Neutrosophic Systems with Applications, Vol. 7, 2023
https://doi.org/10.61356/j.nswa.2023.37

Mitigating Landslide Hazards in Qena Governorate of Egypt: A GIS-based Neutrosophic PAPRIKA Approach

Nabil M. AbdelAziz [1,*] and Safa Al-Saeed [2]

[1,2] Faculty of Computers and Informatics, Zagazig University, Zagazig, Sharqiyah, 44519, Egypt.
Emails: nmabedelaziz@fci.zu.edu.eg; safa.alsaid.1992@gmail.com; SEAbdelKarim@fci.zu.edu.eg.

* Correspondence: nmabedelaziz@fci.zu.edu.eg.

Abstract: This paper presents a novel approach to landslide susceptibility assessment in the Qena Governorate, Egypt, integrating the neutrosophic Multi-Criteria Decision-Making (MCDM) method, the Potentially All Pairwise RanKings of all possible Alternatives (PAPRIKA), and the ArcGIS weighted overlay technique. The research focuses on the quantification and prioritization of eight criteria: slope, aspect, proximity to road, soil type, proximity to river, land cover, elevation, and Lithology. These factors are evaluated under the uncertainty and indeterminacy of the neutrosophic environment by employing the PAPRIKA method. The results of the analysis are visualized and interpreted using ArcGIS weighted overlay, offering spatially explicit insights into the landslide-prone areas. This study's outcomes could significantly contribute to the overall understanding of landslide hazards in Qena, promoting better hazard management and mitigation strategies. The results of the study demonstrated varying levels of landslide susceptibility within the study area: 2% of the area was identified as having Very High Susceptibility, 17% presented High Susceptibility, 28% had Moderate Susceptibility, 44% indicated Low Susceptibility, 8% showed Very Low Susceptibility, and 1% with Practically No Susceptibility. These findings can aid local authorities and policy-makers in prioritizing areas for mitigation efforts based on their susceptibility to landslides. The study also incorporates a sensitivity analysis, exploring ten different scenarios to ensure the robustness and reliability of the results. In the first scenario, we adhere to our initial criteria weights to represent the current situation. In the second scenario, all criteria are accorded equal significance to check the model's steadfastness when no one criterion outweighs another. Scenarios three to ten each elevate the weightage of one criterion, allowing for a comprehensive understanding of each individual criterion's influence on the decision-making process. This systematic alteration helps pinpoint the salient features driving landslides and aids in fortifying our mitigation strategies.

Keywords: Neutrosophic Set; Geographic Information System; PAPRIKA; Multi-Criteria Decision-Making; Qena.

1. Introduction

Landslides represent a significant natural hazard that have the potential to cause substantial socio-economic harm and loss of life, particularly in areas characterized by challenging terrain and environmental conditions [1]. Notably, the Qena Governorate of Egypt is one such area that has been recurrently plagued by such events. As it encompasses a mix of various topographic and environmental features, this region has witnessed a rise in landslide incidents over the past decades [2]. The aftermath of these landslides often leads to severe economic implications, including the destruction of infrastructure, loss of arable land, and disruption of communication routes, thereby causing profound socioeconomic setbacks for the local inhabitants [3]. Moreover, there's a profound impact on the life of the local population, often leading to forced displacement, immediate danger to personal safety, and lasting trauma. As such, mitigating the frequency and intensity of these hazards becomes an issue of utmost importance. Furthermore, the complexities involved due to the various intrinsic and extrinsic factors contributing to landslide occurrences implicate the need for a comprehensive, integrated multi-criteria assessment method. This would not only enable predicting areas with high susceptibility but also aid in drawing effective mitigation strategies, consequently contributing toward a safer and economically stable Qena region.

Traditional solutions to predicting and managing landslide hazards generally revolve around a blend of geotechnical measures, engineering solutions, and land-use planning strategies [4, 5]. Some of these approaches include mechanical stabilization measures, such as building retaining walls and terraces, redirecting landslip flow paths, and slope degrading. Land-use strategies revolve around preventing infrastructural development in landslide-prone areas [6]. While these solutions can be effective, they often come with high implementation costs and feasibility issues, particularly in regions with complex socio-economic and environmental conditions. Additionally, conventional methodologies that aim to predict landslide-prone zones often rely on simple statistical models or deterministic methods. These methods use geological, topographic, and meteorological data to estimate landslide susceptibility. However, they often fail to adequately account for uncertain or indeterminate information and the inherent subjectivity in human decision-making, thereby reducing the overall accuracy of susceptibility maps. Furthermore, there is a limitation in their ability to quantify landslide hazards in a highly efficient, refined manner due to the lack of comprehensive integration of various environmental factors contributing to landslides. Hence, there is a pressing need for an approach that overcomes these shortcomings and enhances the understanding and prediction of landslide hazards.

To address the limitations of existing approaches, the focus of this study is to adopt an innovative approach involving the application of the neutrosophic Multi-Criteria Decision-Making (MCDM) method. This method allows for a more nuanced interpretation of landslide hazards by effectively capturing, representing, and processing uncertain, incomplete, and indeterminate information inherent in the decision-making process. The advantage of using the neutrosophic MCDM method lies in its ability to handle uncertainties and ambiguities, which is a common challenge in the environmental sciences. Besides, the integration of this method with the "Potentially All Pairwise RanKings of all Possible Alternatives" (PAPRIKA) method allows for a simplified, user-friendly, and easily understandable decision-making process. The proposed solution also integrates the use of the ArcGIS weighted overlay, aiding in the unification and management of diverse geographic data for hazard mapping, thus refining the analysis of landslide susceptibility zones. Consequently, it provides improved strategies for hazard mitigation and land-use planning, thereby assisting efforts in controlling landslide hazards in the Qena Governorate. In summary, the proposed neutrosophic MCDM approach using neutrosophic PAPRIKA and ArcGIS weighted overlay offers a more comprehensive, effective, and economically viable solution for landslide risk prediction and mitigation in Qena Governorate, transcending the limitations inherent in traditional methodologies.

1.1 Study Aims and Objectives

The specific aims and objectives of this study are as follows:

- To develop a comprehensive evaluation model for landslide susceptibility using the neutrosophic MCDM method integrated with PAPRIKA and ArcGIS weighted overlay. This model is intended to overcome the limitations of existing approaches, providing not only a more accurate understanding of landslide hazards but also more effective strategies for mitigation.
- To evaluate this model's effectiveness using eight predetermined evaluation criteria. These criteria include geological, hydrological, and environmental factors known to influence landslip occurrence such as slope gradient, slope aspect, elevation, lithology, land cover, distance from

roads, distance from rivers, and soil type. These were specifically chosen because they represent the key factors that contribute to landslide susceptibility.
- To test the models against actual observed landslide events in the Qena Governorate to verify their predictive capability and accuracy.
- To ultimately inform better land-use planning strategies and mitigation measures that can enhance community resilience against landslide hazards in the Qena Governorate of Egypt.
- To conduct sensitivity analysis that serves as a vital step to ascertain how different values of inputs in a given quantitative model influence the outputs. This step enables us to robustly evaluate landslide susceptibility under various scenarios, thereby contributing to our overarching objective of devising effective, scenario-specific mitigation strategies.

In the end, the objective is to provide a practical, cost-effective, and technologically innovative solution for mitigating landslide hazards. This approach has the potential to improve current prediction methods and inform land-use planning strategies, thus managing and reducing the risk of landslides in the Qena Governorate, as well as other regions facing similar hazards.

1.2 Contributions of this Study

This study carries several significant contributions:
- It proposes a novel, integrated approach to landslide hazard mitigation, combining the neutrosophic MCDM method with PAPRIKA and ArcGIS weighted overlay. This multidisciplinary approach brings together insights from environmental science, geographic information science, and decision theory to provide a more comprehensive solution to landslide hazard management.
- By employing the neutrosophic MCDM method, the study contributes to a more nuanced understanding of the complex, uncertain, and often ambiguous nature of landslide hazards. This method presents a way to navigate these uncertainties, thus enhancing the accuracy of landslide susceptibility modelling.
- This work introduces a practical utilization of the PAPRIKA method in environmental science, demonstrating its value in simplifying complex multi-criteria decision-making processes.
- It offers an advance in geospatial analysis for landslide hazard by showcasing the utility of ArcGIS weighted overlay in combining diverse geospatial data for hazard mapping.
- Notably, by testing the model against actual observed landslide events in Qena Governorate, it provides tangible evidence of the model's effectiveness, contributing to future research and practice in landslide hazard mitigation.
- The study ultimately encourages better informed, more sustainable land-use planning and policy decisions, contributing to enhanced community resilience and safety in landslide-prone areas.

