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Challenges of Remote Sensing for Crucial Role in All Phases of Disaster Management: An Uncertain MCDM-Based Study

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Abstract: Remote sensing plays a crucial role in disaster management. Moreover, its effectiveness is severely limited due to operational, technological and environmental challenges. Data acquisition can be disrupted by sensor limitations and by extreme events or natural factors, such as cloud cover. In fact, high-resolution imagery often requires significant processing time, specialized expertise and expensive infrastructure. Therefore, ensuring timely, accurate and accessible remote sensing data at all stages—preparedness, response, recovery and mitigation—is a major challenge. This study explores the application of multi-criteria decision making (MCDM) techniques using bipolar fuzzy numbers (BFNs) to evaluate this. We apply the weighted and ranking MCDM method, i.e., Method Based on the Removal Effects of Criteria (MEREC) and Multi-Attributive Border Approximation Area Comparison (MABAC), respectively, in this paper. The decisions of multiple decision makers (DMs) are considered when collecting this problem related data and BFNs are utilised as mathematical tools to handle uncertainty. In order to address the ambiguity and inconsistency of the system, we finally conclude to conduct the comparative and sensitivity analyses here with the final result.

Keywords: Remote sensor; Disaster management; Bipolar fuzzy numbers; Method Based on the Removal Effects of Criteria; Multi-Attributive Border Approximation Area Comparison

1 Introduction

A remote sensor is a device that collects information about an object or event, mainly from a distance. For example, they can detect reflected or emitted energy from satellites or aircraft. The seven steps of remote sensing are energy source, radiation, and atmosphere, interaction with the target, recording of energy by the sensor, transmission, reception, processing, interpretation, analysis and application. These steps help to cover the entire process, from the initial energy source to the final use of the information obtained. Five common types of sensors are temperature, proximity, pressure, motion, and light sensors. They measure physical properties such as heat, detect the presence of objects, monitor the pressure of liquids, detect movement, and sense ambient light levels. Sensors are generally of two types, namely active and passive. Active sensors emit their own energy to collect information. They project energy (such as lasers or sound waves) onto an object and then accurately measure the reflected energy. For example, a sonar device on a ship sends out sound pulses to map the ocean floor. On the other hand, passive sensors, on the other hand, record natural energy reflected or emitted from the Earth's surface. The most common source of radiation they detect is sunlight. For instance, a satellite camera can capture images of the Earth's surface by reflecting sunlight.

1.1 How Does a Remote Sensor Work

Remote sensors work by detecting energy reflected or emitted from objects without direct physical contact. They use active or passive methods to measure energy by collecting information about physical properties such as temperature, composition or distance. This is usually in the form of electromagnetic radiation. In fact, in this method, they detect natural sunlight or heat (passive sensing), as well as transmitting their own energy, such as radar or laser pulses (active sensing). Then, when this energy interacts with the ground, it is reflected, absorbed or emitted differently by different objects. The sensor accurately measures these differences using specialized detectors. This collected energy is converted into digital signals. These are mainly sent to ground stations for processing. Then, through correction and enhancement, these are converted into usable images or maps. Finally, analysts interpret these products to extract information for applications such as disaster management, agriculture or environmental monitoring.

1.2 Challenges of Remote Sensing for Crucial Role in All Phases of Disaster Management

Remote sensing faces several challenges in fulfilling its important role at all stages of disaster management. Various natural factors, such as cloud cover, smoke and bad weather, often block optical sensors. This results in reduced timely visibility during critical incidents. Moreover, rapid response is required during limited satellite re-imaging, which can delay data availability. On the other hand, high-resolution data and advanced sensors are very expensive and limited, which severely limits access for many organizations. The need for skilled personnel is essential to address this complex process, which slows down analysis. Again, integrating multi-sensor data such as optical, Synthetic Aperture Radar and Unmanned Aerial Vehicle imagery can be technically difficult. Ground verification during disasters is often limited, which affects accuracy. Finally, in a rapidly changing disaster situation, providing clear and actionable information to decision makers (DMs) remains a challenge.

1.3 Motivation and Objectives

Understanding the challenges of remote sensing in disaster management is crucial. Because accurate and timely information directly impacts life-saving decisions. Identifying these limitations can improve the acquisition, processing, and distribution of information in real time. It also inspires the development of advanced technologies, sensor fusion, and management strategies. Ultimately, addressing these challenges strengthens preparedness, response, and recovery efforts for safer and more resilient communities.

The following are the study's primary objectives:

1. Understanding about the concept of remote sensors;
2. Comprehending the importance of remote sensing in all phases of disaster management;
3. Identifying its challenges;
4. Studying different types of remote sensors;
5. Prioritizing the criteria by the MEREC based decision-making method for this paper;
6. Ranking of the best selected alternatives with MABAC based multi-criteria decision making (MCDM) method.

1.4 Research Outline

In this section, we develop the study's research outline based on the above study and motivation. The primary purpose of this study is to find out the main challenges of remote sensing for its crucial role in all phases of disaster management. There are four criteria and four different alternatives that are different in the disaster management phase. Two MCDM techniques, i.e., Method Based on the Removal Effects of Criteria (MEREC) and Multi-Attributive Border Approximation Area Comparison (MABAC), are selected as optimization tools and bipolar fuzzy numbers (BFNs) are appraised as ambiguous tools. Data are gathered in an impartial way and the result is numerically computed. Lastly, comparative analysis and sensitivity analysis are conducted to check the stability and robustness of the proposed model.

1.5 Structure

The research's structure is explained in this portion. The introduction of this study is discussed in Section 1. Then, Section 2 includes the literature review on different perspectives of this study. After that, Section 3 and Section 4 discussed the preliminaries of mathematical tools and MCDM techniques, respectively, in detail. Criteria selection and alternative selection are briefly discussed in Section 5 and Section 6, respectively. The model formulation and data collection are illustrated in Section 7. The numerical illustration and discussion are described in Section 8. Additionally, the study's comparative analysis and sensitivity analysis are briefly examined in Section 9. Furthermore, the research implications of this research are discussed in Section 10. Lastly, the conclusions and the scope of future research are described in Section 11.

2 Literature Survey

The background of this topic is briefly covered in this section. First, we provide a brief literature review of remote sensing studies, followed by a survey of articles on BFNs, their analysis and applications. In addition, we conducted a short survey on the MCDM processes with their utilization in our everyday life.

2.1 Background on Application

Remote sensing began in the 19th and 20th centuries with early aerial photography [1], later expanded to satellite-based sensing after the launch of Landsat-1 in 1972, which revolutionized Earth observation. Remote sensors are devices that detect and measure energy reflected or emitted from objects on the Earth's surface without direct contact. They operate in different parts of the electromagnetic spectrum—such as visible, infrared, thermal and microwave-which allows them to capture a variety of information about land, water, atmosphere, and vegetation. In addition, remote sensors can play an important role in fields such as disaster management, agriculture, environmental monitoring, climate studies, and urban planning because of their ability to provide large, timely and accurate data.

Here, we review recent publications on remote sensing from different perspectives. These are, mathematical models with various methods for remote sensing image analysis [2], discussion of various mathematical models of geometric correction applied to remote sensing images [3], application in remote sensing [4], utilising remote sensing for any type of mathematical modelling [5], talk about on several remote sensing platforms and sensors [6], remote sensing with the cryosphere [7], various applications on remote sensing [8], some fundamentals of remote sensing [9], different application of remote sensing [10], the contribution of remote sensing to the scale issue [11], neural networks in remote sensing [12].

2.2 Background of Mathematical Tool

A BFN extends the traditional fuzzy number by representing both positive and negative dimensions of satisfaction simultaneously. The concept of bipolar fuzzy sets, from which BFNs are derived, was introduced by Zhang [13] in 1994. Unlike classical fuzzy numbers that use a single membership function, BFN uses two functions, namely, a positive membership and a negative membership, which indicate support and opposition, respectively. This dual representation allows for richer modelling. It is essential for MCDM, sentiment evaluation, and uncertain environments. Therefore, BFN serves as a key mathematical tool for capturing complex bipolar information in decision systems. Here, we will study the research papers that have already been published related to BFNs. These are, diagnosis by bipolar fuzzy electre-eye method [14], use in group decision making [15], a computational framework for cognitive modeling and multiagent decision analysis of Bipolar fuzzy sets (BFS) and its relations [16], bipolar fuzzy metric spaces with its proper application [17], structure of regular bipolar fuzzy graphs [18], required solution of fully bipolar fuzzy linear programming models [19], solve linear system of equations in bipolar fuzzy environment [20].

2.3 Literature of MCDM Approaches

An MCDM method is a structured approach to making a choice from multiple alternatives when faced with multiple, often conflicting, criteria. It is actually about finding the weights of the criteria and ranking the alternatives to solve a given problem. This decision-making method is applied to deal with uncertain environments. It helps in solving complete decision-making problems in real life with great ease. There are different types of MCDM methods, such as Analytic Hierarchy Process [21], Entropy [22], Technique for Order Preference by Similarity to Ideal Solution [23], Criteria Importance Through Intercriteria Correlation [24], Complex Proportional Assessment [24, 25], Step-wise Weight Assessment Ratio Analysis [25], MEREC [26], MABAC [27], Decision-Making Trial and Evaluation Laboratory [28], Vlsekriterijumska Optimizacija Kompromisno Resenje [29], Data Envelopment Analysis [30], Measurement of Alternatives and Ranking according to COmpromise Solution [31], etc. Among them, MEREC and MABAC have been used in this paper. Here is a brief discussion of some of the already published papers on these two methods.

The MEREC approach was invented by Keshavarz-Ghorabaee et al. [32]. Some studies applied this method in various areas, including: finding the weights of element [26], developing fuzzy extension with the help of parabolic measure and its applications [33], evaluating objective weights in decision making problems in uncertain environment [34], assessing enterprise that based on Decarbonization Scheme with Grey-MEREC-MAIRCA (Multi-Attributive Ideal-Real Comparative Analysis) Hybrid MCDM Method [35], choosing a perfect renewable energy source in India [36], selecting optimal Spray-Painting robot [37], effectively solving Forklift Selection problem [38].

