64	2.28	2.46	3.72	2.28	2.81	2.64
V_2	8.50	2.23	2.78	1.23	1.04	2.62	2.62	2.46	2.30	3.55	2.13	2.79	2.62
V_3	7.93	2.86	2.59	1.20	0.94	2.22	2.67	2.22	2.08	2.96	2.22	2.37	2.22
V_4	8.29	2.11	2.61	1.85	1.13	2.11	2.11	2.54	2.32	4.44	1.48	1.90	2.54
V_5	8.14	2.06	2.98	1.67	1.23	2.06	2.88	2.26	2.26	4.01	1.23	1.85	2.26
V_6	9.21	2.61	2.86	1.52	0.98	2.95	2.95	2.26	2.61	3.65	2.61	3.48	2.26
V_7	8.79	2.03	3.43	1.88	1.24	1.95	2.31	2.66	2.31	3.52	2.48	2.66	3.02
V_8	9.57	2.16	3.70	1.83	1.11	2.34	2.34	2.93	2.73	3.84	2.73	2.93	3.32
V_9	9.07	2.12	3.24	1.96	1.05	2.97	2.27	2.62	2.62	3.26	2.09	2.97	3.31
V_{10}	9.14	2.29	3.34	1.70	1.23	2.13	2.33	2.91	2.91	3.59	2.33	2.33	3.49
V_{11}	8.93	2.12	3.08	1.97	1.11	2.41	2.41	2.79	2.79	3.56	2.23	2.41	3.16
V_{12}	9.29	2.28	3.30	1.80	1.10	2.88	2.47	2.68	2.68	3.77	2.47	2.88	2.88
V_{13}	8.36	1.77	2.95	1.50	0.91	2.56	2.40	2.40	2.88	3.10	1.76	2.72	2.88
V_{14}	9.43	2.76	3.10	1.74	1.21	1.50	2.79	3.22	2.36	4.58	2.57	2.15	3.00
V_{15}	9.50	2.27	3.03	1.86	1.19	2.39	2.98	2.98	2.98	3.91	2.58	2.98	2.78
V_{16}	8.64	2.57	2.74	2.01	1.32	2.23	2.73	1.47	1.49	5.37	1.41	1.49	2.23
d_i^+	-	6.52	4.11	8.66	10.97	6.64	5.50	5.92	6.24	0.06	7.36	6.34	5.13
d_i^-	-	4.82	7.81	2.48	0.00	5.29	5.90	5.96	5.75	10.96	4.64	6.19	6.91
R_i	-	0.43	0.66	0.22	0.00	0.44	0.52	0.50	0.48	0.99	0.39	0.49	0.57

The results indicate that indicators V_8 (public satisfaction with the performance of responsible institutions) and V_3 (development of flood early warning systems and risk awareness in the watershed) were assigned, respectively, the highest and lowest importance weights in assessing institutional-managerial resilience compared to other indicators, based on expert evaluations. Furthermore, indicators V_8, V_{15}, V_{14}, V_{12}, V_6, and V_{10} were ranked as the top six priority factors in terms of importance. These indicators are among the key metrics emphasized in previous studies by Batica and Gourbesville (2011), Ghasemzadeh *et al.* (2021), Laeni *et al.* (2021), Karunarathne and Lee (2022), Cao *et al.* (2023), and for assessing flood resilience.

Table 5. The computational parameters of the TOPSIS method for calculating the absolute potential of managerial-institutional resilience in flood-prone socio-hydrological units.

Attribute/ Parameter	S1	S-int1	S-int2	S-int3	S-int4	S8-int	S-int5	S8-2	S9	S10	S11	S12	Min	Max
d_i^+	8.80	6.23	10.70	12.76	8.70	7.85	7.96	8.21	3.37	9.31	8.21	7.16	13.31	0.00
d_i^-	4.79	7.45	2.71	0.63	5.20	5.74	5.82	5.64	10.05	4.66	6.04	6.67	0.00	13.31
R_i	0.35	0.54	0.20	0.05	0.37	0.42	0.42	0.41	0.75	0.33	0.42	0.48	0.00	1.00

As shown in Tables 4 and 5, the TOPSIS analysis reveals that the range of relative and absolute TOPSIS index values varies from 0.000 to 0.995 and 0.047 to 0.749, respectively, across different socio-hydrological units in the study area. Notably, units S-int3 and S9 exhibit the minimum and maximum flood resilience potential in both cases (Fig. 3).