1.3 Structure of the Study

This study is methodically organized in the following manner:
- Introduction: This section provides the background and context of the study, presenting the research problem and the proposed solution using a Geographic Information System (GIS)-based neutrosophic MCDM Approach.
- Literature Review: It summarizes the relevant previous research in the field, highlighting gaps that this study aims to fill.
- PAPRIKA: This section provides a basic pseudocode representation of the traditional PAPRIKA method to demonstrate its logic and operation.
- Neutrosophic PAPRIKA: Presents a thorough discussion about the neutrosophic PAPRIKA approach and its innovative application for landslide mitigation.
- Methodology: It outlines the step-by-step flowchart followed in this research, detailing the creation of the evaluation model using the neutrosophic MCDM method, PAPRIKA, and ArcGIS weighted overlay.

- Case Study Application and Discussion: This section applies the methodology to an actual case study of landslide hazard in Qena Governorate of Egypt, accompanied by a thoughtful discussion of the results.
- Sensitivity Analysis: An analysis is conducted to establish the robustness of the model, investigating how slight variations in input parameters affect the results.
- Conclusions: Renders a summary of the study's main findings, the implications for the field, and suggestions for future research.
- References: Cites all sources and previous works referenced throughout the study.

This structured approach ensures a comprehensive presentation of the research undertaken and facilitates a coherent presentation of its findings.

2. Literature Review

Landslides are geological phenomena characterized by the mass movement of rock, debris, or earth down slopes due to gravitational forces [7]. According to the International Association of Engineering Geology and the Environment (IAEG), landslides can be classified along two dimensions: their mechanism of movement and the type of material involved [8]. The three fundamental mechanisms include fall, topple, and slide, with composite movements often observed. The type of material can range from rock to soil and in between. This classification helps experts predict potential landslide events and devise appropriate responses [9].

The understanding of landslides has significantly evolved over time. In the early stages, landslides were perceived as random natural disasters that pose uncontrollable risks [10]. With advancements in geotechnical and geological understanding in the mid-20th century, researchers started to delve into the mechanics and triggers of landslides. Significant works by researchers like Terzaghi (1950), who introduced the concept of effective stress and its impact on soil shear strength [11], and Skempton (1977), who developed the concept of pore pressure and its pivotal role in landslide occurrence, have laid the foundation for our modern understanding of landslides [12].

Landslides generally occur due to a combination of natural and anthropogenic factors [13]. Natural factors include geomorphology (for example, the shape and structure of land), geology (the type of rock or soil, its condition, and water content), climate (specifically, prevailing weather patterns and incidents of heavy rainfall), and seismic activities (such as earthquakes and volcanic eruptions) [14]. Anthropogenic, or man-made factors, tend to exacerbate the vulnerability of areas to landslides [15]. These factors include deforestation, which reduces the water-holding capacity of the soil, and over-exploitation of land resources. Uncontrolled urban development and unregulated mining activities can also destabilize slopes and amplify the risk of landslides [16, 17]. In many instances, it is a combination of these factors that eventually trigger a landslide, which makes their prediction and prevention a complex task. These complexities further underline the need for an advanced and sophisticated approach like the neutrosophic MCDM for landslide hazard mitigation. The field of landslide research is rich with numerous notable studies. A seminal work in this regard is by Aleotti and Chowdhury (1999), who employed Fuzzy Logic to evaluate the uncertainties in the spatial prediction of landslides [18]. This study underscored the importance of accounting for uncertainty in landslide research and further paved the way for the application of advanced decision-making frameworks in this domain. Another pioneering study by Guzzetti et al. (1999) utilized GIS to map landslide susceptibility across Italy and demonstrated the powerful potential of GIS in landslide research [19]. Similarly, a more recent study conducted by Wang et al. (2020) used machine learning algorithms in GIS for landslide susceptibility modeling, revealing a new frontier in the application of artificial intelligence in landslide research [20]. Hungr et al. (2014) comprehensively reviewed and synthesized various quantitative risk assessment tools for landslide hazards, providing a reference point for future methodological development [21]. These studies are instrumental in augmenting the existing knowledge and developing more sophisticated landslide mitigation strategies, including the application of the neutrosophic MCDM approach.

Traditional methods of landslide susceptibility mapping have included deterministic and statistical models. While deterministic models focus on a specified set of physical variables (e.g., slope stability or shear strength), statistical models apply past landslide data to identify and analyze trends. For instance, Guzzetti et al. (1999) employed a traditional deterministic method to produce a map of landslide susceptibility for Italy, incorporating variables such as slope angle and climatology [22]. The resultant map was used in planning developments and managing natural hazards. However, these traditional models have limitations. They often rely heavily on specific physical parameters making it difficult to account for variations in local environmental conditions and human activity. They are also predicated on the availability of accurate historical landslide data, a criterion that is not always met, especially in regions where landslides are less frequent. More worryingly, traditional models are usually unable to effectively project future landslide events, making it challenging to predict when and where landslides might occur next. Their failure to accommodate uncertainty further hampers their effectiveness. Given these concerns with traditional models, it is critical that we explore improved methods for landslide susceptibility mapping. Advanced methodologies, like the one this paper presents, could potentially overcome these limitations and provide a more accurate, comprehensive, predictive tool for landslide risk assessment and mitigation.

GIS have revolutionized the field of environmental studies, offering a robust tool for spatial data analysis and representation. Literature reflects numerous applications of GIS in this field, particularly in hazard or susceptibility mapping. A clear example is illuminated by Carrara et al. (1991), who applied GIS techniques for landslide susceptibility mapping in Italy [23]. Their work set a precedent for the integration of GIS in environmental hazard management. Landslide hazard mapping, along with other forms of environmental susceptibility mapping, would benefit significantly from these GIS capabilities. Yet another compelling application is found in the work of Casagli et al. (2023). They used RS techniques to predict landslide susceptibility – a feat unachievable without GIS technology. However, while the utility of GIS in hazard mapping is well-documented, its scope is seldom fully realized due to inherent complexities in environmental systems. Also, the existing GIS-based models often fall short on adequately handling uncertainties in spatial data and employ static modeling approaches. As such, more advanced, dynamic, and inclusive GIS-based models, like the one proposed in this paper, are required for a comprehensive understanding and prediction of environmental susceptibilities. The neutrosophic MCDM approach could be instrumental in addressing these existing gaps.

MCDM involves navigating complex decision-making scenarios involving multiple, often competing criteria. The neutrosophic set theory, introduced by Smarandache (1999), extends fuzzy sets and introduces the concept of indeterminacy, providing a more flexible and inclusive model for decision-making [24]. In neutrosophic MCDM, decisions can be evaluated based on truth-membership (T), indeterminacy-membership (I), and falsehood-membership (F) functions, allowing for the accommodation of vagueness, ambiguity, and uncertainty in parameters. This approach can prove beneficial when exact data isn't available or when decisions have to be made considering various conflicting criteria. An application of neutrosophic MCDM can be seen in the study by Biswas et al. (2019), where it was used for socioeconomic development ranking [25]. Their work highlighted the robustness and flexibility of the neutrosophic MCDM, particularly when dealing with unstructured and indeterminate information. However, its application in environmental science, specifically in landslide susceptibility mapping, is relatively unexplored. Given its potential to address uncertainties and incorporate multiple criteria in an inclusive and flexible manner, the neutrosophic MCDM holds promise in enhancing the precision and applicability of landslide susceptibility mapping. The use of neutrosophic MCDM, in conjunction with GIS techniques, as proposed in this paper, represents a novel approach to landslide hazard mitigation.

The PAPRIKA Method: The acronym PAPRIKA stands for Potentially All Pairwise RanKings of all possible Alternatives, a multi-criteria decision-making method developed by Hiroshi and Eichler (2008) [26]. The method is known for its simplicity and intuitive appeal. It is used to derive a ratio scale on criteria by comparing pairs of alternatives that differ in at most two factors. Belton and Stewart (2012) emphasized that the PAPRIKA method's advantage lies in its ability to handle complex decisions involving multiple criteria in a simple, hierarchic, and comprehensible way [27]. PAPRIKA's successful applications are numerous, but its integration with neutrosophic principles is still uncommon in literature. The fusion of PAPRIKA's simplicity with the inherent ability of neutrosophic MCDM to handle uncertainty and fuzziness could indeed provide a powerful tool for landslide susceptibility mapping. However, further research is needed to establish this approach's efficacy and reliability.

Egypt's topography, geology, and climate make it prone to various natural hazards, including landslides [28]. According to data from the Egyptian Geological Survey and Mining Authority (EGSMA), the country has experienced several significant landslide events, particularly in mountainous and hilly regions. Qena is one of the 27 governorates of Egypt, located in the south, known for its unique geographical characteristics. The area is characterized by its steep slopes, loose soil composition, and high rainfall during certain seasons, which all contribute to its landslide susceptibility. Moreover, rapid urbanization and human activities, especially in the form of unregulated construction on steep hillsides, have further aggravated the situation. There is a substantial body of literature on landslides in Egypt. However, a comprehensive review indicates that there's a relative dearth of literature on the application of modern decision-making models like MCDM, and especially, neutrosophic-based approaches in assessing landslide susceptibility in Qena. Therefore, the proposed approach of applying GIS-based neutrosophic MCDM using the PAPRIKA method for landslide mitigation in Qena represents a valuable contribution to the field.

