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Inundations and Climatic Fluctuations: Prospects, Difficulties, and Recommendations

Amira Salam [1], Mai Mohamed [1], and Ibrahim M. Hezam [2,*]

[1] Faculty of Computers and Informatics, Zagazig University, Zagazig 44519, Sharqiyah, Egypt; Emails: sallam18@fci.zu.edu.eg; mmgaafar@zu.edu.eg.

[2] Statistics & Operations Research Department, College of Sciences, King Saud University, Riyadh 11451, Saudi Arabia; ialmishnanah@ksu.edu.sa.

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Abstract

At the momentarily, most of the global economic losses resulting from catastrophes are brought about by aerial floods which are expected to intensify due to climate change. Accordingly, sea level rise brought on by climate change will make coastal flooding more likely in many areas. cyclone, however, is also significantly impacted by climate change. Whilst urban flood mitigation and management are becoming more widely acknowledged as worldwide concerns. Moreover, considering catalysts for seeking methodologies for treating these natural disasters. In the era of contemporary technology, leveraging cutting-edge technologies are being utilized extensively to both monitor and reconnoiter flood-affected regions and evacuate individuals and others as crops, livestock and so on from flooded areas. Unmanned aerial vehicles (UAVs) are widely used to solve drought and flood problems through capturing thermal and multispectral images for the regions which suffer from these issues. Moreover, the recommendation for optimal UAV from alternatives of UAVs is a thorny inevitably. Thus, this study is embracing this notion and attempts to treat this issue through constructing soft recommender model for recommending the optimal UAV. The evaluation of these alternatives of UAVs are conducted based on set of influenced criteria and sub-criteria. Thus, the first step toward evaluation ptocess is modeling these criteria and sub criteria into form of tree model through utilizing Tree Soft Model (TrSM). After that, the methods of Multi-Criteria Decision Making (MCDM) as MEthod based on Removal Effects of Criteria (MEREC) is utilized for estimating criteria's weights. Then, the generalized weights are utilized in a combined compromise solution (CoCoSo) for ranking the candidates of UAVs and recommending the optimal UAV. These techniques are united with the uncertain theory of neutrosophic for treating with incomplete information.

Keywords: Climate Change; Floods; Tree Soft Model (TrSM); Method Based On Removal Effects Of Criteria (MEREC); Combined Compromise Solution (CoCoSo); Neutrosophic Theory.

1 | Introduction

Natural disasters around the world have resulted in massive financial damage. These disasters are a result of both climate change and humankind's inadequate treatment of the environment. Some natural disasters, such as droughts, floods, and water shortages, have become more frequent and pose serious problems for countries

Corresponding Author: ialmishnanah@ksu.edu.sa
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on every continent. The rise in natural disasters, especially those with meteorological and hydrological origins, is significantly impacted by the unpredictability of global climate change. Drought and water shortages are among the devastating natural disasters that have profound impacts on the natural course of life. One such impact is the effect on crops, causing a shortage of food supplies for humans. Fortunately, certain crop varieties are resistant to drought, and it is essential to identify them to reduce yield loss and maintain a balance between productivity and water usage.

Recently, UAVs have been employed to contribute to solving drought problems and determining drought-resistant crop varieties by collecting data from images captured by sensors mounted on them, to survey areas affected by droughts or floods due to natural calamities, the UAVs equipped with various sensors and miniature cameras that can capture thermal and multispectral images can fly without human operation [1]. They can take precise photos of these locations, which is beneficial in many situations, such as droughts. It assists in determining the water status of the crops, assessing how resilient the crops are to drought, and finding the crop's water deficit. In cases of flooding, images of the affected areas can be taken to take appropriate action and offer support. Due to the advantages of UAVs, they have a high ability to collect data accurately and reach areas that may be dangerous and difficult to reach by humans[2]. They can also cover large areas efficiently and in a short time, and therefore they can be used to identify drought-resistant crops effectively to minimize yield loss and preserve equilibrium between water consumption and production. But, one of the challenges in using UAVs is determining the best way to make decisions based on the data collected through them, and here comes the role of multi-criteria decision-making (MCDM) techniques.

When evaluating criteria, decision-makers and specialists consider a variety of elements, which is why multi-criteria procedures are employed. In our challenge, decision-makers employ MCDM technology to evaluate which combination of sensors that are equipped with UAVs is most effective for identifying drought-resistant crops based on performance, accuracy, weight restrictions, speed, and other considerations. For dealing with complex decision-making problems where criteria are ambiguous and conflicting, we use the single-valued triangular neutrosophic number, where expert opinions can be analyzed and integrated into the MCDM process.

In this research, we present (MCDM-MEREC-CoCoSo) model integrated with the SVTrN to achieve two goals. The first is to use the MEREC method to determine the weight factors that accurately represent the importance of each criterion. The second is to choose the best UAV by using the CoCoSo method.

2 |Literature Review

The hydrologic sciences and water resources management field has traditionally relied on a combination of remotely sensed data and in situ measurements for research and regulatory purposes. However, the spatial dispersion of in situ measurements is limited by financial and logistical constraints. Remote sensing from manned and satellite aircraft provides spatially broad data, albeit frequently with coarse resolution. These data collection techniques often have limitations in responding to specific, brief occurrences where images and data could help with real-time assessment and decision-making, especially during and immediately after natural disasters. To overcome these limitations in temporal and spatial data resolution, regulators and researchers are increasingly using unmanned aerial vehicles (UAVs) [3]. Using traditional methods for remote sensing or in situ data collection can often be more expensive than utilizing Unmanned Aerial Vehicles (UAVs). The recent advancements in UAV design, power supply, payload capacity, and sensors have led to significant innovations in their use during natural disasters such as floods and droughts. Due to the importance of the quality of the precise cameras and sensors mounted on the UAV, there are many different types of sensors, each of which has its advantages and disadvantages.

