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Single-Valued Neutrosophic MCDM Approaches Integrated with MEREC and RAM for the Selection of UAVs in Forest Fire Detection and Management

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Abstract: In recent times, the world has experienced a rise in the frequency of forest fires. These fires cause severe economic damage and pose a significant threat to human lives. Therefore, it is essential to search for solutions that can help combat fires and detect them early. Once a fire reaches a certain level, it becomes challenging to control it. Various systems have been proposed to collect data and detect forest fires, such as satellites and other traditional methods. However, these solutions have been ineffective in terms of cost, coverage of large areas, accuracy, and the safety of human lives. To address these limitations, Unmanned Aerial Vehicles (UAVs) or drones have been used for detecting, combatting, and early warning of forest fires. UAVs are one of the modern technologies that have achieved great progress in monitoring natural disasters and have been widely used in monitoring, detecting, and predicting fires. They can fly without a human pilot on board, which makes them ideal for preserving human life. In addition, they are equipped with firefighting tools and various tools for remote sensing. This is to take high-quality photos or videos of the area to be detected. Different types of UAVs are used to fight fires, and here decision-makers face a problem in choosing between these types. Therefore, this research proposes a new MCDM model integrated with neutrosophic sets for selecting the optimal UAV to combat forest fires; therefore it helps in effectively detecting and fighting the fire. The proposed model integrates a Method based on Removal Effects of Criteria (MEREC) and Root Assessment Method (RAM) with the context of neutrosophic sets that effectively deal with ambiguity for selecting the optimal UAV which use in the detection and combat forest fires.

Keywords: Forest Fires, MCDM Methods, Root Assessment Method, RAM, MEREC, UAVs, Neutrosophic Set.

1. Introduction

Climate change, environmental disturbances, and human activities have led to many forest fires, which cause significant damage and threaten public safety and human lives [1]. It has now become necessary to manage forest fires, which means a set of measures and policies taken to prevent forest fires, detect them early, predict their occurrence, monitor them, and reduce their harmful effects. Therefore, decision-makers face the challenge of finding the best ways to manage forest fires and protect the environment from them, including early detection and gathering information about their effects. There are traditional methods for monitoring and detecting forest fires, which include, satellite imagery, smoke detectors, and human observers [2]. Authors in [3] used satellite thermal images to report fire risks. To monitor forest fires, the author in [4] used wireless sensor networks. However, there are several issues associated with the current methods of detecting and responding to fires. Firstly, these methods can be quite costly. Secondly, they rely heavily on human intervention, which puts the lives of firefighters at risk. Thirdly, the process of detecting fires can be slow, and the response process can be even slower, especially when it takes time for the firefighting team to arrive at the site of the fire after it has already broken out, and inaccuracy, as satellite images have limited accuracy this is due to noise or the distance.

Recently, there has been a great development in finding more effective methods in fire management, as UAVs have been used as a powerful tool for managing fires, fighting them, tracking them, and predicting their occurrence through the information collected from them [5-7]. The roots of UAVs go back to military applications, and with technological development, they used in many applications such as water management [8, 9], agriculture [10, 11], livestock management [12], and many more applications due to their advantages, ease of deployment, wind resistance, ability to fly long distances and a long time, in addition to its low cost. By utilizing UAVs, it is possible to gather information about the density of smoke, which can help in determining the size and location of a fire. UAVs can be equipped with various tools such as firefighting equipment, thermal cameras, and remote sensors, which make them powerful and effective tools in managing forest fires. With the help of UAVs, it becomes easier to identify the areas that require immediate intervention to prevent the spread of fire.

Authors in [13] studied the benefits of using UAVs in forest fire management as well as the limitations they face. They have proven that fire detection via the Internet of Things networks supported by UAVs is better than using satellite imaging, as discrete-time Markov chain analysis was used to calculate the probability of both early detection of forest fires, where, the UAVs collect both images and signals from sensors to verify whether the fire alarm is false or not. Based on these signals, the UAVs take one of two actions: either resume the normal search process in the case of a "false alarm" or send signals to a firefighting station if there are fires [14]. The use of UAVs equipped with a global positioning system (GPS) that indicates the location of the fire and high-quality cameras that capture accurate images using deep learning capability helps detect and monitor fires better than satellites [15]. A group of UAVs were utilized as a swarm, flying together to search for fires and work together to extinguish them using information collected from the thermal sensors equipped with the UAVs [16]. Multiple UAVs hover around the fire area and send a confirmation signal to the firefighting UAV team, then determine the fire locations and assign a UAV to each spot to overcome the fire [17]. Since UAVs are powerful and effective tools in the process of managing forest fires, many types of UAVs are used in fire management. Hence, decision-makers face a problem in choosing the optimal alternative among the available alternatives with different standards, and therefore an effective methodology is needed to choose the optimal alternative to a specific situation. In this research, the problem was presented as a multi-criteria decision-making problem. The multiple criteria decision-making (MCDM) is a method for analyzing the range of options in a scenario or field of study that includes the social sciences, engineering, medicine, daily living, and many other fields. It has been used in fire detection operations, where, the FSB system is proposed to predict and detect fires using information extracted from sensors that are sent to the fire department through a specific sink and an MCDM controller in a fuzzy environment to help decision-makers determine the number of sinks to use [18]. The fuzzy-VIKOR method was used to create maps that identify fire-prone areas to prevent them and mitigate their effects using multi-criteria decision-making analysis of geographic information systems to make informed decisions and determine effective policies for dealing with and preventing fire [19]. MCDM methods were also used in fire management to evaluate the professional strategies for dealing with firefighters to reduce professional stress. AHP (analytical hierarchy process) and DM (Delphi method) methods were used in a fuzzy environment [20]. The authors used MCDM methods to determine the important criteria for fire management and gave relative weights to each criterion. TOPSIS and SAW methods were applied to choose the best five criteria for successful fire management [21]. They proposed a MCDM model using AHP, ANP, and DEMATEL methods in the context of a fuzzy environment to choose the best three UAVs for combating fires in tall buildings [22]. Also, authors in [23] proposed a hybrid LNN, OS, and MABAC model to choose unmanned aircraft for combating forest fires [23].