While extensive research has been conducted on mitigating landslide hazards, particularly in areas like Qena Governorate with unique geographical attributes, a gap remains in applying more contemporary decision-making models in this context. Notably, most studies dominated by traditional and statistical likelihood approaches have limited abilities to handle complex uncertainties inherent in environmental and geographical data. Furthermore, despite the recognized advantages and potential of the PAPRIKA method in multi-criteria decision-making, its integration with the neutrosophic principles in the context of landslide mitigation is still uncommon. This is evidenced by the limited examples in the existing literature. Therefore, the current study intends to bridge this gap by proposing an innovative GIS-based neutrosophic MCDM approach leveraging the PAPRIKA method's benefits. This new approach is expected to offer a more systematic and robust tool to assess landslide susceptibility, thereby enhancing the current mitigation strategies in Qena Governorate, Egypt.

3. PAPRIKA

Here is a simple pseudocode that outlines the PAPRIKA method:

```
// Input: Decision criteria and alternatives.
ALGORITHM PAPRIKA_Method(decisionCriteria, alternatives)
BEGIN
// function, evaluatePair(), to conduct pairwise comparisons
FUNCTION evaluatePair(alternative1, alternative2)
BEGIN
    ASK the decision-maker to compare alternative1 and alternative2
        STORE the preference by the decision-maker
        RETURN preference
END FUNCTION
```

```
// function, rankPairs(), to sort comparisons.
   FUNCTION rankPairs(pairs)
BEGIN
    FOR each pair in pairs
        CALL evaluatePair() for each pair
        STORE results of each evaluation with its corresponding pair
    SORT pairs based on results with most preferred at the top and least preferred at the bottom
    RETURN most and least-preferred pairs
END FUNCTION
//function, interpolatePoints(), to establish additional ranking points.
   FUNCTION interpolatePoints()
BEGIN
    RETRIEVE most and least preferred pairs using rankPairs()
    FOR each pair between the most and least preferred pairs
        CALCULATE interpolation
    STORE interpolated points in points set
    RETURN points set
END FUNCTION
//function, sortFurther(), to rank remaining comparison pairs.
FUNCTION sortFurther(remainingPairs)
BEGIN
    RETRIEVE reference points by using interpolatePoints()
    FOR each pair in remainingPairs
        COMPARE pair using evaluatePair() with reference points
        RANK pair based on comparison with reference points
            RETURN ranked remaining pairs
END FUNCTION
//function, calcWeights(), to assign weights to criteria.
FUNCTION calcWeights(criteria)
BEGIN
    DECLARE a list weights
    FOR each criterion in criteria
        CALCULATE the difference between the two extreme points of that criterion
        STORE this difference to weights
    RETURN weights
END FUNCTION
// function, rankAlternatives(), to score and rank alternatives.
FUNCTION rankAlternatives(alternatives, criteria)
BEGIN
    RETRIEVE weights by calling calcWeights(criteria)
    FOR each alternative in alternatives
        CALCULATE score of alternative by using weights
        STORE the score of each alternative
    RANK alternatives based on their scores
    RETURN ranked alternatives
END FUNCTION
//Final rankings of alternatives for decision making.
OUTPUT final rankings of alternatives for decision making.
END PAPRIKA_Method
```

4. Neutrosophic PAPRIKA

The PAPRIKA method under a neutrosophic environment follows the same basic steps as classic PAPRIKA, but they are adapted to suit the indeterminacy of neutrosophic decision-making.
Step 1. Identify a panel of experts most suitable for the problem domain.
Step 2. Expert consultation.
Define the criteria suitable for the problem using expert consultations. Each criterion represents a different aspect of the problem you're trying to solve.
Step 3. Assign neutrosophic values for criterion evaluations
The expert assigns a neutrosophic set to each criterion for evaluation. Using the scale shown in Table 1 demonstrates a neutrosophic set that includes three parts - truth, indeterminacy, and falsity.

Table 1. Linguistic variables for determining likelihood of criteria and decision maker's confidence.

Linguistic terms for likelihood	(L, M, U)	Decision maker's confidence degree (DM)
Absolutely unlikely	⟨(0,0,0)⟩	Absolutely unsure (0,1,1)
Presumably unlikely	⟨(0,0,2)⟩	Unsure (0.25 ,0.75, 0.75)
Somewhat likely	⟨(1,2,4)⟩	Somewhat confident (0.45 ,0.60,0.60)
Moderately likely	⟨(2,4,6)⟩	Moderately confident (0.50 ,0.50,0.50)
Likely	⟨(4,6,8)⟩	Confident (0.75 ,0.20,0.20)
Very likely	⟨(6,8,10)⟩	Very confident (0.85 ,0.15,0.15)
Absolutely likely	⟨(8,10,12)⟩	Absolutely confident (1.00 ,0.00, 0.0)

Step 4. Compute average to aggregate experts opinions.
Let j represents the criterion index, k is the expert index, n is the number of experts, and $AggID[j]$ is the aggregated importance degree for criteria$j$.

Compute$SumID[j]$, shown in Eq. (1) which is the sum of importance degree for criterion j across all experts:

$$SumID[j] = \sum(ID\_kj) \quad \text{for all } k \text{ in Experts} \tag{1}$$

Then, compute the aggregated score for each criterion, marked as$AggID[j]$ in Eq. (2):

$$AggID[j] = SumID[j] \,/\, n \quad \text{for all } j \text{ in criteria} \tag{2}$$

Step 5. In order to rank main criteria the score function shown in Eq. (3) is used.
Let $\tilde{B}1 = (B1, B2, B3)$; $\eta\tilde{B}1, \theta\tilde{B}1, \alpha\tilde{B}1$ be a triangular neutrosophic number then the score function equals

$$S\tilde{B}1 = 1/2 * (B1 + 2B2 + B3) * 2 + \eta\tilde{B}1 - \theta\tilde{B}1 - \alpha\tilde{B}1 \tag{3}$$

Step 6. Calculate criteria weights using the traditional PAPRIKA method.

5. Methodology

The methodology of the study began with the identification of the problem, specifically, landslide susceptibility in the Qena Governorate. This fed into an extensive data collection and analysis phase, which incorporated landslide inventory data and relevant environmental and topographical factors. These criteria were then evaluated through a neutrosophic MCDM process, ranking the varying factors according to their contribution to landslide risks. The resulting composite was integrated through the Weighted Overlay Analysis in ArcGIS, combining the data layers with assigned weights. Following this, the neutrosophic PAPRIKA method was deployed to prioritize the areas that needed urgent attention. The culmination of these procedures was visually represented in a Landslide Susceptibility Map. This map was then used to devise suitable mitigation strategies, making the findings of the study practical and implementable. Throughout the methodology, the researched also conducted a sensitivity analysis involving ten separate scenarios to test the robustness and reliability of the model. The study flowchart shown in Figure 1.

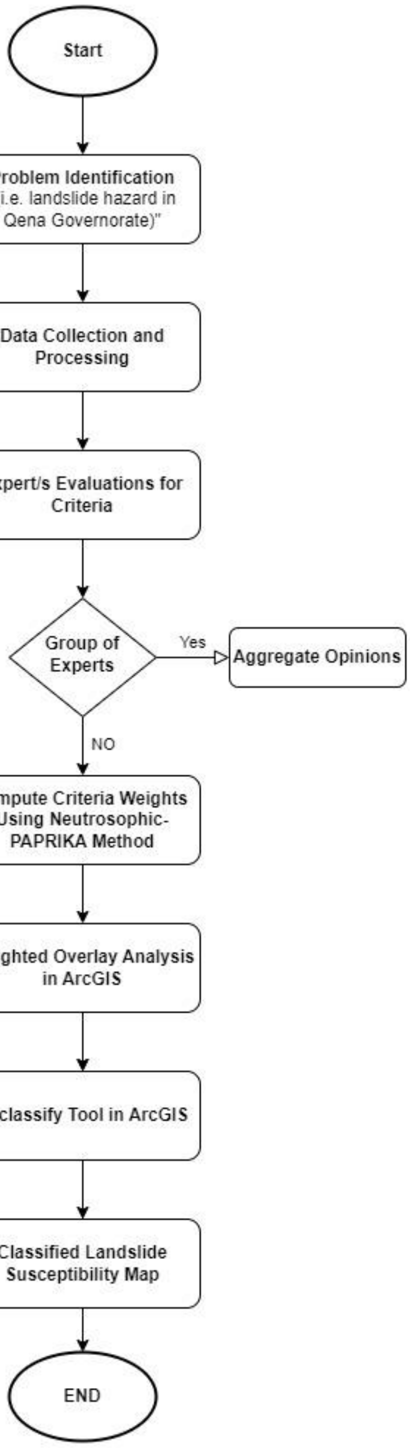


Figure 1. Study Flowchart.