When conducting studies on droughts, floods, and water management, the two most commonly used flight platforms are rotary-wing and fixed-wing UAVs. Rotary-wing UAVs that are used in water management applications are discussed in [4-6]. In contrast, applications that used fixed-wing UAVs are discussed in [7, 8]. Both types of drones are equipped with different types of cameras and sensors that suit each mission, which have their advantages and disadvantages. Therefore, we will present the different types of sensors for UAVs as follows: RGB Sensors (digital cameras), this type produce images with three values for individual RGB pixels, their advantages are portable, lightweight, easy to operate, inexpensive, and a wider bandwidth, but its spectral resolution is limited, it lacks radiometric calibration options, and with the movement of drones, it can capture blurry images [9, 10]. In contrast to the RGB sensors, the Multispectral sensors have a narrow bandwidth, which captures image data within specific wavelength ranges across the electromagnetic spectrum and detects reflections in near-infrared regions. It can obtain more information thanks to its green, red, and blue visual receptors, which are inaccessible to the human eye. But, this sensor depends on the characteristics of the lens used, as it may be susceptible to spectral distortions and noise, which generate an image with a coarse pixel resolution, In addition, the UAVs and multispectral sensors typically arrive separately; therefore, it need to be integrated into the UAV system. it is considered hefty and costly[11]. The thermal sensor is another type, which gathers infrared radiation that is emitted by all objects on Earth's surface to create the images; these sensors operate in the long-wave spectral ranges so they can detect a broad range of temperatures. They are characterized by being light in weight and small in size. Hyperspectral Sensors can gather reflectance in numerous continuous, tiny bands over a broad spectral range because of their extremely high spectral resolutions. But, hyperspectral sensors are expensive compared with multispectral and RGB sensors [3]. Each type of sensor has advantages different from the others, thus choosing among multiple sensor types that are equipped on UAV is very important to evaluate UAV efficiency.

It is worth noting that, not all UAV standards are created equal. Some criteria may be more important for your specific needs than others. Therefore, it is crucial to identify the essential criteria for your operations and adjust the evaluation process accordingly. By doing so, you can weigh the pros and cons of each criterion and determine whether the trade-offs are acceptable. As we mentioned previously, there are different types of sensors, and they are considered an important factor as they affect the accuracy of the results. There is a UAV loaded with normal-quality sensors that take aerial images, integrated images, or digital images, and there are high-quality sensors that take thermal images, multispectral images, or hyperspectral and each of them can be used according to the need of the problem. In this research, we consider both performance and sensor quality as the main criteria. Additionally, we take high-quality sensors and quality sensors as sub-criteria of the sensor accuracy attribute, while speed, endurance, payload capacity, distance coverage, and wind resistance are considered sub-criteria of the performance attribute. It should be noted that all these criteria are benefit types.

- High-quality sensor: this sensor provides a high-resolution image depending on the lens, which takes thermal and multispectral images.
- Normal quality sensor: this sensor provides a normal camera that takes a low-resolution image or aerial images.
- Speed: the maximum speed that a UAV can fly in kilometers per hour.
- Payload: is used to describe the maximum weight that a UAV, including sensors, cameras, and other equipment, can carry while in flight.
- Distance: The maximum distance that a drone can be controlled from its takeoff point, measured in meters in the shortest possible direction.
- Endurance: refers to the amount of time that a UAV can stay airborne without requiring a battery or fuel refill.
- Wind resistance: the aircraft's resistance to wind speed, expressed in kilometers per hour.

UAVs in water management studies are divided into two classes, fixed-wings and rotary-wings. Rotary-wing UAVs are easy to control and maneuver since they can fly at low speeds, hover, and take off and land in any direction, they can also take off and land vertically and quickly [12]. On the other hand, fixed-wing aircraft can lift forward because of their inflexible wings. Its great flight range, straightforward design, and inexpensive maintenance and repair, but the launch and recovery need a lot of space [8]. There are many different types of UAVs. We have only discussed 4 types as a sample of UAVs loaded with sensors.

- 3DR IRIS/SOLO (rotary-wing) denoted as (H1): is designed for aerial photography and cinematography purposes, it is an affordable drone that is specifically made for aerial photography [13].
- OKTO XL (rotary-wing) denoted as (H2): Its features include a Canon G11 camera, which is perfect for aerial photography; a 25-minute flight time; a 1.8-kg payload capacity; and the need for an observer to drive it [14].
- PARROTAR/2.0 (rotary-wing) denoted as (H3): It has multiple sensors, such as a 3-axis accelerometer, gyroscope, magnetometer, pressure sensor, and ultrasonic sensors to measure flying and ground height. Can operate on mobile or tablet operating systems. It has four brushless in-runner motors installed, which enable it to record video at 30 frames per second in 720 pixels [15].
- The DJI Matrice 300 RTK UAV rotary-wing denoted as (H4): is a more recent, bigger, more capable, safe to operate, and adaptable UAV. It was acquired in January 2021 so that the WRMD could carry out advanced operations. This aircraft has more endurance, range, and weather tolerance. Its all-around direction and position sensors help to improve in-flight stability and safety by making obstacle avoidance easier. This UAV can be configured to carry several payloads, enabling the simultaneous mounting of up to three payloads. These payloads can include LiDAR, multispectral imaging cameras (visible, near- and thermal-infrared), laser range finders, water grab samplers, air monitoring sensors, and more. Additionally, there is a built-in satellite navigation receiver on the aircraft.

When making decisions that involve multiple criteria, the importance of each criterion is a critical factor that greatly affects the outcome. Multi-criteria decision-making (MCDM) is an essential and multidisciplinary field of operations research that has gained significant attention in recent years. It consists of two branches, multi-objective decision-making (MODM) and multi-attribute decision-making (MADM) [16]. MODM tackles the challenge of finding an ideal or nearly ideal solution within a viable solution space that is based on numerous objectives and numerous variables, factors, and limitations. Linear and non-linear programming models are popular methods for addressing MODM problems. On the other hand, MADM is a subset of MCDM that focuses on problems with discrete decision variables and a small set of choices and qualities [2-5]. There are various approaches and strategies for Multiple Criteria Decision Making (MCDM) that have been described in the literature. Many researchers have used some of the well-known MCDM techniques in different fields of study. These methods include the Weighted Sum Model (WSM), Weighted Aggregated Sum Product Assessment (WASPAS), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Vise Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE), ELimination Et Choix Traduisant la REalité (ELECTRE), Complex Proportional Assessment (COPRAS), Evaluation based on Distance from Average Solution (EDAS), Analytic Hierarchy Process (AHP), and Best Worst Method (BWM) [17-19]. To address this issue, researchers have developed several techniques for determining the weights of the criteria. Subjective weighting methods (in which the decision-maker preferences determine how much weight each criterion is given, such as pairwise comparison and SMART methods), objective weighting methods (in which the criteria's weights are assessed impartially, unaffected by the decision-makers individual preferences, such as CRITIC, SECA and Entropy methods), and hybrid weighting methods (in which is a combination of subjective and objective weighing techniques is used).

