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Digital Combatant: Harassing Cutting-Edge Technologies Toward Combat Climate Variability Obstacles in Diverse Domains of Real-Life

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Abstract

Many fields face grave threats because of climate change. Consider agriculture, where variability in the climate has an impact on the soil, crop productivity, and accessibility to water. Moreover, this phenomenon threatens livestock due to the effects on livestock and milk production, biodiversity, livestock illnesses, water availability, feed crop and forage quality, and breeding of animals. Accordingly, the variability of climate threatens the sustainability and resilience of resources. Hence, several adaptation strategies are embraced through global conferences. As well as minimizing greenhouse gas emissions which are a direct result of the agricultural sectors' contributions to greenhouse gases by altering land-use management strategies. Concurrently, livestock farming is responsible for 14.5% of the world's greenhouse gas emissions, which exacerbates climate change. Likewise, vehicle exhaust and pollutants. On the other hand, new and cutting-edge technologies are leveraging to mitigate and adapt the climate change through various studies. For instance, Unmanned Aerial Vehicles (UAVs) and drones can play a significant role in combating climate change. This technology offers a cost-effective and efficient way to monitor and track the impacts of climate change, particularly in relation to forest degradation and deforestation. Moreover, drones are also being used in the process of reforestation. Finally, the objective of this study represents in showcases the role of UAVs in climate variability to combat the climate's obstacles. Hence, the evaluating of UAVs implications in climate change is crucial process. Finally, MCDM techniques are main contributors in this process where stepwise weight assessment ratio analysis (SWARA) and the multi-objective optimization on the basis of ratio analysis (MOORA) are used as techniques of MCDM. These techniques have been bolstered in an ambiguity environment by neutrosophic theory.

Keywords: Climate Variability; Unmanned Aerial Vehicles (UAVs); Stepwise Weight Assessment Ratio Analysis (SWARA); Multi-Objective Optimization on the basis of Ratio Analysis (MOORA).

1 | Introduction

The world is currently suffering from climate change resulting from air pollution, high temperatures, and increased carbon emissions as well as greenhouse gases. Therefore, many countries are seeking to find solutions to preserve the climate. Examples of smart cities that address climate change include Singapore,

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which has implemented strict building regulations to protect homes and businesses from rising sea levels, and São Paulo, which has partnered with local water companies to improve water delivery and sanitation in slums. The City of London, an urban heat island, has also re-evaluated its building systems to prioritize energy efficiency and reduce heat absorption by urban structures. The use of forests as a natural solution to mitigate climate change is becoming increasingly popular due to their unparalleled ability to capture and store carbon dioxide (CO2) [1]. Climate change leads to many environmental problems and disasters, including drought, which leads to fires in large forests and the death of many trees, which leads to carbon sequestration. Climate-change-driven droughts threaten the stability of existing forests as carbon sinks and affect the climate change mitigation potential of forests in the long run [2].

Scientists have come up with an early warning metrics system. The development of Early Warning Metrics (EWMs) and indicators for monitoring drought impacts and forest and tree mortality using integrated data streams from satellites, UAVs (unmanned aerial vehicles), and ground-based remote sensing techniques is indeed invaluable [3]. These EWMs can help in predicting and mitigating the effects of drought on forests and trees, which can have significant ecological and socio-economic consequences. By using a combination of remote sensing techniques, researchers can gather comprehensive data on various drought-related parameters, such as soil moisture, vegetation health, and canopy water content, which can be used to develop accurate and reliable EWMs. These EWMs can then be used to identify areas at risk of drought-induced tree mortality, allowing for targeted management interventions and mitigation strategies to be implemented on time. Overall, the development of EWMs and indicators for monitoring drought impacts and forest and tree mortality is a crucial step toward ensuring the long-term sustainability of forests and trees in the face of climate change.

Unmanned aerial vehicles (UAVs), provide scientists with unprecedented abilities to collect detailed spatial and temporal data about the built environment, enabling more robust studies on the impacts of climate change on cities [4]. Advances in the fields of Unmanned Aerial Vehicle (UAV) technology and data processing have broadened the horizons of remote sensing of forestry and acquired high-resolution imagery and 3D data more easily available and affordable [5]. The high-resolution imagery provided by UAVs is crucial for studies that require data at high spatial and temporal resolutions, especially in cloudy areas or densely forested landscapes where satellite imagery is not always reliable.

Hyperspectral sensors, for example, can provide detailed information on the chemical and physical properties of vegetation, such as leaf pigmentation, water content, and nitrogen status. Thermal sensors can measure the temperature of vegetation canopies, which can be used to estimate evapotranspiration and water stress. Multispectral sensors can provide information on vegetation health and productivity, while near-infrared sensors can be used to estimate canopy water content and structure. By integrating these sensors into UAVs, researchers can obtain detailed and accurate data on various drought-related parameters, which can be used to develop EWMs and monitor the health and productivity of forests and trees. Moreover, UAVs can be deployed quickly and easily, allowing for frequent and repeated measurements to be taken over time. This is particularly useful for monitoring the progression of drought and its impacts on forests and trees, as well as for evaluating the effectiveness of mitigation strategies.