5.1 Study Area

Qena Governorate is located in the southern part of Egypt, and it covers an area of about 10798 km² as shown in Figure 2. It is geographically positioned between latitudes 25.5° and 26.6° N and longitudes 32.2° and 33.2° E [29]. Qena is characterized by its rugged and hilly terrain, interrupted by desert plains [30]. The region is significantly influenced by the course of the Nile River, which cuts across it and contributes to its varied topography [31]. Enhanced by its positioning between the Nile and the Eastern Desert, Qena experiences a desert climate with hot summers and moderate winters. The geographic attributes of Qena, along with the complex geology and presence of vulnerable populations and infrastructure, pose significant landslide risks [32]. These systemic factors, therefore, justify Qena as an ideal field for the proposed research on mitigating landslide disasters. It offers a distinctive chance to explore how GIS-based neutrosophic MCDM methods can be employed to enhance existing landslide mitigation strategies.

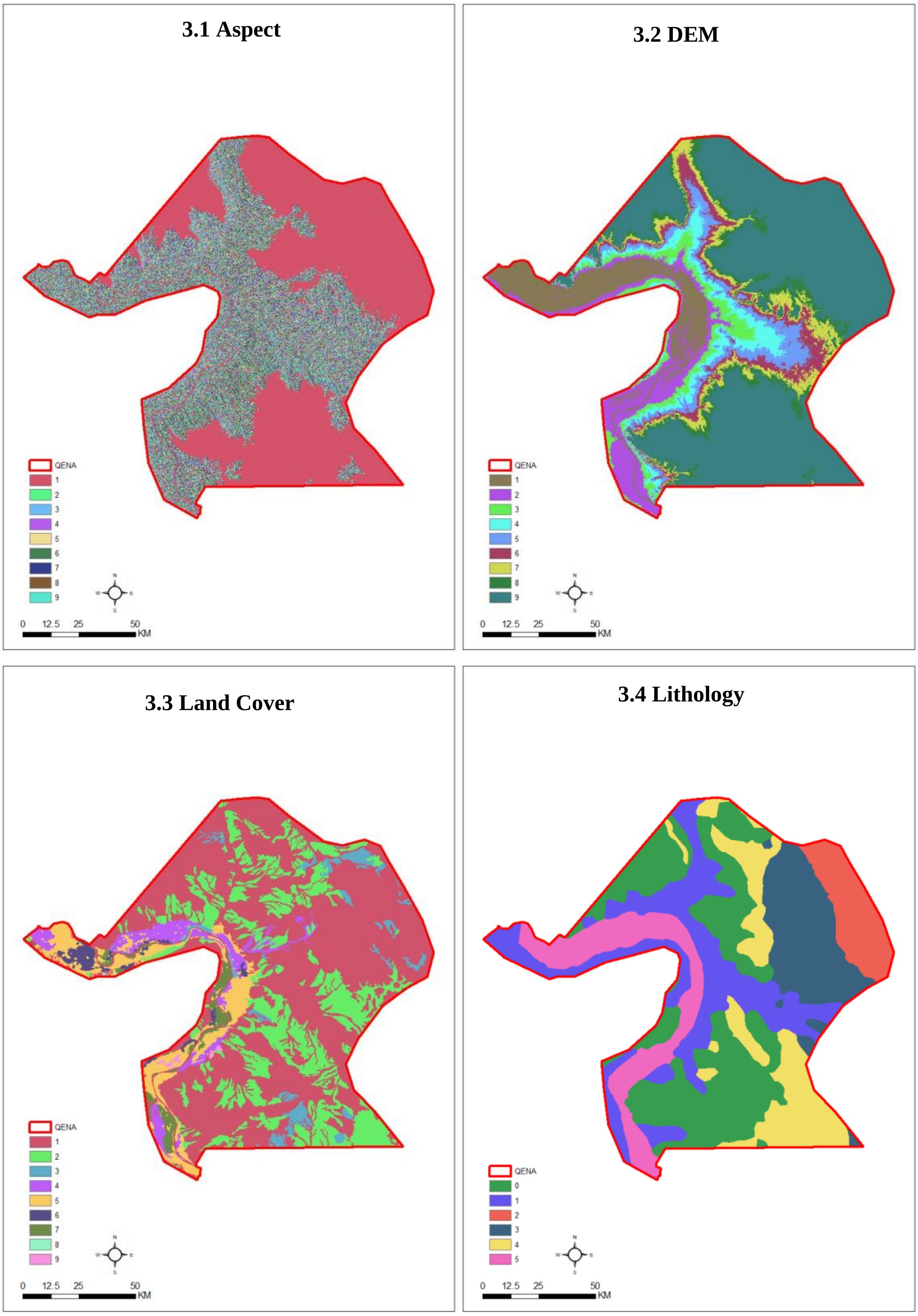
Figure 2. Study Area.

5.2 Data Collection and Processing

This study encompasses eight distinct criteria integral to understanding landslide triggers and susceptibility. These criteria, along with their detailed descriptions and sources, are extensively laid out in Table 2. Further the classified spatial representation of these criteria, illuminating their specific geographic distribution, is visualized in Figure 3. The hierarchical structure of the neutrosophic Preference Ranking Interactive Multi-criteria Analytic (n-PAPRIKA) problem, instrumental in our analysis, can be visualized in Figure 4. This Figure delineates the interconnections and dependencies among the various factors considered in the n-PAPRIKA problem, consequently aiding in a more comprehensive understanding of the landslide mitigation approach we have adopted.

Table 2. Study criteria, description, and source.

Criteria	Relevance to Study	Source
Slope (C1)	Steeper slopes are typically more prone to landslides.	Slope tool ArcGIS
DEM (C2)	Higher elevations may have increased landslide susceptibility.	USGS Earth Explorer website
Soil Type (C3)	Certain soils (e.g., sandy or clay-rich soils) can be particularly susceptible to landslides.	FAO Soil Portal website
Proximity to River (C4)	Areas close to rivers can be more susceptible due to erosion and increased water saturation	The Egyptian National Authority for Remote Sensing and Space Sciences (NARSS)
Land Cover (C5)	Vegetation can stabilize soils and reduce landslide risks.	United Nations Land Cover, Egypt (Africover, FAO)
Aspect (C6)	The direction a slope faces can influence its moisture levels and the freeze-thaw cycle, both factors in landslide risk.	Aspect tool ArcGIS
Proximity to Road (C7)	Construction and maintenance of roads can destabilize slopes and increase landslide risk.	The Egyptian National Authority for Remote Sensing and Space Sciences (NARSS)
Lithology (C8)	The type of bedrock can greatly impact landslide susceptibility.	USGS World Geologic Maps


