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Research article

Applying hesitant q-rung orthopair fuzzy sets to evaluate uncertainty in subsidence causes factors

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A R T I C L E I N F O

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A B S T R A C T

Land subsidence is a widespread problem impacting communities worldwide. Understanding the causes and factors of land subsidence is crucial for identifying and prioritizing effective mitigation measures. One of the main reasons for prioritizing land subsidence causes is the potential impact on infrastructure and the environment. The main objective of this paper is to emphasize the importance of prioritizing the causes of land subsidence. By understanding and prioritizing the factors contributing to land subsidence based on their impact and urgency, the aim is to develop targeted strategies for mitigation, inform policy decisions, and prevent further exacerbation of this problems. The study comprises three phases, where experts in the field provide their opinions and propose a robust hybrid framework. This framework integrates the Failure Mode and Effect Analysis (FMEA) and Step-wise Weight Assessment Ratio Analysis (SWARA) with Hesitant q-rung orthopair fuzzy set (Hq-ROFS). The performance of the proposed technique was then compared with two other decision-making techniques for evaluating and ranking land subsidence causes. According to the results, extraction of groundwater, excessive irrigation using groundwater, and oxidation and drainage of organic soils were identified as primary drivers of subsidence.

1. Introduction

Land subsidence is a widespread problem that has global implications [1]. Land subsidence refers to the progressive or abrupt descent of the earth's surface [2] and is often attributed to a variety of factors, both natural and human-induced [3]. The causes of land subsidence are multifaceted and can vary depending on the geographical location and specific environmental conditions [4], as seen in Fig. 1. Land subsidence is a widespread geological occurrence that has been documented in more than 150 countries and regions worldwide [5,6]. Understanding the factors that contribute to land subsidence is crucial for developing effective mitigation strategies and preventing further damage to the Earth's surface [5]. The phenomenon of ground collapse can be explained by the creation of subsurface voids or the exhaustion of subsurface materials, which can happen naturally or as a result of human activities [7]. Land subsidence is a complex and inelastic phenomenon that has a wide range of impacts on geological, environmental, hydrogeological,

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human, and economic systems [8–10] Although the manifestation of land subsidence is subtle, the consequences can be far-reaching and harmful. Understanding the causes and factors of land subsidence is crucial for identifying and prioritizing effective mitigation measures. The purpose of this research is to clearly highlight the motivations and the gap for prioritizing land subsidence causes factors. By doing so, we aim to provide a general understanding of the diverse aspects that contribute to land subsidence as well as the significance of prioritizing these factors in order to effectively address this problem. One of the main encouragmenet for prioritizing land subsidence causes factors is the potential repercussions of land subsidence on infrastructure and the environment. As the ground sinks, it can lead to damage to constructions, roads, and other structures, as well as disruptions to water and drainage systems. In addition, land subsidence can result in the loss of valuable agricultural land and natural habitats. By prioritizing the causes of land subsidence, we can identify the most critical aspects and thrive targeted strategies to mitigate their effects. Supplementary to this, is the need to understand the role of human activities in exacerbating this phenomenon. While natural processes such as tectonic activity and soil compaction play a role in land subsidence, human activities such as groundwater extraction, mining, and construction can significantly accelerate the process. By prioritizing the causes of land subsidence, we can better grasp the impact of these activities and thrive policies and regulations to mitigate their effects. Despite the importance of this subject, there is a gap in the current literature and research on this field. While there is a wealth of information on the diverse causes of land subsidence, there is a lack of comprehensive analysis that prioritizes these factors based on their impact and importunity. This gap prevents our ability to effectively address land subsidence and thrive targeted strategies for mitigation. In order to bridge this gap, it is essential to conduct a thorough analysis of the causes of land subsidence and prioritize them based on their impact and importunity. This will provide us to thrive targeted mitigation measures that address the most critical factors and allocate resources effectively. Additionally, by prioritizing land subsidence causes factors, we can better inform policy decisions and regulations to prevent further exacerbation of this problem. To encapsulate, the objective of this paper is to highlight the motivations and the gap for prioritizing land subsidence causes factors. By understanding the diverse factors that contribute to land subsidence and prioritizing them based on their impact and importunity, we can thrive targeted strategies for mitigation and inform policy decisions to prevent further exacerbation of this problem. This will ultimately help to ensure the stability of the ground and the structures built upon it, as well as protect valuable agricultural land and natural habitats.

In recent years, there has been a growing interest in applying multi-criteria decision-making methods to address the uncertainty in land subsidence causes factors. One of the key challenges in this area is the integration of multiple criteria, such as geological, hydrological, and anthropogenic factors, to make informed decisions in the presence of uncertainty. To address this challenge, scholars have proposed diverse multi-criteria decision-making approaches that take into account the uncertainty in the decision-making process. As an illustration [11], utilized this methodology to determine 14 elements that influence subsidence, whereas [12] applied it to forecast subsidence within an underground mine [13]. implemented fuzzy logic to delineate the susceptibility of

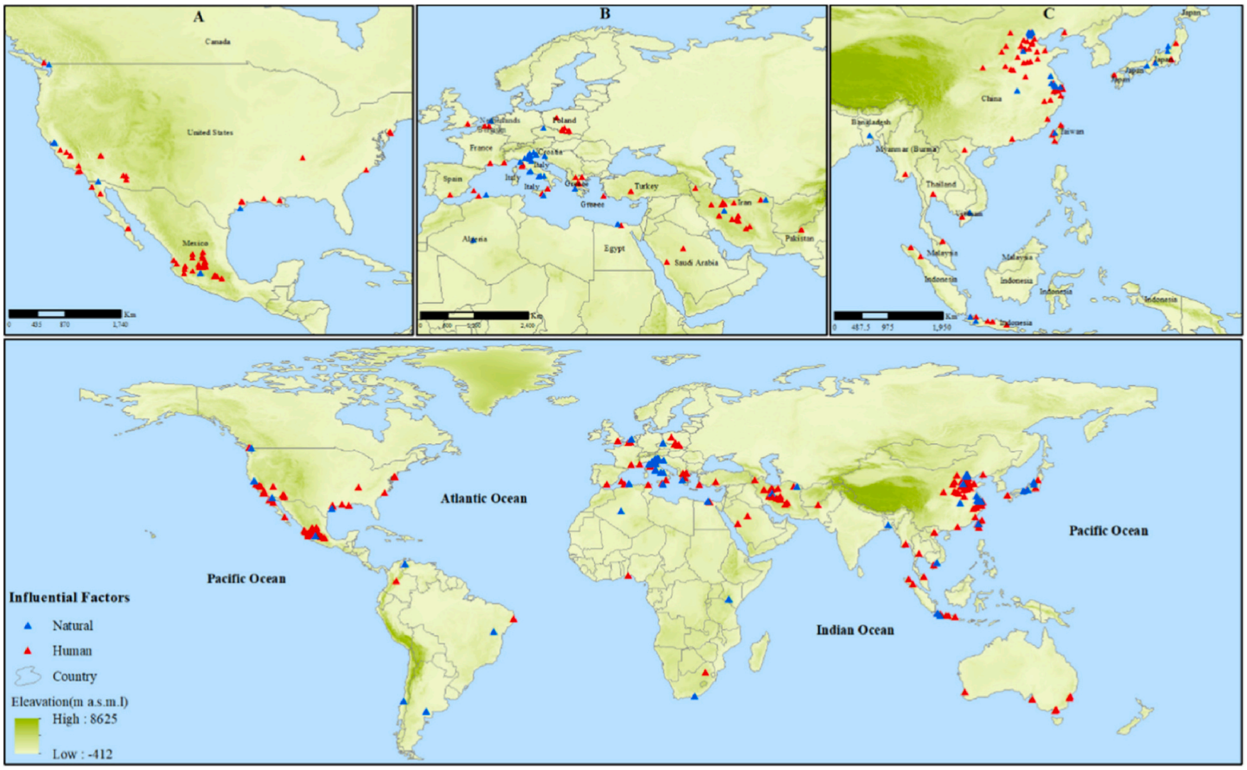

Fig. 1. The investigation of the spatial distribution of land subsidence over a prolonged period [3].