Due to the progress in platforms and sensors and the opening of the dedicated market, unmanned aerial vehicle–remote sensing (UAV–RS) is improving its key role in the forestry sector as a tool for sustainable management [6]. Sustainable forest management requires an understanding of how macroscopic patterns of forests emerge, in a timely and accurate manner, to make informed decisions [7]. Reforestation of agricultural lands in Europe increases local and downwind summer rainfall, according to a new analysis of rain-gauge measurements from across the continent. Realistic levels of tree planting could therefore mitigate future droughts expected with climate change [8].

Indeed, the potential of UAVs (Unmanned Aerial Vehicles) in climate change research began to emerge in the early 2000s with advancements in sensor miniaturization, GPS navigation, and battery technology. These developments enabled the creation of lightweight remote sensing platforms capable of collecting valuable data for atmospheric research. NASA scientists were among the pioneers in demonstrating the utility of small fixed-wing UAVs for studying various aspects of the atmosphere, including dynamics, composition, and thermodynamics in the early 2000s [9]. By leveraging UAV technology, researchers gained new insights into atmospheric processes and their implications for climate change. UAVs offer the flexibility to deploy rapidly in response to extreme weather events such as hurricanes, wildfires, or severe storms. By collecting real-time data in hazardous environments, UAVs help improve forecasting, disaster preparedness, and response efforts. UAVs equipped with temperature, humidity, and radiation sensors can study thermodynamic processes such as heat transfer, cloud formation, and energy balance. These observations contribute to improved climate models and predictions of future climate scenarios. UAV-based instruments can measure concentrations of greenhouse gases, aerosols, and pollutants in the atmosphere. By mapping spatial and temporal variations in atmospheric composition, researchers can assess sources and sinks of greenhouse gases and their impact on climate change.

In climate change research, UAVs are emerging as a valuable tool for monitoring environmental impacts through flexible high-resolution aerial mapping, and have been deployed in multiple climate change research domains [10]. Unmanned aerial vehicles (UAVs) or Drones are airplanes that operate without human pilots and are gaining popularity in military, private, and public sectors due to their versatility and their use in a wide range of applications. They are gaining more popularity among applications that do not require human operators or where human intervention is risky, dangerous, impossible, or expensive [11]. UAVs have found a variety of applications in the reforestation sector to date. For instance, this technology has been used to disperse seeds of mangroves in Myanmar and the UAE (United Arab Emirates), which can foster marine life and biodiversity while mitigating coastal erosion if a high germination success rate is achieved [12]. A startup called BioCarbon Engineering has created drones that can plant up to 100,000 trees per day, which is a significant contribution to reducing carbon emissions.

UAV-supported seed sowing, coupled with seed enablement technology, indeed presents a promising approach for enhancing seedling survival rates in water-stressed environments and safeguarding forest biomass in secondary forests against ecological weed management (EWM) challenges. While UAVs offer numerous benefits for monitoring drought impacts, environmental monitoring, and forest health, they also face several limitations that need to be addressed for effective implementation. The high-resolution data collected by UAVs can be challenging to process and analyze, requiring specialized software and expertise. This can be time-consuming and expensive, limiting the scalability of UAV-based monitoring. While UAVs can be cost-effective compared to other remote sensing techniques, the cost of purchasing and maintaining UAVs, as well as the cost of sensors and data processing, can still be prohibitive for some researchers and organizations. UAVs typically have limited payload capacities, which restricts the amount of equipment, sensors, or supplies they can carry. This limitation can impact the versatility and effectiveness of UAV-based endeavors, particularly when deploying heavy payloads such as large quantities of seeds or specialized equipment for remote sensing. UAV operations are highly weather-dependent, with adverse weather conditions such as high winds, rain, or fog posing significant challenges to flight safety and performance. Inclement weather can disrupt scheduled missions, delay critical operations, and increase the risk of accidents or equipment damage. Robust weather monitoring systems and contingency plans are essential for mitigating these risks.

The use of UAVs in smart cities and climate change mitigation efforts presents several challenges. For smart cities, some of the challenges include ensuring safety, protecting privacy, and complying with regulations. UAVs can pose safety risks if they are not properly integrated into the city's airspace management system. Privacy concerns arise when UAVs are equipped with cameras or other sensors that can capture images or data about individuals without their consent. Additionally, regulations regarding the use of UAVs in urban areas can be complex and vary from city to city, making it challenging for operators to comply [13].

For climate change mitigation efforts, some of the challenges include ensuring the accuracy and reliability of data collected by UAVs, managing power consumption and battery life, and integrating UAVs with other climate change mitigation technologies. Data collected by UAVs must be accurate and reliable to inform effective climate change mitigation strategies. However, UAVs have limited battery life and power capacity, which can limit their effectiveness in certain applications. Furthermore, integrating UAVs with other climate change mitigation technologies, such as renewable energy systems or carbon capture and storage systems, can be technically challenging [14].