The very low resilience of unit S-int3 (R=0.000 relative, R=0.047 absolute) is attributable to consistently low scores across nearly all 16 indicators, with particularly severe deficiencies in V_{14} (flood insurance development) and V_{16} (flood preparedness drills), where values are less than one-third of those observed in the highest-performing unit (S9). Similarly, weak performance in V_1 (institutional-community interaction) and V_6 (social networks) indicates limited institutional connectivity and community support structures. These combined deficiencies across all five resilience dimensions (institutional collaboration, education and awareness, performance and public satisfaction, prevention and reconstruction, and participatory planning) explain the extremely low resilience potential of this unit. In contrast, unit S9 achieves the highest resilience potential due to consistently high scores across most indicators, particularly in V_8 (public satisfaction), V_{14} (flood insurance), V_{15} (participatory planning), and V_{16} (flood preparedness drills), reflecting stronger institutional performance, better risk communication, and more effective community engagement.

In this regard, Figure 3 ranks the socio-hydrological units by resilience potential using sorted index values. Furthermore, building on the prioritization in Figure 3, Figure 5 illustrates the classified resilience potential of the units.

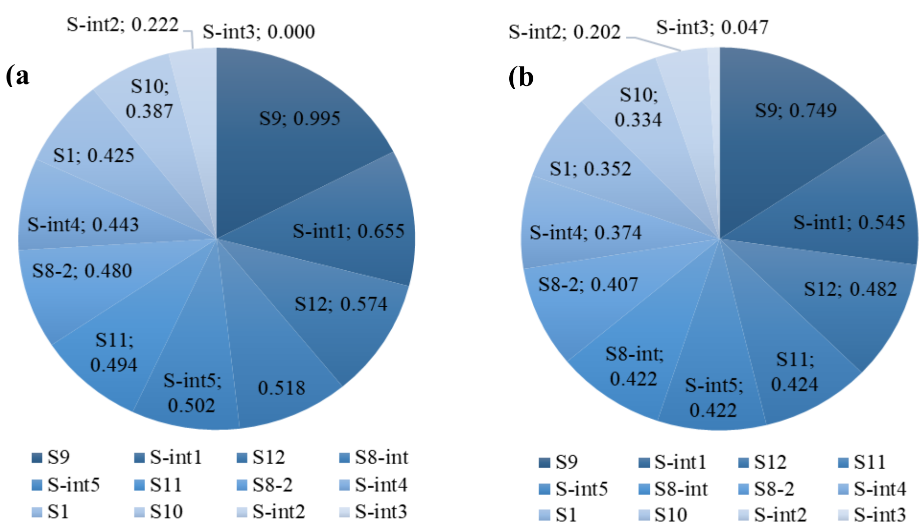

Fig. 3. Prioritization of relative and absolute flood resilience potential in socio-hydrological units of the study area (label: unit ID; TOPSIS index value, (a)/(b): relative/absolute resilience potential).

The results demonstrate that the area under the ROC curves (AUC) for both relative and absolute managerial-institutional resilience potential in flood-prone socio-hydrological units, obtained through the TOPSIS method, are 0.917 (Fig. 4). Furthermore, internal consistency reliability was confirmed through Cronbach's alpha (α = 0.857), exceeding the recommended minimum of 0.7 (Streiner, 2003), thereby verifying the strong internal consistency among items. In other words, the questionnaire, as a measurement instrument, exhibits good reliability (George and Mallery, 2003).