subsidence in the Grosseto plain, while [14] amalgamated multi-criteria decision-making and artificial intelligence to chart the risk of subsidence in the Tasuj plain. The study by Ref. [15] in a highly populated slum area along the Musi River in Palembang, Indonesia, used the Analytical Hierarchy Process (AHP) method to develop a land subsidence susceptibility map, providing an analysis of the factors contributing to land subsidence [16]. used the Best–Worst Method (BWM), was used to determine the relative importance of factors such as groundwater depletion, lithology, and groundwater extraction in assessing land subsidence hazard [17]. employed seven different hydrological and geological parameters to evaluate the vulnerability to subsidence using a fuzzy logic approach within the confines of the Salmas and Shabstar aquifers. Incorporating a diverse set of parameters [18], conducted a subsidence assessment utilizing the AHP-fuzzy approach. The eight parameters employed included annual groundwater level drawdown, aquifer medium, land use, discharge, aquifer saturation thickness, net recharge, fault proximity, and topography [19]. has exclusively examined the factors that are associated with the emergence of land subsidence in the course of urbanization. However, the author has not given due consideration to other facets of the development of land subsidence. Research conducted by Ref. [20] delved into the multifarious aspects of land subsidence including geological structure, irrational planning, groundwater extraction, and management of underground urban infrastructure. Researchers [21] have applied fuzzy multi-criteria decision-making techniques to assess the impact of groundwater extraction, land use changes, and soil properties on land subsidence, taking into account the uncertainty in the input data and criteria weights. The study [22] used the Analytic Network Process (ANP) and the Combined Compromise Solution method with Maximum Variance (MV-CoCoSo) to prioritize natural hazards, specifically landslides, in order to improve the city's resilience against these threats. Land subsidence is a critical issue that has significant implications for the environment, infrastructure, and human settlements. Despite its importance, there is a lack of comprehensive classification of the factors contributing to land subsidence. Previous research has highlighted the need for a thorough evaluation of the parameters related to the effectiveness of subsidence, yet this has not been adequately addressed. In response to this gap in the literature, our research aims to make a significant contribution by conducting a meticulous assessment of the multifaceted factors that affect land subsidence. Unlike previous studies that have focused on specific regional factors, our study covers all variables that influence the subsidence of land. By doing so, we seek to provide a comprehensive understanding of the factors contributing to land subsidence, thereby addressing the limitations of existing research. The significance of our research problem lies in its potential to inform policy-making, urban planning, and infrastructure development. Land subsidence poses a threat to the stability of buildings, roads, and other structures, as well as to the integrity of natural ecosystems. By gaining a deeper understanding of the factors driving land subsidence, we can develop more effective strategies for mitigating its impacts and preventing further degradation of the environment. In comparison to related papers, our research stands out for its holistic approach to the study of land subsidence. While previous studies have focused on specific regional factors, our research takes into account all variables that contribute to land subsidence, providing a more comprehensive and nuanced understanding of this complex phenomenon. By doing so, we aim to fill a critical gap in the literature and offer valuable insights for researchers, policymakers, and practitioners working in the field of land subsidence. All in all, our research makes a significant contribution to the study of land subsidence by undertaking a meticulous assessment of the multifaceted factors that affect this phenomenon. By addressing the limitations of existing research and providing a comprehensive understanding of the factors driving land subsidence, our study has the potential to inform more effective strategies for mitigating its impacts and preserving the integrity of natural and built environments. In this context, the innovative value of the contribution of Failure Mode and Effect Analysis (FMEA), and Step-wise Weight Assessment Ratio Analysis (SWARA) with Hesitant q-rung orthopair fuzzy set (Hq-ROFS) in the study of land subsidence causes factors by the authors is of great significance.

Therefore, the main objective and contributions of this research study are as follows:

- **Development of a Robust Hybrid Framework:** The contribution of FMEA, SWARA, and Hq-ROFS in the study of land subsidence causes factors by the authors is significant in providing a comprehensive and flexible approach to understanding and analyzing the complex and uncertain nature of land subsidence. By integrating these techniques, the authors are able to identify the most critical factors contributing to land subsidence, assess their relative importance, and model their interactions in a more realistic and accurate manner.
- **Application for a thorough study:** This allows for a more informed and efficient decision-making process in developing strategies for mitigating and managing land subsidence.
- **Comparison with Other Techniques:** In our study, we will assess the effectiveness of our proposed method by comparing it with two other decision-making techniques used to evaluate and rank factors contributing to land subsidence. This comparison will provide valuable insights into the strengths and limitations of our framework, adding depth to our research.
- **Detailed Evaluation of land subsidence factors:** In order to conduct this investigation, we have consulted experienced technicians and considered a range of potential factors contributing to land subsidence. The study provides a thorough assessment of 20 potential causes, which can be an important tool for policymakers, urban planners, and researchers working in the field of land subsidence.
- **Identification of Most and Least Effective land subsidence causes:** The study has pinpointed the most and least effective causes of land subsidence, unlike other studies that focus on specific regions. This specific finding could provide valuable guidance for future endeavors aimed at reducing the factors contributing to land subsidence.

This research method focuses on utilizing uncertainty and a multitude of variables related to land subsidence. We understand that effective research requires a comprehensive approach that takes into account various factors that can contribute to land subsidence, including geological, hydrological, and anthropogenic factors. By incorporating uncertainty into our research methodology, we aim to account for the inherent unpredictability of these complex systems and ensure that our results are robust and reliable. Additionally, by analyzing a wide range of variables, we can gain a more nuanced understanding of the causes and consequences of land subsidence, which can inform more effective mitigation and adaptation strategies. Overall, our research method is designed to be rigorous, comprehensive, and responsive to the complexities of land subsidence dynamics.

The following section of this study is organized as follows: Section 2 outlines the methodologies employed, including FMEA, the SWARA method, and the Hesitant q-rung orthopair fuzzy set method. The proposed approach is elucidated in Section 3. Section 4 analyzes the implementation of two techniques and deliberates on the prioritization of the most significant causes of land subsidence.

2. Methodology

In this segment, we offer a comprehensive elucidation of the methodologies employed within this study. In the field of geotechnical engineering, the integration of FMEA and SWARA with Hq-ROFS provides several advantages in prioritizing land subsidence causes factors. Firstly, the use of FMEA allows for a systematic approach to identifying and evaluating potential failure modes and their effects on the system. This helps in understanding the critical factors leading to land subsidence, thereby enabling better decision-making in terms of risk management and mitigation strategies. Secondly, the integration of SWARA with Hq-ROFS provides a comprehensive and structured method for assigning weights to the identified factors. This allows for a more accurate and objective prioritization of the causes of land subsidence, taking into account the uncertainties and hesitancies in the decision-making process. The SWARA method entails the ranking of criteria in a hierarchical fashion, with the most important criteria being prioritized over the least important ones. The involvement of experts in determining the weightage of these criteria is crucial to the process [23]. SWARA enables decision-makers to establish priorities based on predefined policies, particularly when these priorities align with known situations. It effectively evaluates the relative importance of multiple criteria simultaneously [24]. The versatility of SWARA makes it applicable in various decision-making contexts, and its adoption by researchers has witnessed a significant increase in recent years [25]. In terms of prioritization, contextual consideration, comprehensive evaluation of multiple criteria, and widespread application, the SWARA method offers advantages over the Analytic Hierarchy Process (AHP), the analytic network process (ANP), and the Best Worst Method (BWM) [26]. Supplementary to these, the use of Hq-ROFS enhances the analysis by capturing the hesitant and uncertain nature of human judgment, which is often present in complex geotechnical problems such as land subsidence. This ensures that the prioritization process is more reflective of real-world conditions and considerations. All in all, the integration of FMEA and SWARA with Hq-ROFS offers a robust and comprehensive approach to prioritizing land subsidence causes factors. This methodology provides a systematic and objective way of identifying critical factors and assigning weights, ultimately leading to more informed decision-making in the management of land subsidence.

2.1. *Failure Mode and Effect Analysis (FMEA)*

The concept of FMEA was developed in the 1960s by leading figures in the aerospace industry [27]. The primary aim of the FMEA method is to assess the possible causes and outcomes of failure modes, while also identifying any possible failure modes. To evaluate the risk, FMEA uses the Risk Priority Number (RPN) and the analysis results can be used to recognize and address the impact of failure modes on the management process.

The FMEA is a valuable methodology that is used to identify and eliminate potential or known failures in complex systems. This helps to enhance the safety and reliability of these systems and provides important information for making informed risk management decisions. The assessment of each failure mode is based on three parameters: difficulty of detection (D), likelihood of occurrence (O) and severity (S) [28]. And These parameters are typically evaluated using numerical scales ranging from 1 to 10, with the evaluation being performed using ordinal scales of measurement. The risk priorities of the failure modes are determined by the RPN, equation (1), which is the product of the S, O, and D of a failure. In other words, the RPN is calculated by multiplying the probabilities of the severity, occurrence, and detection of the failure. This helps in determining the risk priorities of the failure modes [29].

$$\text{That is, } RPN = S \times O \times D. \tag{1}$$

Table 1 provides a 10-point scale for evaluating the factors of three risk, S (severity), O (likelihood of occurrence), and D (difficulty of detection). These risk factors are assessed using this scale.

Table 1
Traditional ratings for SOD factors.

Rating	Severity (S)	Occurrence (O)	Detection (D)
10	Hazardous without warning	Very high: failure is almost inevitable	Absolute uncertainty
9	Hazardous with warning		
8	Very high	High: repeated failures	High: repeated failures
7	High		
6	Moderate	Moderate: occasional failures	Moderate: occasional failures
5	Low		
4	Very low		
3	Minor	Low: relatively few failures	Low: relatively few failures
2	Very minor		
1	None	Remote: failure is unlikely	Remote: failure is unlikely

2.2. SWARA method

The Step-wise Weight Assessment Ratio Analysis (SWARA) technique is a decision-making approach that involves determining weight values that are critical to the process. This method, which was created by Keršuliene et al. [23], boasts a crucial feature in its capacity to evaluate the opinions of experts on significant criteria, while simultaneously ascertaining their respective weights [23]. In order to implement the SWARA method, several steps are required following the identification and creation of a comprehensive list of criteria involved in the decision-making process [30].