Pamučar and Ćirović [39] developed the MABAC methodology in 2015. Here are some papers on these approaches. These are, the literature review of MABAC methodology for sustainability and circularity [40], bibliometric analysis of various MCDM methods [27], an innovative multi-criteria integrated supplier selection model [41], ranking of green universities with the help of MCDM process [42], evaluating the best E-Commerce platform for online business [43], preference for high-performing work systems [44], find the best input factors for Powder-Mixed Electrical Discharge Machining 90CrSi tool steel [45], perfect material selection with incomplete weight information [46].

3 Preliminaries of Mathematical Tools

Preliminaries of mathematical tools are presented in detail in this section. In this study, we consider fuzzy sets [47] as a tool of uncertainty. The fuzzy set was invented by Zadeh [48] in 1965. The definitions and properties of fuzzy sets and their extensions are discussed as follows:

3.1 Fuzzy Set and Fuzzy Numbers

In crisp set theory, every element either belongs to the set or does not belong to the set, but there are no intermediate states. However, in the fuzzy set theory [49], every element may belong partially based on its degree of belonging value. Every element of the fuzzy set is assigned a membership value that lies between $[0, 1]$. The fuzzy set is defined as:

Definition 1. Fuzzy set [48]

Consider $\mathcal{X}$ to be a universal set of discourse. A fuzzy set denoted by $\tilde{\mathcal{F}}$, define on $\mathcal{X}$ and define as:

$$\tilde{\mathcal{F}} = \{(\xi, \mu_{\tilde{\mathcal{F}}}(\xi)) : \xi \in \mathcal{X}\} \tag{1}$$

where, $\mu_{\tilde{\mathcal{F}}}(\xi)$ represent the membership function of fuzzy set $\tilde{\mathcal{F}}$ with $\mu_{\tilde{\mathcal{F}}} : \mathcal{X} \to [0, 1]$ for all $\xi \in \mathcal{X}$.

Definition 2. α-cut of fuzzy set [50]

Consider $\mathcal{X}$ to be the universal set of discourse and $\tilde{\mathcal{E}}$ to be a fuzzy set defined on it. Then the $\alpha-$cut of fuzzy set $(\tilde{\mathcal{E}}_\alpha)$ is the collection of elements of fuzzy set $\tilde{\mathcal{E}}$ whose membership value $(\mu_{\tilde{\mathcal{E}}})$ are greater or equal to α $(\in [0, 1])$, i.e.,

$$\tilde{\mathcal{E}}_\alpha = \{\zeta : \mu_{\tilde{\mathcal{E}}}(\zeta) \geq \alpha \;\&\; \zeta \in \mathcal{X}\} \tag{2}$$

Definition 3. Fuzzy number [51]

Assume the set of real numbers $(\mathbb{R})$ to be a universal set of discourse. A fuzzy set $\tilde{\mathcal{E}}$ is called fuzzy number, if it define on $\mathbb{R}$ and satisfies following properties:

A. Fuzzy set $(\tilde{\mathcal{E}})$ is normal, i.e., $\exists\, \zeta \in \mathbb{R}$ such that $\mu_{\tilde{\mathcal{E}}}(\zeta) = 1$;

B. Support of fuzzy set $(\tilde{\mathcal{E}})$ is bounded, i.e., Suport$\left(\tilde{\mathcal{E}}\right) = \{\zeta : \mu_{\tilde{\mathcal{E}}}(\zeta) > 0 \;\&\; \zeta \in \mathbb{R}\} \subset \mathbb{R}$;

C. Membership function $(\mu_{\tilde{\mathcal{E}}}(\zeta))$ of fuzzy set $\tilde{\mathcal{E}}$ is piecewise continuous;

D. Fuzzy set $(\tilde{\mathcal{E}})$ is convex, i.e., $\mu_{\tilde{\mathcal{E}}}(\lambda\zeta_1 + (1-\lambda)\zeta_2) \geq \min\{\mu_{\tilde{\mathcal{E}}}(\zeta_1), \mu_{\tilde{\mathcal{E}}}(\zeta_2)\}$ for arbitrary $\zeta_1, \zeta_2 \in \mathbb{R}$ and $\lambda \in [0, 1]$.

3.2 BFS

BFS was first introduced by Zhang [52] in 1994. BFS is an extension of fuzzy sets where two membership values are assigned to every element in the set [53]. The first membership function represents the satisfaction and the second membership function describes the violation of the elements in the BFS. The definitions and properties of BFS are described as follows:

Definition 4. BFS [54]

Let $\mathcal{Y}$ be the non-empty universal set. A bipolar fuzzy set $\tilde{\mathcal{B}}$ define on $\mathcal{Y}$ and define as:

$$\tilde{\mathcal{B}} = \{(\zeta, \mu_{\tilde{\mathcal{B}}}(\zeta), \nu_{\tilde{\mathcal{B}}}(\zeta)) : \zeta \in \mathcal{Y}\} \tag{3}$$

where, $\mu_{\tilde{\mathcal{B}}}$ be the positive membership function $\mu_{\tilde{\mathcal{B}}}(\zeta) : \mathcal{Y} \to [0, 1]$ and $\nu_{\tilde{\mathcal{B}}}$ be the negative membership function $\mu_{\tilde{\mathcal{B}}}(\zeta) : \mathcal{Y} \to [-1, 0]$, respectively.

Remark 1. In a fuzzy set, every element has exactly one membership function to describe the belongingness of the element in the set. However, in a bipolar fuzzy set [53], every element has two membership values to represent a more specific position in the set, the first positive membership function $(\mu_{\tilde{\mathcal{B}}})$ describes the belongingness of the element in the set and the second negative membership function $(\nu_{\tilde{\mathcal{B}}})$ shows the non-belongingness of the element in the set, respectively.

Example 1. Consider $\mathcal{X} = [\pi/2, \pi]$ to be a universal set of discourse. Then a bipolar fuzzy set $\tilde{\mathcal{A}}$ define on $[\pi/2, \pi]$ and define as:

$$\tilde{\mathcal{A}} = \{(\eta, \sin(\eta), \cos(\eta)) : \eta \in [\pi/2, \pi]\}$$

In the bipolar fuzzy set $\tilde{\mathcal{A}}$, the positive membership function $\mu_{\tilde{\mathcal{A}}}(\eta) : [\pi/2, \pi] \to [0, 1]$ and negative membership function $\mu_{\tilde{\mathcal{A}}}(\eta) : [\pi/2, \pi] \to [-1, 0]$ for all $\eta \in [\pi/2, \pi]$.

Definition 5. k-cut of bipolar fuzzy set [55]

Consider $\tilde{\mathcal{C}}$ to be a bipolar fuzzy set defined on the universal set $\mathcal{Y}$. Then the $k-$cut of the bipolar fuzzy set $\tilde{\mathcal{C}}$ is defined as:

$$\begin{aligned}\tilde{\mathcal{C}}_k &= \tilde{\mathcal{C}}_k^+ \cap \tilde{\mathcal{C}}_k^- \\ &= \{\zeta : \mu_{\overline{\mathcal{B}}}(\zeta) \geq k \& \zeta \in \mathcal{Y}\} \cap \{\zeta : \nu_{\overline{\mathcal{B}}}(\zeta) \leq -k \& \zeta \in \mathcal{Y}\}\end{aligned} \tag{4}$$

where, $\tilde{\mathcal{C}}_k^+ = \{\zeta : \mu_{\tilde{\mathcal{B}}}(\zeta) \geq k \;\&\; \zeta \in \mathcal{Y}\}$ is the positive $k-$cut and $\tilde{\mathcal{C}}_k^- = \{\zeta : \mu_{\tilde{\mathcal{B}}}(\zeta) \geq k \;\&\; \zeta \in \mathcal{Y}\}$ is the negative $k-$cut of the bipolar fuzzy set $\tilde{\mathcal{C}}$ with $k \in [0, 1]$.

3.3 Bipolar Triangular Fuzzy Number (BTFN)

This section discusses the BTFN [56] in detail. In the BTFNs, the membership functions are triangular in shape. The BTFN can be defined as follows:

Definition 6. BTFN [55]

Consider the set of real numbers $\mathbb{R}$ to be a universal set of discourse. A BTFN is defined as $\tilde{\mathcal{T}} = \{(\xi, \mu_{\tilde{\mathcal{T}}}(\xi), \nu_{\tilde{\mathcal{T}}}(\xi))\,;\, \big(A^l, B^n, C^p, D^r\big)\}$ with the positive membership function $(\mu_{\tilde{\mathcal{T}}}(\xi))$ and negative membership function $(\nu_{\tilde{\mathcal{T}}}(\xi))$ defined as:

$$\mu_{\tilde{\mathcal{T}}}(\xi)) = \begin{cases} \frac{\xi - A^l}{C^p - A^l} & ; A^l \leq \xi \leq C^p \\ \frac{D^r - \xi}{D^r - C^p} & ; C^p < \xi \leq D^r \\ 0 & ; \text{otherwise} \end{cases} \quad \text{and} \quad \nu_{\tilde{\mathcal{T}}}(\xi)) = \begin{cases} \frac{A^l - \xi}{B^n - A^l} & ; A^l \leq \xi \leq B^n \\ \frac{\xi - D^r}{D^r - B^n} & ; B^n < \xi \leq D^r \\ 0 & ; \text{otherwise} \end{cases} \tag{5}$$

where, A^l, B^n, C^p, D^r are real numbers with increasing order, i.e., $(A^l \leq B^n \leq C^p \leq D^r)$.

Remark 2. To maintain the text limit and reduce computational complexity a BTFN $\tilde{\mathcal{T}} = \{(\xi, \mu_{\tilde{\mathcal{T}}}(\xi), \nu_{\tilde{\mathcal{T}}}(\xi))\,;\, \big(A^l, B^n, C^p, D^r\big)\}$ can be written as $\tilde{\mathcal{T}} = \big\{\xi; (A^l, B^n, C^p, D^r)\big\}$.