Multi-criteria Decision Making (MCDM) is an umbrella term that encompasses various methodologies for evaluating and selecting the best alternative(s) based on multiple, often conflicting, criteria. MCDM methods can be helpful in various fields, such as project management, finance, logistics, environmental impact assessment, and manufacturing, among others. Many researchers have reported on the application of multi-criterion Decision-Making (MCDM) methods in solving diverse decision problems in various fields of engineering [15]. There are generally two main categories of MCDM methods [16]. Multi-Objective Decision Making (MODM). These methods are used to find the best solution that maximizes or minimizes a set of conflicting objectives, such as cost and quality like the SWARA method. Multi-Attribute Decision Making (MADM): These methods are used to rank or choose the best alternative from a set of discrete alternatives, such as the MOORA method. the SWARA method is a valuable MCDM technique for estimating the relative weights of decision-making criteria. It is a flexible and intuitive method that can handle conflicting opinions and subjectivity, leading to a more comprehensive and balanced understanding of the decision-making problem. The SWARA method is a valuable MCDM technique for estimating the relative weights of decision-making criteria. It is a flexible and intuitive method that can handle conflicting opinions and subjectivity, leading to a more comprehensive and balanced understanding of the decision-making problem [17]. The MOORA method is a simple and effective method for solving MCDM problems. It can handle both beneficial and non-beneficial criteria, and it can provide a clear ranking of alternatives based on their overall performance. The MOORA method has been applied in various fields, such as engineering, finance, and management, to solve complex decision-making problems [18].

In this study, we introduce a new hybrid method that combines between SWARA method and MOORA method using Type-2 Neutrosophic Numbers under the TreeSoft Set approach. The approach of tree soft set is introduced by Smarandache [19] who is the founder of this approach.

2 | Literature Review

In this section, we introduce some related studies for methods used in this study.

2.1 | T2NN Environment

T2NN refers to Type-2 Neutrosophic Numbers, which is a mathematical tool used to handle uncertain and incomplete information in decision-making processes. It is a fuzzy set theory that can deal with indeterminate and ambiguous data by using a membership function with a range of values. T2NN sets can capture the degree of truthiness, falsity, and indeterminacy, making it a useful tool for handling complex decision-making problems. It has been used in various fields such as engineering, finance, and logistics. Type-2 neutrosophic number (T2NNS) is an extension of the concept of a T1NN to a higher level of indeterminacy. The neutrosophic sets proved to be a valid workspace in describing incompatible and indefinite information. z(T, I, F) is a Type-1 Neutrosophic Number. But z((T_t, T_i,T_f), (I_t, I_i,I_f), (F_t, F_i, F_f)) is a Type-2 Neutrosophic Number, which means that each neutrosophic component T,I, and F is split into its truth, indeterminacy, and falsehood subparts [20]. Then T2NN has become a preferred tool by scholars and researchers in recent times [20]. Görçün et al. presented research for extending the version of the Weighted Aggregated Sum Product Assessment (WASPAS) technique under T2NNs based on the Bonferroni function (WASPAS'B) for selecting the suitable Ro-Ro vessel that has been used in the second-hand vessel market. Mehdi Keshavarz-Ghorabaee et al. [21] introduced a new method Based on the Removal Effects of Criteria (MEREC). This method is used for determining criteria weights [21]. Mohamad Shahiir Saidin et al. [22] mention that MEREC can solve fuzzy Multi-Criteria Decision-Making Problems . Shanmugasundar et al. [23]

introduce Application of MEREC in Multi-Criteria Selection. The multi-attribute ideal–real comparative analysis (MAIRCA) compares both theoretical and empirical alternative ratings [24]. Dragan S. Pamucar et al, introduce a new hybrid multi-criteria decision-making DEMATEL-MAIRCA model [25].

2.2 | SWARA-MOORA Method

The Stepwise Weight Assessment Ratio Analysis (SWARA) is a multi-criteria decision-making (MCDM) method used to determine the weights of evaluation criteria. SWARA is a simple and effective method for prioritizing indicators in a decision-making problem [26]. It is an extension of the WASPAS (Weighted Aggregated Sum-Product Assessment) method [27], which is based on the weighted sum and product models. SWARA is a useful tool for decision-makers to evaluate complex systems with multiple criteria, especially in situations where the criteria are not equally important. In the SWARA method, experts are asked to compare the criteria and provide their opinions on the relative importance of each criterion. The opinions are then converted into numerical values, and the criteria are ranked based on their weights. The SWARA method is particularly useful in situations where there is uncertainty or ambiguity in the decision-making process, as it can handle imprecise and incomplete information.

MOORA (Multi-Objective Optimization by Ratio Analysis) is a decision-making method used to rank alternatives based on multiple criteria. It is particularly useful when there are conflicting objectives and decision-makers need to consider both qualitative and quantitative factors in their evaluations. MOORA helps in identifying the most preferable alternative by comparing their performance across different criteria. MOORA (Multi-Objective Optimization based on a Ratio Analysis) method is a Multi-Criteria Decision-Making (MCDM) approach introduced in 2006 by Brauers and Zavadskas. MOORA combines Ratio System and Reference Point Approach to rank alternatives based on multiple objectives [28, 29]

3 | Methodology

This section presents the methods used in this approach to be used in this study. This section is divided into three parts to propose the T2NN-SWARA-MOORA in Tree Soft set approach.