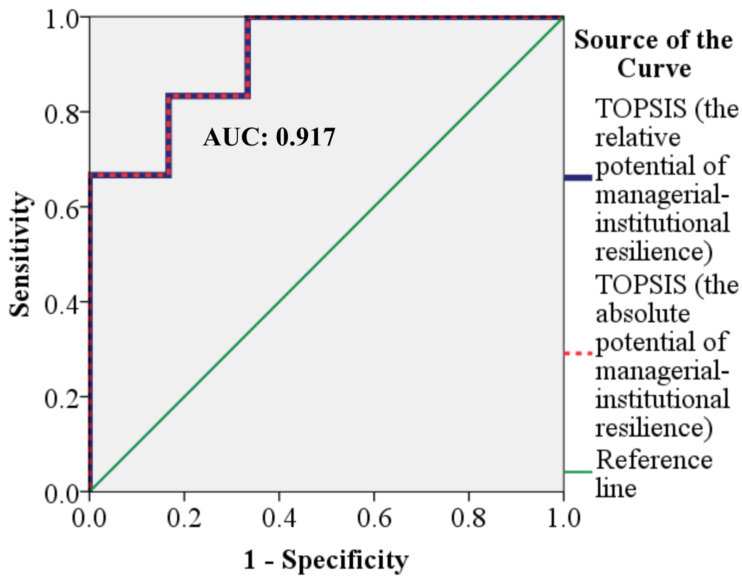

Figure 4 ROC curves for relative and absolute managerial-institutional resilience potential in flood-prone socio-hydrological units derived from the TOPSIS method.

ROC curve analysis measures predictive accuracy, with the area under the curve (AUC) reflecting a model's ability to distinguish between event occurrence and non-occurrence (Pourghasemi *et al.*, 2013; Verbakel *et al.*, 2020; Salehpour Jam *et al.*, 2021a). According to Hosmer Jr *et al.* (2013) widely cited classification, model discrimination based on AUC values can be categorized as: poor (0.5-0.7), acceptable (0.7-0.8), excellent (0.8-0.9), or outstanding ($\geq$0.9). Therefore, the robust AUC value of 0.917 ($\geq$0.9 threshold) demonstrates the outstanding discriminative capacity of the TOPSIS model in assessing both relative and absolute managerial-institutional resilience potentials across flood-prone socio-hydrological systems.

The lack of observational validation data for resilience potential modeling outputs has led to unverified model results being used without proper validation (Estelaji *et al.*, 2025). We therefore strongly recommend the development of robust model verification initiatives.

It is important to acknowledge the assumptions and limitations inherent in this expert-based validation approach. First, it assumes that the aggregated expert judgments accurately reflect the true resilience status, a reasonable assumption given the panel's extensive experience and local familiarity, but one that remains subject to individual expertise and potential bias. Second, the dichotomization of continuous expert scores (≤3 vs. >3) introduces a degree of simplification that may not fully capture nuanced variations in resilience. Third, the validation is limited to the specific socio-hydrological context of the Sang Sefid region; generalizability to other regions should be tested through replication. To mitigate these limitations, we employed a diverse panel of experts from four institutions (research, academic, and executive), ensured anonymity to reduce social desirability bias, and used Cronbach's alpha ($\alpha = 0.857$) to confirm inter-rater reliability. Despite these limitations, the high AUC value (0.917) provides strong evidence for the model's discriminative capacity and supports the validity of the TOPSIS-based resilience assessments.