Step 1. The prioritization of criteria necessitates a meticulous evaluation of their importance. Esteemed experts undertake this phase, whereby they bestow a ranking upon the specified criteria based on their respective levels of significance. Specifically, the preeminent criterion receives the foremost rank, conversely, the subordinate criterion is bestowed with the final rank and the intermediate criteria are ranked in accordance with their relative importance.

Step 2. **To** calculate S_j, the relative significance of the mean value, the determination of the significance of each criterion is essential, commencing from the second ranked criterion. It is imperative to ascertain the extent of the importance of criterion C_j in relation to criterion C_j +1.

Step 3. Calculate coefficient kj as follows:

$$K_j = \begin{cases} 1 & j = 1 \\ S_j + 1 & j > 1 \end{cases} \tag{2}$$

Step 4. Determine recalculated weight q_j as follows:

$$q_j = \begin{cases} 1 & j = 1 \\ \dfrac{q_j - 1}{k_j} & j > 1 \end{cases} \tag{3}$$

Step 5. To determine the weight values of the criteria, it is necessary to perform acomputation in which the sum of these values is equal to one.

$$W_j = \frac{a_j}{\sum_{k=1}^{m} a_j} \tag{4}$$

2.3. Hesitant q-rung orthopair fuzzy set (Hq-ROFS)

In 2020 [31], introduced a new technique called Hesitant q-Rung Orthopair Fuzzy weighted average (Hq-ROFWA), which combines Hq-ROFS and hesitant fuzzy sets (HFS). This technique is a generalization of various fuzzy set types, including fuzzy sets, HFS, intuitionistic fuzzy sets, Pythagorean fuzzy sets (PFS), intuitionistic hesitant fuzzy sets (IHFS) and hesitant Pythagorean fuzzy sets (HPFS). The Hq-ROFA approach provides decision-makers with a wider range of options for selecting non-membership and membership scores compared to other fuzzy set types such as IHFS and PFS. The Hq-ROFA concept is more adaptable and flexible for decision-makers, which makes it more beneficial.

[31] has shown that the Hq-ROFWA technique is consistent with the concept of hesitant q-rung orthopair fuzzy numbers (Hq-ROFN).

2.3.1. Definition (1)

[32,33] Let B denote a general set. A Probabilistic Fuzzy Set (PFS) P, defined on B, can be expressed as follows Eq (5):

$$P = \{ < t, k_p(t), l_p(t) > | t \in B \} \tag{5}$$

the function $k_p(t) : B \rightarrow$ [0,1] is utilized to indicate the score of membership, while the function $l_p(t) : B \rightarrow [0, 1]$ is utilized to express the non-membership score of the element $t \in B$ to P, respectively. For each $t \in B$, it is imperative that the condition $0 \le (k_p(t))^2 + (l_p(t))^2 \le 1$ is satisfied. The degree of hesitancy/indeterminacy, $\pi_p(t)$, is given by Eq (6):

$$\pi_p(t) = \sqrt{1 - (k_p(t))^2 - (l_p(t))^2}. \tag{6}$$

2.3.2. Definition (2)

[34,35] Let B denote a general set. An object denoted as q-Rung orthopair fuzzy sets (q-ROFS) F is defined on B in the form of Eq (7):

$$F = \{ < t, k_F(t), l_F(t) >_q | t \in B, q \geq 1 \} \tag{7}$$

Here, $k_F(t) : B \rightarrow [0,1]$, express the membership score, and $l_F(t) : B \rightarrow [0,1]$, express the non-membership score of an element $t \in B$ to F. It must be noted that for any $t \in B$, the condition $0 \leq (k_F(t))^q + (l_F(t))^q \leq 1$ must be satisfied. Moreover, the measure of uncertainty associated with an element $t \in B$ with respect to F can be expressed as: $\pi_F(t) = \sqrt[q]{1 - (k_F(t))^q + (l_F(t))^q}$, where $q \geq 1$ Eq (8). In the absence of ambiguity, $F(t) = (k_F(t), (l_F(t))$ is commonly referred to as q-rung orthopair fuzzy element (q-ROFE).

2.3.3. Definition (3)

[36] Consider a given set *B,* in this context, we define the hesitant fuzzy set (HFS) H on B as an entity that takes the form Eq (9):

$$H = \{ < t, k_H(t) > | t \in B \}. \tag{9}$$

Here, $k_H(t)$ denotes the membership grade of an element $t \in B$ to the set H, which is represented by a set of discrete numbers in the range of [0,1]. To simplify notation, we shall refer to the hesitant fuzzy element (HFE) as $k_H(t)$. Additionally, we denote the number of elements in $k_H(t)$ as $\# \ k_H(t)$.

2.3.4. Definition (4)

[37] Let B be a general set. A dual hesitant fuzzy set (DHFS) D on B is a mathematical construct that takes the form Eq (10):

$$D = \{ < t, k_D(t), l_D(t) > | t \in B \} \tag{10}$$

Here, $k_D(t)$ and $l_D(t)$ are two finite subsets of the unit interval [0,1], which respectively express the possible dual hesitant non-membership scores and dual hesitant membership scores of the element $t \in B$ to D. It is important to note that for any $t \in B$, the following condition must hold: $0 \leq \mathfrak{P}, \lambda \leq 1, 0 \leq \mathfrak{P}^+ + \lambda^+ \leq 1$.

Furthermore, $\mathfrak{J} \in k_D(t), \lambda \in l_D(t), \mathfrak{B}^+ = \max_{\mathfrak{P} \in k_D(t)} \{\mathfrak{B}\}$ and $\lambda^+ = \max_{\lambda \in l_D(t)} \{\lambda\}$ for all $t \in B$.

2.3.5. Definition (5)

[38] Consideration of a general set B necessitates an examination of IHFS I, an object that can be indicated as Eq (11):

$$H = \{ < t, k_H(t), l_H(t) > | t \in B \} \tag{11}$$

In this representation, $k_H(t)$ and $l_H(t)$ denote the subsets of [0,1], which are indicative of the intuitionistic hesitant membership and intuitionistic hesitant non-membership scores of $t \in B$ to H. For every element $t \in B$, it can be established that $\forall \mathfrak{P}(t) \in k_H(t)$, a corresponding $\lambda(t) \in l_H(t)$ exists such that $0 \leq \mathfrak{B}(t) + \lambda(t) \leq 1$. In the same way, $\forall \lambda(t) \in l_H(t)$, there exist $\mathfrak{B}(t) \in k_H(t)$ such that the condition $0 \leq \mathfrak{B}(t) + \lambda(t) \leq 1$ is met.

2.3.6. Definition (6)

[31] Let B denote a general set. A Hq-ROFS $\mathscr{G}$, defined on B, Eq (12) can be used to represent the object:

$$\mathscr{G} = \{ < t, k_{\mathscr{G}}(t), l_{\mathscr{G}}(t) >_q | t \in B, q \geq 1 \} \tag{12}$$

Here, $k_{\mathscr{G}}(t)$ and $l_{\mathscr{G}}(t)$ are two subsets of [0,1], the q-rung orthopair of hesitancy, representing both the non-membership and membership scores of an object $t \in B$ to the set $\mathscr{G}$, are respectively denoted.

Furthermore, for every item $t \in B$, if $\forall \mathfrak{P}(t) \in k_H(t)$, then there exists $\lambda(t) \in l_H(t)$ such that the condition $0 \leq (\mathfrak{B}(t))^q + (\lambda(t))^q \leq 1$ holds. In the same way, if, $(t) \in l_H(t)$, then there exists $\mathfrak{B}(t) \in k_H(t),$ such that the condition $0 \leq (\mathfrak{B}(t))^q + (\lambda(t))^q \leq 1$ holds.

2.3.7. Definition (7)

[31] For an Hq-ROFN $\varepsilon = \mathscr{G}(k, l)$ that is described by the variables k and l, the function of score of ε can be defined as Eq (13):

$$\widehat{S}(\varepsilon) = \frac{1}{\#k} \sum_{\mathfrak{P} \in k} \mathfrak{J}^q - \frac{1}{\#l} \sum_{\lambda \in l} \lambda^q \tag{13}$$

In the given context, the symbols $\#k$ and $\#l$ represent the number of elements in sets k and l, respectively. Another way to express this is to say that $\#k$ indicates the size or cardinality of set k, while $\#l$ indicates the size or cardinality of set l.

Let ε denote the Hq-ROFN, where $\varepsilon = \mathscr{G}(k, l)$ The precision function of ε is given by Eq (14):

$$A(\varepsilon) = \frac{1}{\#k} \sum_{\mathfrak{B} \in k} \mathfrak{B}^q + \frac{1}{\#l} \sum_{\lambda \in l} \lambda^q \tag{14}$$

2.3.8. Definition (8)

Consider the assemblage of Hq-ROFNs denoted by $\varepsilon_i = \mathscr{G}(k_i, l_i)(i = 1, 2, \ldots, n)$. Let $\widetilde{w} = (\widetilde{w_1}, \ldots, \widetilde{w_n})^T$ be the ranking weights of ε_i where by $\widetilde{W} \geq 0(i = 1, \ldots, n)$ and $i \in [0, 1]$ with $\sum_{i=1}^n \widetilde{w}_i = 1$. As follows Eq (15):

$$\text{Hq-ROFWA}(\varepsilon_1,\varepsilon_2,\ldots,\varepsilon_n)=\bigcup_{\mathfrak{B}_i\in h_i,\lambda_i\in l_i}\left\{\left\{\sqrt[q]{1-\prod_{i=1}^{n}\left(1-\mathfrak{B}_i^{q}\right)^{\tilde{w}_i}}\right\},\left\{\prod_{i=1}^{n}\lambda_i^{\tilde{w}_i}\right\}\right\}. \tag{15}$$

2.3.9. Hq-ROFS in MCDM problem

The present discourse endeavors to elaborate the principal measures comprising the decision-making methodology along with its corresponding procedure. The subsequent section will enumerate and expound on the sequential steps integral to the aforementioned approach.