3.1 | T2NN Environment

In this part definitions and some concepts and operations associated with T2NN are given below:

Definition 1. [20]:

We consider that Z is a limited universe of discourse and $F\ [0,1]$ is the set of all triangular neutrosophic numbers on $F\ [0,1]$.

A Type 2 neutrosophic number set (T2NNS) $\widetilde{U}$ in Z is represented by

$$\widetilde{U} = \left\langle \left(T_{T_{\widetilde{U}}}(z), T_{I_{\widetilde{U}}}(z), T_{F_{\widetilde{U}}}(z)\right), \left(I_{T_{\widetilde{U}}}(z), I_{I_{\widetilde{U}}}(z), I_{F_{\widetilde{U}}}(z)\right), \left(F_{T_{\widetilde{U}}}(z), F_{I_{\widetilde{U}}}(z), F_{F_{\widetilde{U}}}(z)\right) \right\rangle \tag{1}$$

Where $\check{T}_{\widetilde{U}}(z) : Z \rightarrow F[0,1]$, $\check{I}_{\widetilde{U}}(z) : Z \rightarrow F[0,1]$, $\check{F}_{\widetilde{U}}(z) : Z \rightarrow F[0,1]$.

The type-2 neutrosophic number set $\check{T}_{\widetilde{U}}(z) = \left(T_{T_{\widetilde{U}}}(z), T_{I_{\widetilde{U}}}(z), T_{F_{\widetilde{U}}}(z)\right)$, $\check{I}_{\widetilde{U}}(z) = \left(I_{T_{\widetilde{U}}}(z), I_{I_{\widetilde{U}}}(z), I_{F_{\widetilde{U}}}(z)\right)$, $\check{F}_{\widetilde{U}}(z) = \left(F_{T_{\widetilde{U}}}(z), F_{I_{\widetilde{U}}}(z), F_{F_{\widetilde{U}}}(z)\right)$ defined as the truth, indeterminacy, and falsity of member-ships of z in $\widetilde{U}$.

Definition 2. [20] Suppose that:

$\widetilde{U}_1 = \left\langle \left(T_{T_{\widetilde{U}1}}(z), T_{I_{\widetilde{U}1}}(z), T_{F_{\widetilde{U}1}}(z)\right), \left(I_{T_{\widetilde{U}1}}(z), I_{I_{\widetilde{U}1}}(z), I_{F_{\widetilde{U}1}}(z)\right), \left(F_{T_{\widetilde{U}1}}(z), F_{I_{\widetilde{U}1}}(z), F_{F_{\widetilde{U}1}}(z)\right) \right\rangle$ and $\widetilde{U}_2 = \left\langle \left(T_{T_{\widetilde{U}2}}(z), T_{I_{\widetilde{U}2}}(z), T_{F_{\widetilde{U}2}}(z)\right), \left(I_{T_{\widetilde{U}2}}(z), I_{I_{\widetilde{U}2}}(z), I_{F_{\widetilde{U}2}}(z)\right), \left(F_{T_{\widetilde{U}2}}(z), F_{I_{\widetilde{U}2}}(z), F_{F_{\widetilde{U}2}}(z)\right) \right\rangle$

Are two T2NNs then the following equations describe some T2NN operators.

$$\widetilde{U}_1 \oplus \widetilde{U}_2 = \left\langle \begin{array}{c} \begin{pmatrix} T_{T_{\widetilde{U}_1}}(z) + T_{T_{\widetilde{U}_2}}(z) - T_{T_{\widetilde{U}_1}}(z).T_{T_{\widetilde{U}2}}(z),\ T_{I_{\widetilde{U}1}}(z) + T_{I_{\widetilde{U}2}}(z) - T_{I_{\widetilde{U}1}}(z).T_{I_{\widetilde{U}2}}(z), \\ T_{F_{\widetilde{U}1}}(z) + T_{F_{\widetilde{U}2}}(z) - T_{F_{\widetilde{U}1}}(z).T_{F_{\widetilde{U}2}}(z) \end{pmatrix}, \\ \left(I_{T_{\widetilde{U}1}}(z).I_{T_{\widetilde{U}2}}(z), I_{I_{\widetilde{U}1}}(z).I_{I_{\widetilde{U}2}}(z), I_{F_{\widetilde{U}1}}(z).I_{F_{\widetilde{U}2}}(z)\right), \\ \left(F_{T_{\widetilde{U}1}}(z).F_{T_{\widetilde{U}2}}(z), F_{I_{\widetilde{U}1}}(z).F_{I_{\widetilde{U}2}}(z), F_{F_{\widetilde{U}1}}(z).F_{F_2}(z)\right) \end{array} \right\rangle \quad (2)$$