Previous studies have demonstrated the importance of multi-criteria decision-making (MCDM) technology in making decisive and knowledgeable decisions. In light of this, we introduce a new MCDM model integrated with the neutrosophic set that effectively deals with ambiguity in the decision-making process to evaluate and choose the best UAV for fire management.

1.1 Research Contribution

Appling new MCDM technique to select the optimal UAV for controlling the forest fire:

i. Appling the MEREC (Method based on Removal Effects of Criteria) method to determine the weight of criteria related to UAVs used for detecting and breaking out forest fire, integrated with the neutrosophic set that deals with the concept of truth, falsity, and indeterminacy (T, I, and F) to solve the ambiguous information that commonly arises in the decision-making.

ii. Applying the RAM (Root Assessment Method) method to rank the UAVs (alternatives) to select the optimal one for a specific situation, the RAM method is characterized by being easy in the computation process, as it relies on the aggregation function and does not use the pairwise comparison method, unlike other MCDM methods.

iii. Also, we applied the MABAC and MARICA methods to the same selection problem, the rank results obtained by these MCDM and RAM methods are the same but the RAM method is the easiest of them all.

2. Methodology

We propose an integrated MEREC- RAM method with the context of single-valued neutrosophic sets to evaluate the efficiency of UAVs in fire forest management and select the optimal one for a specific scenario. We utilize the MEREC method to generate the weight of the evaluation criteria and the RAM method to rank the UAVs to select the best one. The framework of our model consists of three phases as shown in Figure 1, as the following:

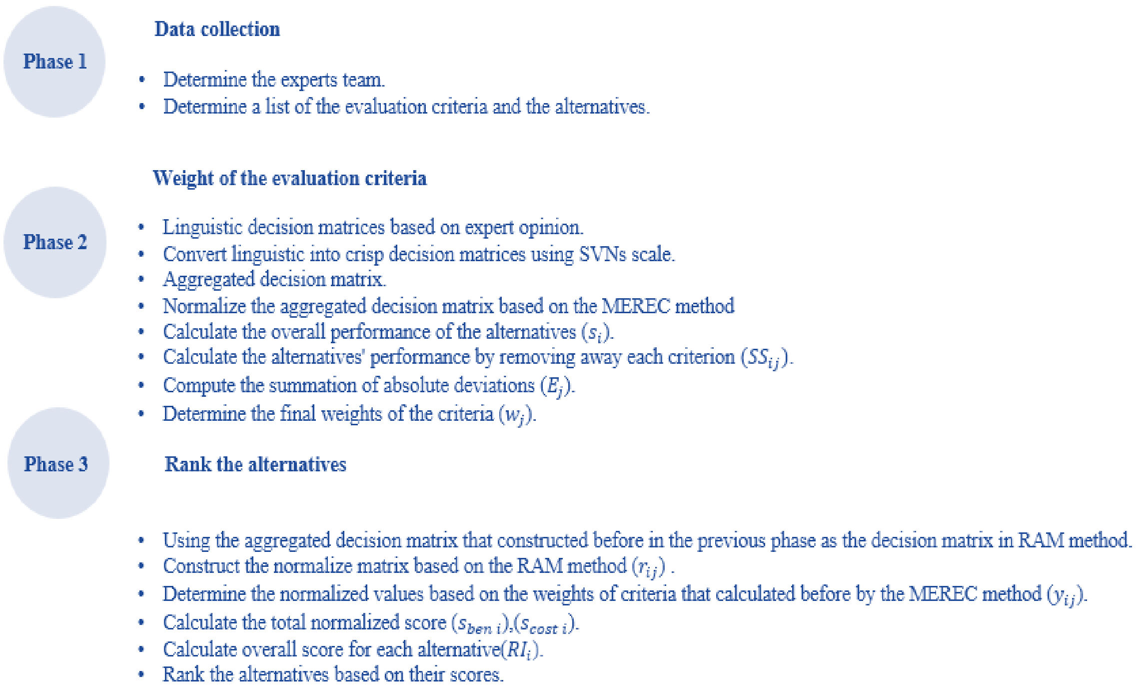


Figure 1. The framework of our methodology.