Let X be a set of n feasible alternatives denoted as $\{t_1, t_2, \ldots, t_n\}$ and C be a finite set of criteria given as $\{C_1, C_2, \ldots, C_M\}$. Moving ahead, we will consider the ranking weights $\widetilde{w} = (\widetilde{w_1}, \widetilde{w_2}, \ldots, \widetilde{w_3})^T$ that cover all the criteria, with $0 \leq \widetilde{w}_i \leq 1$ and $\sum_{i=1}^{n}\widetilde{w}_i = 1$ for $i = 1, \ldots, m$. The decision makers D_{mem} and $D_{non-mem}$ provide evaluation scores for each option $t_i(1, \ldots, n)$ associated with the given set of criteria $C_j(j = 1, \ldots, m)$ through k_{ij} and l_{ij}, respectively. The combination of these two values as a Hq-ROFN results in $\varepsilon_{ij} = (k_{ij}, l_{ij})$. This implies that decision maker D_{mem} assigns a membership grade h_{ij} to alternative t_i based on criteria C_j, while decision maker $D_{non-mem}$ assigns a non-membership grade g_{ij} to alternative t_i based on criteria C_j. On the basis of the examination of D_{mem} and $D_{non-mem}$, it is possible to formulate the Hq-ROF decision matrix $D = (\varepsilon_{ij})_{m\times n}$.

Moreover, based on the Hq-ROFWA operator for multi-criteria decision making problems, the process of decision-making, which involves the usage of Hq-ROF information, can be explicated in the ensuing manner:

Step 1. By employing the Hq-ROFWA operator Eq (16), it is possible to aggregate the Hesitant q-Rung Orthopair Fuzzy weighted elements ε_{ij} pertaining to each criterion C_j. This entails the calculation of all preference values ε_i for the alternatives t_i.

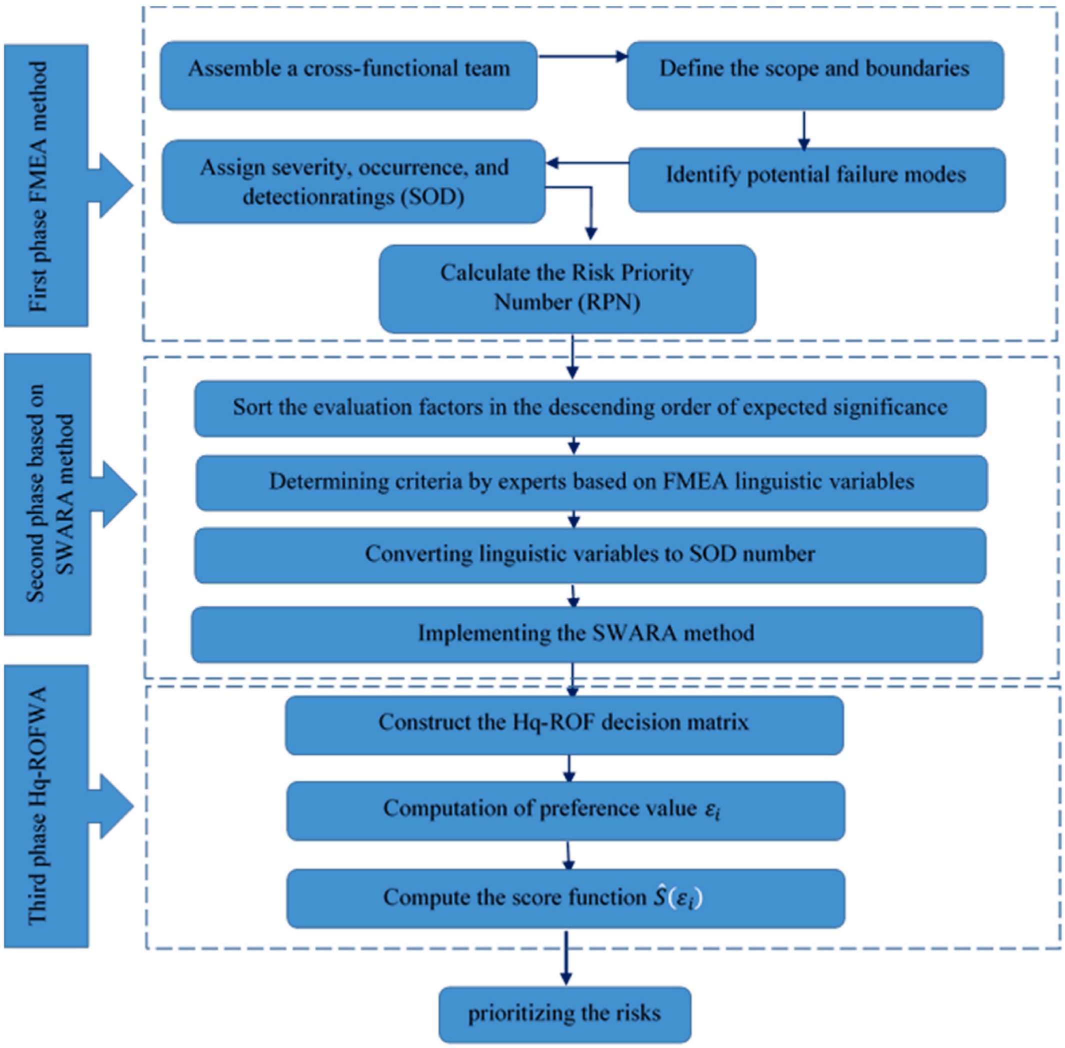

Fig. 2. Proposed research approach to prioritize causes.

$$\begin{aligned}\varepsilon_i &= Hq-ROFWA(\varepsilon_{i1},\varepsilon_{i2},\ldots,\varepsilon_{in})\\ &= \bigoplus_{j=1}^{n}\widetilde{\omega}_j\varepsilon_{ij}\\ &= \bigcup_{\mathfrak{P}_{ij}\in k_{ij},\lambda_{ij}\in l_{ij}}\left\{\left\{\sqrt[q]{1-\prod_{j=1}^{n}\left(1-\mathfrak{P}_{ij}^{q}\right)^{\widetilde{\omega}_j}}\right\},\left\{\prod_{j=1}^{n}\lambda_{ij}^{\widetilde{\omega}_j}\right\}\right\}\end{aligned} \tag{16}$$

Step 2. With regards to Equation (13), it is possible to calculate the score function $\check{S}(\varepsilon_i)(i=1,2,\ldots,m)$ for all hesitant q-rung orthopair fuzzy preference values ε_i. In the event of any similarities among the score functions, Equation (14) can be utilized to determine the reliability functions of all Hq-ROF preference values ε_i.

Step 3. The rank of the alternatives, t_i, is determined using the score function, and the most suitable alternative is chosen based on the result. It is important to note that the superiority of an alternative is directly proportional to the value of its score function.

3. Proposed approach

This particular research endeavor posits a highly sophisticated, multi-faceted methodological framework designed to holistically approach the analysis and assessment of potential risks inherent in various processes. Specifically, the proposed approach is comprised of three distinct but complementary components, namely, FMEA, SWARA, and Hq-ROFS methodology, as seen in detail in Fig. 2.

Firstly, the FMEA approach shall be employed to discern probable modes of failure, their resulting effects, and underlying causes within the process. Subsequently, the cross-functional team shall evaluate and determine the RPN assigned to each failure mode based on the severity, occurrence, and detection ratings.

The SWARA method, an expert-based approach for determining weights and rankings, will be utilized to prioritize the failure modes. In order to identify the paramount criteria for failure prioritization, a literature review and team input will be conducted. Experts will be tasked with assigning a comparative importance value to each criterion, which will then be utilized in calculating overall weights.

Finally, the Hq-ROFS model shall be utilized to address the issue of uncertainty in assessments made by experts. The incorporation of hesitancy and accuracy of each expert's assessments shall be achieved through the utilization of orthopair fuzzy sets. These sets are capable of representing varying degrees of precision and uncertainty. The calculation of aggregated risk scores shall be carried out by means of q-rung orthopair fuzzy weighted averaging operators.

The integrated FMEA, SWARA and Hq-ROFS approach provides a comprehensive methodology to assess risk, incorporate expert input, and address vagueness in linguistic assessments. The results will enable prioritization of failure modes and support decision-making to mitigate high risks in the process design.

Table 2
Identified causes in the process of land subsidence.