3 | Preliminaries

In this part, some significant concepts of tree soft and neutrosophic principles are presented.

3.1 | Tree Soft

Tree soft is described in [20] as follows: Let U be a universe of discourse, and H a non-empty subset of U, with $P(H)$ the powerset of H. Let A be a set of attributes (parameters, criteria, etc.), $A = \{A_1, A_{2,}, \dots, A_{n,}$ for integer$n \geq 1$, where $A1, A2, \dots, An$ are considered attributes of first level (since they have one-digit indexes). Each attribute $Ai, 1 \leq i \leq n$,is formed by sub-attributes:

$A_1 = \{A_{11,} A_{12,}, \dots .\}$, $A_2 = \{A_{21,} A_{22,}, \dots .\}$, $A_n = \{A_{n1,} A_{n2,}, \dots .\}$ given that the aforementioned A_{ij}have two-digit indexes, making them sub-attributes or second-level attributes. Once more, sub-sub-attributes (third-level attributes) combine to generate each sub-attribute $A_{ij}$is: A_{ijk} And so on, as much refinement as needed into each application, up to sub-sub-…-sub-attributes (or attributes of m-level (or having m digits into the indexes) : $A_{i1,i2\dots..im}$,

Consequently, a graph tree is created, which we refer to as Tree (A), with A as its root (which is regarded as level zero), followed by nodes at levels 1, 2, and m. All nodes that have no descendants are referred to as terminal nodes. Then the Tree Soft Set is:

$$F : P(Tree(A)) \rightarrow P(H)$$

The graph tree's collection of all nodes and leaves (from level 1 to level m) is called Tree (A), and its power set is denoted by $P(Tree(A))$.

All node sets of the Tree Soft Set of level m are:

$$Tree(A) = \{ A_{i1} | i1 = 1,2, \dots \}$$

3.2 | Neutrosophic Concepts

Neutrosophic set (NS): A neutrosophic set is a generalization of a classical set, fuzzy set, and intuitionistic fuzzy set since it takes into account an indeterminacy function I_D in addition to the truth T_D and falsity membership, where T_D, I_D and F_D are real standard elements of $[0,1]$ [21], which is highly evident in real-world scenarios. It can be represented as $D = \{< x , (T_D(x), I_D(x), F_D(x)) >: x \in E, T_D, I_D, F_D \in]0^{-1}, 1^{+}[\}$ There is no limitation on the sum of $T_D(x), I_D(x) and\ F_D(x)$ so,

$$0^{-1} \leq T_D(x) + I_D(x) + F_D(x) \geq 1^{+} \tag{1}$$

The score function (SF) is used to obtain the crisp values in SVTrN represented as follows:

$$Score\ Function\ (SF) = \frac{(L_{ij} + M_{ij} + U_{ij})}{9} * (2 + T - I - F) \tag{2}$$

$(\mathrm{SVTrN - Number})$ $(\tilde{D_1} =< a_1, b_{1,}, c_1; T_D, I_D, F_D >), T, I, F$ memberships are represented as follows:

$$T_D = \begin{cases} (x - a_1)T_D \big/ (b_1 - a_1) & , (a_1 \leq x \leq b_1) \\ T_D & , (x = b_1) \\ (c_1 - x)T_D \big/ (c_1 - b_1) & , (b_1 \leq x \leq c_1) \\ 0 & , otherwise \end{cases} \tag{3}$$

$$I_D = \begin{cases} (b_1 - x - I_D(x - a_1)) \big/ (b_1 - a_1) & , (a_1 \leq x \leq b_1) \\ I_D & , (x = b_1) \\ (x - b_1 + I_D(c_1 - x)) \big/ (c_1 - b_1) & , (b_1 \leq x \leq c_1) \\ 1 & , otherwise \end{cases} \tag{4}$$

$$F_D = \begin{cases} (b_1 - x + F_D(x - a_1)) \big/ (b_1 - a_1) & ,(a_1 \le x \le b_1) \\ F_D & ,(x = b_1) \\ (x - c_1 + F_D(c_1 - x)) \big/ (c_1 - b_1) & ,(b_1 \le x \le c_1) \\ 1 & ,otherwise \end{cases} \tag{5}$$

.

4 | Methodology

This study utilized two decision-making techniques to assess the effectiveness of Unmanned Aerial Vehicles (UAVs) for water management applications, specifically during droughts or floods. We are exploiting MEREC to obtain attributes' weights, which are represented in soft trees, while the CoCoSo method is used to rank the UAVs within their respective categories based on the weights derived from MEREC. As shown in Figure 1, Level 0 (the root); Level 1 is formed by the nodes: sensor quality denoted as $(A1)$, performance denoted as $(A2)$; Level 2 is formed by the nodes, high quality, normal quality, Speed, Payload, Distance, Endurance, wind resistance, which denoted as $\{A11, A12, A21, A22, A23, A24, A25\}$ respectively.

Let's consider $H = \{h_1, h_2, h_3, h_4\}$ be a set of UAV's type, and P (H) the power set of H. The set of attributes is $\{A_1, A_2\}$, since A_1 is sensor quality, A_2 is performance. Then, $A_1 = \{A_{11}, A_{12}\} = \{\text{high quality}, \text{normal quality}\}$, $A_2 = \{A_{21}, A_{22}, A_{23} A_{24}, A_{25}\}$={Speed, Payload, Distance, Endurance, Resistance to wind}.