Example 2. Assume the set of real numbers $\mathbb{R}$ to be a universal set of discourse. A BTFN is defined as $\tilde{\mathcal{S}} = \{(\tau, \mu_{\tilde{\mathcal{S}}}(\tau), \nu_{\tilde{\mathcal{S}}}(\tau))\,; (3, 5, 6, 8)\}$ with the positive membership function $(\mu_{\tilde{\mathcal{S}}}(\tau))$ and negative membership function $(\nu_{\tilde{\mathcal{S}}}(\tau))$ defined as:

$$\mu_{\tilde{\mathcal{S}}}(\tau)) = \begin{cases} \frac{\tau - 3}{6 - 3} & ; 3 \leq \tau \leq 6 \\ \frac{8 - \tau}{8 - 6} & ; 6 < \tau \leq 8 \\ 0 & ; \text{otherwise} \end{cases} \qquad \nu_{\tilde{\mathcal{T}}}(\xi)) = \begin{cases} \frac{3 - \tau}{5 - 3} & ; 3 \leq \tau \leq 5 \\ \frac{\tau - 8}{8 - 5} & ; 5 < \tau \leq 8 \\ 0 & ; \text{otherwise} \end{cases}$$

$$= \begin{cases} \frac{\tau - 3}{3} & ; 3 \leq \tau \leq 6 \\ \frac{8 - \tau}{2} & ; 6 < \tau \leq 8 \\ 0 & ; \text{otherwise} \end{cases} \quad \text{and} \quad = \begin{cases} \frac{3 - \tau}{2} & ; 3 \leq \tau \leq 5 \\ \frac{\tau - 8}{3} & ; 5 < \tau \leq 8 \\ 0 & ; \text{otherwise} \end{cases}$$

where, 3, 5, 6, 8 are real numbers $(\mathbb{R})$ with increasing order, i.e., $(3 \leq 5 \leq 6 \leq 8)$.

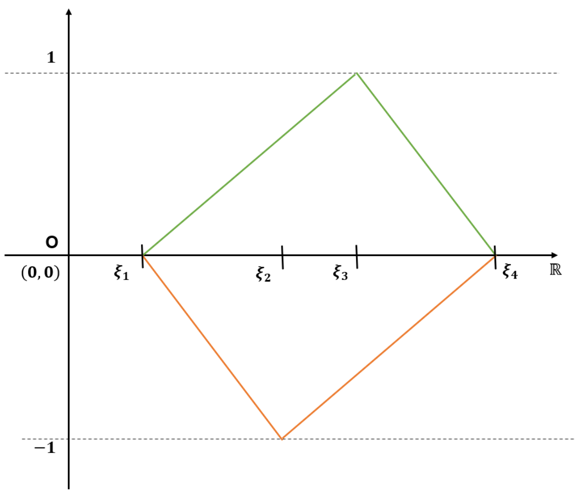

Figure 1. Geometric representation of bipolar triangular fuzzy number (BTFN)

The graphical structure of a BTFN is presented in Figure 1. The upper half shows the positive membership function and the lower half shows the negative membership function, respectively.

Definition 7. Normalized BTFN [55, 56]

Assume a BTFN $\tilde{\mathcal{S}} = \left\{(\xi, \mu_{\tilde{\mathcal{S}}}(\xi), \nu_{\tilde{\mathcal{S}}}(\xi))\,; (A^l, B^n, C^p, D^r)\right\}$ defined on the set of ral numbers $(\mathbb{R})$. Then the normalized BTFN $(\tilde{\mathcal{S}}^n)$ is evaluated as:

$$\begin{aligned}\tilde{\mathcal{S}}^n &= \left\{(\xi, \mu_{\tilde{\mathcal{S}}}(\xi), \nu_{\tilde{\mathcal{S}}}(\xi))\,; \left(\frac{A^l}{D^r}, \frac{B^n}{D^r}, \frac{C^p}{D^r}, \frac{D^r}{D^r}\right)\right\} \\ &= \left\{(\xi, \mu_{\tilde{\mathcal{S}}}(\xi), \nu_{\tilde{\mathcal{S}}}(\xi))\,; \left(\frac{A^l}{D^r}, \frac{B^n}{D^r}, \frac{C^p}{D^r}, 1\right)\right\}\end{aligned} \tag{6}$$

3.4 Arithmetic Operations on BTFNs

Arithmetic operations on BTFNs are defined in this section. Since BTFNs have no order relation, the arithmetic operation on BTFN is defined for various operations.

Assume that $\tilde{\mathcal{S}} = \left\{\xi; (A^l, B^n, C^p, D^r)\right\}$ and $\tilde{\mathcal{T}} = \left\{\xi; (E^l, F^n, G^p, H^r)\right\}$ are two BTFNs and λ is a scalar number. Then the arithmetic operations [55] on BTFNs are defined as:

A. Addition of two BTFNs:

$$\tilde{\mathcal{S}} \oplus \tilde{\mathcal{T}} = \left\{\xi; (A^l + E^l, B^n + F^n, C^p + G^p, D^r + H^r)\right\} \tag{7}$$

B. Subtraction from BTFN to BTFN:

$$\tilde{\mathcal{S}} \ominus \tilde{\mathcal{T}} = \left\{\xi; (A^l - H^r, B^n - G^p, C^p - F^n, D^r - E^l)\right\} \tag{8}$$

C. Scalar multiplication of BTFN:

$$\lambda \times \tilde{\mathcal{S}} = \left\{\xi; (\lambda \times A^l, \lambda \times B^n, \lambda \times C^p, \lambda \times D^r)\right\} \tag{9}$$

where, λ is a non-negative scalar (≥ 0).

$$\lambda \times \tilde{\mathcal{S}} = \left\{\xi; (\lambda \times D^r, \lambda \times C^p, \lambda \times B^n, \lambda \times A^l)\right\} \tag{10}$$

where, λ is a negative scalar (< 0).

D. Multiplication of two BTFNs:

$$\tilde{\mathcal{S}} \otimes \tilde{\mathcal{T}} = \left\{\xi; (A^l E^l, B^n F^n, C^p G^p, D^r H^r)\right\} \tag{11}$$

where, A^l and E^l are two non-negative (≥ 0) real numbers.

E. Scalar power of BTFN:

$$\tilde{\mathcal{S}}^\lambda = \left\{\xi; \left((A^l)^\lambda, (B^n)^\lambda, (C^p)^\lambda, (D^r)^\lambda\right)\right\} \tag{12}$$

where, λ is a positive scalar.

3.5 De-Fuzzification of BTFN

De-fuzzification is a numerical process that crispifies fuzzy numbers, since there is no order relation on them. Several defuzzification formulas have been proposed in previous studies. In this research, we proposed a new de-fuzzification formula to crispify the BTFNs [57, 58]. The proposed de-fuzzification formula is presented as follows:

Definition 8. De-fuzzification of BTFN [58]

Let a BTFN be defined as $\tilde{\mathcal{T}} = \left\{(\xi, \mu_{\tilde{\mathcal{T}}}(\xi), \nu_{\tilde{\mathcal{T}}}(\xi))\,; (A^l, B^n, C^p, D^r)\right\}$ on the set of real numbers $(\mathbb{R})$. Then the de-fuzzification of BTFN $\mathscr{D}\left(\tilde{\mathcal{T}}\right)$ is evaluated by Eq. (13), as follows:

$$\mathscr{D}\left(\tilde{\mathcal{T}}\right) = \frac{2 \times A^l + 3 \times B^n + 3 \times C^p + 2 \times D^r}{10} \tag{13}$$

Example 3. Consider a BTFN $(\tilde{\mathcal{U}})$ is defined as $\tilde{\mathcal{U}} = \{(\tau, \mu_{\tilde{\mathcal{U}}}(\tau), \nu_{\tilde{\mathcal{U}}}(\tau))\,; (2, 5, 6, 9)\}$ defined on the set of real numbers $(\mathbb{R})$. Then the de-fuzzified value of BTFN $\tilde{\mathcal{U}}$ is:

$$\begin{aligned}\mathscr{D}\left(\tilde{\mathcal{U}}\right) &= \frac{2 \times 2 + 3 \times 5 + 3 \times 6 + 2 \times 9}{10} \\ &= \frac{4 + 15 + 18 + 18}{10} = \frac{55}{10} = 5.5\end{aligned}$$

4 Proposed Methodology

This section discusses the mathematical methods of two MCDM methods [59] used in the BTFN environment, namely MEREC and MABAC. MCDM is a popular optimization technique for dealing with multiple conflicting criteria and alternatives. First, describe the MEREC method for evaluating the weights of criteria and the MABAC method for ranking alternatives are further disclosed.

4.1 MEREC Method

In 2021, Keshavarz-Ghorabaee et al. [32] first represented the MEREC method. It is an objective process for analysing the weights of factors [37]. With this important process, this methodology is used to objectively find perfect criterion weights by measuring how the removal of each criterion affects the total decision performance.

The mathematical procedure of the MEREC method is formulated here. There are $\mathcal{Q}$ number of criteria and $\mathcal{P}$ number of alternatives are considered for the numerical process. $\mathcal{R}$ number of DMs give opinions based on their knowledge and experience, in an unbiased way. All the data are expressed in linguistic terms and further converted to Triangular Type-2 Fuzzy Number (TT2FN) using a conversion table. The decision matrices are formed in $\mathcal{P} \times \mathcal{Q}$ order. The numerical procedure of the MEREC method proceeds as follows:

Step A. Structured the decision matrices ($\tilde{\mathscr{D}}_k$):

Select the criteria and alternatives based on the literature survey and detailed discussion with decision experts. There are $\mathcal{Q}$ number of criteria and $\mathcal{P}$ number of alternatives considered for this study. Further $\mathcal{R}$ number of decision experts are given opinions for decision matrix construction. Therefore, $\mathcal{R}$ number of decision matrices structured with $\mathcal{P} \times \mathcal{Q}$ order in linguistic terms and then transferred into a BTFN using Table 1.