Symbol	Factor Name	Severity (S)			Occurrence (O)			Detection (D)		
		TM1	TM2	TM3	TM1	TM2	TM3	TM1	TM2	TM3
C1	Overuse of groundwater for irrigation	8	7	9	9	8	9	2	3	4
C2	Oil and gas extraction	5	5	6	7	8	8	3	3	2
C3	Underground mining	5	4	6	7	7	9	2	3	1
C4	Construction of large buildings or infrastructure, such as dams or highways	4	5	7	7	6	7	1	2	1
C5	Destruction of forests	7	6	7	7	7	6	3	3	2
C6	Converting agricultural lands to urban areas	5	4	6	6	5	5	2	2	1
C7	Population growth and urbanization	5	5	6	6	7	5	3	3	4
C8	Groundwater extraction	8	7	9	8	8	7	3	4	4
C9	fault activities	6	5	6	6	5	6	7	7	6
C10	tectonic movement	5	7	6	7	5	7	6	7	7
C11	consolidation/compaction of recent deposits	6	4	5	6	7	6	8	7	8
C12	the collapse of loess	7	6	8	5	6	4	8	8	7
C13	sea-level rise	6	6	7	5	4	5	5	5	6
C14	oxidation and drainage of organic soils	8	7	6	6	7	4	4	5	4
C15	karst erosion	6	7	7	7	6	5	5	4	5
C16	permafrost degradation	7	6	8	6	7	5	3	4	4
C17	Heavy rains	8	7	8	5	4	5	2	1	2
C18	Drought	8	7	9	6	5	6	2	2	1
C19	storm	7	6	7	5	4	4	1	1	2
C20	Changes in the climate system	8	7	9	6	7	6	2	2	2

4. Result and discussion

Within this particular section, we shall conduct a thorough analysis of the outcomes that arise from the implementation of the recommended approach in the assessment of the causes of land subsidence. Consistent with the initial phase of this methodology, the FMEA team undertakes the identification of potential risks while concurrently establishing the triple factor values for each cause, as presented in Table 2.

In the second phase of the research methodology, subsequent to the implementation of the SWARA method, the values of the coefficient k and the weights of q and w are ascertained for each decision-maker in evaluating the causal factors presented in Table 3, utilizing Equations (2)–(4). The ultimate weight of the principal criteria for each decision-maker can be discerned from Table 4.

In the ultimate phase of the evaluation process, when faced with the circumstances of a somewhat hesitant q-rung orthopair fuzzy environment, it is imperative for the experts to thoroughly assess the various alternatives by utilizing Hq-ROFNs. It is important to note, however, that certain values may be reiterated in this context, but it should not be assumed that these repeated values hold a greater significance than those that are not repeated as frequently. Based on the informed opinions of the experts, a well-constructed Hq-ROF decision matrix can be formulated and subsequently presented in Table 5.

Ultimately, the underlying reasons for the observed phenomena are assessed utilizing both the Hq-ROFS and FMEA methodologies, thereby ensuring a comprehensive analysis. Within this section, two distinct approaches are employed in accordance with Tables 1 and 4, and the resultant outcomes are expounded upon, taking into account the inherent uncertainty associated with the SOD factors as well as the reliability of the identified causes on Table 6. Moreover, a score function is ascertained via the Hq-ROFSs approach for various q values on Table 6. Finally, the available options are meticulously compared based on their respective rankings as per Tables 7 and 8.

The results indicate clear differences in the prioritization of land subsidence factors between the Hq-ROFS and FMEA approaches. Using the Hq-ROFS method, causes C8 and C1 consistently ranked first and second across all values of q, while C14 consistently ranked third. Causes C7 and C5 also consistently shared the lowest ranking. However, the FMEA approach produced a different prioritization, with C12 ranking first (RPN = 268), C10 ranking second (RPN = 253), and C11 ranking third (RPN = 242). The FMEA method identified C19 as the lowest priority factor (RPN = 38).

In summary, the two multi-criteria decision making techniques resulted in divergent rankings of the most critical factors contributing to ground subsidence. The Hq-ROFS method prioritized C8, C1, and C14 as the top factors, while the FMEA approach prioritized C12, C10, and C11. Both methods agreed that C7, C5, and C19 were low priorities. Further research could help determine which technique provides greater accuracy in evaluating these complex geotechnical hazards. Nonetheless, this study demonstrates the sensitivity of factor prioritization to the choice of multi-criteria decision methodology.

This study demonstrates the differences in risk prioritization outcomes among two multi-criteria decision-making techniques (Fig. 3): traditional FMEA and Hq-ROFS, approach. The results highlight the limitations of traditional FMEA and the advantages of using more advanced fuzzy set techniques that incorporate uncertainty and expert opinion in evaluating complex criteria.

The proposed q-rung orthopair fuzzy set method addresses key weaknesses in traditional FMEA and basic Hesitant fuzzy approaches. By utilizing uncertainty degrees for each criterion and multiple prioritization levels, it better represents real-world conditions and expert perspectives. The introduction of Hq-ROFS theory further expands the reliability of the criteria data by capturing a wider range of expert opinions and uncertainties. Consequently, the proposed technique produced more nuanced, reliable, and realistic risk rankings compared to simpler methods.

4.1. Validation of proposed approach

In this section, we conducted two validation studies to ensure the reliability and validity of our rankings. The first study involved comparing the results from our proposed approach (Hq-ROFWA) with two existing approaches, IHFWA and PHFWA, to assess the consistency and effectiveness of our method in prioritizing causes of land subsidence. In the second study, we used Spearman's correlation analysis to validate the results obtained from the MCDM methods.

4.1.1. Comparative analysis

The purpose of this section is to show how reliable, accurate, and effective the proposed methodology is in real-world situations. To

Table 3
The weights of cause factors.

Team number	*Risk factor*	*Comparative importance of average valueS~j*			*Coefficient*			*Recalculated weight*			*Weight*		
	S				1	1	1	1.000	1.000	1.000	0.440	0.461	0.492
TM1	O	0.4	0.5	0.666	1.4	1.5	1.666	0.600	0.667	0.714	0.264	0.307	0.352
	D	0.285	0.333	1.285	1.4	1.333	1.285	0.429	0.500	0.556	0.188	0.230	0.273
	S				1	1	1	1.000	1.000	1.000	0.414	0.425	0.440
TM2	D	0.285	0.333	0.4	1.285	1.333	1.4	0.714	0.750	0.778	0.295	0.319	0.342
	O	0.222	0.25	0.285	1.222	1.25	1.285	0.556	0.600	0.636	0.230	0.255	0.280
	O				1	1	1	1.000	1.000	1.000	0.483	0.533	0.593
TM3	S	0.666	1	1.5	1.666	2	2.5	0.400	0.500	0.600	0.193	0.266	0.355
	D	0.285	0.333	0.4	1.285	1.333	1.4	0.286	0.375	0.467	0.138	0.2	0.276

Table 4
Final SWARA weights of causes factors.

Risk factors	Final weight
S	0.386
O	0.366
D	0.250

Table 5
Decision Matrix of Hq-ROFWA.

Crit.	S	O	D
C1	{(0.8,0.2),(0.2,0.3)}	{(0.9,0.1),(0.5,0.2)}	{(0.2,0.8),(0.4,0.6)}
C2	{(0.5,0.3),(0.2,0.4)}	{(0.7,0.2),(0.3,0.1)}	{(0.3,0.6),(0.3,0.7)}
C3	{(0.5,0.5),(0.3,0.4)}	{(0.8,0.2),(0.4,0.3)}	{(0.2,0.8),(0.3,0.6)}
C4	{(0.4,0.3),(0.5,0.4)}	{(0.7,0.2),(0.2,0.3)}	{(0.1,0.9),(0.2,0.8)}
C5	{(0.7,0.2),(0.5,0.3)}	{(0.9,0.1),(0.5,0.2)}	{(0.3,0.6),(0.3,0.7)}
C6	{(0.5,0.5),(0.4,0.4)}	{(0.6,0.3),(0.2,0.4)}	{(0.1,0.7),(0.2,0.8)}
C7	{(0.5,0.3),(0.5,0.4)}	{(0.6,0.4),(0.4,0.2)}	{(0.3,0.5),(0.4,0.6)}
C8	{(0.8,0.2),(0.1,0.3)}	{(0.8,0.2),(0.2,0.1)}	{(0.3,0.6),(0.4,0.6)}
C9	{(0.6.0.4),(0.5,0.3)}	{(0.6,0.4),(0.3,0.4)}	{(0.7,0.2),(0.5,0.3)}
C10	{(0.5,0.4),(0.3,0.2)}	{(0.7,0.3),(0.5,0.4)}	{(0.6,0.3),(0.4,0.2)}
C11	{(0.6,0.4),(0.4,0.3)}	{(0.6,0.3),(0.4,0.2)}	{(0.8,0.1),(0.5,0.2)}
C12	{(0.7,0.2),(0.4,0.2)}	{(0.5,0.4),(0.2,0.3)}	{(0.8,0.2),(0.6,0.1)}
C13	{(0.6,0.4),(0.3,0.2)}	{(0.5,0.3),(0.4.0.2)}	{(0.5,0.3),(0.5,0.2)}
C14	{(0.8,0.1),(0.3,0.2)}	{(0.6,0.3),(0.3,0.2)}	{(0.4,0.5),(0.5,0.2)}
C15	{(0.6,0.2),(0.4,0.3)}	{(0.7,03),(0.5,0.4)}	{(0.5,0.3),(0.4,0.2)}
C16	{(0.7,0.2),(0.2,0.4)}	{(06,0.3),(0.3,0.2)}	{(0.3,0.6),(0.4,0.6)}
C17	{(0.8,0.2),(0.4,0.2)}	{(0.5,0.4),(0.4,0.2)}	{(0.2,0.8),(0.3,0.7)}
C18	{(0.8,0.1),(0.1,0.3)}	{(0.6,0.4),(0.5,0.4)}	{(0.2,0.8),(0.4,0.5)}
C19	{(0.7,0.2),(0.5,0.3)}	{(0.5,0.3),(0.4,0.3)}	{(0.1,0.8),(0.4,0.5)}
C20	{(0.8,0.2),(0.3,0.2)}	{(0.6,0.3),(0.2,0.3)}	{(0.2,0.6),(0.3,0.7)}

Table 6
Hq-ROFWA Score Functions for Diffirent q.