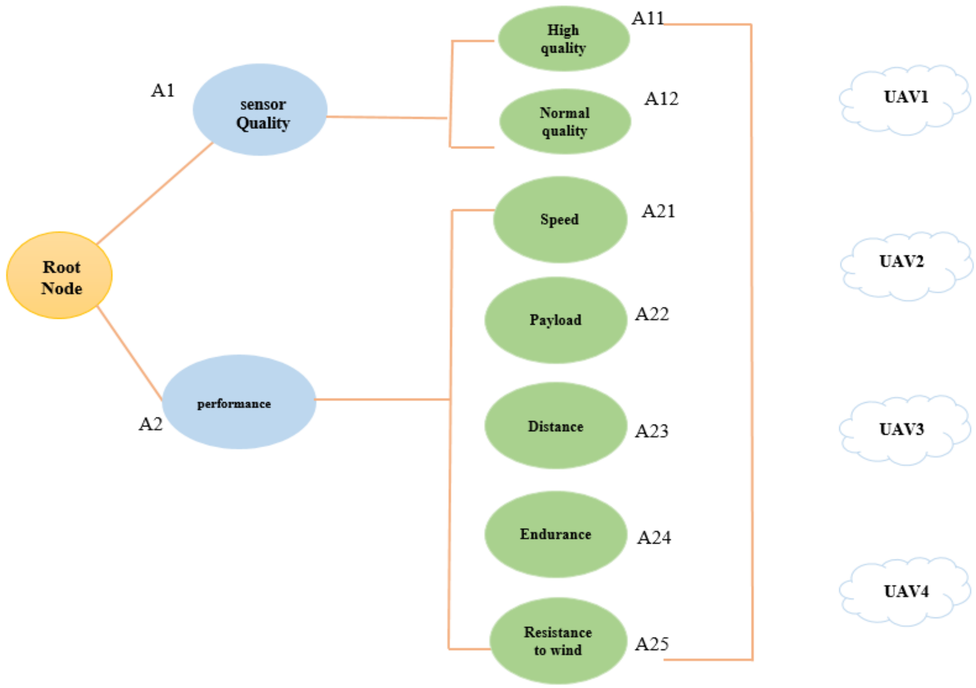

Figure 1. Determined Leaves in our tree.

Step 1: Construct the tree set.

- Determining influential attributes of UAV as main attributes (An) in level 1 in form $\{A1, A2, \ldots An\}$. The inherent attribute of main in level 1 form in level 2 which entails sub-attributes related to level 1 as $\{A1i, A2i, ..Ani\}$.
- Determining the set of alternatives as $\{H_1, H_2, \ldots . H_n\}$

Step 2: Evaluating and analyzing level 1 and level 2 characteristic data.

- Created expert linguistics' decision matrix for evaluating attributes (An) in level 1 $\{A1, A2 \ldots An\}$. Also, it is created for evaluating attributes (Ani) in level 2 $\{A1i, A2i, .. Ani\}$.
- Constructed decision matrices are valuing based on the scale of single value Triangular Neutrosophic sets (SVTNSs), which are used to convert the linguistic scale into a corresponding numerical scale, using the terminology used by experts to construct decision matrices, using score function (SF) shown in equation 2. Decision makers may evaluate and rank attributes objectively thanks to this process, which facilitates more data-driven decision–making.
- The decision matrix that is created, displays the ratings or values of each possibility according to each attribute. The elements of this matrix, labeled as x_{ij}, should be greater than zero: $x_{ij} > 0$. In case the decision matrix contains negative values, those values should be converted into positive values by appropriate means. Assuming there are m attributes and n alternatives, the decision matrix would have 'm' rows and 'n' columns. The decision matrix forms as follows:

  $$X = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix}$$

- MEREC technique starts to be implemented in constructed decision matrices for UAV's sensor over criteria (An) in level 1 and UAV's sensor over criteria (Ani) in level 2 through the following sub-steps:

Step 2.1: Decision matrices are transformed into crisp matrices by Eq. (2).

Where, L_{ij}, M_{ij}, U_{ij} refers to lower, medium, upper, and T, I, F refers to truth, false, and indeterminacy respectively.

Step 2.2: (Aggregated decision matrix): Eq. (6) is utilized to combine all these matrices into one matrix called aggregated matrix

$$Y_{ij} = \frac{\sum_{j=1}^{N} q_{ij}}{N} \tag{6}$$

Where q_{ij} represents the value of the attribute in the matrix, N represents the number of experts

Step 3: Normalize the decision matrix based on the MEREC technique.

To create a normalized decision matrix (N), 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} . If B represents the beneficial attribute and H represents the non-beneficial attribute, we can use the following normalizing formula:

$$n_{ij}^{x} = \begin{cases} \dfrac{\min x_{kj}}{x_{ij}} & if\ j \in B \\ \dfrac{x_{ij}}{\max x_{kj}} & if\ j \in H \end{cases} \tag{7}$$

Step 4: Apply the MEREC technique to calculate the weight of attributes [22]:

Step 4.1: Calculate the overall performance of the alternatives (s_i).

During this stage, we obtain the overall performance of different alternatives by using a logarithmic metric with equal weights for different attributes. This measure is calculated based on a non-linear function, which uses 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:

$$s_i = \ln(1 + (\frac{1}{m} \sum_j \left|\ln(n_{ij}^{x})\right|)) \tag{8}$$

Step 4.2: Calculate the alternatives' performance by removing away each attribute.

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 attribute independently. This means that there are m sets of performances connected to m attributes. To indicate how well the ith alternative performed overall in terms of eliminating the jth attribute, we use the notation SS_{ij}(overall performance of ith alternative concerning the removal of jth attribute). The calculations for this step are done using the following equation:

$$ss_{ij} = \ln(1 + (\frac{1}{m} \sum_{k,k\neq j}\left|\ln\left(n_{ij}^{x}\right)\right|)) \tag{9}$$

Step 4.3: Compute the summation of absolute deviations.

The elimination effect of the jth attribute is determined using the values from Steps 4.1 and 4.2. Let E_j be the result of eliminating the jth condition. The values of E_j can be calculated using the following formula.

$$E_j = \sum_i \left|ss_{ij} - s_i\right| \tag{10}$$

Step 4.4: Determine the final weights of attributes.

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

$$w_j = \frac{E_j}{\sum_k E_k} \tag{11}$$

Step 5: Apply CoCoSo (Combined Compromise Solution) for ranking the alternative [23]

Step 5.1: Develop the initial decision matrix.