Table 1. Conversion table between linguistic terms and Bipolar Triangular Fuzzy Numbers (BTFNs)

Linguistic Terms	BTFN	De-Fuzzified Value
ER	$\left\{\left(\xi, \mu_{\tilde{\mathcal{T}}_7}(\xi), \nu_{\tilde{\mathcal{T}}_7}(\xi)\right); (7,9,10,12)\right\}$	9.5
SR	$\left\{\left(\xi, \mu_{\tilde{\mathcal{T}}_6}(\xi), \nu_{\tilde{\mathcal{T}}_6}(\xi)\right); (6,8,9,11)\right\}$	8.5
HR	$\left\{\left(\xi, \mu_{\tilde{\mathcal{T}}_5}(\xi), \nu_{\tilde{\mathcal{T}}_5}(\xi)\right); (5,7,8,10)\right\}$	7.5
MR	$\left\{\left(\xi, \mu_{\tilde{\mathcal{T}}_4}(\xi), \nu_{\tilde{\mathcal{T}}_4}(\xi)\right); (4,6,7,9)\right\}$	6.5
WR	$\left\{\left(\xi, \mu_{\tilde{\mathcal{T}}_3}(\xi), \nu_{\tilde{\mathcal{T}}_3}(\xi)\right); (3,5,6,8)\right\}$	5.5
BR	$\left\{\left(\xi, \mu_{\tilde{\mathcal{T}}_2}(\xi), \nu_{\tilde{\mathcal{T}}_2}(\xi)\right); (2,4,5,7)\right\}$	4.5
LR	$\left\{\left(\xi, \mu_{\tilde{\mathcal{T}}_1}(\xi), \nu_{\tilde{\mathcal{T}}_1}(\xi)\right); (1,3,4,6)\right\}$	3.5

Note: ER = Extremely Relevant; SR = Strongly Relevant; HR = High Relevant; MR = Moderate Relevant; WR = Weekly Relevant; BR = Below Relevant; and LR = Low Relevant.

The decision matrix in BTFN given by kth DMs is $\tilde{\mathscr{D}}_k$ and formulate as:

$$\tilde{\mathscr{D}}_k = \begin{bmatrix} (\tilde{\mathscr{B}}_{11})_k & (\tilde{\mathscr{B}}_{12})_k & \dots & (\tilde{\mathscr{B}}_{1j})_k & \dots & (\tilde{\mathscr{B}}_{1\mathcal{Q}})_k \\ (\tilde{\mathscr{B}}_{21})_k & (\tilde{\mathscr{B}}_{22})_k & \dots & (\tilde{\mathscr{B}}_{2j})_k & \dots & (\tilde{\mathscr{B}}_{2\mathcal{Q}})_k \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ (\tilde{\mathscr{B}}_{i1})_k & (\tilde{\mathscr{B}}_{i2})_k & \dots & (\tilde{\mathscr{B}}_{ij})_k & \dots & (\tilde{\mathscr{B}}_{i\mathcal{Q}})_k \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ (\tilde{\mathscr{B}}_{\mathcal{P}1})_k & (\tilde{\mathscr{B}}_{\mathcal{P}2})_k & \dots & (\tilde{\mathscr{B}}_{\mathcal{P}j})_k & \dots & (\tilde{\mathscr{B}}_{\mathcal{P}\mathcal{Q}})_k \end{bmatrix}_{\mathcal{P}\times\mathcal{Q}} \tag{14}$$

where, $(\tilde{\mathscr{B}}_{ij})_k$ is the opinions of ith alternatives with respect to jth criteria in BTFN by kth DMs, with $j = 1, 2, \dots, \mathcal{Q}$, $i = 1, 2, \dots, \mathcal{P}$ and $k = 1, 2, \dots, \mathcal{R}$, respectively.

The ijth coefficient of the decision matrix $(\tilde{\mathscr{D}}_k)$ is $\tilde{\mathscr{B}}_{ij})_k$ in a BTFN is formed as:

$$\begin{aligned} \left(\tilde{\mathscr{B}}_{ij}\right)_k &= \left(\left\{\left(\tau, \mu_{\tilde{\mathscr{B}}_{ij}}(\tau), \nu_{\tilde{\mathscr{B}}_{ij}}(\tau)\right); (E^l, F^n, G^p, H^r)\right\}_{ij}\right)_k \\ &= \left\{\left(\tau_{ij}, \mu_{\tilde{\mathscr{B}}_{ij}}(\tau_{ij}), \nu_{\tilde{\mathscr{B}}_{ij}}(\tau_{ij})\right); (E^l, F^n, G^p, H^r)_{ij}\right\}_k \end{aligned} \tag{15}$$

where, $j = 1, 2, \dots, \mathcal{Q}$, $i = 1, 2, \dots, \mathcal{P}$ and $k = 1, 2, \dots, \mathcal{R}$.

Step B. Determine the aggregated fuzzy decision matrix ($\tilde{\mathscr{D}}$):

The aggregated fuzzy decision matrix $(\tilde{\mathscr{D}})$ evaluated from all the $\mathcal{R}$ number of decision matrices $(\tilde{\mathscr{D}}_k)$ by using

Eq. (16), as follows:

$$
\begin{aligned}
\tilde{\mathscr{D}} &= \left[\tilde{\mathscr{B}}_{ij}\right]_{\mathcal{P}\times\mathcal{Q}} \\
&= \left[\left\{\left(\tau, \mu_{\tilde{\mathscr{B}}_{ij}}(\tau), \nu_{\tilde{\mathscr{B}}_{ij}}(\tau)\right); (E^l, F^n, G^p, H^r)\right\}_{ij}\right]_{\mathcal{P}\times\mathcal{Q}} \\
&= \left[\left\{\left(\tau, \mu_{\tilde{\mathscr{B}}_{ij}}(\tau), \nu_{\tilde{\mathscr{B}}_{ij}}(\tau)\right); \left(\min_{k=1,2,\ldots,\mathcal{R}}\left\{E_k^l\right\}, \prod_{k=1}^{\mathcal{R}} F_k^n, \prod_{k=1}^{\mathcal{R}} G_k^p, \max_{k=1,2,\ldots,\mathcal{R}}\left\{H_k^r\right\}\right)\right\}_{ij}\right]_{\mathcal{P}\times\mathcal{Q}}
\end{aligned}
\tag{16}
$$

where, $j = 1, 2, \ldots, \mathcal{Q}$, $i = 1, 2, \ldots, \mathcal{P}$ and $k = 1, 2, \ldots, \mathcal{R}$.

Step C. Evaluate the uniform fuzzy decision matrix $(\tilde{\mathscr{D}}^u)$:

Determine the uniform fuzzy decision matrix $(\tilde{\mathscr{D}}^u)$ from the aggregated fuzzy decision matrix $(\tilde{\mathscr{D}})$ by normalizing every entry of the modified decision matrix. The uniform fuzzy decision matrix $(\tilde{\mathscr{D}}^u)$ is formulated as:

$$
\begin{aligned}
\tilde{\mathscr{D}}^u &= \left[\tilde{\mathscr{B}}_{ij}^u\right]_{\mathcal{P}\times\mathcal{Q}} \\
&= \left[\left\{\left(\tau, \mu_{\tilde{\mathscr{B}}_{ij}^u}(\tau), \nu_{\tilde{\mathscr{B}}_{ij}^u}(\tau)\right)^u; (E^l, F^n, G^p, H^r)^u\right\}_{ij}\right]_{\mathcal{P}\times\mathcal{Q}} \\
&= \left[\left\{\left(\tau_{ij}^u, \mu_{\tilde{\mathscr{B}}_{ij}^u}(\tau_{ij}^u), \nu_{\tilde{\mathscr{B}}_{ij}^u}(\tau_{ij}^u)\right); (E_{ij}^{lu}, F_{ij}^{nu}, G_{ij}^{pu}, H_{ij}^{ru})\right\}\right]_{\mathcal{P}\times\mathcal{Q}} \\
&= \left[\left\{\left(\tau_{ij}^u, \mu_{\tilde{\mathscr{B}}_{ij}^u}(\tau_{ij}^u), \nu_{\tilde{\mathscr{B}}_{ij}^u}(\tau_{ij}^u)\right); \left(\frac{E_{ij}^{lu} - E_j^{l-}}{H_j^{r+} - E_j^{l-}}, \frac{F_{ij}^{nu} - E_j^{l-}}{H_j^{r+} - E_j^{l-}}, \frac{G_{ij}^{pu} - E_j^{l-}}{H_j^{r+} - E_j^{l-}}, \frac{H_{ij}^{ru} - E_j^{l-}}{H_j^{r+} - E_j^{l-}}\right)\right\}_{ij}\right]_{\mathcal{P}\times\mathcal{Q}}
\end{aligned}
\tag{17}
$$

where, $\begin{cases} E_j^{l-} = \min\limits_{i=1,2,\ldots,\mathcal{P}}\left\{E_{ij}^{lu}\right\} \\ H_j^{r+} = \max\limits_{i=1,2,\ldots,\mathcal{P}}\left\{H_{ij}^{ru}\right\} \end{cases}$ with $j = 1, 2, \ldots, \mathcal{Q}$ and $i = 1, 2, \ldots, \mathcal{P}$.

Step D. Calculate the de-fuzzified decision matrix $(\mathscr{D})$:

The uniform fuzzy decision matrix $(\tilde{\mathscr{D}}^u)$ is transferred into a de-fuzzified decision matrix $(\mathscr{D})$ by de-fuzzifying every entry of it. The BTFN is de-fuzzified using Eq. (13) and the de-fuzzified decision matrix $(\mathscr{D})$ constructed as follows:

$$
\mathscr{D} = [\mathfrak{B}_{ij}]_{\mathcal{P}\times\mathcal{Q}}
\tag{18}
$$

where, $j = 1, 2, \ldots, \mathcal{Q}$ and $i = 1, 2, \ldots, \mathcal{P}$.

Step E. Evaluate the overall performance $(\mathfrak{M}_i)$ of each alternative:

Calculate the overall performance $(\mathfrak{M}_i)$ of each alternative (i) by using Eq. (19), as follows:

$$
\mathfrak{M}_i = \frac{\sum\limits_{j=1}^{\mathcal{Q}} \ln(1 - \mathfrak{B}_{ij})}{\mathcal{Q}}
\tag{19}
$$

where, $i = 1, 2, \ldots, \mathcal{P}$.

Step F. Determine the performance of the alternative $(\mathfrak{N}_{ij})$ by eliminating each criteria:

The performance of the alternative value $(\mathfrak{N}_{ij})$ is evaluated from the de-fuzzified decision matrix $(\mathscr{D})$ for each entry (ij) by using Eq. (20). The performance of the alternative value $(\mathfrak{N}_{ij})$ calculate as follows:

$$
\mathfrak{N}_{ij} = \frac{\sum\limits_{j=1,\, j\neq i}^{\mathcal{Q}} \ln(1 - \mathfrak{B}_{ij})}{\mathcal{Q}}
\tag{20}
$$

where, $j = 1, 2, \ldots, \mathcal{Q}$ and $i = 1, 2, \ldots, \mathcal{P}$.