Phase 1: Data collection.

Step 1: Determine the expert's team according to the problem area. The members of the expert team have a high level of knowledge and experience in the field of firefighting and UAV engineering.

Step2: Determine the list of alternatives and evaluation criteria based on the experts' opinion, which $C = \{C1, C2 \dots \dots Cn\}$ represents the evaluation criteria, and $A = \{A1, A2, \dots . Am\}$ are the alternatives representing the UAVs firefighter type.

Phase 2: Weight of the evaluation criteria.

Step 3: Determine the decision matrix.

Step 3.1: Decisions are often characterized by linguistic ambiguity and uncertainty, and even with linguistic variables, they are insufficient to resolve the ambiguity. Therefore, we use the neutrosophic set that can effectively deal with uncertainty in decision-making and ambiguity. To convert the linguistic scale to an equivalent numerical scale, we use the SVNs scale as shown in Table 1. Experts first construct the linguistic decision matrix using terms that have the properties of truth, indeterminacy, and falsity, collectively referred to as SVNS. Then, they transform the linguistic decision matrix into a decision matrix with clear values using the scoring function represented in Eq. (1) [24].

$$Score\ Function = \frac{2+(Tr-F-Id)}{3} \tag{1}$$

Where$Tr, F,\ Id$ refers to truth, false, and indeterminacy respectively.

Step 3.2: Aggregate all matrices into one aggregated matrix by utilizing Eq. (2) as the following:

$$Y_{ij} = \frac{\sum_{j=1}^{N} q_{ij}}{N} \tag{2}$$

Where q_{ij} represents the value of the criterion in the matrix, and N represents the number of experts.

Step 4: Calculate the normalized decision matrix (N) based on the MEREC method. We need to scale the elements of the decision matrix using a simple linear normalization. The normalized matrix elements are denoted by n_{ij}^{x}, (N) calculated as the following:

$$n_{ij}^{x} = \begin{cases} \frac{\min x_{kj}}{x_{ij}} & if\ j \in benefit \\ \frac{x_{ij}}{\max x_{kj}} & if\ j \in cost \end{cases} \tag{3}$$

Step 5: Utilize the MEREC method (Method based on Removal Effects of Criteria) to calculate the weight of criteria [25]:

Step 5.1: Calculate the overall performance of the alternatives (s_i). In this stage, we evaluate the overall performance of various alternatives by using a logarithmic metric with equal weights for different criteria. This metric is calculated using a non-linear function, which takes into account the normalized value obtained from the previous phase. Note that, Lower values of n_{ij}^{x} will result in higher performance values (s_i).). The equation used to calculate this measure is as follows:

$$s_i = \ln(1 + (\frac{1}{m} \sum_j \left|\ln\left(n_{ij}^{x}\right)\right|)) \tag{4}$$

Step 5.2: Calculate the alternatives' performance by removing away each criterion. The process of using a logarithmic measure is similar to the previous step. However, in this step, we determine the performance of each alternative by eliminating each criterion independently. This means that there are m sets of performances connected to m criteria. To indicate how well the ith alternative performed overall in terms of eliminating the jth criterion, we use the notation SS_{ij} (overall performance of ith alternative concerning the removal of jth criterion). The calculations for this step are done using the following Eq. (5):

$$ss_{ij} = \ln(1 + (\frac{1}{m} \sum_{k,k \neq j} \left|\ln\left(n_{ij}^{x}\right)\right|)) \tag{5}$$

Step 5.3: Compute the summation of absolute deviations. The elimination effect of the jth criterion is determined using the values from Steps 5.1 and 5.2. Let E_j be the result of eliminating the jth condition. The values of E_j can be calculated using the following formula.

$$E_j = \sum_i \left|ss_{ij} - s_i\right| \tag{6}$$

Step 5.4: Determine the final weights of the criteria.

In this phase, the weight of each criterion is determined objectively by using the removal effects (E_j) from the previous step. The weight of the jth criteria is represented as w_j. The formula used to calculate w_j is as follows:

$$w_j = \frac{E_j}{\sum_k E_k} \tag{7}$$

Phase 3: Rank the alternatives.

Step 6: Utilize the RAM method to rank the alternatives, The RAM method aggregates option scores across decision criteria to determine each option's utility value. The overall ranking is then determined based on these utility values. It included the following steps [26] :

Step 6.1: Construct a decision matrix with m rows and n columns, where rows represent the number of alternatives $A_i = \{A1, A2, \dots . Am\}$ and columns represented the evaluation criteria for each alternative $C_j = \{C1, C2 \dots \dots Cn\}$. The criteria are divided into benefit criteria, preferable to obtain higher values, and cost criteria, preferable to obtain lower values. The decision matrix for m alternatives and n criteria is constructed as the following:

$$X = \begin{bmatrix} x_{01} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad where\ i = 0{:}\,m\,, j = 1{:}\,n \tag{8}$$

Step 6.2: Construct the normalized matrix based on the RAM method as the following:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{9}$$

Where, x_{ij} represent the value of criterion j for alternative$i$, where $= 1 \div n\ and\ i = 1 \div m$.