Step 5.2: Apply the linear normalization technique to make all the elements of the decision matrix comparable.

$$r_{ij} = \begin{cases} \frac{x_{ij} - \min x_{ij}}{x_{ij}} & \text{for beneficial attribute} \\ \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} & \text{for non} - \text{beneficial attribute} \end{cases} \tag{12}$$

Where r_{ij} represents alternative i's normalized rating with respect to attribute$j$, and x_{ij} represents alternative i's rating with respect to attribute j.

Step 5.3: based on WSM & WPM methods, the corresponding performance indexes s_i and p_i for each alternative are estimated.

$$s_i = \sum_{j=1}^{n} r_{ij}\, w_j \tag{13}$$

$$p_i = \sum_{j=1}^{n} (r_{ij})^\wedge w_i$$

Where s_i and p_i represent the sum of weight-comparable sequences and weight-multiplied comparable sequences of the alternative i, and w_j denotes weights of the attribute j , which we got in step 4.4 by the MEREC technique.

Step 5.4: Ranking the alternatives.

The CoCoSo approach computes a relative performance score, k_i, for ranking using three aggregate estimated results, k_{ia}, k_{ib}, and k_{ic} as follows:

$$k_i = \frac{1}{3}\,(k_{ia} + k_{ib} + k_{ic}) + (k_{ia}\, k_{ib}\, k_{ic})^{\frac{1}{3}} \tag{14}$$

With

$$k_{ia} = \frac{s_i + p_i}{\sum_{i=1}^{m}(s_i + p_i)} \tag{15}$$

$$k_{ib} = \frac{s_i}{\min s_i} + \frac{p_i}{\min p_i} \tag{16}$$

$$k_{ic} = \frac{\lambda s_i + (1-\lambda)\, p_i}{\lambda max s_i + (1-\lambda) max\, p_i} \tag{17}$$

Table 1. Linguistic variables of criteria and alternative in form of SVTrN-number [21].

Terms	$\mathbf{L, M, U}$	Confirmation degree $(\mathbf{T, I, F})$
Absolutely Low (AL)	$<(0.0.1)>$	Absolutely not sure (ANS) $<(0.1.1)>$
Very Low (VL)	$<(0.1.2)>$	Not sure (NS)$<(0.2\,, 0.8, 0.8)>$
Low (L)	$<(1.2.3)>$	Slightly sure (SLS)<(0.3,0.7,0.7)>
Medium (M)	<(2.3.4)>	Median sure (MS)$<(0.5, .05, .05)>$
High (H)	<(3.4.5)>	Sure (S)$<(0.7{,}0.4{,}0.4)>$
Very High (VH)	<(4.5.6)>	Strongly sure (STS)$<(0.8{,}0.2{,}0.2)>$
Strongly very high (SVH)	<(5.6.7)>	Very strongly sure (VSS $<(0.9{,}0.1{,}0.1)>$
Absolutely High (AH)	<(7.8.9)>	Absolutely sure (AS) $<(1{,}0{,}0)>$

5 | Result and Analysis

Three experts were tasked with evaluating the main criteria judgment using a single-valued triangular neutrosophic scale as in Table 1. Depending on our study, 7 criteria are presented as follows: {high quality, normal quality, speed, payload, distance, endurance, wind resistance}. Also, we take 4 UAVs alternatives, {H1, H2, H3, H4}.

5.1 | MEREC-based tree soft set: Calculating attributes level 1's weights

Firstly, we create an expert linguistics decision matrix by using the SVTrN scale in Ref [21]. After that, these matrices are transformed into crisp matrices based on Equation (2) as appears in Tables 2 to 7. As shown in Table 8, the aggregated matrix created for attributes $\{A_1, A_2\}$ based on Eq. (6), after that calculate the normalized matrix of attributes$\{A_1, A_2\}$ at level 1 as shown in Table 9 by use Eq. (7). In Table 12 calculate the weights of attributes$\{A_1, A_2\}$ based on Eq. (11), as shown in Figure 2, the A_2 is the highest criterion with the highest value of weight $= 0.658828$ while A_1 is at least one.

Table 2. Linguistic expert's decision matrices for main attributes by the first expert in level 1.

Alternative	**LEVEL 1**	
	A1	A2
H1	AL	L
H2	M	H
H3	AH	H
H4	AH	SVH

Table 3. Linguistic expert's decision matrices for main attributes by the second expert in level 1.

Alternative	**LEVEL 1**	
	A1	A2
H1	VL	L
H2	H	L
H3	VH	H
H4	AH	H

Table 4. Linguistic expert's decision matrices for main attributes by the third expert in level 1.

Alternative	LEVEL 1	
	A1	A2
H1	L	M
H2	H	H
H3	VH	VH
H4	SVH	AH

Table 5. Crisp decision matrix for first expert evaluation in level 1.

Alternative	LEVEL 1	
	A1	A2
H1	0	0.6
H2	1.5	2.533
H3	8	2.533
H4	8	5.4

Table 6. Crisp decision matrix for second expert evaluation in level 1.

Alternative	LEVEL 1	
	A1	A2
H1	0.2	0.6
H2	2.533	0.6
H3	4	2.533
H4	8	2.533

Table 7. Crisp decision matrix for third expert evaluation in level 1.

Alternative	LEVEL 1	
	A1	A2
H1	0.6	1.5
H2	2.533	2.533
H3	4	4
H4	5.4	8

Table 8. An aggregated matrix of attributes A1, A2 at level 1.

Alternative	A1	A2
H1	0.26666667	0.9
H2	2.18866667	1.88866667
H3	5.33333333	3.022
H4	7.13333333	5.311

Table 9: Normalized matrix of attributes A1, A2 at level 1.

Alternative	A1	A2
H1	1	1
H2	0.1218398	0.4765267
H3	0.05	0.297816
H4	0.0373832	0.1694596

Table 10. Calculated performance of alternatives by merec at level 1.

Alternative	A1	A2	Si
H1	1	1	0
H2	0.1218398	0.4765267	0.885064
H3	0.05	0.297816	1.132532
H4	0.0373832	0.1694596	1.261535

Table 11. Overall performance matrix (ssi) of alternative by merec at level 1.

Alternative	A1	A2	Si
	SSi		
H1	0	0.405465	0
H2	0.31526	0.059136	0.885064
H3	0.473522	0.024693	1.132532
H4	0.63529	0.018519	1.261535

Table 12. Weight of attributes at level 1 by merec.