Step G. Evaluate the aggregated of the absolute deviations $(\mathfrak{O}_j)$:

Calculate the aggregate of the absolute deviations $(\mathfrak{O}_j)$ for every criteria (j) from the performance of the alternative $(\mathfrak{N}_{ij})$ and the overall performance $(\mathfrak{M}_i)$ values by using Eq. (21), as follows:

$$
\mathfrak{O}_j = \sum_{i=1}^{\mathcal{P}} |\mathfrak{N}_{ij} - \mathfrak{M}_i|
\tag{21}
$$

where, $j = 1, 2, \ldots, \mathcal{Q}$.

Step H. Determine the weight of the criteria $(\mathfrak{W}_j)$:

The weight of the criteria $(\mathfrak{W}_j)$ is evaluated by normalized deviation value $(\mathfrak{O}_j)$ as follows:

$$\mathfrak{W}_j = \frac{\mathfrak{O}_j}{\sum_{j=1}^{\mathcal{Q}} \mathfrak{O}_j} \tag{22}$$

where, $j = 1, 2, \ldots, \mathcal{Q}$.

Finally, the optimal weight of the criteria $(\mathfrak{W}_j)$ is given by Eq. (22) using the fuzzy-based MEREC methodology. These criteria weights are operational in further ranking techniques. The MEREC algorithm in the TT2FN environment is presented in Algorithm 1.

Algorithm 1 Method based on the removal effects of criteria (MEREC) algorithm in triangular type-2 fuzzy number (TT2FN) environment

---

Require: decision matrices $(\tilde{\mathscr{D}}_k)$
Ensure: $\mathcal{Q}$ number of criteria, $\mathcal{P}$ number of alternatives and $\mathcal{R}$ number of decision experts
  aggregated fuzzy decision matrix $(\tilde{\mathscr{D}})$
  uniform fuzzy decision matrix $(\tilde{\mathscr{D}}^u)$
  de-fuzzified decision matrix $(\mathscr{D})$
  performance of the alternative value $(\mathfrak{N}_{ij})$
  aggregated of the absolute deviations $(\mathfrak{O}_j)$
  weight of the criteria $(\mathfrak{W}_j)$
  while $k \leq \mathcal{R}$ **do**
    determine $\tilde{\mathscr{D}}$
    for $i \leq \mathcal{P}$ and $j \leq \mathcal{Q}$ **do**
      evaluate $\tilde{\mathscr{D}}^u$
      calculate $\mathscr{D}$
      determine $\mathfrak{N}_{ij}$
      calculate $\mathscr{D}$
      for $j \leq \mathcal{Q}$ **do**
        evaluate $\mathfrak{O}_j$
        determine $\mathfrak{W}_j$
      end for
    end for
  end while

4.2 MABAC Method

MABAC method was introduced by Pamučar and Ćirović [39] in 2015. The fuzzy set integrated with the MABAC method can make the model more reliable and evaluate the result optimally. This desicion maling MABAC method [46] is used to rank the selected alternatives in MCDM by measuring their distances from a defined border approximation area (BAA).

The numerical procedure of the MCDM-based MABAC method is presented in this section under a TT2FN environment. There are $\mathcal{Q}$ number of criteria, $\mathcal{P}$ number of alternatives and $\mathcal{R}$ number of DMs who give opinions based on their knowledge and experience. Therefore, the decision matrices are constructed into $\mathcal{P} \times \mathcal{Q}$ order in linguistic terms and further converted into TT2FN using conversion Table 1. The fuzzy MABAC method is processed as follows:

Step 1. Constructing the decision matrices $(\tilde{\mathscr{D}}_k)$:

Criteria and alternatives are chosen based on a detailed literature review and consultation with the decision experts. The decision matrices are structured in the $\mathcal{P} \times \mathcal{Q}$ order in linguistic terms and converted to a BTFN using a conversion table. The decision matrix $(\tilde{\mathscr{D}}_k)$ given by the kth DMs in linguistic terms and further converted into BTFN is shown in Eq. (14) of Step A in the MEREC method.

Step 2. Evaluating the aggregated decision matrix $(\tilde{\mathscr{D}})$:

All the kth number of decision matrices $(\tilde{\mathscr{D}}_k)$ are aggregated into a single aggregated decision matrix $(\tilde{\mathscr{D}})$ using Eq. (16), shown in Step B of the MEREC method.

Step 3. Determine weighted aggregated decision matrix $(\tilde{\mathscr{E}}^w)$:

The weighted aggregated decision matrix $(\tilde{\mathscr{E}}^w)$ evaluated from the aggregated decision matrix $(\tilde{\mathscr{D}})$ in Eq. (16) and the criteria weights $(\mathfrak{W}_j)$ in Eq. (22) using scalar multiplication of BTFN defined in Eq. (9). The weighted aggregated decision matrix ($\tilde{\mathscr{E}}^w$) is structured as

$$\tilde{\mathscr{E}}^w = \left[\tilde{\mathscr{C}}_{ij}^w\right]_{\mathcal{P}\times\mathcal{Q}} = \left[\mathfrak{W}_j \times \tilde{\mathscr{B}}_{ij}\right]_{\mathcal{P}\times\mathcal{Q}} \tag{23}$$

where, $j = 1, 2, \ldots, \mathcal{Q}$ and $i = 1, 2, \ldots, \mathcal{P}$.

Step 4. Calculating unified weighted decision matrix ($\tilde{\mathscr{E}}^u$):

The unified weighted decision matrix ($\tilde{\mathscr{E}}^u$) is calculated by normalizing every element from the weighted aggregated decision matrix ($\tilde{\mathscr{E}}^w$), using Eq. (17), described in Step D of the MEREC method.

Step 5. Determine the de-fuzzified decision matrix ($\mathscr{E}$):

Now, de-fuzzify the unified weighted decision matrix ($\tilde{\mathscr{E}}^u$) and evaluate the de-fuzzified decision matrix ($\mathscr{E}$) using the de-fuzzification formula defined in Eq. (13).

Algorithm 2 Multi-attributive border approximation area comparison (MABAC) algorithm in triangular type-2 fuzzy number (TT2FN) environment

---

Require: decision matrices ($\tilde{\mathscr{D}}_k$)
Ensure: $\mathcal{Q}$ number of criteria, $\mathcal{P}$ number of alternatives and $\mathcal{R}$ number of decision experts
  aggregated fuzzy decision matrix ($\tilde{\mathscr{D}}$)
  weighted aggregated decision matrix ($\tilde{\mathscr{E}}^w$)
  unified weighted decision matrix ($\tilde{\mathscr{E}}^u$)
  de-fuzzified decision matrix ($\mathscr{E}$)
  border approximation area (BAA) value ($\mathscr{F}_j$)
  weight of the criteria ($\mathfrak{W}_j$)
  distance of alternative from BAA ($\mathscr{S}_i$)
  while $k \leq \mathcal{R}$ **do**
    determine $\tilde{\mathscr{D}}$
    for $i \leq \mathcal{P}$ and $j \leq \mathcal{Q}$ **do**
      calculate $\tilde{\mathscr{E}}^w$
      determine $\tilde{\mathscr{E}}^u$
      evaluate $\mathscr{E}$
      for $j \leq \mathcal{Q}$ **do**
        determine $\mathscr{F}_j$
        calculate $\mathfrak{W}_j$
        for $i \leq \mathcal{P}$ **do**
          evaluate $\mathscr{S}_i$
        end for
      end for
    end for
  end while

Step 6. Calculate the BAA ($\mathscr{F}_j$):

The BAA value ($\mathscr{F}_j$) of each criteria (j) is determined from the de-fuzzified decision matrix ($\mathscr{E}$) using Eq. (24), as follows:

$$\mathscr{F}_j = \sqrt[\mathcal{P}]{\prod_{i=1}^{\mathcal{P}} \mathscr{C}_{ij}} \tag{24}$$

where, $\mathscr{C}_{ij}$ is the ijth entry of the de-fuzzified decision matrix ($\mathscr{E}$) with $j = 1, 2, \ldots, \mathcal{Q}$ and $i = 1, 2, \ldots, \mathcal{P}$.

Step 7. Evaluating the distance ($\mathscr{S}_i$) of alternative from BAA:

Find out the distance ($\mathscr{S}_i$) of the alternative (i) from BAA ($\mathscr{F}_j$) using Eq. (25), as follows:

$$\mathscr{S}_i = \sum_{j=1}^{\mathcal{Q}} (\mathscr{C}_{ij} - \mathscr{F}_j) \tag{25}$$

where, $\mathscr{C}_{ij}$ is the ijth entry of the de-fuzzified decision matrix ($\mathscr{E}$) with $i = 1, 2, \ldots, \mathcal{P}$.

Step 8. Rank the alternatives:

Finally, rank the alternatives based on the distance ($\mathscr{S}_i$) of the alternative from BAA evaluated by Eq. (25) in descending order. The higher the $\mathscr{S}_i$ value, the more prioritized the alternative is among the alternatives.

Alternatives are ranked based on the relative distance values ($\mathscr{S}_i$) of the alternative (i) where $i = 1, 2, \ldots, \mathcal{P}$, from BAA and calculated using Eq. (25). The MABAC algorithm in the TT2FN environment is presented in Algorithm 2.

5 Criterion as Remote Sensing Challenges in Disaster Management

Due to limited real-time data, atmospheric interference, and resolution constraints that affect timely and accurate decision-making, remote sensing faces different challenges in disaster management. Moreover, high costs, data processing complexity, and sensor limitations hinder rapid analysis and effective disaster response. Selecting criteria is the most important, as well as a complex task to be done through evaluation with extreme consideration. The following criteria are based on a range of publications and resources on the difficulties associated with remote sensing in disaster management. The final decision on the collection of criteria will be finalised through deliberations of wise DMs.

5.1 Data Resolution and Accuracy (C_1)

Data resolution [60] and its accuracy are vital in remote sensing. They regulate the comprehensiveness, accuracy and reliability of the information used in disaster management. Spatial resolution mainly helps in classifying small features such as dented buildings or flood-affected areas. On the other hand, temporal resolution ensures timely warnings during disasters as well as frequent monitoring for updates. Again, spectral resolution allows the identification of particular conditions, such as moisture levels in burned areas, and radiometric resolution increases the ability to detect subtle changes in intensity. High accuracy ensures that mapped locations and measurements truly represent ground reality. Together, high-quality resolution and accuracy enable rapid assessment, precise mutilation estimation and effective decision-making supporting all phases of disaster management preparedness, early warning, response, and recovery.