Step 6.3: Determine the normalized values based on the weights of criteria that were calculated before by the MEREC method, as the following:

$$y_{ij} = w_j . r_{ij} \tag{10}$$

Step 6.4: Calculate the total normalized score, taking into account the criteria weights, as the following:

$$s_{ben\ i} = \sum_{j=1}^{n} y_{ben\ ij}\ \ , if\ j\ \in benefit \tag{11}$$

$$s_{cost\ i} = \sum_{j=1}^{n} y_{cost\ ij}\ \ , if\ j\ \in cost \tag{12}$$

Step 6.5: Calculate the overall score for each alternative, as the following:

$$RI_i = \sqrt[2+s_{cost\ i}]{2 + s_{ben\ i}} \tag{13}$$

Step 6.6: Rank the alternatives based on their scores, the optimal alternative has a higherRI_i.

Table 1. Scale of single-valued neutrosophic scale (SVNs) [27].

Linguistic Variables	Abbreviation	True	Indeterminacy	False
Extremely Bad	EB	0.00	1.00	1.0
Very Very Bad	VVB	0.10	0.90	0.90
Very Bad	VB	0.20	0.85	0.80
Bad	B	0.30	0.75	0.70
Medium Bad	MB	0.40	0.65	0.60
Medium	M	0.50	0.50	0.50
Medium Good	MG	0.60	0.35	0.40
Good	G	0.70	0.25	0.30
Very Good	VG	0.80	0.15	0.20
Very Very Good	VVG	0.90	0.10	0.10
Extremely Good	EG	1.00	0.00	0.00

3. Case Study

Our experiment study is to evaluate our proposed model for selecting the optimal UAV for the management of forest fires especially in California wildfires. There is a series of forest fires that occur frequently in the state of California, which usually occur in August and November when the winds are hot and dry. In 2017, California witnessed multiple forest fires that destroyed approximately 1,331,014 acres and caused economic losses amounting to 180 billion. In 2020, approximately 78,823 acres were burned and destroyed, and in 2023, massive forest fires occurred that reached 3,237 kilometers, their smoke obscured the sun's rays, and smoke fog covered the views of the mountains surrounding the city and its suburbs. Therefore, there is a need for an effective method to overcome the burning of California's forests in light of dangers such as blazing fires, foggy visibility, hot winds, and the covering of vast expanses of forest. Therefore, using UAVs to combat California wildfires is an effective solution and our methodology was applied to select the appropriate UAV for those conditions.

Phase1: Data Collection:

Step 1: In our model, the expert team consists of four highly experts in different specializations in the field of firefighting and UAV engineering, as shown in Table 2.

Step 2: There are five UAVs (alternatives) that are denoted as $A = \{A_1, A_2, A_3, A_4, A_5\}$, each with specific criteria $C = \{C1, C2, C3, C4, C5, C6, C7\}$ as shown in Tables 3 & 4 respectively.

Table 2. Experts definition.

Experts	The description
Expert 1	PhD degree in the aeronautical engineering field.
Expert 2	PhD degree in Fire and safety engineering field.
Expert 3	PhD degree in Fire science field.
Expert 4	PhD degree in machine learning engineering field.

Table 3. UAVs alternatives for forest fire management.

Alternatives	Description
$A1$	(Mavic Enterprise 3T Series): This thermal version is designed to meet the unique needs of aerial operations for firefighting, search and rescue, inspections, and night missions. To help professionals locate critical points and make quick choices, the Mavic 3T's thermal camera provides point and area temperature measurements, high-temperature alarms, color palettes, and isotherms. With simultaneous split-screen zoom, the Mavic 3T's thermal and zoom cameras support 28× continuous side-by-side zoom for easy comparisons
$A2$	(CXFIRE- drone-Throwing Type): this type uses a powerful and efficient power system and firefighting which carries 12 ultra-precise powder fire extinguishing bombs and a projectile throwing system. The deployment time of the system is less than 30 seconds, the wind resistance is up to 12 m/s, and the operating radius is up to 6 km. The machine is flexible and can effectively suppress the fire situation on the spot and open up rescue channels for firefighters.
$A3$	(CXFIRE-drone powder Fire Extinguishing Drone): this type is used for Petroleum and petrochemical sites, urban high-rise buildings, forest fields, and other emergency rescue and fire-fighting situations, It can carry 200W pixels, a 1080P high-definition camera, 1W power green laser aiming device, and digital wireless broadband image transmission system, that can conduct thorough on-site reconnaissance, Window braking function, which distance of 10 meters, capable of breaking 10mm+10mm to extinguish the fire, in addition to can carry rescue materials with an effective weight of ≥20kg. Flying height is 300m climb for 30 sec.
$A4$	(Matrice 300 RTK + Zenmuse H20T): this type is suitable for fire prevention, which Offers up to 55 minutes of flight time, and advanced AI. A leading combination of smart features, high performance, and reliability. Its triple H20T payload combines an RGB camera with a 640x512p thermal sensor and laser rangefinder, which allows operators to see what the human eye cannot due to high thermal sensitivity and 30 fps video definition.
$A5$	(CXFIRE- Water Mist Fire Fighting Drone): A drone with a high-level water spray that extinguishes fires using water-based solvents and flame retardants, in addition to the surface of the aircraft being insulated to ensure the safety of the drone at high temperatures. Effective loading of 40 kg, single sortie fire extinguishing 100 m3, it can climb 300 meters in 30 seconds and complete a sortie firefighting task in 3 minutes. Flying height is 300m climb for 30 sec.