Crit	q values						
	q = 1	q = 2	q = 3	q = 5	q = 10	q = 15	q = 20
C1	0.254024415	−0.040360904	0.034122341	−0.004673724	−0.000043750	−0.000000507	−0.000000006
C2	0.167087212	−0.056184746	0.001330122	−0.002693084	−2.168556E-05	−2.304069E-07	−2.663167E-09
C3	0.162251899	−0.08493925	−0.008467925	−0.006212217	−6.19057E-05	−7.87397E-07	−1.14935E-08
C4	0.121960482	−0.081916606	−0.018607438	−0.00605258	−8.23329E-05	−1.49878E-06	−3.03986E-08
C5	0.15948424	−0.097673001	3.0543E-05	−0.012504919	−0.000365029	−1.44216E-05	−6.3842E-07
C6	0.114973988	−0.091898587	−0.023095106	−0.006055765	−8.87099E-05	−1.84039E-06	−4.2575E-08
C7	0.049479843	−0.129724227	−0.040714983	−0.010334643	−0.000171356	−3.39931E-06	−7.44178E-08
C8	0.315739695	−0.004097098	0.043347493	−0.000682117	−1.29268E-06	−3.03591E-09	−7.59656E-12
C9	0.127884561	−0.108764547	−0.018814369	−0.008056564	−0.000101486	−1.56703E-06	−2.73699E-08
C10	0.156444884	−0.076791465	−0.00205726	−0.003608585	−1.92744E-05	−1.25462E-07	−9.24483E-10
C11	0.175692143	−0.074834111	0.004374268	−0.004344996	−3.50965E-05	−3.72816E-07	−4.47151E-09
C12	0.22141384	−0.047604789	0.018166157	−0.002517543	−1.62654E-05	−1.37391E-07	−1.27393E-09
C13	0.15097245	−0.064330595	−0.002829181	−0.002314266	−1.0512E-05	−6.48774E-08	−4.56186E-10
C14	0.212480383	−0.040806266	0.021477637	−0.00156233	−4.16124E-06	−1.44844E-08	−5.80017E-11
C15	0.101712812	−0.105020616	−0.015273769	−0.006751283	−6.41615E-05	−7.20193E-07	−9.0593E-09
C16	0.161220897	−0.065945293	0.001272152	−0.003106113	−1.91322E-05	−1.5394E-07	−1.37836E-09
C17	0.176485721	−0.071193276	−0.001073535	−0.005349388	−6.66014E-05	−1.14257E-06	−2.20208E-08
C18	0.205736198	−0.054238486	0.00981808	−0.003756897	−3.08052E-05	−2.98648E-07	−3.0635E-09
C19	0.073405804	−0.116281674	−0.031148835	−0.009279334	−0.000124762	−1.9561E-06	−3.36942E-08
C20	0.201980245	−0.046968866	0.017128489	−0.00210123	−8.63226E-06	−4.79492E-08	−3.02763E-10

do this, we carefully compared the results obtained from the Hq-ROFWA technique with those from other established methodologies such as Intuitionistic hesitant fuzzy weighted average (IHFWA) and Pythagorean hesitant fuzzy weighted average (PHFWA). Our analysis revealed a consistent pattern in the ranking results across all methods, with C8, C1, and C14 consistently placed in the top three positions (see. Table 9).

Upon further examination, we found that the causes of land subsidence identified by all three approaches were remarkably similar, indicating the validity and reliability of the proposed method. The consistency in the identification of land subsidence causes across all three methods confirms the robustness of our approach and instills confidence in the accuracy of the prioritization process. The use of

Table 7
The cause priority number for FMEA.

Crit.	RPN	Crit.	RPN
C1	208	**C11**	242.78
C2	109.04	**C12**	268.33
C3	76.667	**C13**	157.63
C4	47.407	**C14**	171.89
C5	118.52	**C15**	186.67
C6	44.444	**C16**	154
C7	106.67	**C17**	59.63
C8	224.89	**C18**	75.556
C9	214.07	**C19**	38.519
C10	253.33	**C20**	101.33

Table 8
Comparison of causes prioritization based on two approaches.

Symbol	Rank							
	Hq-ROFWA							
	FMEA	q = 1	q = 2	q = 3	q = 5	q = 10	q = 15	q = 20
C1	6	2	2	2	1	1	1	1
C2	12	9	7	8	7	9	9	9
C3	15	10	14	14	15	12	13	13
C4	18	16	13	16	13	15	15	16
C5	11	12	16	10	20	20	20	20
C6	16	17	15	18	14	16	17	18
C7	13	20	20	20	19	19	19	19
C8	4	1	1	1	2	2	2	2
C9	5	15	18	17	17	17	16	15
C10	2	13	12	12	9	8	6	6
C11	3	8	11	7	11	11	11	11
C12	1	3	5	4	6	6	7	7
C13	9	14	8	13	5	5	5	5
C14	8	4	3	3	3	3	3	3
C15	7	18	17	15	16	13	12	12
C16	10	11	9	9	8	7	8	8
C17	17	7	10	11	12	14	14	14
C18	16	5	6	6	10	10	10	10
C19	20	19	19	19	18	18	18	17
C20	14	6	4	5	4	4	4	4

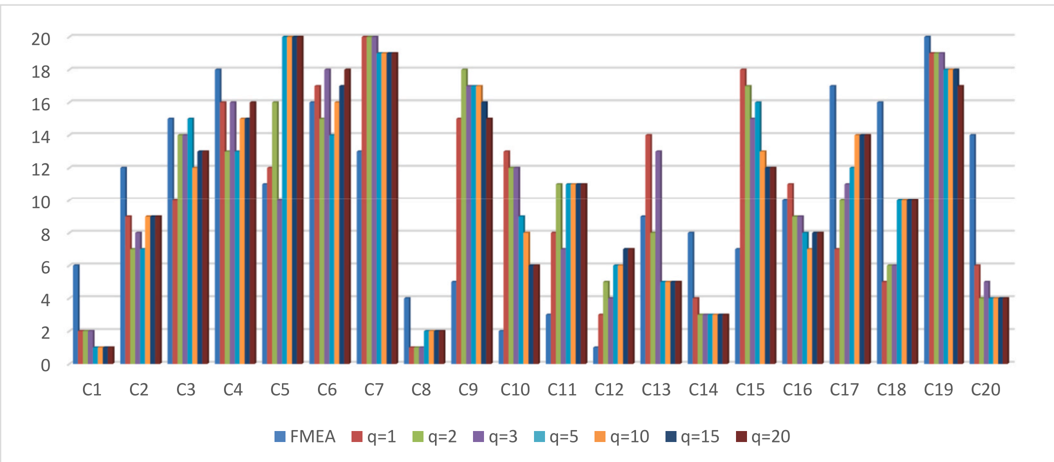

Fig. 3. Comparison of causes prioritization based on FMEA and Hq-ROFWA.

Table 9
Comparison of land subsidence factors based on various methods.

	Hq-ROFWA		IHFWA		PHFWA	
	q = 3		q = 3		q = 3	
Symbol	Score Function	Rank	Score Function	Rank	Score Function	Rank
C1	0.034	2	0.566	2	0.86	2
C2	0.001	8	0.477	8	0.147	8
C3	−0.008	14	0.395	14	0.095	14
C4	−0.019	16	0.328	16	0.001	16
C5	0.000	10	0.444	10	0.128	10
C6	−0.023	18	0.243	18	−0.0245	18
C7	−0.041	20	0.154	20	−0.0571	20
C8	0.043	1	0.638	1	0.87	1
C9	−0.019	17	0.267	17	−0.017	17
C10	−0.002	12	0.421	12	0.108	12
C11	0.004	7	0.483	7	0.24	7
C12	0.018	4	0.516	4	0.62	4
C13	−0.003	13	0.412	13	0.101	13
C14	0.021	3	0.537	3	0.74	3
C15	−0.015	15	0.371	15	0.031	15
C16	0.001	9	0.458	9	0.13	9
C17	−0.001	11	0.439	11	0.113	11
C18	0.010	6	0.501	6	0.52	6
C19	−0.031	19	0.206	19	−0.0344	19
C20	0.017	5	0.508	5	0.61	5

multiple techniques and the acquisition of consistent results in this study enhance its credibility and overall reliability in assessing causes of land subsidence. This alignment among different methods further supports the conclusion that the proposed approach is indeed valid and can be relied upon for effective causes of land subsidence.