5.2 Limited Real-Time Data Availability (C_2)

Limited real-time data [61] availability remains a major challenge in the use of remote sensing for effective disaster management. The main reason for this is that satellite revision times and sensor delays often pose significant barriers to the timely capture of rapidly changing events [62]. Various natural barriers, such as cloud cover, atmospheric disturbances, and technological limitations, can further limit access to immediate data at critical moments. Moreover, high-resolution real-time imagery is very expensive and not always accessible to all agencies, creating gaps in monitoring. Data processing and transmission bottlenecks create difficulties in emergency situations by slowing down rapid interpretation. This reduces situational awareness and limits the effectiveness of early warning. Overall, the lack of immediate, continuous data undermines decision-making during the preparation, response, and recovery phases, making it crucial.

5.3 High Cost of Data and Technology (C_3)

The high cost of data and technology poses a significant challenge in effectively using remote sensing at all stages of disaster management [63]. Advanced sensors, high-resolution imagery, and dedicated satellites require high financial investments. Developing countries have to bear the premium datasets required for accurate monitoring in disaster-prone areas. Data licensing, use of hardware and specialized software increase these costs and limit their accessibility. Ground station maintenance and infrastructure processing further increase these costs. Moreover, skilled personnel are also required for this work. These financial constraints delay the timely acquisition and analysis of necessary information. As a result, DMs rely on low-quality data, which reduces the accuracy of disaster assessments. Ultimately, high costs limit the widespread and equitable use of remote sensing for effective disaster preparedness, response, and recovery, making it important.

5.4 Lack of Technical Expertise and Infrastructure (C_4)

The effective use of remote sensing at all stages of disaster management [64] is severely hampered by a lack of infrastructure and technical knowledge, as specialist personnel are required to operate sensors, manage complex datasets and interpret imagery accurately. Many regions lack trained personnel due to high costs, leading to delays and errors in data analysis. Various inadequate infrastructures, such as limited computing power, inadequate internet connectivity, and outdated software, severely limit the smooth operation of large remote sensing datasets. These are hampered by the lack of proper training and equipment. This gap weakens early warning systems and hampers rapid response. This is a long-term plan, which also affects post-disaster recovery assessments. Finally, limited expertise and weak infrastructure reduce the reliability and efficiency of remote sensing in supporting disaster-related decisions, so it is necessary to consider this.

6 Alternative as Different in Disaster Management Phase

Remote sensing is crucial in disaster management as it provides rapid, accurate information for hazard assessment and large-scale monitoring of affected areas. Its timely information helps in better decision-making at the preparation, response, recovery and mitigation stages. Different options at each stage of disaster management, such as prediction and early warning, preparation, response, recovery, mitigation, etc., help DMs choose the most effective strategy for risk reduction. The five options are discussed in detail below.

6.1 Disaster Prediction and Early Warning (D_1)

Disaster forecasting [60, 65] and early warning through remote sensing play a vital role in disaster management at all levels. These satellites and sensors provide continuous monitoring of environmental patterns. Moreover, changes in weather, land conditions and ocean parameters are detected, which remote sensing can predict hazards such as cyclones, floods, droughts and landslides [66]. This timely forecasting can issue early warnings to the authorities. And, therefore, communities can be prepared in advance. In many cases, it is seen that high-resolution imagery signals emerging threats, and rapid detection of these anomalies becomes necessary. Moreover, remote sensing also enhances situational awareness during disasters, which is much needed. Subsequently, it helps to refine future forecasting models by assessing the impacts. In simple terms, it improves reaction, recuperation, and readiness by making proactive, well-informed judgements.

6.2 Disaster Preparedness (D_2)

By offering precise baseline data on sensitive locations, population distribution, and climatic conditions, remote sensing-assisted disaster preparedness is essential to all stages of disaster management [67]. High-resolution satellite data helps identify risk zones for floods, landslides, cyclones, and wildfires, enabling better planning and resource allocation [68]. Mapping evacuation routes, shelter locations, and vital infrastructure is made easier with the help of remote sensing. Continuous monitoring allows authorities to track changes in land use, vegetation, and water bodies that may increase future risks. These insights help develop effective preparedness plans and mitigation strategies. Training and drills can be improved using realistic remote sensing–based simulations. So, remote sensing improves community preparedness and lessens possible effects prior to a disaster.

6.3 Disaster Response (D_3)

Remote sensing-assisted disaster response is essential for crisis management, as satellite and aircraft imagery provide rapid, comprehensive assessments of impacted areas [67, 69]. Remote sensing helps identify damaged infrastructure, blocked roads, flooded zones, and areas requiring immediate rescue. It makes it possible for rescuers to effectively deploy relief teams and prioritise resources. Real-time or near-real-time data improves situational awareness when ground access is limited or dangerous. Thermal and radar sensors assist in locating survivors, monitoring fires, and tracking ongoing hazards. Remote sensing also supports communication and coordination among agencies by offering a common visual reference. These capabilities significantly speed up decision-making during critical hours. All things considered, it improves precision, security, and efficiency throughout the catastrophe response stage.

6.4 Disaster Recovery and Mitigation (D_4)

In order to restore impacted areas and lower future risks, remote sensing-assisted disaster recovery and mitigation are essential. Post-disaster imagery helps assess the extent of damage to infrastructure, agriculture, and natural resources, enabling accurate planning for reconstruction [70]. Remote sensing tracks changes in land use, soil moisture, and vegetation recovery, guiding long-term restoration efforts [71]. It also identifies hazard-prone zones that require structural improvements or relocation. Authorities can assess the success of prior mitigation efforts by comparing data collected before and after the event. Remote sensing supports designing better flood control systems, landslide prevention structures, and resilient infrastructure. These insights strengthen community resilience and reduce vulnerability to future disasters. In general, it guarantees well-informed choices for both long-term mitigation planning and recovery.

7 Model Formulation and Data Collection

This section presents the model formulation and data collection for the proposed remote sensor for the crucial role model. There are four criteria and four alternatives are considered on the basis of a detailed discussion of the literature survey on this topic and consulting with the decision experts. Hierarchical structure of the proposed remote sensors model is presented in Figure 2. Then the decision matrices are structured in a 4×4 order, with linguistic terms provided by DMs who are professional, experienced, knowledgeable and unbiased in their fields. All the DMs are selected as follows:

DM1: An associate professor from the department of management with more than 10 years of experience;

DM2: A senior social science researcher from the crisis management department with more than 5 years of experience;

DM3: A social worker working with a Non-Governmental Organization (NGO) for more than 15 years.

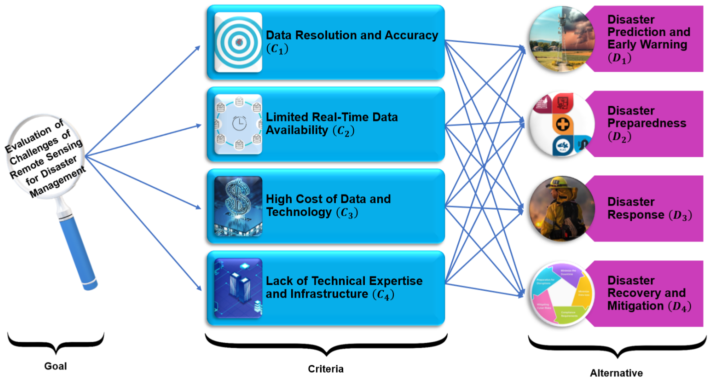

Figure 2. Hierarchical structure of the proposed remote sensors model

Table 2. Decision matrices in linguistic terms given by three decision makers (DMs)

	Criteria vs. Alternatives	Data Resolution and Accuracy (C_1)	Limited Real-Time Data Availability (C_2)	High Cost of Data and Technology (C_3)	Lack of Technical Expertise and Infrastructure (C_4)
DM_1	Disaster Prediction and Early Warning (D_1)	ER	SR	LR	WR
	Disaster Preparedness (D_2)	SR	ER	BR	WR
	Disaster Response (D_3)	HR	HR	LR	BR
	Disaster Recovery and Mitigation (D_4)	HR	MR	HR	SR
	Criteria vs. Alternatives	**Data Resolution and Accuracy (C_1)**	**Limited Real-Time Data Availability (C_2)**	**High Cost of Data and Technology (C_3)**	**Lack of Technical Expertise and Infrastructure (C_4)**
DM_2	Disaster Prediction and Early Warning (D_1)	ER	ER	LR	LR
	Disaster Preparedness (D_2)	HR	SR	LR	WR
	Disaster Response (D_3)	SR	SR	WR	LR
	Disaster Recovery and Mitigation (D_4)	SR	MR	SR	HR
	Criteria vs. Alternatives	**Data Resolution and Accuracy (C_1)**	**Limited Real-Time Data Availability (C_2)**	**High Cost of Data and Technology (C_3)**	**Lack of Technical Expertise and Infrastructure (C_4)**
DM_3	Disaster Prediction and Early Warning (D_1)	SR	SR	BR	LR
	Disaster Preparedness (D_2)	SR	HR	BR	LR
	Disaster Response (D_3)	ER	ER	BR	BR
	Disaster Recovery and Mitigation (D_4)	SR	MR	HR	HR

Note: ER = Extremely Relevant; SR = Strongly Relevant; HR = High Relevant; MR = Moderate Relevant; WR = Weekly Relevant; BR = Below Relevant; and LR = Low Relevant.

The DMs are given their opinions in linguistic terms in decision matrices, which are then converted into BTFNs using Table 1. The de-fuzzified values of the BTFNs are calculated by using Eq. (13) and presented in the conversion table. The decision matrices given by the three DMs are shown in Table 2 and further applied in numerical computation in the later section.