$$\widetilde{U}_1 \otimes \widetilde{U}_2 = \left\langle \begin{array}{c} \left(\left(T_{T_{\widetilde{U}_1}}(z).T_{T_{\widetilde{U}_2}}(z), T_{I_{\widetilde{U}1}}(z).T_{I_{\widetilde{U}2}}(z), T_{F_{\widetilde{U}1}}(z).T_{F_{\widetilde{U}2}}(z)\right)\right), \\ \left(\left(I_{T_{\widetilde{U}1}}(z) + I_{T_{\widetilde{U}2}}(z) - I_{T_{\widetilde{U}1}}(z).I_{T_{\widetilde{U}2}}(z)\right), \left(I_{I_{\widetilde{U}1}}(z) + I_{I_{\widetilde{U}2}}(z) - I_{I_{\widetilde{U}1}}(z).I_{I_{\widetilde{U}2}}(z)\right), \begin{pmatrix} I_{F_{\widetilde{U}1}}(z) + I_{F_{\widetilde{U}2}}(z) - \\ I_{F_{\widetilde{U}1}}(z).I_{F_{\widetilde{U}2}}(z) \end{pmatrix}\right) \\ \left(\left(F_{T_{\widetilde{U}1}}(z) + F_{T_{\widetilde{U}2}}(z) - F_{T_{\widetilde{U}1}}(z).F_{T_{\widetilde{U}2}}(z)\right), \left(F_{I_{\widetilde{U}1}}(z) + F_{I_{\widetilde{U}2}}(z) - F_{I_{\widetilde{U}1}}(z).F_{I_{\widetilde{U}2}}(z)\right), \begin{pmatrix} F_{F_{\widetilde{U}1}}(z) + F_{F_2}(z) - \\ F_{F_{\widetilde{U}1}}(z).F_{F_2}(z) \end{pmatrix}\right) \end{array} \right\rangle \quad (3)$$

T2NNWA to aggregate T2NN decision matrices:

Let $\widetilde{U}_p = \left\langle \left(T_{T_p}(z), T_{I_p}(z), T_{F_p}(z)\right), \left(I_{T_p}(z), I_{I_p}(z), I_{F_p}(z)\right), \left(F_{T_p}(z), F_{I_p}(z), F_{F_p}(z)\right) \right\rangle$ is a group of T2NN where p =1, 2, ……., then the aggregate value will be obtained using Eq (4)

$$\text{T2NNWA} = \left\langle \begin{array}{c} \left(1 - \prod_{p=1}^{n}(1 - T_{T_p}(z)^w, 1 - \prod_{p=1}^{n}(1 - T_{I_p}(z)^w, 1 - \prod_{p=1}^{n}(1 - T_{f_p}(z)^w\right), \\ \left(\prod_{p=1}^{n}(I_{T_p}(z)^w, \prod_{p=1}^{n}(I_{I_p}(z)^w, \prod_{p=1}^{n}(I_{f_p}(z)^w\right), \\ \left(\prod_{p=1}^{n}(F_{T_p}(z)^w, \prod_{p=1}^{n}(F_{I_p}(z)^w, \prod_{p=1}^{n}(F_{f_p}(z)^w\right) \end{array} \right\rangle \quad (4)$$

Score Function:

$$S(\widetilde{U}) = \frac{1}{12}\left\langle 8 + \left(T_{T_{\widetilde{U}1}}(Z) + 2\left(T_{I_{\widetilde{U}1}}(Z)\right) + T_{F_{\widetilde{U}1}}(Z)\right) - \left(I_{T_{\widetilde{U}1}}(Z) + 2\left(I_{I_{\widetilde{U}1}}(Z)\right) + I_{F_{\widetilde{U}1}}(Z)\right) - \left(F_{T_{\widetilde{U}1}}(Z) + 2\left(F_{I_{\widetilde{U}1}}(Z)\right) + F_{F_{\widetilde{U}1}}(Z)\right)\right\rangle \quad (5)$$

Definition 3. [20] to build the evaluation matrix $A_i \times Œ_{ip}$ to assess the classification of alternatives to each criterion.

$$\check{R} = \begin{array}{c c} & \begin{array}{ccc} Œ_{ip} & \cdots & Œ_{in} \end{array} \\ \begin{array}{c} Alt_1 \\ \vdots \\ Alt_m \end{array} & \begin{bmatrix} \check{Z}_{11} & \cdots & \check{z}_{1n} \\ \vdots & \ddots & \vdots \\ \check{Z}_{m1} & \cdots & \check{Z}_{mn} \end{bmatrix} \end{array} \quad (6)$$

Aggregate the weights of decision makers as follows:

$$\widetilde{Z_{ip}} = \frac{[T_{T_{ip}}(Z), T_{I_{ip}}(Z), T_{F_{ip}}(Z), I_{T_{ip}}(Z), I_{I_{ip}}(Z), I_{F_{ip}}(Z), F_{T_{ip}}(Z), F_{I_{ip}}(Z), F_{F_{ip}}(Z)]}{n} \quad (7)$$

Abdel-Basset et al. [20] proposed a linguistic variable that expresses the DMs' opinions in T2NN for relative importance criteria as in Table 1 and Table 2.

Table 1. Linguistic variables and corresponding scale.