3.1 Aspect
3.2 DEM
3.3 Land Cover
3.4 Lithology
QENA
0 12.5 25 50
KM

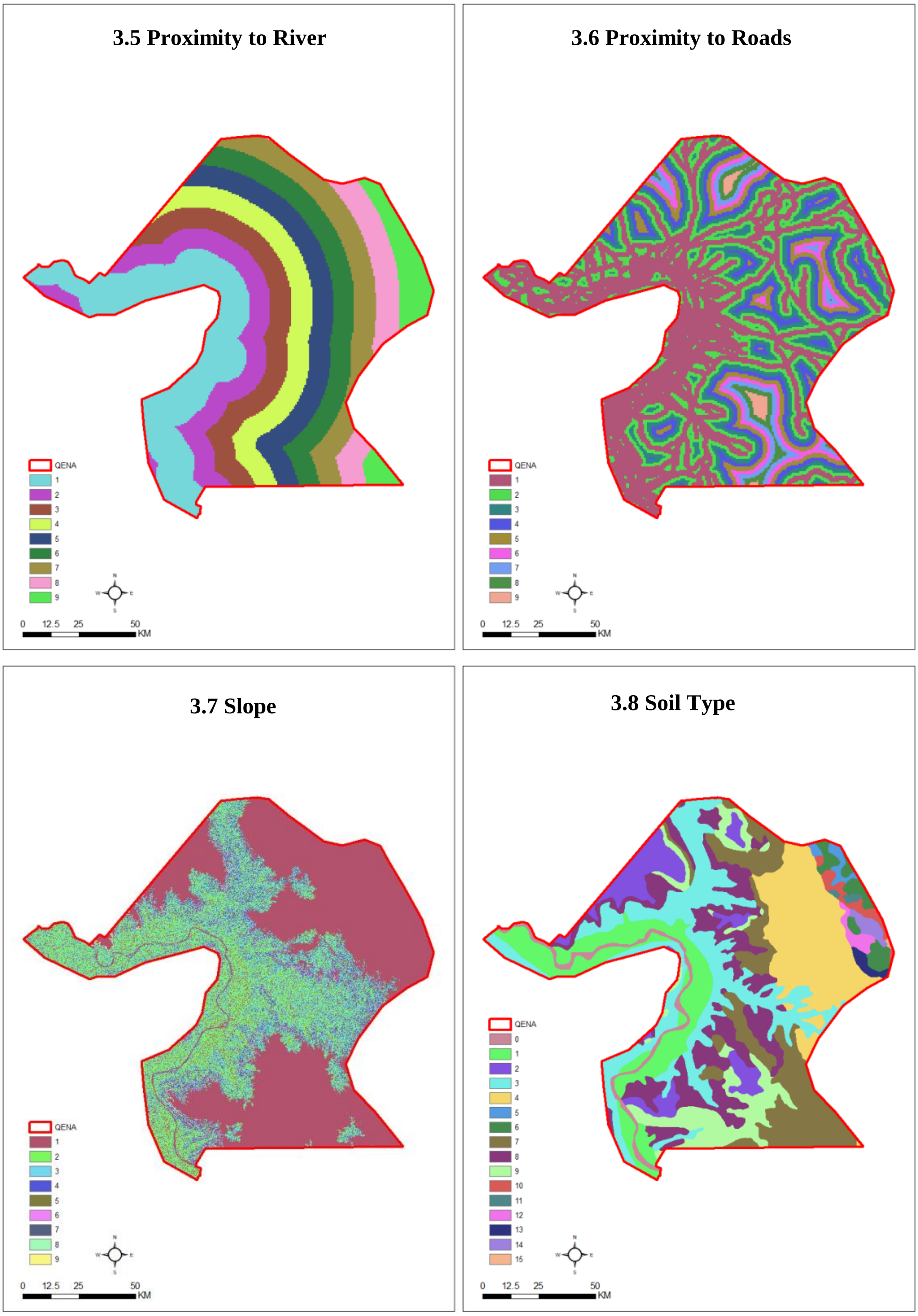


Figure 3. Classified Spatial Maps of the criteria.

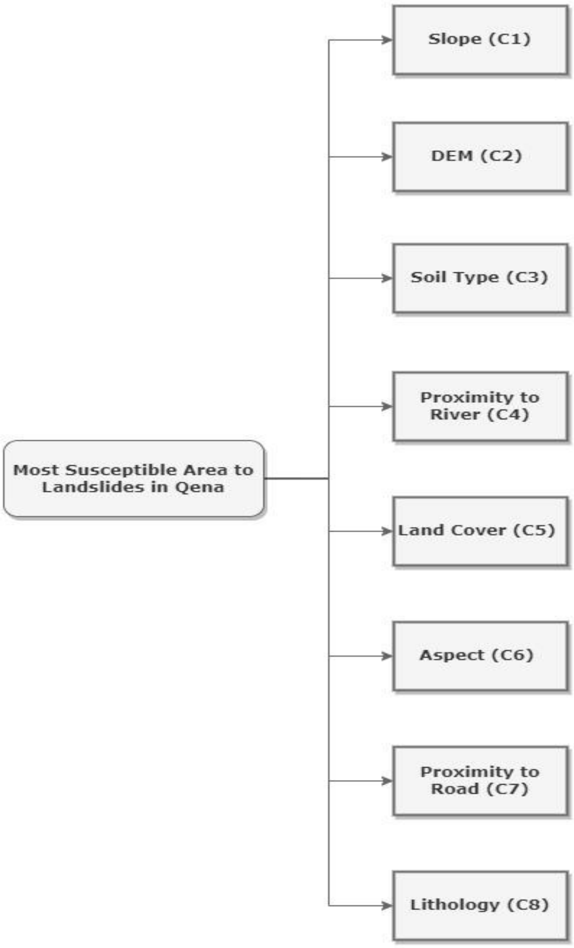


Figure 4. Hierarchy of the N-PAPRIKA MCDM problem.

5.3 Panel of Experts

The panel of experts for examining the mitigation of landslide hazards in Qena Governorate using a GIS-based neutrosophic MCDM approach includes the following:

E1. Geologist: Geologist is vital as they understand the processes causing landslides and can provide valuable data about the geological properties of local areas.

E2. Civil Engineer (Geotechnical Specialist): Provide insights on infrastructure vulnerability and the effectiveness of proposed landslide mitigation strategies.

E3. Emergency Manager /Disaster Risk Reduction Expert: Professional that can identify vulnerable populations and infrastructure in Qena, and propose measures to increase resistance against landslides.

E4. Urban Planner or Local Government Official: Provide details about local zoning codes and land development plans for future prevention of landslide-prone areas.

This multidisciplinary panel would aid in creating comprehensive, evidence-based solution for landslide mitigation in the Qena Governorate.

6. Case Study: Results and Discussion

1. After selecting the group of experts and the criteria appropriate for the study. The expert's panel begins to evaluate the main criteria using the linguistic variables shown in Table 1. The evaluations of the expert panel are available in Table 3.

2. Since group expert opinions are being assessing the criteria aggregation of the opinions is necessary as shown in Table 2.

Table 3. Experts evaluations and ranks of the main criteria.

Criteria	Aggregated Experts Opinions	Score Function	Criteria Rank
Slope (C1)	⟨(24,32,40), (3.45,0.5,0.5)⟩	11.87	1
DEM (C2)	⟨(16,24,32), (2.75,1.2,1.2)⟩	4.7	4
Soil Type (C3)	⟨(22,30,38), (3.35,0.55,0.55)⟩	10.63	2
Proximity to River (C4)	⟨(12,20,28), (2.5,1.4,1.4)⟩	2.83	5
Land Cover (C5)	⟨(10,18,26), (2.25,1.7,1.7)⟩	1.275	6
Aspect (C6)	⟨(9,16,24), (2.2,1.8,1.8)⟩	0.81	7
Proximity to Road (C7)	⟨(8,14,22), (2.15,1.9,1.9)⟩	0.42	8
Lithology (C8)	⟨(20,28,36), (3.1,0.85,0.85)⟩	7.93	3

3. After opinion aggregation, score function shown in Eq. (3) is used to compute criteria ranks.

Applying the PAPRIKA method for criteria (C1 to C8) based on their ranks:

- Calculate Minimum-to-Preference Point Distances (MPP): The distance is the difference between the least preferred level and the ranking. Here, since the ranks themselves act as the preference point, the MPP distances are:

$C1 = 8$

$C2 = 4$

$C3 = 6$

$C4 = 4$

$C5 = 3$

$C6 = 2$

$C7 = 1$

$C8 = 5$

- Normalize the Distances: Divide each MPP distance by the sum of all MPP distances to calculate the weights for each criterion. Sum all distances (C1 to C8) as shown in Eq. (4):

$$Sum = 4 + 1 + 3 + 8 + 6 + 4 + 5 + 2 = 33 \tag{4}$$

The weight of each criterion is calculated as follows:

$W(C1) = 8/33 \approx 0.242$

$W(C2) = 4/33 \approx 0.121$

$W(C3) = 6/33 \approx 0.182$

$W(C4) = 4/33 \approx 0.121$

$W(C5) = 3/33 \approx 0.09$

$W(C6) = 2/33 \approx 0.06$

$W(C7) = 1/33 \approx 0.03$

$W(C8) = 5/33 \approx 0.152$

These weights reflect the relative importance of each criterion as informed by the decision-maker's ranking and are shown in Figure 5.

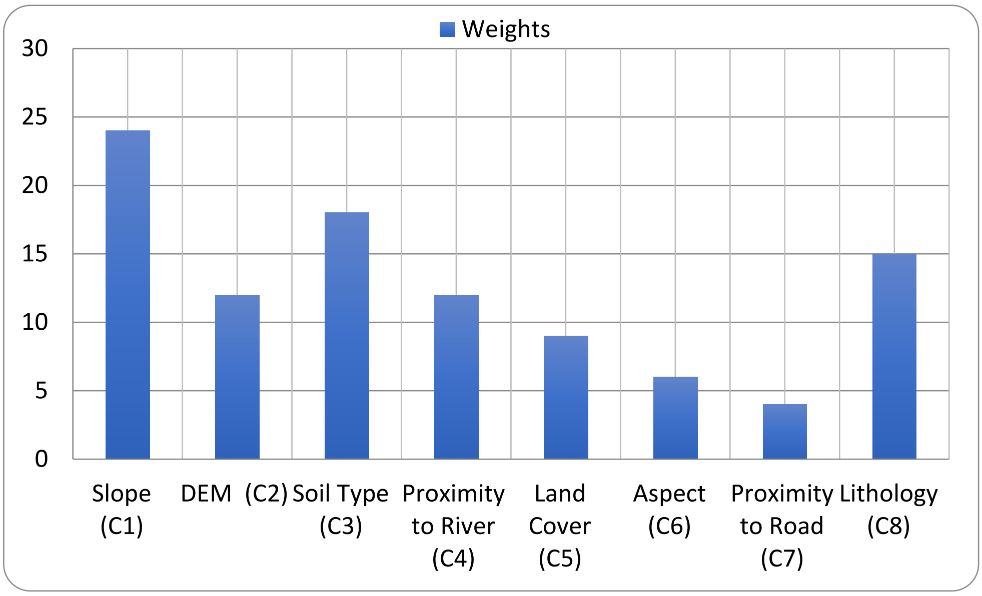


Figure 5. Weights of the main criteria.