8 Numerical Illustration and Discussion

This section presents a numerical illustration of the proposed finding the challenges of remote sensing for a crucial role in all phases of the disaster management model. There are two MCDM-based optimization methodologies used to calculate the results in a BTFN environment. First, we evaluate the criteria weights using the MEREC method and rank the alternatives using the MABAC method. The numerical computations were processed as follows:

The weight of the criteria is determined by using the MEREC technique, as discussed in Section 4.1 under the BTFN environment, described in Section 3. The dataset is considered from the decision matrices given by three DMs and presented in Table 2. The decision matrices $(\tilde{\mathscr{D}}_k)$ are converted from linguistic terms to BTFN using Table 1. Fourth, aggregate the decision matrices $(\tilde{\mathscr{D}}_k)$ and build a single fuzzy decision matrix $(\tilde{\mathscr{D}})$ using Eq. (16) and determine the uniform aggregated fuzzy decision matrix $(\tilde{\mathscr{D}}^u)$ with the help of Eq. (17), respectively. After that, the de-fuzzified decision matrix $(\mathscr{D})$ is calculated using Eq. (13) and presented in Table 3. Then, we determined the overall performance of each alternative $(\mathfrak{M}_i)$ by Eq. (19) and showed it in Table 4. Further, the performance of the alternative $(\mathfrak{N}_{ij})$ by eliminating each criteria are evaluated by Eq. (20) and presented in Table 5. After that, the aggregate of the absolute deviations $(\mathfrak{O}_j)$ is calculated using Eq. (21) and shown in Table 6. Finally, the weight of the criteria $(\mathfrak{W}_j)$ is evaluated for the criteria of different challenges of remote sensing in the disaster management model using Eq. (22) and presented in Table 6.

From the MEREC method and Table 6, we conclude that the criteria Limited Real-Time Data Availability (C_2) gets the maximum weight and the criteria Data Resolution and Accuracy (C_1) got the second maximum weight for this model. Then, the criteria Lack of Technical Expertise and Infrastructure (C_4) and High Cost of Data and Technology (C_3) are the second-least and least-weighted criteria for this study, respectively. Figure 3 represents the Pie diagram of the criteria weights using the fuzzy MEREC method. The weights of the criteria are further utilised in the ranking method sections.

The ranking of the different disaster management phases as alternatives is evaluated by the MABAC method, as described in Section 4.2 under the BTFN environment, which is discussed in Section 3. All the datasets are presented in decision matrices $(\tilde{\mathscr{D}}_k)$ in linguistic terms and later converted into BTFN using the conversion table. Then determine the aggregated decision matrix $(\tilde{\mathscr{D}})$ by using Eq. (16) from $\tilde{\mathscr{D}}_k$. Furthermore, evaluate the weighted aggregated decision matrix $(\tilde{\mathscr{E}}^w)$ from $\tilde{\mathscr{D}}$ and criteria weight $(\mathfrak{W}_j)$ by scalar multiplication of BTFN defined in Eq. (23). Further, calculate the unified weighted decision matrix $(\tilde{\mathscr{E}}^u)$ using Eq. (17) and de-fuzzified decision matrix $(\mathscr{E})$ using Eq. (13) and presented in Table 7, respectively. Then determine the BAA $(\mathscr{F}_j)$ of each criteria (j) using Eq. (24) and shown in Table 8. Then the distance $(\mathscr{S}_i)$ of the alternative from BAA is calculated by Eq. (25) and shown in Table 9. Finally, the total distance $(\mathscr{S}_i)$ of each alternative from BAA is calculated by Eq. (25) and ranked then in descending order. The ranking of the alternatives based on corresponding $\mathscr{S}_i$ values is presented in Table 10.

From Table 10, we conclude that the Disaster Recovery and Mitigation (D_4) disaster management phase is optimal according to the proposed model. Further, Disaster Prediction and Early Warning (D_1) and Disaster Response (D_3) are the second and third optimal disaster management phases. Finally, the Disaster Preparedness (D_2) occupied the least optimal phase in the MABAC method for disaster management. The graphical representation of the evaluated results is presented through a Bar diagram with $\mathscr{S}_i$ values in Figure 4.

Table 3. De-fuzzified decision matrix $(\mathscr{D})$

Criteria vs. Alternatives	C_1	C_2	C_3	C_4
Disaster Prediction and Early Warning (D_1)	0.585	0.612	0.288	0.324
Disaster Preparedness (D_2)	0.442	0.560	0.308	0.364
Disaster Response (D_3)	0.497	0.560	0.345	0.308
Disaster Recovery and Mitigation (D_4)	0.442	0.313	0.689	0.689

Table 4. Overall performance value ($\mathfrak{M}_i$) of each alternative

Alternative	**Disaster Prediction and Early Warning (D_1)**	**Disaster Preparedness (D_2)**	**Disaster Response (D_3)**	**Disaster Recovery and Mitigation (D_4)**
$\mathfrak{M}_i$ value	-0.639	-0.556	-0.575	-0.824

Table 5. Performance of the alternative ($\mathfrak{N}_{ij}$) by eliminating each criteria

Criteria vs. Alternatives	C_1	C_2	C_3	C_4
Disaster Prediction and Early Warning (D_1)	-0.419	-0.403	-0.554	-0.541
Disaster Preparedness (D_2)	-0.410	-0.351	-0.464	-0.443
Disaster Response (D_3)	-0.403	-0.370	-0.469	-0.483
Disaster Recovery and Mitigation (D_4)	-0.678	-0.730	-0.531	-0.531

Table 6. Criteria weight evaluated using fuzzy Method Based on the Removal Effects of Criteria (MEREC)

Criteria	$\mathfrak{Q}_j$	**Weight**
Data Resolution and Accuracy (C_1)	0.683	0.263
Limited Real-Time Data Availability (C_2)	0.740	0.285
High Cost of Data and Technology (C_3)	0.575	0.222
Lack of Technical Expertise and Infrastructure(C_4)	0.595	0.230

Table 7. De-fuzzified weighted decision matrix ($\mathscr{E}$)

Criteria vs. Alternatives	C_1	C_2	C_3	C_4
Disaster Prediction and Early Warning (D_1)	0.585	0.612	0.288	0.324
Disaster Preparedness (D_2)	0.442	0.560	0.308	0.364
Disaster Response (D_3)	0.497	0.560	0.345	0.308
Disaster Recovery and Mitigation (D_4)	0.442	0.313	0.689	0.689

Table 8. Border approximation area (BAA) ($\mathscr{F}_j$) value

Alternative	**Disaster Prediction and Early Warning (D_1)**	**Disaster Preparedness (D_2)**	**Disaster Response (D_3)**	**Disaster Recovery and Mitigation (D_4)**
$\mathfrak{M}_i$ value	0.488	0.495	0.381	0.398

Table 9. Distance ($\mathscr{S}_i$) of alternative from border approximation area (BAA)

Criteria vs. Alternatives	C_1	C_2	C_3	C_4
Disaster Prediction and Early Warning (D_1)	0.097	0.117	-0.093	-0.074
Disaster Preparedness (D_2)	-0.046	0.065	-0.073	-0.034
Disaster Response (D_3)	0.009	0.065	-0.036	-0.090
Disaster Recovery and Mitigation (D_4)	-0.046	-0.182	0.308	0.291

Table 10. Alternative ranking with associate data determined using fuzzy Multi-Attributive Border Approximation Area Comparison (MABAC) technique

Criteria	$\mathscr{S}_i$	**Rank**
Disaster Prediction and Early Warning (D_1)	0.047	2
Disaster Preparedness (D_2)	-0.088	4
Disaster Response (D_3)	-0.052	3
Disaster Recovery and Mitigation (D_4)	0.371	1

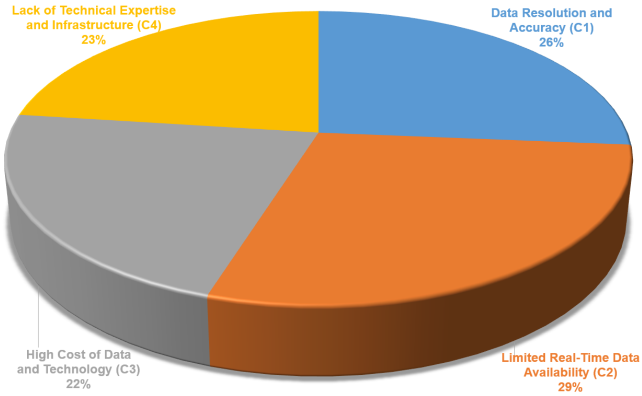

Figure 3. Pie diagram of the criteria weight by fuzzy Method Based on the Removal Effects of Criteria (MEREC)

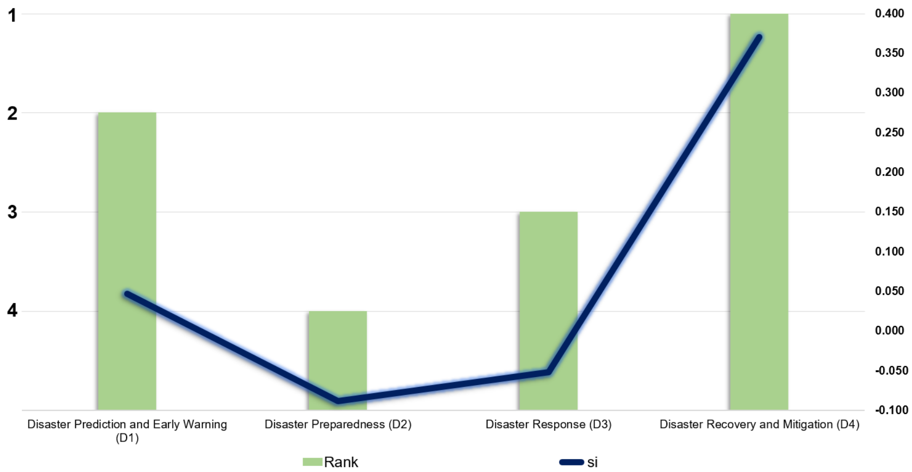

Figure 4. Bar diagram of the alternative ranking based on $\mathscr{S}_i$ values

9 Comparative Analysis and Sensitivity Analysis

This section discusses on comparative analysis and sensitivity analysis in detail to verify the stability and flexibility of the evaluated results.

9.1 Comparative Analysis

Comparative analysis was conducted on this section based on two MCDM methodologies to examine the results' flexibility and robustness. The Weighted Aggregated Sum Product Assessment method [72] and the Combined Compromise Solution method [73] are two MCDM-based ranking methods that were invented by Zavadskas et al. [74] in 2012 and Yazdani et al. [75] in 2019, respectively. The ranking of the alternatives is presented in Table 11.