Linguistic variables	The type 2 neutrosophic number scale for the relative importance of each criteria $[(T_t,T_i,T_f),(I_t,I_i,I_f),(F_t,F_i,F_f)]$
Weakly importance (WI)	((0.20,0.30,0.20), (0.60,0.70,0.80), (0.45,0.75,0.75))
Equal importance (EI)	((0.40,0.30,0.25), (0.45,0.55,0.40), (0.45,0.60,0.55))
Strong importance (SI)	((0.65,0.55,0.55), (0.40,0.45,0.55), (0.35,0.40,0.35))
Very strongly important (VSI)	((0.80,0.75,0.70), (0.20,0.15,0.30), (0.15,0.10,0.20))
Absolutely important (AI)	((0.90,0.85,0.95), (0.10,0.15,0.10), (0.05,0.05,0.10))

Also, propose a linguistic variable that expresses the DMs' opinions in T2NN for the importance of alternatives.

Table 2. Alternatives linguistic variables.

Linguistic variables	The type 2 neutrosophic number scale for the relative importance of comparison matrix $[(T_t,T_i,T_f),(I_t,I_i,I_f),(F_t,F_i,F_f)]$
Very Bad (VB)	((0.20,0.20,0.10), (0.65,0.80,0.85), (0.45,0.80,0.70))
Bad (B	((0.35,0.35,0.10), (0.50,0.75,0.80), (0.50,0.75,0.65))
Medium Bad (MB)	((0.50,0.30,0.50), (0.50,0.35,0.45), (0.45,0.30,0.60))
Medium (M)	((0.40,0.45,0.50), (0.40,0.45,0.50), (0.35,0.40,0.45))
Medium Good (MG)	((0.60,0.45,0.50), (0.20,0.15,0.25), (0.10,0.25,0.15))
Good (G)	((0.70,0.75,0.80), (0.15,0.20,0.25,), (0.10,0.15,0.20))
Very Good (VG)	((0.95,0.90,0.95), (0.10,0.10,0.05), (0.05,0.05,0.05))

3.2 | SWARA Method [26]

The Stepwise Weight Assessment Ratio Analysis (SWARA) is a multi-criteria decision-making (MCDM) method used to determine the weights of evaluation criteria as follows:

Step 1: The first step in the SWARA method is to identify the criteria that will be used to evaluate the alternatives. Once the criteria are identified, decision-makers assign weights to each criterion based on their relative importance. The weights reflect the significance of each criterion with the overall objective of the decision.

Step 2: Calculation of Performance Scores ($\mathcal{S}_j$), calculated by comparing its importance to the previous criterion.

Step 3: The coefficient $\mathcal{K}_j$, which is a function of the relative importance value of each criterion, is calculated by:

$$\mathcal{K}_j = \begin{cases} 1 & if\ j = 1 \\ \mathcal{S}_j + 1 & if\ j > 1 \end{cases} \quad \text{where j= 1, 2, …., n} \tag{8}$$

Step 4: Compute the significant weight (q_j) for each criterion.

$$q_j = \begin{cases} 1 & if\ j = 1 \\ \frac{q_{j-1}}{\mathcal{K}_j} & if\ j > 1 \end{cases} \quad (9)$$

Step 5: The relative weight of the indicators ($\mathcal{W}_j$) is determined as follows:

$$\mathcal{W}_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \quad (10)$$

3.3 | MOORA Method [28]

MOORA (Multi-Objective Optimization by Ratio Analysis) is a decision-making method used to rank alternatives based on multiple criteria as follows:

Step 1: The first step of the MOORA method is constructing the decision matrix of the problem. The criteria and alternatives.

$$\mathcal{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (11)$$

where x_{ij} presents the value of ith alternative on jth criterion, m, and n are the numbers of alternatives and criteria, respectively.

Step 2: Normalize the decision matrix.

$$r_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \qquad \text{where } i = 1, 2, \ldots \ldots, m \quad (12)$$

Step 3: Considering the positive or negative state of each attribute, the reference points for the negative attributes are minimum values, and for the positive attributes are maximum values.

Step 4: For the weight of the attribute$\mathcal{W}_1$; $\mathcal{W}_2$, ... $\mathcal{W}_n$ the assessment values of each attribute are obtained through Eq. (9)

$$\tilde{y}_j = \sum_{j=1}^{g} r_{ij}^{*} . \mathcal{W}_j - \sum_{j=g+1}^{n} r_{ij}^{*} . \mathcal{W}_j \quad (13)$$

where g represents the number of positive attributes and n-g displays the number of negative attributes.

Step 5: The Final Ranking of Alternatives Based on the previous step, the obtained maximum values of $\tilde{y}_j$ are determined for ith alternative, and then, the values are ranked in a descending order, and the highest amount has the highest rank.

4 | Case Study

4.1 | Problem Definition

UAVs, or drones, are indeed being used in various ways to help combat climate change. For instance, they are used to monitor and document the effects of climate change. UAVs are also used to monitor tree degradation and illegal logging, which helps in reducing carbon emissions. In addition, UAVs are being used in reforestation efforts. Moreover, UAVs are expected to play a crucial role in reducing the environmental footprint of delivery services. In terms of protecting rainforests, UAVs are used for monitoring forest cover and ensuring protective efforts are working. They can detect criminal activity such as illegal logging or poaching in real-time, and produce high-quality, time-stamped images for evidence in future legal proceedings. This helps in the conservation of rainforests, which are responsible for a significant portion of net global carbon emissions.