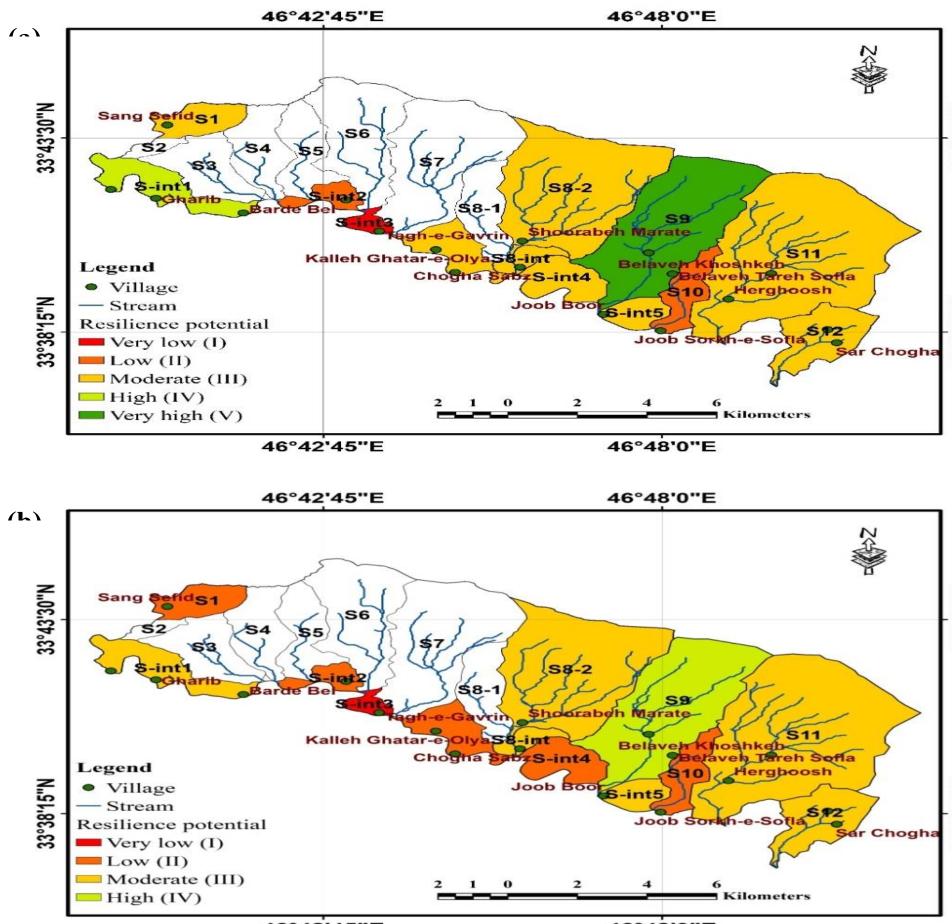

Fig. 5. Mapping of (a) relative and (b) absolute flood resilience potential across socio-hydrological units in the study area using the TOPSIS index (uncolored areas indicate hydrological units without rural settlements, which were excluded from the resilience assessment).

The assessment of flood resilience potential in the study area revealed distinct spatial patterns across social-hydrological units (Fig. 5). Relative resilience potential was classified into five categories: very low (unit S-int3), low (units S-int2 and S10), moderate (units S1, S8-2, S8-int, S-int4, S-int5, S11, and S12), high (unit S-int1), and very high (unit S9). The distribution of these categories highlights significant variability in adaptive capacity, with certain units exhibiting strong inherent resilience due to their favorable status in managerial-institutional resilience indicators. In contrast, areas with very low relative resilience exhibit less favorable conditions in terms of managerial-institutional resilience indicators. Consistent with other studies assessing resilience potential, this classification underscores the importance of context-specific resilience strategies tailored to local conditions (Jacinto *et al.*, 2020; Ganase *et al.*, 2024; Samanta *et al.*, 2025).

In terms of absolute resilience potential, four classes were identified: very low (unit S-int3), low (units S1, S-int2, S-int4, and S10), moderate (units S8-2, S8-int, S-int1, S-int5, S11, and S12), and high (unit S9). The results indicate that while some areas demonstrate moderate to high absolute resilience, others remain highly vulnerable (Fig. 5). Notably, no units reached a very high absolute resilience class, which reflects systemic managerial-institutional deficiencies throughout the region. Unlike the relative potential of resilience in flood-prone socio-hydrological units of the study area, which considers intra-regional comparisons (Mabrouk and Haoying, 2023), the absolute potential of resilience reflects the intrinsic capacity of units to withstand flooding, enabling both intra- and inter-regional comparisons.

A comparative analysis between relative and absolute resilience reveals critical insights. The disparities between relative and absolute resilience metrics highlight the importance of employing dual frameworks in flood risk management. Relative assessments identify "hotspots" of vulnerability or resilience within a specific regional context, aiding localized policy targeting. Absolute assessments, however, provide a universal baseline, revealing whether a unit's resilience is fundamentally insufficient even if it appears adequate compared to its neighbors. For instance, a unit with moderate absolute resilience but high relative resilience (e.g., S-int1) might still require improvements to meet broader safety standards. Policymakers must integrate both perspectives to avoid complacency in relatively resilient but intrinsically fragile units and to allocate resources equitably across the region. Furthermore, strategic planning to enhance resilience potential is strongly recommended. In this regard, the application of Problem-Structuring Methods (PSMs), such as TOPSIS, SWOT, or S_tW_tOT, is proposed to identify solutions or strategies for improving the managerial-institutional resilience potential of socio-hydrological units exposed to flood risk (Salehpour Jam *et al.*, 2021b; Salehpour Jam and Mosaffaie, 2025).