	A1	A2
$\boldsymbol{E_j}$	1.855059	3.582249
$\boldsymbol{W_{j=}\frac{E_j}{\sum_k E}}$	0.341172	0.658828

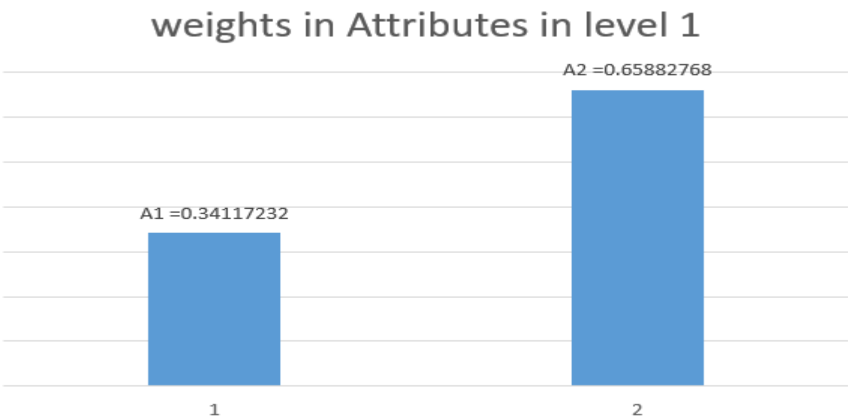

Figure 2. Weights of attributes at level 1.

5.2 | MEREC-based tree soft set: Calculating attributes level 2's weights

We need to perform calculations on two sets of attributes - performance attributes $\{A_{21} : A_{25}\}$ and sensor quality attribute $\{A_{11}: A_{12}\}$. We will follow the same steps as we did in the first level to calculate the weights in the second level. Tables 13, 14, and 15, show linguistic expert's decision matrices for the main attributes of the three experts. Tables 16, 17, and 18, show a crisp decision matrix for three experts' evaluation in level 2. Table 19 aggregated matrix of performance attributes $A_{21} : A_{25}$ at level 2 are calculated. Table 20 shows the normalized matrix of performance attributes $A_{21} : A_{25}$ at level 2. The weight of performance attributes $A_{21} : A_{25}$ at level 2 is shown in Table 22, which A_{22} is the highest attribute with the highest value of weight while A_{24} is least one

The sensor quality attribute $\{A_{11}, A_{12}\}$ Calculation: Table 23 shows, the aggregated matrix of sensor quality attributes A_{11}, A_{12} at level 2. In Table 24 the normalized matrix of sensor quality attributes A_{11}, A_{12} at level 2 is calculated by Equation 9. Table 26 shows, the weight of sensor quality attributes A_{11}, A_{12} at level 2.

Figures 4 and 5 represent the final weights for the tree's attributes. According to Figures 4 and 5, the high-quality sensor (A_{11}) attribute is the optimal with weight $= 0.232248$, while (A_{12}) is the least with weight $= 0.108924$.

Table 13. Linguistic expert's decision matrices for sub-attribute by the first expert in level 2.

Alternative	LEVEL 2						
	A11	A12	A21	A22	A23	A24	A25
H1	AL	VL	VL	L	M	L	M
H2	L	M	M	H	M	H	H
H3	H	VH	H	VH	M	M	H
H4	AH	SVH	VH	H	VH	VH	H

Table 14. linguistic expert's decision matrices for main sub-attribute by the second expert in level 2.

Alternative	LEVEL 2						
	A11	A12	A21	A22	A23	A24	A25
H1	VL	L	VL	M	M	H	L
H2	H	M	H	L	H	M	M
H3	VH	H	M	VH	VH	H	M
H4	SVH	H	VH	H	H	VH	VH

Table 15. Linguistic expert's decision matrices for sub-attribute by the third expert in level 2.

Alternative	LEVEL 2						
	A11	A12	A21	A22	A23	A24	A25
H1	AL	VL	L	VL	M	L	L
H2	M	M	H	VH	H	M	H
H3	H	VH	M	H	H	SVH	M
H4	AH	SVH	VH	H	VH	VH	H

Table 16. Crisp decision matrix for second expert evaluation in level 2.

Alternative	LEVEL 2						
	A11	A12	A21	A22	A23	A24	A25
H1	0	0.2	0.2	0.6	1.5	0.6	1.5
H2	0.6	1.5	1.5	2.533	1.5	2.533	2.533
H3	2.533	4	2.533	4	1.5	1.5	2.533
H4	8	5.4	4	2.533	4	4	2.533

Table 17. Crisp decision matrix for second expert evaluation in level 2.

Alternative	LEVEL 2						
	A11	A12	A21	A22	A23	A24	A25
H1	0.2	0.6	0.2	1.5	1.5	2.533	0.6
H2	2.533	1.5	2.533	0.6	2.533	1.5	1.5
H3	4	2.533	1.5	4	4	2.533	1.5
H4	5.4	2.533	4	2.533	2.533	4	4

Table 18. Crisp decision matrix for third expert evaluation in level 2.

Alternative	LEVEL 2						
	A11	A12	A21	A22	A23	A24	A25
H1	0	0.2	0.6	0.2	1.5	0.6	0.6
H2	1.5	1.5	2.533	4	2.533	1.5	2.533
H3	2.533	4	1.5	2.533	2.533	5.4	1.5
H4	8	5.4	4	2.533	4	4	2.533

Table 19. Aggregated matrix of performance attributes $A_{21} : A_{25}$ at level 2.

Alternative	LEVEL 2				
	Speed	Payload	Distance	Endurance	Resistance to wind
H1	0.33333333	0.76666667	1.5	1.54433333	0.9
H2	2.18866667	2.37766667	2.18866667	1.84433333	2.18866667
H3	1.84433333	3.511	2.67766667	3.14433333	1.84433333
H4	4	2.533	3.511	4	3.022

Table 20:. Normalized matrix of performance attributes $A_{21} : A_{25}$ at level 2.

Alternative	LEVEL 2				
	Speed	Payload	Distance	Endurance	Resistance to wind
H1	1	1	1	1	1
H2	0.1523	0.322445	0.685349	0.83734	0.411209259
H3	0.180734	0.218361	0.560189	0.491148	0.487981205
H4	12	0.302671	0.386083	0.386083	0.297816016

Table 21. Overall performance matrix (SSi) of alternative by MEREC at level 2.