Table 4. The evaluation criteria of UAVs for forest fire management.

	Criteria	Type	Definition
$C1$	Payload capacity	Max	The largest capacity that UAVs can carry
$C2$	Duration of flight	Max	The ability of the UAV to fly in the air for long periods to cover large areas and monitor the fire effectively
$C3$	Data transmission speed	Max	Transfer data quickly to deliver photos, videos, and location coordinates to the firefighting team
$C4$	Sensors capabilities	Max	The UAVs are equipped with high sensors such as thermal and multi-spectral imaging cameras that capture accurate images of fire-affected areas at night or in the presence of smoke, a GPS to accurately locate fire locations and determine coordinates effectively, gas detector
$C5$	Risk	Min	such as collision, wind, exposure to damage, burning, and other risks that hinder the UAV from performing its mission
$C6$	durability	Max	the rigidity of the outer structure and the ability to avoid collisions and move through the flames of fire and smoke
$C7$	Cost	Min	The financial cost of UAVs in terms of maintenance, operation, and acquisition

Phase 2: We utilize the MEREC method integrated with single-valued neutrosophic sets to calculate the weight of the evaluation criteria.

Step 3.1: Initially, the linguistic decision matrices are constructed by the expert team, which represent the expert assessments of the criteria, as shown in Tables 5, 6, 7, and 8. We use the SVNs scale in Table 1 by utilizing Eq. (1) to convert the linguistic decision matrices into crisp decision matrices to solve the uncertainty and ambiguity in the linguistic variables, as shown in Tables 9, 10, 11, and 12.

Step 3.2: All crisp decision matrices are collected into one matrix called aggregated decision matrix by utilizing the arithmetic mean in Eq. (2), as shown in Table 13.

Step 4: Each element in the aggregated decision matrix needs to be scaled whether it is benefit or cost to construct the normalized decision matrix based on the MEREC method by utilizing Eq. (3), as shown in Table 14.

Step5.1 and *5.2:* We calculate the overall performance of the alternatives s_i based on the logarithmic metric in Eq. (4), we calculate the performance of each alternative SSi by removing each criterion independently utilizing Eq. (5), as shown in Table 15.

Step5.3 and *5.4:* We calculate the sum of absolute deviation E_j by utilizing Eq. (6) depending on the result of Table 15, after calculating the final weight of each evaluation criteria by using the removal effect E_j by utilizing Eq. (7), as shown in Table 16. Figure 2 shows that the risk criteria $C5$ is the highest priority with a weight equal to 0.38438462, and the next most important criterion is sensors capabilities $C4$ with a weight equal to 0.17259869. The order of criteria in terms of importance is as follows: $C5 > C4 > C2 > C3 > C6 > C1 > C7$.

Reducing the risks to which the UAV is exposed, such as collision, wind, exposure to damage, burning, and other risks that hinder the UAV from performing its mission promptly is the highest priority, next priority is the Sensors' capabilities where, the UAVs are equipped with high sensors as, thermal and multi-spectral imaging cameras that capture accurate images of fire-affected areas at night or in the presence of smoke, GPS to accurately locate fire locations and determine coordinates effectively, gas detector all of these to performing its mission efficiently.

Phase 3: We utilize the RAM method to rank the alternatives:

Step 6.1: We use the aggregated matrix in Table 13 as the decision matrix for the RAM method based on the formula in Eq. (8).

Step 6.2: We construct the normalized decision matrix by utilizing Eq. (9), as shown in Table 17.

Step 6.3: We determine the weight of the normalized decision matrix y_{ij} using the weight of the criteria that we calculated before with the MEREC method in Table 16 by utilizing Eq. (10), as shown in Table 18.

Steps 6.4 and *6.5:* We calculate the total of weighted normalized scores for all alternatives by utilizing Eq. (11) for benefit criteria $s_{ben\ i}$ and Eq. (12) for cost criteria $s_{cost\ i}$, to clarify: Taking the data considered in Table 18, $s_{ben\ i}$ & $s_{cost\ i}$ of alternative $A1$ can be calculated as follows:

$$S_{ben\ 1} = y_{11} + y_{12} + y_{13} + y_{14} + y_{16}, \qquad S_{cost\ 1} = y_{15} + y_{17}$$

After the total weighted normalized score is calculated, we utilize Eq. (13) to calculate the overall score for each alternative RI_i, as shown in Table 19.

Step 6.6: According to the overall score RI_i, the alternatives will rank, and the optimal alternative has a higher RI_i, as shown in Figure 3, alternative $A3$ is the optimal alternative, immediately followed by $A5$, as the A3 is excellent concerning benefit criteria and cost criteria. Also, based on RI_i the second choice $A5$ is very close to the first choice $A3$. Therefore, $A3$ and $A5$ should be ranked high.