UAVs can be useful in climate change mitigation efforts in smart cities through various applications such as monitoring and managing air quality, waste management, and precision agriculture. For instance, UAVs can monitor greenhouse gas emissions and air pollutants, and provide real-time data to assist policymakers in implementing measures to reduce emissions [30] [31] [32]. Some challenges faced by UAVs to be applied and the effect on their results and quality Ali Karaşan et al. (2020) propose some of the criteria for UAVs [33].

4.2 | Define Criteria and Alternatives

Criteria are divided into levels and we have four alternatives as shown in Figure 1.

C1: Functional criteria: which define the functional attributes of UAVs:

C11: influence of maximum distance: these maximum distance capabilities may be limited by factors such as the UAV's endurance, payload, and operating conditions.

C12: influence of maximum altitude: the maximum altitude of UAVs can have several implications, including communication, endurance, environmental impact, safety, regulation, and sensor and payload capabilities.

C13: influence of maximum velocity: the maximum velocity of UAVs It is affected by speed, power consumption, flight time, stability, payload, range, navigation, and regulation.

C2: Non-functional criteria: which define the non-functional attributes of UAVs:

C21: weight: UAV weight can have several impacts on its operation and performance, including payload, endurance, flight time, stability, navigation, regulation, power consumption, and environmental impact.

C22: Cyber security: UAVs can collect and transmit sensitive data, such as images, videos, and location information, which can be valuable to cybercriminals. Therefore, it is essential to ensure the cybersecurity of UAVs to protect the privacy and security of individuals and organizations.

C23: Flexibility: UAVs' flexibility in smart cities is attributed to their versatile design and adaptability to various applications, which can lead to efficient and effective services.

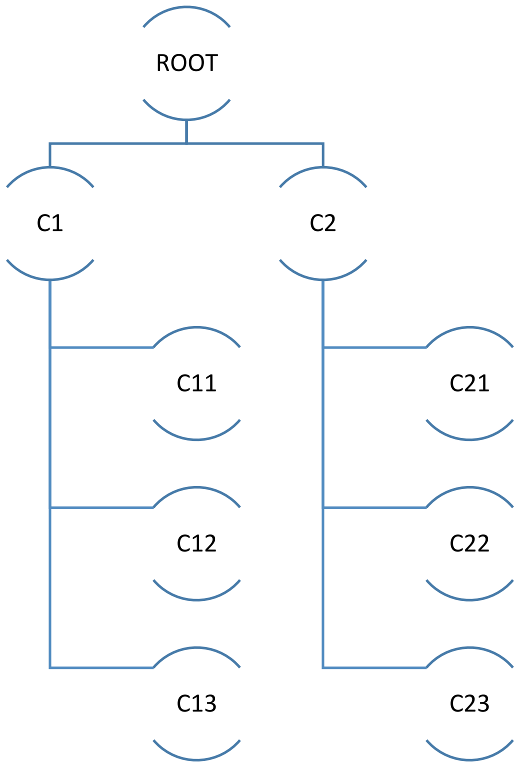

Figure 1. TreeSoft Set.

4.3 | Applying Hybrid Method

In this part, we apply the T2NN-SWARA-MOORA method to these criteria and alternatives based on the TreeSoft approach.

First: Using the SWARA method to get weight:

First Level:

For the first level of the tree, DMs express their opinion using Table 1 to get Table 3.

Then, use Eq. (7) to aggregate the DMs' opinions in one T2NN value. After that, use Eq. (5) to convert into crisp numbers, and Eq. (8) to get the Kj coefficient.

Also, use Eq. (9) to calculate the qi significant weight and Eq. (10) to calculate the relative weight Wj. All these steps are presented in Table 4.

Table 3. DMs opinions for level 1.

DMs	C1	C2
DM1		WI
DM2		EI
DM3		EI
DM3		EI

Table 4. SWARA steps.

	Aggregate matrix by T2NN	Crisp	Relative importance	Coefficient (K)	initial weight qi	Weight
C1				1	1	0.580
C2	((0.33,0.30,0.23), (0.50,0.60,0.53), (0.45,0.65,0.62))	0.38	0.38	1.38	1/1.38 = 0.725	0.420

Level of C1:

For the second level of the tree, DMs express their opinion to get Table 5. The previous steps are applied here and presented in Table 6.

Table 5. DMs opinions for level C1.

DMs	C11	C12	C13
DM1		SI	AI
DM2		AI	SI
DM3		AI	SI

Table 6. SWARA steps.