The weighted average Tool in ArcGIS plays a pivotal role in our study by enabling us to allocate appropriate weights to each criterion, reflecting its relative significance in landslide occurrence. The integration of Criteria Weights and geographic features through this approach facilitates a nuanced computation of areas predisposed to landslides a process captured in Figure 6. These visual insights thus underscore the spatial heterogeneity of landslide vulnerability across the Qena Governorate. The classified susceptibility resulting map classified into the following classes:

- Very High Susceptibility: Areas with steep slopes, certain soil types - clay-rich or sandy soils, high elevations, near rivers, with certain types of bedrock, high levels of human activities like road construction, and sparse vegetation.
- High Susceptibility: Areas with moderately steep slopes, near rivers, higher elevations, certain risky soil types, and lesser vegetation.
- Moderate Susceptibility: Areas with moderate slopes, some distance from rivers, middle range elevations, mixed soil types, and light to moderate vegetation.
- Low Susceptibility: Areas with gentle slopes, further from rivers, lower elevations, stable soil types, and substantial vegetation.
- Very Low Susceptibility: Areas with very gentle slopes, far from rivers, at the lowest elevations, with stable types of soil, and dense vegetation.
- Practically No Susceptibility: Areas with flat terrain, far from rivers, at the lowest elevations, with highly stable soil types, dense vegetation, and little to no human activity.

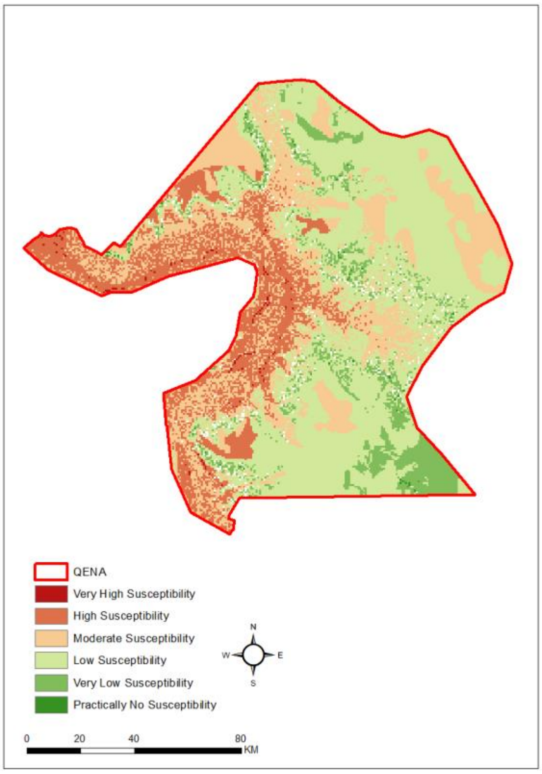


Figure 6. Classified Susceptibility Map.

7. Sensitivity Analysis

Sensitivity analysis holds significant importance to this study because it provides insightful details regarding the robustness of our model and the impact of individual parameters on landslides susceptibility. By analyzing how variations in input parameters influence the model outcome, it enables us to discern critical parameters and more accurately predict potential landslide-prone areas. The current study scenarios are as follows:

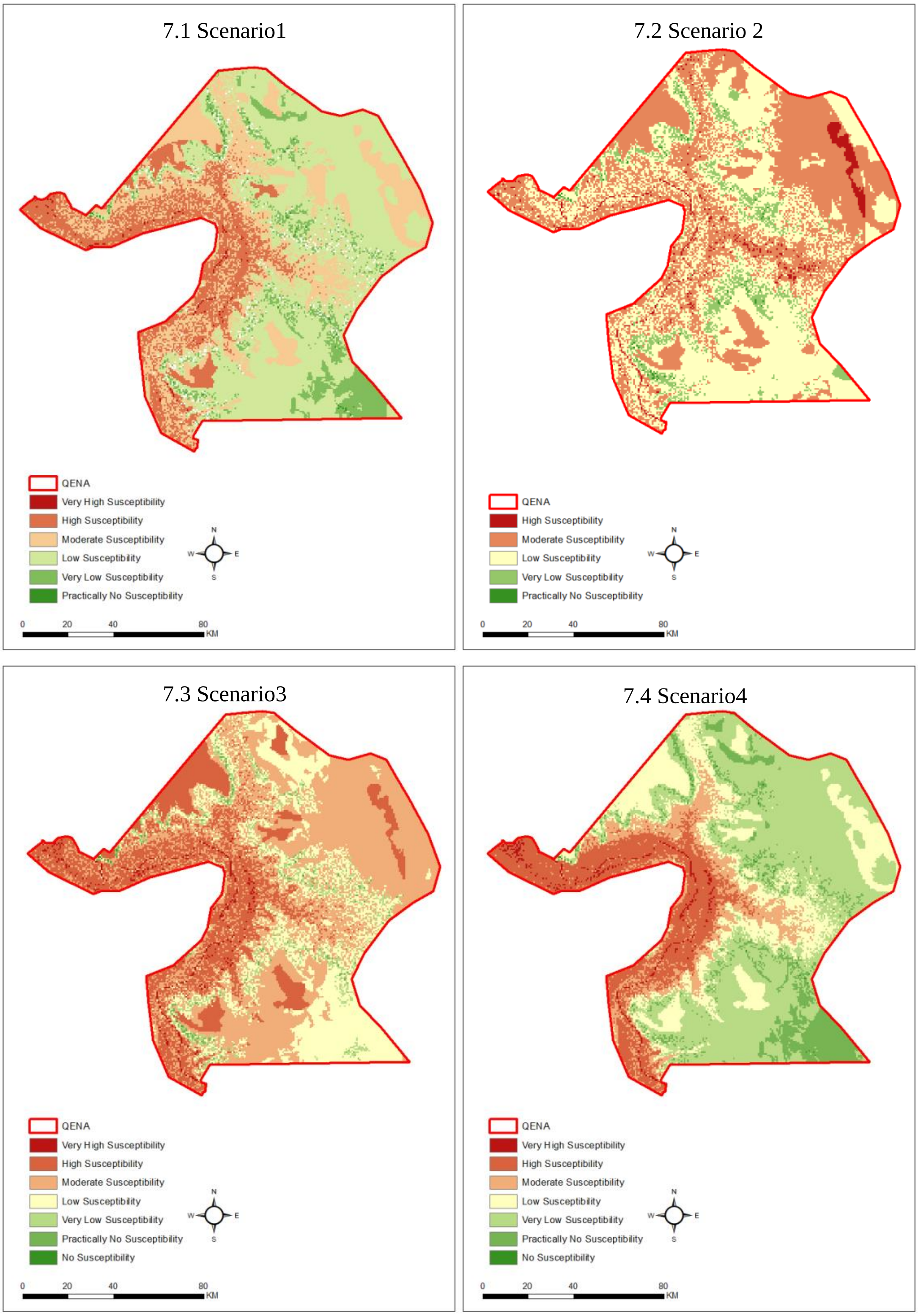
- Scenario 1: maintain the obtained criteria weights. This is the base scenario, reflecting the existing situation without any modifications.
- Scenario 2: Assign equal weights to each criterion. This scenario checks the robustness of the model when all criteria have equal significance.
- Scenarios 3-10: Increase the weight of each criterion (C1 to C8 consecutively) by 20% individually. These scenarios help understand the influence of each criterion on the overall decision-making process.

The detailed scenarios can be shown in Table 4. Classified sensitivity analysis maps shown in Figure 7.

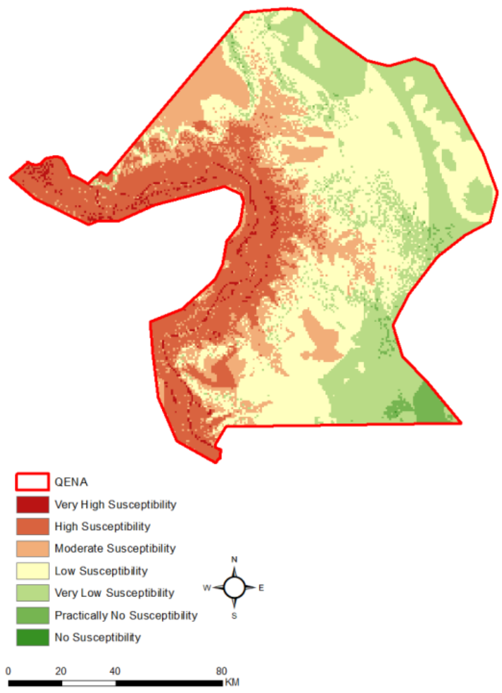
Table 4. Sensitivity analysis scenarios.