We also applied the MABAC and MARICA methods to the same selection problem, the rank results obtained by these MCDM and RAM methods are compared in Table 20. As is shown in Figure 4 the priority of alternatives using various MCDM techniques shows that A3 is considered the optimal alternative using all methods.

Table 5. The linguistic decision matrix by Expert 1.

Alternatives	C1	C2	C3	C4	C5	C6	C7
	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
***A*1**	EG	M	EG	MG	MB	VVG	MG
***A*2**	VVG	MG	VG	G	MB	G	G
***A*3**	VG	G	G	MG	MB	MG	G
***A*4**	EG	MG	VG	G	VB	G	G
***A*5**	VG	M	VG	MG	VB	MG	G

Table 6. The linguistic decision matrix by Expert 2.

Alternatives	C1	C2	C3	C4	C5	C6	C7
	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
***A*1**	VVG	G	VVG	G	MB	VG	MG
***A*2**	VG	MG	VG	G	B	G	G
***A*3**	EG	MG	VVG	G	VB	VG	VG
***A*4**	VVG	M	G	M	VVB	M	G
***A*5**	EG	M	VG	M	B	G	MG

Table 7. The linguistic decision matrix by Expert 3.

Alternatives	C1	C2	C3	C4	C5	C6	C7
	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
***A*1**	EG	MG	VVG	G	MB	VG	MG
***A*2**	VVG	M	VG	M	B	G	G
***A*3**	VVG	G	VVG	G	VB	VG	VG
***A*4**	VG	M	G	MB	B	MG	G
***A*5**	G	M	G	MB	VB	MG	MG

Table 8. The linguistic decision matrix by Expert 4.

Alternatives	C1	C2	C3	C4	C5	C6	C7
	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
A1	VVG	G	VG	G	M	G	G
A2	EG	M	VVG	VG	VB	VG	G
A3	VG	MG	G	MG	B	MG	MG
A4	VVG	M	VG	MG	VB	G	MG
A5	G	M	M	M	B	G	G

Table 9. The crisp decision matrix by Expert 1.

Alternatives	C1	C2	C3	C4	C5	C6	C7
	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
A1	1	0.5	1	0.616667	0.38333333	0.9	0.61666667
A2	0.9	0.616667	0.816667	0.716667	0.38333333	0.716667	0.71666667
A3	0.816667	0.716667	0.716667	0.616667	0.38333333	0.616667	0.71666667
A4	1	0.616667	0.816667	0.716667	0.18333333	0.716667	0.71666667
A5	0.816667	0.5	0.816667	0.616667	0.18333333	0.616667	0.71666667

Table 10. The crisp decision matrix by Expert 2.

Alternatives	C1	C2	C3	C4	C5	C6	C7
	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
A1	0.9	0.716667	0.9	0.716667	0.383333	0.816667	0.616667
A2	0.816667	0.616667	0.816667	0.716667	0.283333	0.716667	0.716667
A3	1	0.616667	0.9	0.716667	0.183333	0.816667	0.816667
A4	0.9	0.5	0.716667	0.5	0.1	0.5	0.716667
A5	1	0.5	0.816667	0.5	0.283333	0.716667	0.616667

Table 11. The crisp decision matrix by Expert 3.

Alternatives	C1	C2	C3	C4	C5	C6	C7
	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
A1	1	0.616667	0.9	0.716667	0.383333	0.816667	0.61666667
A2	0.9	0.5	0.816667	0.5	0.283333	0.716667	0.71666667
A3	0.9	0.716667	0.9	0.716667	0.183333	0.816667	0.81666667
A4	0.816667	0.5	0.716667	0.383333	0.283333	0.616667	0.71666667
A5	0.716667	0.5	0.716667	0.383333	0.183333	0.616667	0.61666667

Table 12. The crisp decision matrix by Expert 4.

Alternatives	C1	C2	C3	C4	C5	C6	C7
	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
A1	0.95	0.6375	0.904167	0.691667	0.4125	0.8125	0.641667
A2	0.904167	0.558333	0.8375	0.6875	0.283333	0.741667	0.716667
A3	0.883333	0.666667	0.808333	0.666667	0.258333	0.716667	0.741667
A4	0.904167	0.529167	0.766667	0.554167	0.1875	0.6375	0.691667
A5	0.8125	0.5	0.7125	0.5	0.233333	0.666667	0.666667

Table 13. Aggregated decision matrix.

Alternatives	C1	C2	C3	C4	C5	C6	C7
	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
A1	0.95	0.6375	0.904167	0.691667	0.4125	0.8125	0.641667
A2	0.904167	0.558333	0.8375	0.6875	0.283333	0.741667	0.716667
A3	0.883333	0.666667	0.808333	0.666667	0.258333	0.716667	0.741667
A4	0.904167	0.529167	0.766667	0.554167	0.1875	0.6375	0.691667
A5	0.8125	0.5	0.7125	0.5	0.233333	0.666667	0.666667

Table 14. Normalized decision matrix based on the MERE method.