4.1.2. Spearman's correlation analysis

Spearman's correlation analysis is a valuable tool for evaluating the consistency of the decision-making process. By examining the correlations between score functions and rankings, decision makers can ensure that their evaluations and rankings are logically consistent and aligned with their preferences. Additionally, Spearman's correlation analysis can be used to validate the results obtained from MCDM methods. When the correlations between alternatives align with the expected relationships, it provides confidence in the accuracy and reliability of the decision-making outcomes [26]. The formula for Spearman's correlation coefficient is presented below.

$$\rho = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x}) * (y_i - \overline{y})}{\sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right) * \left(\frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y})^2\right)}} \tag{17}$$

All in all, Spearman's correlation analysis is crucial in MCDM methods as it enhances the understanding of relationships between criteria, ensures consistency in the decision-making process, identifies redundancies, validates results, and facilitates sensitivity analysis. It empowers decision makers to make informed and reliable decisions based on a comprehensive analysis of the alternatives.

The results of the conducted study have revealed that the Hq-ROFWA method has demonstrated a significantly higher correlation coefficient of 0.9713 in comparison to the IHFWA and PHFWA methods, which have shown correlation coefficients of 0.9643 and 0.9163, respectively. These findings have effectively demonstrated the reliability and accuracy of the Hq-ROFWA method in producing highly precise results. A comprehensive visual representation of the correlation results obtained through the use of the Hq-ROFWA, IHFWA, and PHFWA methodologies is depicted in Fig. 4. As a result, decision-makers can confidently focus on preventing land subsidence, knowing that the results obtained from this approach are dependable, reliable, and can be trusted with utmost confidence.

Despite its strengths, this study has limitations that provide opportunities for future research. The proposed approach does not account for interrelationships between criteria, which may be linear or non-linear. Extending the method to model such interdependencies could improve accuracy. Additionally, the relatively small expert sample size restricts the breadth of perspectives and analysis. Including more experts would enhancereliability and confidence in the results.

In conclusion, the proposed Hq-ROFS approach shows promise as a powerful decision-making tool for evaluating land subsidence risks and causes under uncertainty. The technique meaningfully advances standard FMEA and Hq-ROFS methods by integrating multiple levels of analysis and additional expert knowledge factors. Further research into criteria interrelationships and expanded expert data would build on the strengths of this approach.

Future research in this area should aim to further explore the interactions between different factors contributing to land subsidence. Future research could also focus on developing predictive models to forecast the occurrence and severity of land subsidence, taking into account the complex interplay of geological, hydrological, and anthropogenic factors. However, it is advisable to explore

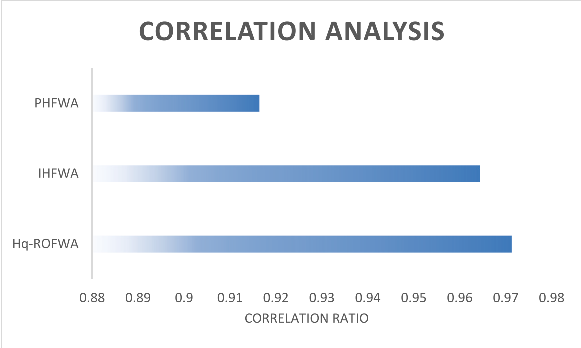

Fig. 4. Comparison of Spearman's correlation among three approach.

alternative methodologies such as the Full Consistency Method (FUCOM), which presents a comprehensive strategy for assessing criteria by taking into account the consistency of pairwise comparisons [39], or Level Based Weight Assessment (LBWA), which provides a systematic and structured approach for assigning weights to criteria [40], in order to determine the criteria.

5. Conclusion

This study has successfully demonstrated an effective integrated approach for evaluating and prioritizing the complex causes of land subsidence by combining FMEA and Hq-ROFS techniques. The primary goal of this work was to comprehensively assess the multifaceted factors influencing land subsidence and provide valuable insights for researchers, policymakers, and practitioners working in this field. The results of the study have shown clear differences in the prioritization of land subsidence factors between the Hq-ROFS and FMEA approaches. The Hq-ROFS method consistently ranked causes C8 and C1 as the top factors, while the FMEA approach prioritized C12 as the highest-ranking factor. This disparity in rankings underscores the sensitivity of factor prioritization to the choice of multi-criteria decision methodology. Furthermore, the study identified 20 key subsidence factors through preliminary research and expert opinion, and analyzed them using both methods. The findings revealed that the Hq-ROFS method consistently ranked causes C8, C1, and C14 as the top factors, while the FMEA approach prioritized C12, C10, and C11. Both methods agreed that causes C7, C5, and C19 were low priorities. The importance of these results lies in their potential to inform policy-making, urban planning, and infrastructure development. Land subsidence poses a significant threat to the environment, infrastructure, and human settlements, and a comprehensive understanding of the factors driving this phenomenon is crucial for developing effective strategies to mitigate its impacts and prevent further degradation of the environment. This study stands out for its holistic approach to the study of land subsidence, as it covers all variables that contribute to this complex phenomenon, addressing the limitations of existing research. While previous studies have focused on specific regional factors, this research provides a more comprehensive and nuanced understanding of land subsidence, filling a critical gap in the literature. In conclusion, this research makes a significant contribution to the study of land subsidence by undertaking a meticulous assessment of the multifaceted factors that affect land subsidence. By doing so, it offers valuable insights for researchers, policymakers, and practitioners, and has the potential to inform strategies for mitigating the impacts of land subsidence and preventing further environmental degradation. Further research could help determine which technique provides greater accuracy in evaluating these complex geotechnical hazards, thus advancing our understanding and management of land subsidence. The proposed Hq-ROFS method meaningfully advances traditional FMEA by accounting for distinct criteria weights, multiple prioritization levels, and inherent uncertainty. This approach produced more differentiated, certain, and realistic cause rankings compared to FMEA alone. The fuzzy set method overcomes limitations of FMEA through its consideration of nuanced expert perspectives and treatment of uncertainty.

These findings provide valuable direction for future research on evaluating and mitigating threats from land subsidence. The proposed technique could be readily adapted to assess risks for other subsidence-related issues or in other geographical areas. Further development of complementary multi-criteria decision making methods is recommended to continue improving this complex risk domain.

In conclusion, the integration of FMEA and Hq-ROFS theory shows promise for robust, reliable prioritization of subsidence factors. This study demonstrates the advantages of modeling expert uncertainty and multi-level criteria analysis when tackling intricate geotechnical hazards. The proposed approach meaningfully advances subsidence evaluation and provides a flexible framework to build upon in future research.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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Availability of data and materials