Scenario #	Description
S1	Original obtained criteria weights
S2	Equal criteria weights
S3	Slope Criteria (C1) + 20%
S4	DEM Criteria (C2) + 20%
S5	Soil Type Criteria (C3) + 20%
S6	Proximity to River Criteria (C4) + 20%

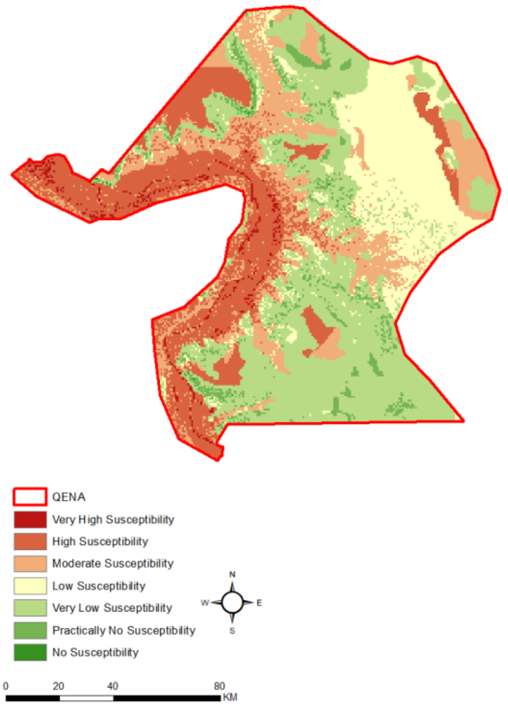
S7	Land Cover Criteria (C5) + 20%
S8	Aspect Criteria (C6) + 20%
S9	Proximity to Road Criteria (C7) + 20%
S10	Lithology Criteria (C8) + 20%



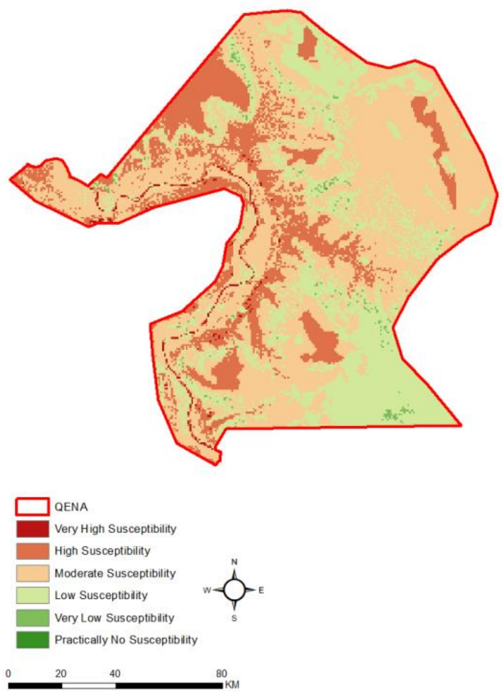
7.5 Scenario 5



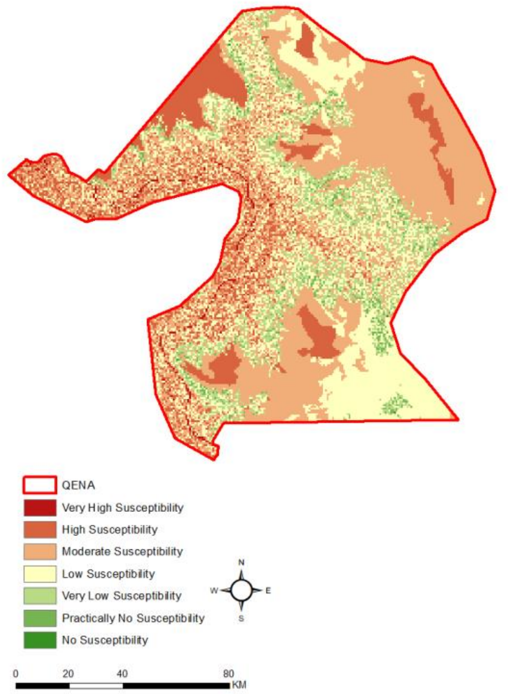
7.6 Scenario 6



7.7 Scenario 7



7.8 Scenario 8



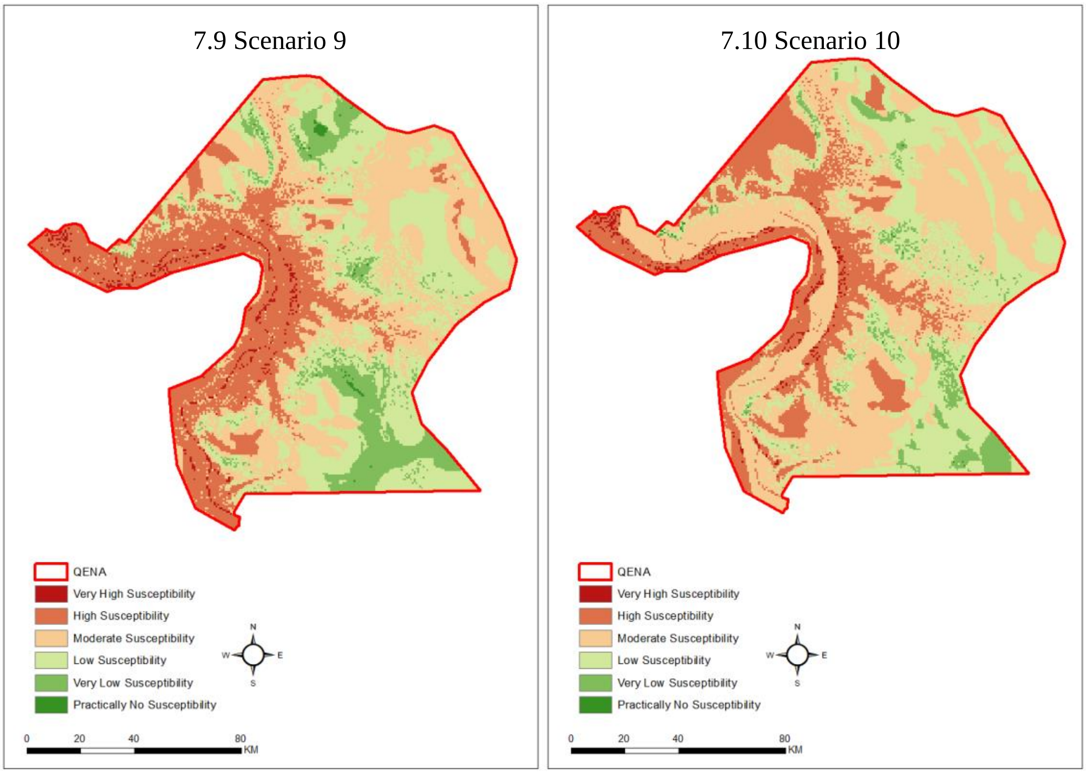


Figure 7. Classified sensitivity snalysis Maps.

The sensitivity analysis results in Figure 8 demonstrate that there are significant variations in the susceptibility categories across the different scenarios. Scenario 2, for instance, reveals a larger percentage of areas with High Susceptibility (43%) and Moderate Susceptibility (48%) than most others, implying more vulnerability to landslides under the conditions of that scenario. Conversely, Very Low Susceptibility is absent, which may indicate extreme risk conditions. In contrast, Scenarios 4 and 5 depict a comparatively higher percentage of areas with Very Low Susceptibility (42% and 34% respectively), suggesting less vulnerability to landslides under those conditions. Overall, most of the scenarios indicated Moderate to High Susceptibility, highlighting the need for prioritized and bespoke mitigation strategies. Also, the variation in susceptibility across scenarios underscores the importance of considering multiple future scenarios in vulnerability assessment for more robust mitigation planning.

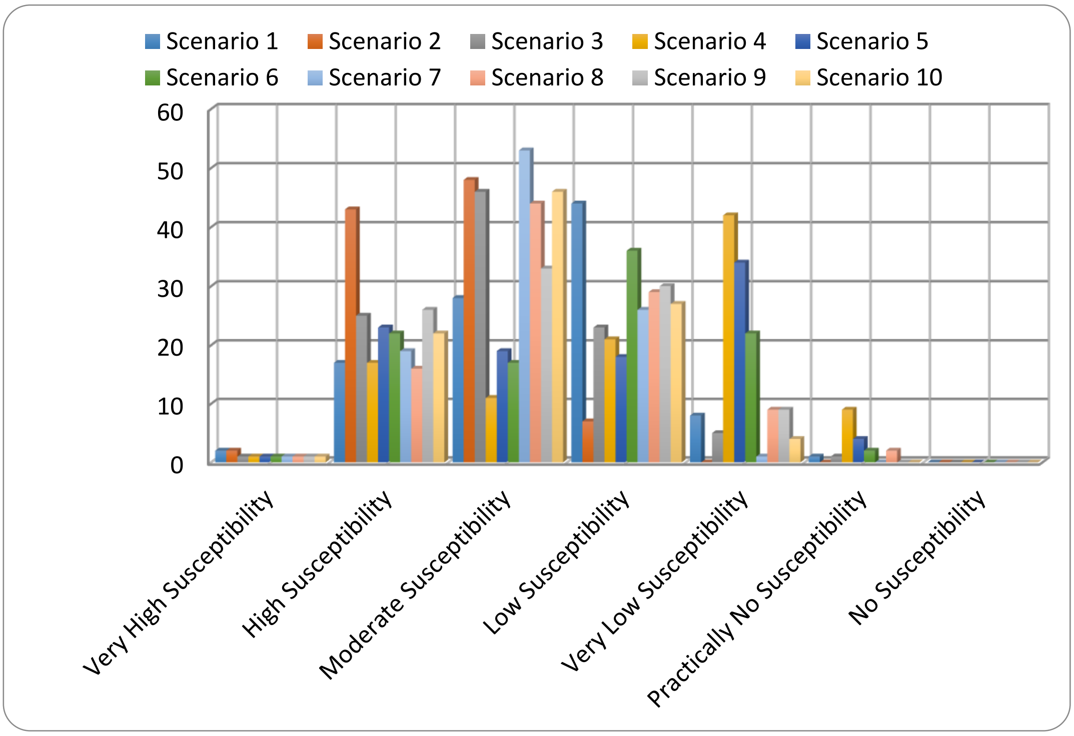


Figure 8. Susceptibility classes for sensitivity analysis.