Table 11. Comparative analysis on three different multi-criteria decision making (MCDM) methods

Alternative	Multi-Attributive Border Approximation Area Comparison (MABAC)	Weighted Aggregated Sum Product Assessment	Combined Compromise Solution
Disaster Prediction and Early Warning (D_1)	2	2	2
Disaster Preparedness (D_2)	4	4	4
Disaster Response (D_3)	3	3	3
Disaster Recovery and Mitigation (D_4)	1	1	1

From Table 11, we can easily see that the ranking of the alternatives remains unchanged across three MCDM-based ranking methodologies. This implies that the ranking of the alternatives for evaluating different challenges in remote sensing across all phases of disaster management is optimal compared to the different methods. Therefore, Disaster Recovery and Mitigation (D_4) is the most preferred alternative and the remaining are present in the table. A comparative ranking analysis of the alternatives using different methods is graphically shown in Figure 5.

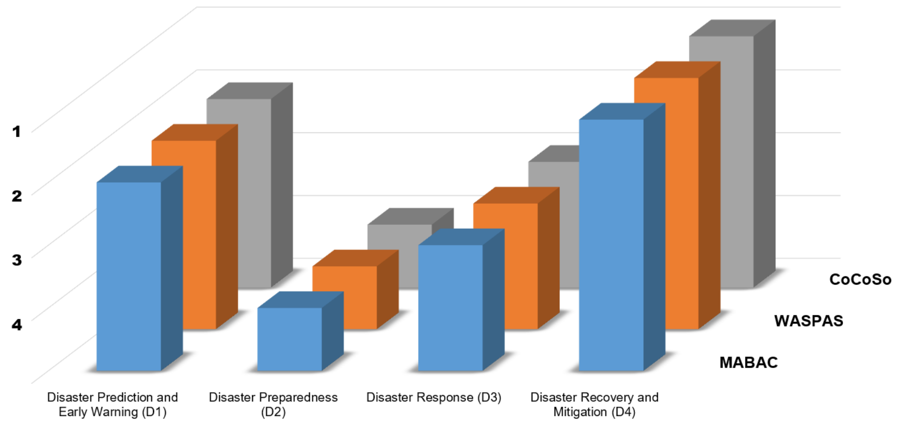

Figure 5. Comparative ranking of the alternatives by three multi-criteria decision making (MCDM) methods

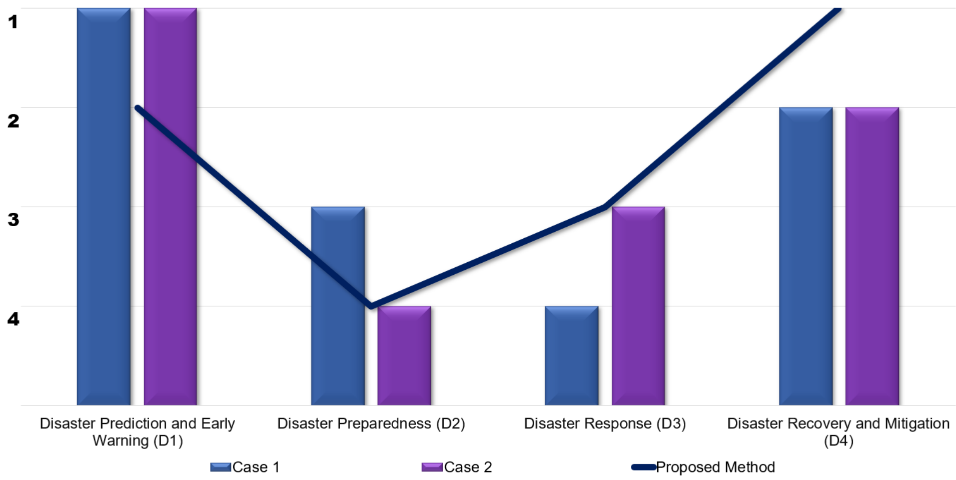

Figure 6. Sensitivity analysis on two cases and compare with the proposed model

9.2 Sensitivity Analysis

Sensitivity analysis was conducted based on two scenarios to assess the stability and flexibility of the results. Two scenarios are:

Case 1. Remove the criteria High Cost of Data and Technology (C_3):

Since the criteria High Cost of Data and Technology (C_3) may be less important in some situations and less weighted criteria, we remove the criteria and evaluate the results based on the modified model. The results are presented in Table 12.

Case 2. Remove the criteria Lack of Technical Expertise and Infrastructure (C_4):

The technical expertise and infrastructure may increase; therefore, the criteria Lack of Technical Expertise and Infrastructure (C_4) we removed in the modified model. It's also the 2nd least weighted criterion. The ranking of the alternatives based on the new model is shown in Table 12.

Table 12 presents the sensitivity analysis for two cases and the proposed model. From the evaluated results, Disaster Prediction and Early Warning (D_1) becomes the most prioritized alternative, as in the proposed model, Disaster Recovery and Mitigation (D_4) is in the optimal position. The remaining rankings are shown in the above table and graphically picturised with the proposed model in Figure 6.

Table 12. Sensitivity analysis based on two different cases

Alternative	Case 1	Case 2	Proposed Method
Disaster Prediction and Early Warning (D_1)	1	1	2
Disaster Preparedness (D_2)	3	4	4
Disaster Response (D_3)	4	3	3
Disaster Recovery and Mitigation (D_4)	2	2	1

10 Research Implication

Remote sensing primarily faces challenges such as limited spatial and temporal resolution and delays in data availability due to cloud cover. This helps to limit timely hazard detection. Furthermore, sensor variability, accuracy issues, and difficulty in integrating multi-source information reduce reliability at the disaster stage. Furthermore, high cost and the requirement of technical expertise hinder its effective use. Therefore, the difficulties in using remote sensing to effectively deal with disasters at each specific stage have significant research implications in various fields, such as:

1. Advanced hazard mapping and risk assessment as needed: High-resolution, multi-temporal satellite and sky imagery creates more accurate exposure and enables vulnerability maps to improve pre-incident risk modelling and planning.

2. Evidence-based rapid emergency response: The flood of near-real-time optical and Synthetic Aperture Radar data after a natural disaster helps in rapid mapping of the extent of damage. This, in turn, allows for prioritization of rescue, which is crucial for resource allocation.

3. Improved monitoring during reconstruction and recovery: Longitudinal remote sensing records help researchers measure the trajectory of damage recovery. Additionally, remote sensing reconstruction results can be used to identify secondary hazards, such as erosion and vegetation loss.

4. AI, fusion, and near-real-time analytics are catalysts for new approaches: The connection of remote sensing with machine learning, data fusion (where, multi-sensor, in-situ and GIS) and cloud processing makes the research methodology more automated, leading to scalable disaster analysis.

5. In terms of validity, quality and reproducibility requirements: Remote-sensing results need to be credible in the context of high-level decisions. In that case, a robust research campaign is needed to standardize benchmarking data, validation protocols, and reproducibility.

6. Research implications for policy and decision-support phenomena: Translational research is urgently needed to transform remote sensing outputs into actionable decisions, increasing communication during times of uncertainty, efficient workflows, and increasing local capacity.

11 Conclusions and Future Research Scope

Despite its great potential, remote sensing still faces obstacles such as resolution limitations, data latency, and environmental constraints, which somewhat reduce its effectiveness in disaster management. In addition, integration challenges and sensor inaccuracies make reliable multi-source analysis at all stages very difficult. Additional costs, infrastructure, and technological capability gaps greatly limit its operational use. Therefore, in times of widespread disasters, it is imperative to address these obstacles to fully utilize remote sensing as a timely, accurate, and effective tool for management. The challenges of remote sensing, which plays a crucial role in all stages of disaster management, are complex, as they involve many conflicting criteria.

In our problem, we want to find the most important criteria and determine an accurate ranking of different disaster mitigation options. For this, we considered 4 criteria and their corresponding 4 alternatives. Here, two MCDM methodologies, namely MEREC and MABAC, are used. Applying the MEREC approach, we have obtained the criteria weight. After that, the MABAC method is used to rank the considered alternatives, which are alternative mechanisms for various disaster mitigation. In this problem, we have also developed a new de-fuzzification of BTFN, which is given in Eq. (13). After numerical calculations, we have obtained the result that "Limited Real-Time Data Availability (C_2)" is the most weighted criteria and "High Cost of Data and Technology (C_3)" is the least weighted criteria. Besides this, "Disaster Recovery and Mitigation (D_4)" got the first rank among all alternatives. Moreover, in the comparative and sensitivity analysis, "Disaster Recovery and Mitigation (D_4)" and "Disaster Prediction and Early Warning (D_1)" rank first in this research work.

There are some limitations or constraints of this study which help to expand this work in future research. The scope of possible future research is discussed below, i.e.:

1. We select four criteria with four alternative types to process this problem. We may consider many other criteria and alternatives in future.

2. More disaster mitigation processes and important criteria can be adopted for future analysis. We may expand our overall dataset to ensure exact results.

3. Many other MCDM techniques can be used to determine criterion weights and rank alternatives.

4. Various fuzzy numbers, such as triangular, trapezoidal, pentagonal, hexagonal, heptagonal, intuitionistic, etc., can be considered to reflect the ambiguity of data collection. Furthermore, various de-fuzzification processes can also be considered to obfuscate the considered fuzzy numbers.

5. For comparative and sensitivity analysis of the proposed model, more cases may be taken in future studies.

Author Contributions

Conceptualization, K.H.G., A.B., and S.P.M.; methodology, A.B., S.P.M., and A.G.; software, K.H.G., and A.B.; validation, K.H.G., S.P.M., and A.G.; formal analysis, K.H.G., A.B., and A.G.; investigation, K.H.G., S.P.M., and A.G.; resources, S.P.M. and A.G.; data curation, K.H.G., A.B., and S.P.M.; writing—original draft preparation, K.H.G. and A.B.; writing—revew and editing, A.B., S.P.M., and A.G.; visualization, K.H.G., S.P.M., and A.G.; supervision, S.P.M. and A.G.; project administration, K.H.G., A.B., and S.P.M. All authors have read and agreed to the published version of the manuscript.

Informed Consent Statement

Ethical approval was not required for this study as it involved the use of publicly available data and did not involve any human or animal participants directly.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

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Conflicts of Interest

The authors declare no conflicts of interest.

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