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

CRediT authorship contribution statement

Saeid Jafarzadeh Ghoushchi: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Sahand Vahabzadeh:** Writing – review & editing, Writing – original draft, Validation, Conceptualization. **Dragan Pamucar:** Writing – review & editing, Writing – original draft, Validation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] J.N. Galloway, A.R. Townsend, J.W. Erisman, M. Bekunda, Z. Cai, J.R. Freney, M.A. Sutton, Transformation of the nitrogen cycle: recent trends, questions, and potential solutions, Science 320 (5878) (2008) 889–892. http://pubs.usgs.gov/circ/circ1182/.
[2] R.L. Hu, Z.Q. Yue, L.C. Wang, S.J. Wang, Review on current status and challenging issues of land subsidence in China, Eng. Geol. 76 (1–2) (Dec. 2004) 65–77, https://doi.org/10.1016/j.enggeo.2004.06.006.
[3] N. Akhtar, M.I. Syakir Ishak, S.A. Bhawani, K. Umar, Various natural and anthropogenic factors responsible for water quality degradation: a review, Water 13 (19) (Sep. 2021) 2660, https://doi.org/10.3390/w13192660.
[4] R. Siriwardane-de Zoysa, et al., The 'wickedness' of governing land subsidence: policy perspectives from urban Southeast Asia, PLoS One 16 (6) (Jun. 2021) e0250208, https://doi.org/10.1371/journal.pone.0250208.
[5] M. Bagheri-Gavkosh, et al., Land subsidence: a global challenge, Sci. Total Environ. 778 (Jul. 2021) 146193, https://doi.org/10.1016/j.scitotenv.2021.146193.
[6] C.C. Faunt, M. Sneed, J. Traum, J.T. Brandt, Water availability and land subsidence in the Central Valley, California, USA, Hydrogeol. J. 24 (3) (May 2016) 675–684, https://doi.org/10.1007/s10040-015-1339-x.
[7] D.J.R.B.N. Whittaker, Subsidence: Occurrence, Prediction and Control Issue 56 of Developments in Geotechnical Engineering, ISSN 0165-1250, Elsevier Science, 1989.
[8] F. Cigna, D. Tapete, Urban growth and land subsidence: multi-decadal investigation using human settlement data and satellite InSAR in Morelia, Mexico, Sci. Total Environ. 811 (Mar. 2022) 152211, https://doi.org/10.1016/j.scitotenv.2021.152211.
[9] T.L. Holzer, State and local response to damaging land subsidence in United States urban areas, Eng. Geol. 27 (Dec. 1989) 449–466, https://doi.org/10.1016/0013-7952(89)90041-0, 1–4.
[10] Y. Liu, T. Ma, Y. Du, Compaction of muddy sediment and its significance to groundwater chemistry, Procedia Earth Planet. Sci. 17 (2017) 392–395, https://doi.org/10.1016/j.proeps.2016.12.099.
[11] G. Mohebbi Tafreshi, M. Nakhaei, R. Lak, Land subsidence risk assessment using GIS fuzzy logic spatial modeling in Varamin aquifer, Iran, Geojournal 86 (3) (Jun. 2021) 1203–1223, https://doi.org/10.1007/s10708-019-10129-8.
[12] N. Hosseini Alaee, A. Mozafari, M. Mirzaee, A. Faghihi, K. Tolouei, Fuzzy evaluation method for the identification of subsidence susceptibility in an underground mine (case study in Tabas coal mine of Iran), Nat. Hazards 99 (2) (Nov. 2019) 797–806, https://doi.org/10.1007/s11069-019-03774-2.
[13] Bianchini, et al., Ground subsidence susceptibility (GSS) mapping in Grosseto plain (tuscany, Italy) based on satellite InSAR data using frequency Ratio and fuzzy logic, Rem. Sens. 11 (17) (Aug. 2019) 2015, https://doi.org/10.3390/rs11172015.
[14] A.A. Nadiri, M. Moazamnia, S. Sadeghfam, R. Barzegar, Mapping risk to land subsidence: developing a two-level modeling strategy by combining multi-criteria decision-making and artificial intelligence techniques, Water 13 (19) (Sep. 2021) 2622, https://doi.org/10.3390/w13192622.
[15] S.N. Mohamad Deros, N. Md Din, S.M. Norzeli, R.C. Omar, F. Usman, S.A. Hamim, Land subsidence susceptibility projection for Palembang slum area by complex MCDM-AHP technique, J. Eng. Technol. Sci. 54 (1) (Jan. 2022) 220104, https://doi.org/10.5614/j.eng.technol.sci.2022.54.1.4.
[16] S. Mehrnoor, M. Robati, M.M. Kheirkhah Zarkesh, F. Farsad, S. Baikpour, Land subsidence hazard assessment based on novel hybrid approach: BWM, weighted overlay index (WOI), and support vector machine (SVM), Nat. Hazards 115 (3) (Feb. 2023) 1997–2030, https://doi.org/10.1007/s11069-022-05624-0.
[17] A.A. Nadiri, Z. Taheri, R. Khatibi, G. Barzegari, K. Dideban, Introducing a new framework for mapping subsidence vulnerability indices (SVIs): ALPRIFT, Sci. Total Environ. 628–629 (Jul. 2018) 1043–1057, https://doi.org/10.1016/j.scitotenv.2018.02.031.
[18] M. Chitsazan, G. Rahmani, H. Ghafoury, Land subsidence susceptibility mapping using PWRSTFAL framework and analytic hierarchy process: fuzzy method (case study: damaneh-Daran Plain in the west of Isfahan Province, Iran), Environ. Monit. Assess. 194 (3) (Mar. 2022) 192, https://doi.org/10.1007/s10661-021-09645-3.
[19] Y.-S. Xu, L. Ma, Y.-J. Du, S.-L. Shen, Analysis of urbanisation-induced land subsidence in Shanghai, Nat. Hazards 63 (2) (Sep. 2012) 1255–1267, https://doi.org/10.1007/s11069-012-0220-7.
[20] Q.T. Nguyen, The main causes of land subsidence in Ho chi minh city, Procedia Eng. 142 (2016) 334–341, https://doi.org/10.1016/j.proeng.2016.02.058.
[21] H. Li, et al., Land subsidence due to groundwater pumping: hazard probability assessment through the combination of Bayesian model and fuzzy set theory, Nat. Hazards Earth Syst. Sci. 21 (2) (Mar. 2021) 823–835, https://doi.org/10.5194/nhess-21-823-2021.
[22] M. Bitarafan, K. Amini Hosseini, S. Hashemkhani Zolfani, Evaluating natural hazards in cities using a novel integrated MCDM approach (case study: tehran city), Mathematics 11 (8) (Apr. 2023) 1936, https://doi.org/10.3390/math11081936.
[23] V. Keršulienė, E.K. Zavadskas, Z. Turskis, Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA), J. Bus. Econ. Manag. 11 (2) (Jun. 2010) 243–258, https://doi.org/10.3846/jbem.2010.12.
[24] R. Chaurasiya, D. Jain, Hybrid MCDM method on pythagorean fuzzy set and its application, Decision Making: Applications in Management and Engineering 6 (1) (2023) 379–398, https://doi.org/10.31181/dmame0306102022c.

[25] M.B. Bouraima, B. Ibrahim, Y. Qiu, M. Kridish, M. Dantonka, Integrated spherical decision-making model for managing climate change risks in africa, Journal of Soft Computing and Decision Analytics 2 (1) (2024) 71–85, https://doi.org/10.31181/jscda21202435.
[26] S. Jafarzadeh Ghoushchi, S. Shaffiee Haghshenas, S. Vahabzadeh, G. Guido, Development of a robust hybrid framework for evaluating and ranking smartification measures for sustainable mobility: a case study of Sicilian roadways, Southern Italy, Expert Syst. Appl. 241 (May 2024) 122595, https://doi.org/10.1016/j.eswa.2023.122595.
[27] J.B. Bowles, C.E. Peláez, Fuzzy logic prioritization of failures in a system failure mode, effects and criticality analysis, Reliab. Eng. Syst. Saf. 50 (2) (Jan. 1995) 203–213, https://doi.org/10.1016/0951-8320(95)00068-D.
[28] M. Mardani Shahri, A. Eshraghniaye Jahromi, M. Houshmand, Failure Mode and Effect Analysis using an integrated approach of clustering and MCDM under pythagorean fuzzy environment, J. Loss Prev. Process. Ind. 72 (Sep. 2021) 104591, https://doi.org/10.1016/j.jlp.2021.104591.
[29] S.J. Ghoushchi, S.M. Jalalat, S.R. Bonab, A.M. Ghiaci, G. Haseli, H. Tomaskova, Evaluation of wind turbine failure modes using the developed SWARA-CoCoSo methods based on the spherical fuzzy environment, IEEE Access 10 (2022) 86750–86764, https://doi.org/10.1109/ACCESS.2022.3199359.
[30] S. Jafarzadeh Ghoushchi, S. Sarvi, Prioritizing and evaluating risks of ordering and prescribing in the chemotherapy process using an extended SWARA and MOORA under fuzzy Z-numbers, Journal of Operations Intelligence 1 (1) (2023) 44–66, https://doi.org/10.31181/jopi1120238.
[31] M. I. A., T.M.A. Hussain, Hesitant q-rung orthopair fuzzy aggregation operators with their applications in multi-criteria decision making, Iran. J. Fuzzy Syst. 17 (2020) 117–134, https://doi.org/10.22111/IJFS.2020.5353.
[32] R.R. Yager, Pythagorean membership grades in multicriteria decision making, IEEE Trans. Fuzzy Syst. 22 (4) (Aug. 2014) 958–965, https://doi.org/10.1109/TFUZZ.2013.2278989.
[33] R.R. Yager, Pythagorean fuzzy subsets, in: 2013 Joint IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS), IEEE, Jun. 2013, pp. 57–61, https://doi.org/10.1109/IFSA-NAFIPS.2013.6608375.
[34] R.R. Yager, N. Alajlan, Approximate reasoning with generalized orthopair fuzzy sets, Inf. Fusion 38 (Nov. 2017) 65–73, https://doi.org/10.1016/j.inffus.2017.02.005.
[35] R.R. Yager, Generalized orthopair fuzzy sets, IEEE Trans. Fuzzy Syst. 25 (5) (Oct. 2017) 1222–1230, https://doi.org/10.1109/TFUZZ.2016.2604005.
[36] V. Torra, Hesitant fuzzy sets, Int. J. Intell. Syst., p. n/a-n/a (2010), https://doi.org/10.1002/int.20418.
[37] B. Zhu, Z. Xu, M. Xia, Dual hesitant fuzzy sets, J. Appl. Math. 2012 (2012) 1–13, https://doi.org/10.1155/2012/879629.
[38] J.J. Peng, J.Q. Wang, X.H. Wu, H.Y. Zhang, X.H. Chen, The fuzzy cross-entropy for intuitionistic hesitant fuzzy sets and their application in multi-criteria decision-making, Int. J. Syst. Sci. 46 (13) (Oct. 2015) 2335–2350, https://doi.org/10.1080/00207721.2014.993744.
[39] D. Pamučar, Ž. Stević, S. Sremac, A new model for determining weight coefficients of criteria in MCDM models: Full consistency method (FUCOM), Symmetry (Basel) 10 (9) (Sep. 2018) 393, https://doi.org/10.3390/sym10090393.
[40] M. Žižović, D. Pamučar, New model for determining criteria weights: level Based Weight Assessment (LBWA) model, Decis. Mak. Appl. Manag. Eng. 2 (2) (Oct. 2019), https://doi.org/10.31181/dmame1902102z.