Alternative	LEVEL 2				
	SSi				
	Speed	Payload	Distance	Endurance	Resistance to wind
H1	0	0	0	0	0
H2	0.415525	0.509935	0.596626	0.618446	0.538723
H3	0.534101	0.556032	0.658641	0.644933	0.644254
H4	0.621629	0.751377	0.774081	0.774081	0.749851

Table 22. Weight of performance Attributes $A_{21} : A_{25}$ at level 2 by MEREC.

	LEVEL 2				
	Speed	Payload	Distance	Endurance	Resistance to wind
$\boldsymbol{E_j}$	0.7151532	0.728561	0.561965	0.553853	0.610025
$\boldsymbol{W_j = \frac{E_j}{\sum_k E}}$	0.22563181	0.229862	0.177301	0.174741	0.192464

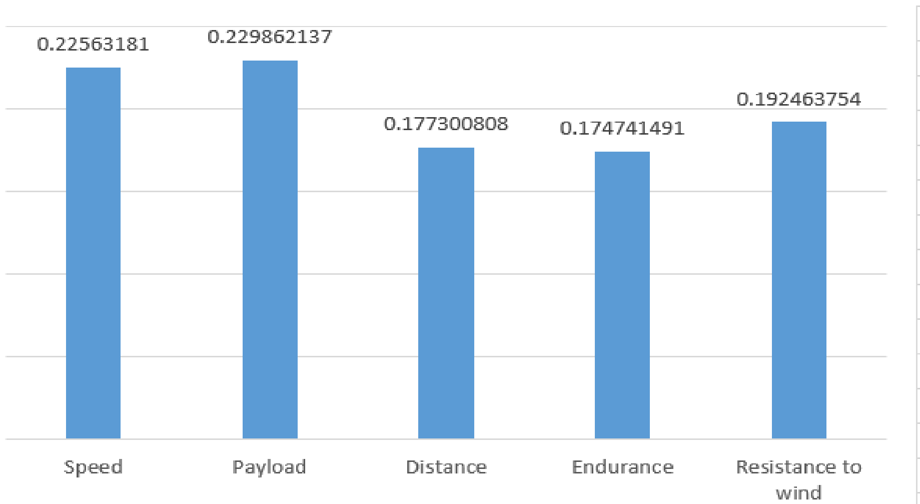

Figure 3. Weights of performance attributes $A_{21} : A_{25}$at level 2.

Table 23. Aggregated matrix of sensor quality attributes A_{11}, A_{12} at level 2.

Alternative	Max	Max
	A11	A12
H1	0.06666667	0.333333
H2	1.54433333	1.5
H3	3.022	3.511
H4	7.13333333	4.444333

Table 24. Normalized matrix of sensor quality attributes A_{11}, A_{12} at level 2.

Alternative	Max	Max
	A11	A12
H1	1	1
H2	0.043169	0.222222
H3	0.02206	0.09494
H4	0.009346	0.075002

Table 25. Performance of alternative by merec at level 2 over sensor quality attribute.

Alternative	Max	Max	Si
	A11	A12	
H1	1	1	0
H2	0.043169	0.222222	1.200975
H3	0.02206	0.09494	1.407138
H4	0.009346	0.075002	1.532886

Table 26. Weight of sensor quality attributes A_{11} at level 2 by MEREC.

	A11	**A12**
$\boldsymbol{E_j}$	1.971368361	0.924568
$\boldsymbol{W_{j}= \frac{E_j}{\sum_k E}}$	0.68073613	0.319264

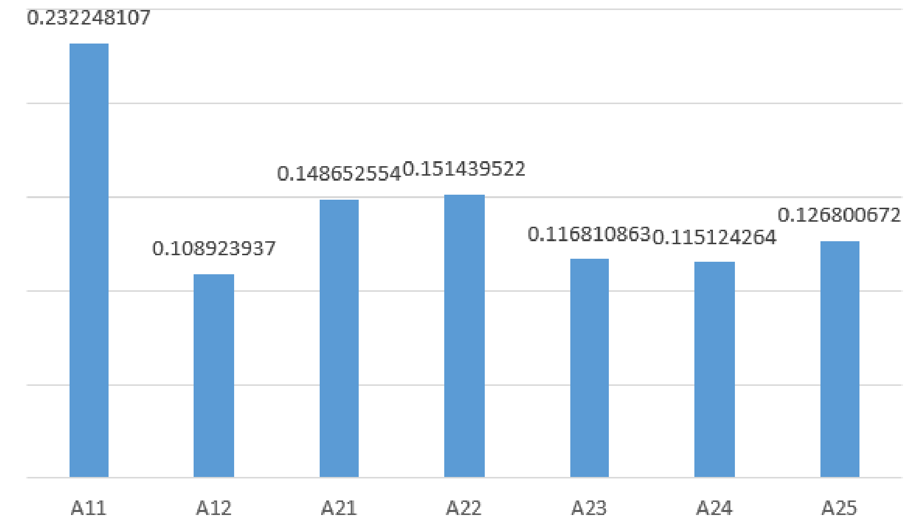

Figure 4. Final weights of all attributes.