The observed discrepancies between relative and absolute resilience align with broader debates in disaster resilience research. Existing research consistently demonstrates that relative evaluations frequently obscure the core potential of vulnerabilities by employing localized assessment frameworks that fail to account for critical minimum/maximum resilience potential thresholds (Gul and Ak, 2018; Salehpour Jam *et al.*, 2023; Xiao *et al.*, 2025). This methodological gap manifests clearly in cases like unit S-int1, which exhibits high relative yet only moderate absolute resilience.

The findings of this study are broadly consistent with previous resilience assessments conducted in flood-prone regions. For instance, Mabrouk and Haoying (2023) and Miao *et al.* (2025) similarly reported significant spatial variability in urban flood resilience and emphasized the importance of institutional and governance factors. However, most prior studies have relied solely on relative rankings, which only permit intra-regional comparisons. In contrast, our dual-scale framework enables both intra- and inter-regional comparisons, providing a more comprehensive understanding of resilience potential. This finding aligns with the arguments of Cao *et al.* (2023) and Prashar *et al.* (2023), who highlighted the need for standardized and replicable resilience metrics. The observed deficiencies in institutional collaboration and participatory planning in low-resilience units (e.g., S-int3) are also consistent with the findings of Nahid *et al.* (2021) and Ghasemzadeh *et al.* (2021), who identified similar governance-related weaknesses in flood-prone communities in Iran and elsewhere.

While this study provides a robust and replicable framework for resilience assessment, several limitations should be acknowledged. First, the study relies on perceptual data collected through Likert-scale surveys, which may be subject to respondent bias and social desirability effects. Although Cronbach's alpha confirmed acceptable reliability, future studies could complement perceptual data with objective indicators (e.g., infrastructure quality, institutional performance records). Second, the expert panel, while carefully selected, represents a specific institutional and regional context; the generalizability of the indicator weights may be limited to similar socio-hydrological settings. Third, the study focuses exclusively on managerial-institutional resilience; other dimensions (social, economic, physical) were not assessed, which may provide a more holistic understanding of flood resilience. Finally, the analysis is cross-sectional and does not capture temporal dynamics; longitudinal studies are needed to track resilience changes over time. Despite these limitations, the framework provides a valuable tool for comparative resilience assessment and adaptive governance.

Based on the findings of this study, the following specific policy recommendations are proposed to enhance managerial-institutional flood resilience in the Sang Sefid region and similar socio-hydrological systems: (1) Strengthen institutional-community interaction (V_1) by establishing regular consultative meetings between local governance bodies and community representatives to improve trust, communication, and collaborative decision-making; (2) Expand flood insurance coverage (V_{14}) through subsidized schemes tailored to rural agricultural communities, particularly in low-resilience units, to reduce financial vulnerability and promote risk-transfer mechanisms; (3) Enhance flood preparedness drills (V_{16}) by implementing annual community-based exercises, with special attention to units with very low resilience (e.g., S-int3); (4) Promote participatory planning (V_{15}) by integrating local knowledge and community priorities into watershed management plans through formal participatory processes, as recommended by Laeni *et al.* (2021); (5) Develop early warning systems (V_3) through investment in community-based flood early warning infrastructure, particularly in remote and vulnerable units, to improve risk awareness and timely response; (6) Foster social networks (V_6) by supporting the formation of community-based disaster management groups to strengthen social capital and mutual aid during flood events; and (7) Adopt the dual-scale framework at regional and national levels for systematic and comparable resilience mapping across watersheds, enabling evidence-based resource allocation and priority setting. These recommendations are consistent with best practices identified in the international literature and are tailored to the specific institutional and socio-hydrological context of the study area.

4. Conclusions

This study introduces a novel framework for absolute flood resilience potential mapping in socio-hydrological units by integrating theoretical benchmark alternatives (min/max flood resilience scenarios) into a TOPSIS-based assessment to quantify absolute flood resilience potential beyond conventional ordinal and relative rankings. In this study, sixteen key indicators for assessing managerial-institutional flood resilience were identified and systematically classified into five categories: (1) institutional collaboration, (2) education and awareness, (3) performance and public satisfaction, (4) prevention and reconstruction, and (5) participatory planning.