Alternatives	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$
	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
A1	0.85526316	0.78431373	0.78801814	0.72289122	1	0.78461538	0.8651686
A2	0.89861718	0.89552292	0.85074627	0.72727273	0.68686788	0.85955018	0.9662921
A3	0.91981167	0.74999963	0.88144366	0.74999963	0.62626182	0.88953447	1
A4	0.89861718	0.94488129	0.92934742	0.9022551	0.45454545	1	0.9325843
A5	1	1	1	1	0.56565576	0.95624952	0.8988764

Table 15. The performance of each alternative.

Alternatives	Si	SSi						
		C1	C2	C3	C4	C5	C6	C7
		Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
A1	0.176281	0.15737845	0.14675227	0.14733337	0.13664142	0.17628138	0.14679971	0.15878294
A2	0.165344	0.15231524	0.15189201	0.14557703	0.12602018	0.11879533	0.14684772	0.16118305
A3	0.178766	0.16872998	0.14379193	0.16357494	0.14379193	0.12123139	0.16468267	0.17876637
A4	0.157977	0.14485203	0.1510375	0.1489993	0.14535124	0.05685558	0.15797737	0.14942715
A5	0.098049	0.09804872	0.09804872	0.09804872	0.09804872	0.02139045	0.09223784	0.08414496

Table 16. The calculation of the weight of the evaluation criteria.

Alternatives	$\lvert ss_{ij} - s_i \rvert$						
	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$
	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
A1	0.01890293	0.02952911	0.02894802	0.03963996	0	0.02948168	0.01749844
A2	0.01302838	0.01345161	0.01976659	0.03932344	0.04654829	0.0184959	0.00416057
A3	0.01003639	0.03497444	0.01519143	0.03497444	0.05753498	0.0140837	0
A4	0.01312534	0.00693987	0.00897807	0.01262613	0.10112179	0	0.00855022
A5	0	0	0	0	0.07665827	0.00581088	0.01390376
E_j	0.05509304	0.08489503	0.07288411	0.12656397	0.28186333	0.06787216	0.04411299
w_j	0.07513186	0.11577364	0.09939403	0.17259869	0.38438462	0.09255909	0.06015807

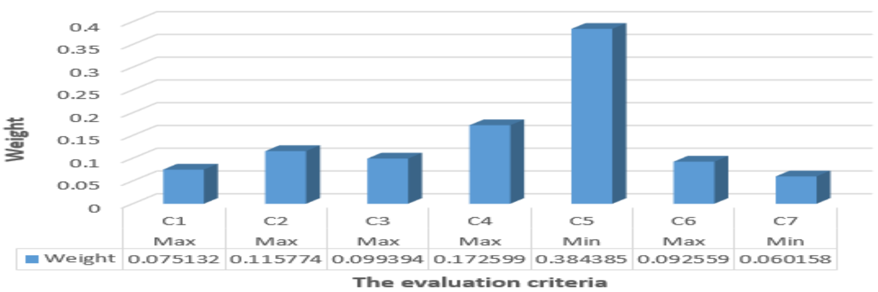


Figure 2. The Final weight of the evaluation criteria.

Table 17. The normalized decision matrix is based on the RAM method.

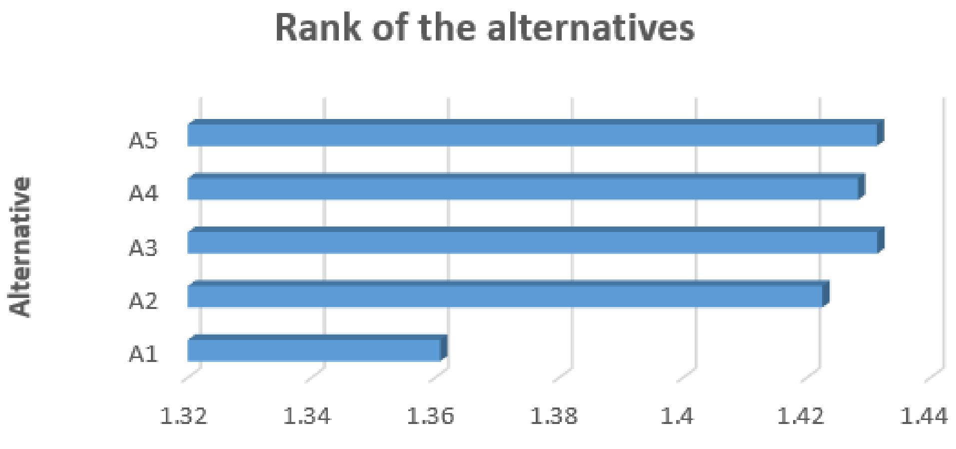
Alternatives	C1	C2	C3	C4	C5	C6	C7
	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
***A*1**	0.21328343	0.22046107	0.22440544	0.22311832	0.30000022	0.22727266	0.18554218
***A*2**	0.20299351	0.19308344	0.20785934	0.22177412	0.20606051	0.20745924	0.20722891
***A*3**	0.19831609	0.23054764	0.20062038	0.2150538	0.18787868	0.20046624	0.21445782
***A*4**	0.20299351	0.18299721	0.19027928	0.17876349	0.13636374	0.17832163	0.2
***A*5**	0.18241346	0.17291064	0.17683556	0.16129027	0.16969685	0.18648023	0.19277109

Table 18. Weighted normalized decision matrix based on RAM method.