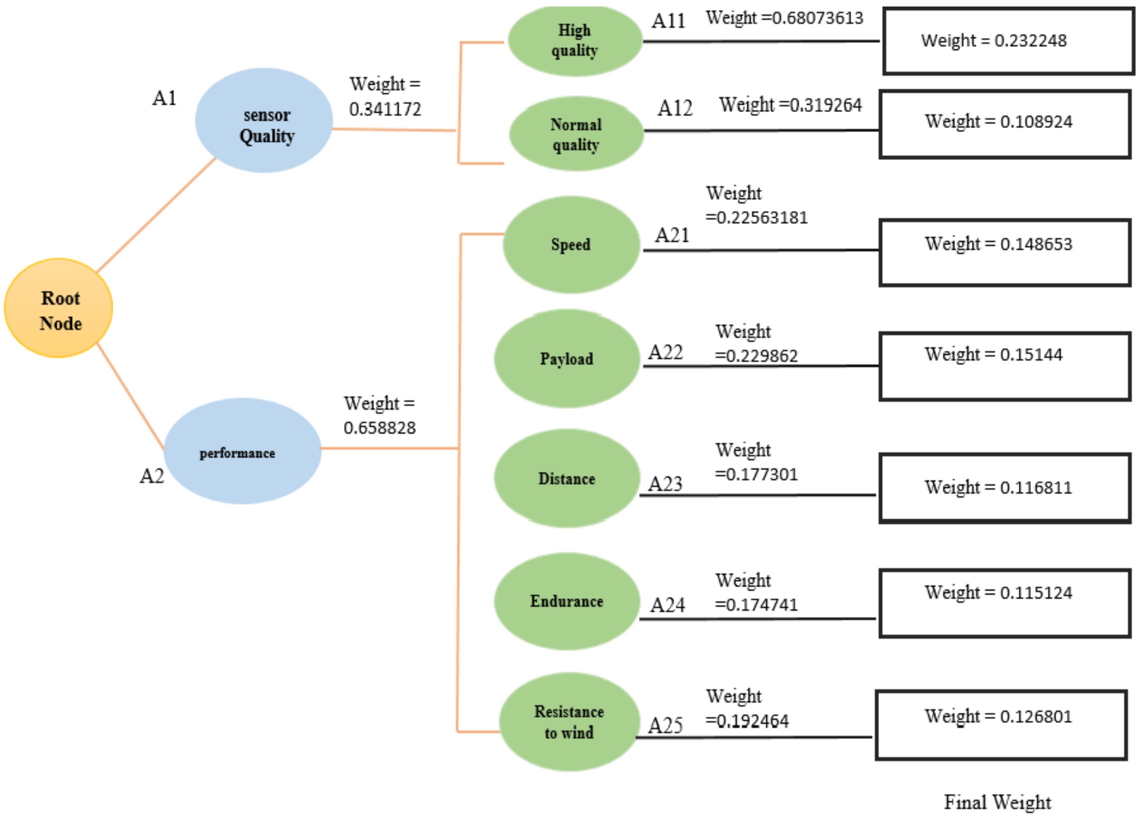

Figure 5. Tree with final weights of all attributes.

5.3 | CoCoSo Method

Choosing the best candidate from UAV's type over A1:A2 in level 1: Exploiting the aggregated matrix in Table 8 that was constructed before from Eq. (6) and using the weight of attribute A1, A2 based on the MEREC method, which was previously calculated in Table 19. Calculate the normalized matrix based on Eq. (12), as shown in Table 27. Also, calculate the sum of the weighted comparability matrix by applying Eq. (13), as shown in Table 28. After that, calculate the power of the weighted comparability matrix by applying Eq. (13), as appears in Table 29. Aggregation of Appraisal score by applying Equation 14, as it is shown in Table 30. The final ranking for UAV's type {3DR IRIS/SOLO, OKTO XL, PARROTAR/2.0, DJI Matrice 300 RTK } based on the attributes in level 1, we demonstrated that the (DJI Matrice 300 RTK UAV), denoted as (H4) is the best one. For choosing the best candidate from UAV's sensor over A21:A25 in level 2, we repeat the same previous steps using the aggregated matrix in Table 19 and using the weight of attribute A21:A25, which was previously calculated in Table 22. The DJI Matrice 300 RTK UAV is the best one over attribute A21:A25 in level 2. Also, for choosing the best candidate from UAV's sensor over A11:A12 in level 2 using the aggregated matrix in Table 23 and weight of attributes A_{11}:A_{12} in Table 26, repeat the previous steps. The DJI Matrice 300 RTK UAV is the best over attribute A_{11}:A_{12} in level 1.

Table 27. Normalized matrix based on CoCoSo method in Level 1.

Alternative	A1	A2
H1	0	0
H2	0.279903	0.224137
H3	0.737864	0.48107
H4	1	1

Table 28. The sum of the weighted comparability matrix in level 1.

Alternative	A1	A2	Si
H1	0	0	0
H2	0.279903	0.224137	0.095495
H3	0.737864	0.48107	0.251739
H4	1	1	0.341172

Table 29. Power of weighted comparability matrix in level 1.

Alternative	A1	A2	Pi
H1	0	0	0
H2	0.647641	0.373336	1.020977
H3	0.901482	0.61749	1.518972
H4	1	1	2

Table 30. Aggregation of appraisal score in level 1.

Alternative	Ka	Kb	Kc	K	Rank
H1	0	0	0	0	4
H2	0.199021	0	0.42138	0.2068	3
H3	0.328672	0	0.695884	0.341519	2
H4	0.472308	0	1	0.490769	1

Table 31. Aggregation of appraisal score over A_{21}: A_{25} in level2.

Alternative	Ka	Kb	Kc	K	Rank
H1	0	0	0	0	4
H2	0.296463	0	0.076961	0.124475	3
H3	0.329821	0	0.882544	0.404122	2
H4	0.373716	0	1	0.457905	1

Table 32. Aggregation of appraisal score over A_{11}: A_{12} in level 2.

Alternative	Ka	Kb	Kc	K	Rank
H1	0	0	0	0	4
H2	0.19939	0	0.415492	0.204961	3
H3	0.32072	0	0.66832	0.32968	2
H4	0.47989	0	1	0.493297	1

6 | Conclusion

Drought and a lack of water greatly affected the production of crops, which caused a shortage of food resources that represented a threat to humanity. Recently, drones loaded with different types of sensors have been used to evaluate and research the ability of crops to resist drought. The problem is the optimal selection of the types of UAVs according to a set of attributes that fall under the quality of the sensor and performance. These attributes are divided into sub-attributes. Therefore, the problem was represented in the form of a tree. The result of the implementation MEREC method indicated that the high-quality sensor (A_{11}) attribute is optimal based on the final value of its weight. We used the CoCoSo method after that, to rank the UAV's type and select the best, the result shows that the DJI Matrice 300 RTK UAV is better than other candidates, since it has a high weather tolerance and a large payload, which allows the simultaneous installation of up to three payloads, include multi-spectral imaging cameras (visible, thermal and infrared) and laser rangefinders, which allows for the effective detection of drought-resistant crops.

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Author Contribution

All authors contributed equally to this work.

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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.

Conflicts of Interest

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

Ethical Approval

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

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