8. Conclusion

In conclusion, this study puts forth a robust method for mitigating landslide hazards in the Qena Governorate using a GIS-based neutrosophic MCDM approach, employing the neutrosophic paprika and ArcGIS weighted overlay. Through the rigorous application of sensitivity analysis and careful consideration of multiple criteria, we identify potential landslide-prone areas in the region. This research serves as a substantial contribution to the field, providing a framework for similar studies focused on landslide hazard mitigation using GIS technologies and neutrosophic decision-making. Regarding future research directions, it would be beneficial to validate and refine this model with new and updated datasets as they become available. Future studies might also consider additional criteria or alternative decision-making methods to cater to the complex and dynamic nature of landslides. A greater focus on integrating local community inputs and incorporating socio-economic considerations could also offer further depth and applicability to these models.

Data availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflict of interest

The authors declare that there is no conflict of interest in the research.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

References

1. R. Ali, A. Kuriqi, and O. Kisi, "Human–environment natural disasters interconnection in China: a review," Climate, vol. 8, no. 4, p. 48, 2020.
2. W. M. Elsadek, M. G. Ibrahim, and W. E. Mahmod, "Runoff hazard analysis of Wadi Qena Watershed, Egypt based on GIS and remote sensing approach," Alexandria Eng. J., vol. 58, no. 1, pp. 377–385, 2019.
3. M. Porter et al., "The estimated economic impacts of prairie landslides in western Canada," in Proceedings of the 72nd Canadian Geotechnical Conference, St. John's, NL, Canada, 2019, vol. 29.
4. N. Sultana and S. Tan, "Landslide mitigation strategies in southeast Bangladesh: Lessons learned from the institutional responses," Int. J. Disaster Risk Reduct., vol. 62, p. 102402, 2021.
5. F. A. Abija, J. I. Nwosu, A. I. Ifedotun, and C. C. Osadebe, "Landslide susceptibility assessment of Calabar, Nigeria using Geotechnical," Remote Sens. Multi-Criteria Decis. Anal. Im-plications urban Plan. Dev., pp. 774–788, 2019.
6. A. Patel, "The Role of Land Use and Land Cover in Shaping Landslide Susceptibility: A Comprehensive Analysis," Available SSRN 4522782.
7. S. K. Wadhawan, B. Singh, M. N. Kumar, N. Vasudevan, and M. V. Ramesh, "A Novel Application of Catchment Approach to Assessment of 2021 Rockfall and Landslides Vulnerabilities in Tirumala Hills, Andhra Pradesh, India," J. Geol. Soc. India, vol. 99, no. 5, pp. 599–606, 2023.
8. C. J. Van Westen, E. Castellanos, and S. L. Kuriakose, "Spatial data for landslide susceptibility, hazard, and vulnerability assessment: An overview," Eng. Geol., vol. 102, no. 3–4, pp. 112–131, 2008.
9. E. Eberhardt, "Rock slope stability analysis–utilization of advanced numerical techniques," Earth Ocean Sci. UBC, vol. 41, 2003.
10. M. A. Hurley and R. B. Corotis, "Perception of risk of natural hazards: a hazard mitigation plan framework," Int. J. Risk Assess. Manag., vol. 17, no. 3, pp. 188–211, 2014.
11. M. M. Carroll and N. Katsube, "The role of Terzaghi effective stress in linearly elastic deformation," 1983.
12. G. Castro and S. J. Poulos, "Factors affecting liquefaction and cyclic mobility," J. Geotech. Eng. Div., vol. 103, no. 6, pp. 501–516, 1977.
13. S. Martino et al., "Impact of landslides on transportation routes during the 2016–2017 Central Italy seismic sequence," Landslides, vol. 16, pp. 1221–1241, 2019.
14. S. Ali, P. Biermanns, R. Haider, and K. Reicherter, "Landslide susceptibility mapping by using a geographic information system (GIS) along the China–Pakistan Economic Corridor (Karakoram Highway), Pakistan," Nat. Hazards Earth Syst. Sci., vol. 19, no. 5, pp. 999–1022, 2019.
15. S. Saha et al., "Measuring landslide vulnerability status of Chukha, Bhutan using deep learning algorithms," Sci. Rep., vol. 11, no. 1, p. 16374, 2021.
16. A. M.-T. Manchado, J. A. Ballesteros-Cánovas, S. Allen, and M. Stoffel, "Deforestation controls landlside susceptibility in Far-Western Nepal," Catena, vol. 219, p. 106627, 2022.
17. E. Bozzolan, E. A. Holcombe, F. Pianosi, I. Marchesini, M. Alvioli, and T. Wagener, "A mechanistic approach to include climate change and unplanned urban sprawl in landslide susceptibility maps," Sci. Total Environ., vol. 858, p. 159412, 2023.
18. A. A. Isyaku, "Qualitative Assessment of the Sham Tseng San Tsuen Landslide in Hong Kong."
19. A. Carrara, F. Guzzetti, M. Cardinali, and P. Reichenbach, "Use of GIS technology in the prediction and monitoring of landslide hazard," Nat. hazards, vol. 20, pp. 117–135, 1999.
20. H. Wang, L. Zhang, K. Yin, H. Luo, and J. Li, "Landslide identification using machine learning," Geosci. Front., vol. 12, no. 1, pp. 351–364, 2021.
21. O. Hungr, S. Leroueil, and L. Picarelli, "The Varnes classification of landslide types, an update," Landslides, vol. 11, pp. 167–194, 2014.
22. Y. Xing, J. Yue, Z. Guo, Y. Chen, J. Hu, and A. Travé, "Large-scale landslide susceptibility mapping using an integrated machine learning model: A case study in the Lvliang mountains of China," Front. Earth Sci., vol. 9, p. 722491, 2021.
23. B. Feizizadeh and T. Blaschke, "GIS-multicriteria decision analysis for landslide susceptibility mapping: comparing three methods for the Urmia lake basin, Iran," Nat. hazards, vol. 65, pp. 2105–2128, 2013.
24. F. Smarandache, "A unifying field in Logics: Neutrosophic Logic.," in Philosophy, American Research Press, 1999, pp. 1–141.
25. P. Biswas, S. Pramanik, and B. C. Giri, "Neutrosophic TOPSIS with group decision making," fuzzy multi-criteria Decis. using neutrosophic sets, pp. 543–585, 2019.

26. P. Hansen and F. Ombler, “A new method for scoring additive multi-attribute value models using pairwise rankings of alternatives,” J. Multi-Criteria Decis. Anal., vol. 15, no. 3-4, pp. 87–107, 2008.
27. P. Hansen, A. Hendry, R. Naden, F. Ombler, and R. Stewart, “A new process for creating points systems for prioritising patients for elective health services,” Clin. Gov. An Int. J., vol. 17, no. 3, pp. 200–209, 2012.
28. S. M. Abuzied and H. A. Alrefaee, “Spatial prediction of landslide-susceptible zones in El-Qaá area, Egypt, using an integrated approach based on GIS statistical analysis,” Bull. Eng. Geol. Environ., vol. 78, pp. 2169–2195, 2019.
29. S. T. Hamed, M. G. Sheded, and M. Owis, “Floristic composition of some riverian islands at Qena governorate–Egypt,” in Egypt. J. Bot., 2nd International Conference, April, 2012, pp. 29–30.
30. A. A. A. Moneim, “Hydrogeological conditions and aquifers potentiality for sustainable development of the desert areas in Wadi Qena, Eastern Desert, Egypt,” Arab. J. Geosci., vol. 7, pp. 4573–4591, 2014.
31. R. Said, The River Nile: geology, hydrology and utilization. Elsevier, 2013.
32. S. A. Mohamed, “Application of satellite image processing and GIS-Spatial modeling for mapping urban areas prone to flash floods in Qena governorate, Egypt,” J. African Earth Sci., vol. 158, p. 103507, 2019.

Received: Mar 10, 2023. Accepted: Jul 10, 2023