The validation of the TOPSIS method through ROC curve analysis and an expert-based approach demonstrated the outstanding discriminative capacity of the MADM method in assessing the relative and absolute managerial-institutional resilience potentials across flood-prone socio-hydrological units. **This should be viewed as an expert-based validation rather than a definitive confirmation of universal validity.** The results indicated that, in contrast to the relative resilience potential classification, which encompasses categories ranging from very low to very high resilience, the absolute resilience potential classification lacks a very high resilience category within the study area. The absolute approach offers two key advantages: (1) it reflects the **benchmark-referenced resilience potential** of the study area, revealing the actual intensity of resilience capacity. For instance, units with high relative resilience (e.g., S_9) may be classified into either high or lower absolute resilience categories, and (2) it enables intra- and inter-regional resilience potential comparisons, supporting the development of local, regional, and national-scale mapping. Additionally, it facilitates the assessment of temporal trends, allowing for dynamic resilience monitoring over time.

Furthermore, it is recommended that: (1) future studies utilize additional MADM methods with indices ranging from zero to one, such as VIKOR or EDAS, to assess the absolute managerial-institutional resilience potential alongside other dimensions of resilience, including social-cultural, economic, and physical resilience, within flood-prone socio-hydrological units; (2) given the prevalence of very low, low, and moderate resilience potentials in the study area, strategic planning to enhance the managerial-institutional resilience of rural environments, particularly through the application of Problem-Structuring Methods such as SWOT, S_tW_tOT, and DPSIR, is strongly advised.

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ارزیابی دومقیاسه پتانسیل تاب‌آوری مدیریتی-نهادی در برابر سیل: چارچوب MADM تقویت‌شده با مرجع‌سازی مجازی برای سامانه‌های اجتماعی-هیدرولوژیکی

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چکیده

پژوهش حاضر چارچوبی نوآورانه برای نقشه‌برداری پتانسیل تاب‌آوری مطلق در برابر سیل در واحدهای اجتماعی-هیدرولوژیکی منطقه سنگ سفید، ایران، با تلفیق گزینه‌های مرجع نظری در ارزیابی مبتنی بر TOPSIS ارائه می‌دهد. با استفاده از رویکرد دومقیاسه (نسبی و مطلق)، تاب‌آوری مدیریتی-نهادی در برابر سیل از طریق ۱۶ شاخص تأییدشده توسط خبرگان در پنج بعد ارزیابی شد: همکاری نهادی، آموزش و آگاهی، عملکرد و رضایت عمومی، پیشگیری و بازسازی و برنامه‌ریزی مشارکتی. داده‌ها از طریق نظرسنجی مبتنی بر پرسش‌نامه دارای مقیاس لیکرت از ۶۶۳ سرپرست خانوار جمع‌آوری شد و پایایی پرسشنامه تأیید گردید (α=۰/۷۶۸). تاب‌آوری با استفاده از TOPSIS با سناریوهای حداقل/حداکثر فرضی به عنوان بنچمارک، کمی‌سازی شد. نتایج تنوع مکانی قابل ملاحظه‌ای را نشان داد: تاب‌آوری نسبی از بسیار کم (S-int3، R=۰/۰۰) تا بسیار زیاد (S9، R=۰/۹۹) متغیر بود، در حالی که تاب‌آوری مطلق از بسیار کم (S-int3، R=۰/۰۵) تا زیاد (S9، R=۰/۷۵) با عدم وجود طبقه «بسیار زیاد» متغیر بود که تمایزات اساسی بین دو رویکرد را برجسته می‌سازد. اعتبارسنجی مدل از طریق تحلیل منحنی مشخصه عملکرد گیرنده (AUC=0/917) و آلفای کرونباخ (α=۰/۸۵۷) عملکرد و پایایی برجسته مدل را تأیید کرد. این چارچوب امکان مقایسه‌های نظام‌مند درون‌منطقه‌ای و بین‌منطقه‌ای تاب‌آوری و پایش زمانی را فراهم می‌سازد و به عنوان ابزاری قابل‌تکرار برای نگاشت تاب‌آوری در مقیاس‌های چندگانه و برای ارتقای حکمرانی تطبیقی و مدیریت پایدار سیل در سامانه‌های اجتماعی-هیدرولوژیکی عمل می‌کند.