Alternatives	C1	C2	C3	C4	C5	C6	C7
	Benefit	Benefit	Benefit	Benefit	Cost	Benefit	Cost
Weight	0.07513186	0.11577364	0.09939403	0.17259869	0.38438462	0.09255909	0.06015807
***A*1**	0.01602438	0.02552358	0.02230456	0.03850993	0.11531547	0.02103615	0.01116186
***A*2**	0.01525128	0.02235397	0.02065998	0.03827792	0.07920649	0.01920224	0.01246649
***A*3**	0.01489986	0.02669134	0.01994047	0.037118	0.07221768	0.01855497	0.01290137
***A*4**	0.01525128	0.02118625	0.01891262	0.03085434	0.05241612	0.01650529	0.01203161
***A*5**	0.01370506	0.02001849	0.0175764	0.02783849	0.06522886	0.01726044	0.01159674

Table 19. The overall score for each alternative.

Alternatives	$s_{ben\ i}$	$s_{cost\ i}$	$\sqrt[2+s_{cost\ i}]{2+s_{ben\ i}}$	Rank
***A*1**	0.1233986	0.44454269	1.360755969	5
***A*2**	0.11574539	0.12647733	1.422501865	4
***A*3**	0.11720464	0.09167298	1.431339705	1
***A*4**	0.10270979	0.08511904	1.428240667	3
***A*5**	0.09639889	0.06444774	1.431261828	2



	A1	A2	A3	A4	A5
Overall score	1.360755969	1.422501865	1.431339705	1.428240667	1.431261828

Figure 3. The rank of the alternatives is based on the RAM method.

Table 20. Ordering of alternatives using various MCDM techniques.

Priority of alternatives	RAM	MABAC	MARICA
1	$A3$	$A3$	$A3$
2	$A5$	$A2$	$A2$
3	$A4$	$A1$	$A1$
4	$A2$	$A4$	$A4$
5	$A1$	$A5$	$A5$

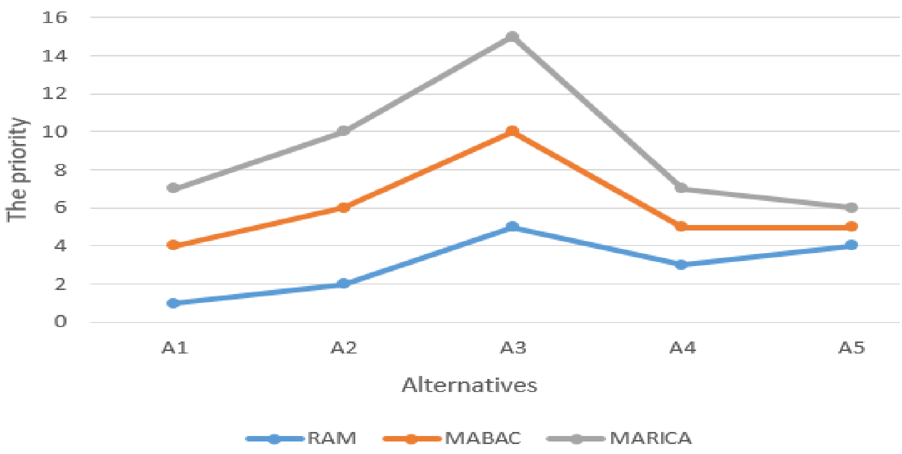


Figure 4. The priority of alternatives using various MCDM techniques.

4. Conclusion

The forests of California and others are exposed to many fires, causing huge economic and human losses. The traditional methods used to put out fires are not satisfactorily effective, and therefore UAVs have been used to manage fires effectively. Given the presence of many types of drones used to put out fires, the purpose of this study is to select the most appropriate UAV to manage forest fires effectively using MCDM methods through a neutrosophic environment to deal with ambiguity in the decision-making process, where five types of UAVs (alternatives) and seven criteria were presented for evaluation by 4 specialized experts. The MEREC method was applied to calculate the relative weights of each criterion, and then the RAM method was applied to arrange the alternatives and choose the optimal one. The RAM method is characterized by ease in the calculation process because it relies on the aggregation function and less time spent. We also applied MABAC and MARICA methods to arrange the alternatives, and all methods led to A3 (CXFIRE-drone powder Fire Extinguishing Drone) being the optimal choice for the problem proposed as it is equipped with a 1080P high-definition camera that can capture images with a resolution. It also has a 1W power green laser aiming device and a digital wireless broadband image transmission system for conducting thorough on-site reconnaissance. Additionally, it has a window braking function that can break glass up to a distance of 10 meters and a thickness of 10mm+10mm to extinguish the fire. Furthermore, this device can carry rescue materials with an effective weight of at least 20kg.

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Author Contributions

All authors contributed equally to this research.

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.

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Conflict of interest

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

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