	Aggregate matrix by T2NN	Crisp	Relative importance	Coefficient (K)	Initial weight qi	Weight
C11				1	1	0.529
C12	((0.82,0.75,0.82), (0.20,0.25,0.25), (0.15,0.17,0.18))	0.7933	0.7933	1.7933	1/1.7933 = 0.558	0.295
C13	((0.73,0.65,0.68), (0.30,0.35,0.40), (0.25,0.28,0.27))	0.6858	0.6858	1.6858	0.558/1.6858 = 0.331	0.175

Level of C2:

For the second level of the tree, DMs express their opinion to get Table 7. All previous steps are applied here and presented in Table 8.

Table 7. DMs opinions for Level C2.

DMs	C21	C22	C23
DM1		EI	EI
DM2		WI	SI
DM3		EI	VSI

Table 8. SWARA steps.

	Aggregate matrix by T2NN	Crisp	Relative importance	Coefficient (K)	Initial weight qi	Weight
C21				1	1	0.459
C22	((0.33,0.30,0.23), (0.50,0.60,0.53), (0.45,0.65,0.62))	0.38	0.38	1.38	1/1.38 = 0.725	0.333
C23	((0.62,0.53,0.50), (0.35,0.38,0.42), (0.32,0.37,0.37))	0.6017	0.6017	1.6017	0.725 / 1.6017 = 0.453	0.208

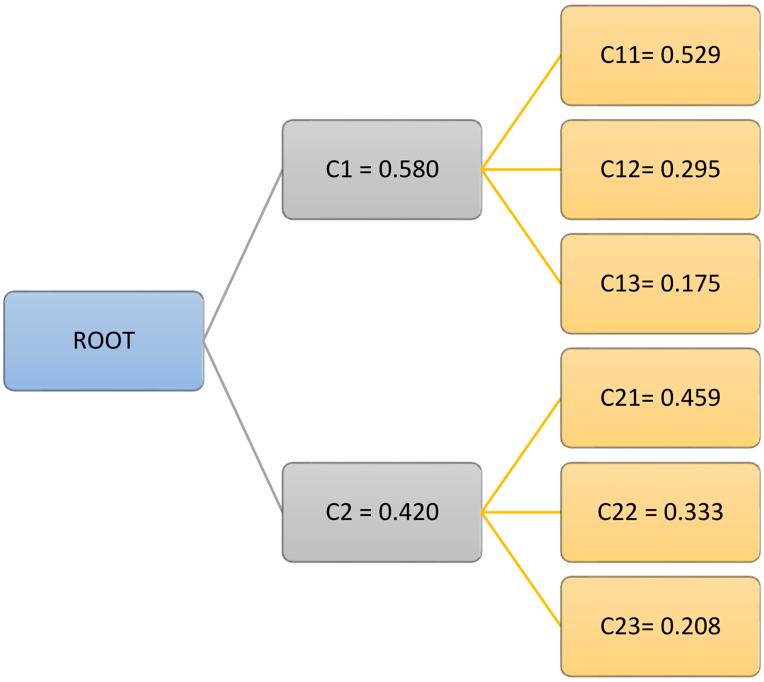

Figure 2. Final weights.

Rank alternatives:

First: Using the MOORA method to rank alternatives. For the first level of the tree, DMs express their opinion using Table 2 to get Table 9. Then use Eq. (2) to aggregate the DMs as in Table 10.

Use Eq. (5) to get crisp numbers as shown in Table 11. Also, calculate normalized decision matrix using Eq. (12) to get Table 12. Calculate the weight normalized matrix by multiplying the weight by the normalized matrix to get Table 13. Calculate the Yj using Eq. (13) then rank as shown in Table 14.

Table 9. Decision matrix for level 1.

DMs	Altn	C1	C2
DM1	Alt1	MG	G
	Alt2	VB	VG
	Alt3	MG	MG
	Alt4	G	MB
DM2	Alt1	G	MB
	Alt2	MB	VB
	Alt3	VG	MG
	Alt4	VG	VB
DM2	Alt1	VG	B
	Alt2	M	VG
	Alt3	G	B
	Alt4	B	MB

Table 10. Aggregate matrix.

	C1	C2
Alt1	((0.617,0.599,0.623), (0.001,0.001,0.001), (0.0001,0.0006,0.0005))	((0.476,0.440,0.453), (0.013,0.018,0.030), (0.008,0.011,0.026))
Alt2	((0.353,0.308,0.358), (0.043,0.042,0.064), (0.024,0.032,0.063))	((0.640,0.613,0.637), (0.002,0.003,0.007), (0.0004, 0.0007, 0.0006))
Alt3	((0.617,0.599,0.623), (0.001,0.001,0.001), (0.0001,0.0006,0.0005))	((0.475 ,0.393,0.358), (0.006, 0.006 ,0.017), (0.002,0.016,0.005))
Alt4	((0.589,0.588,0.591), (0.003,0.005,0.003), (0.0008,0.002,0.002))	((0.383,0.261,0.358), (0.054,0.033,0.057), (0.030,0.024,0.084))

Table 11. Crisp numbers.

	C1	C2
Alt1	0.8694	0.8054
Alt2	0.7488	0.8738
Alt3	0.8694	0.7954
Alt4	0.8611	0.7437

Table 12. Normalized matrix.

	C1	C2
Alt1	0.518	0.499
Alt2	0.446	0.542
Alt3	0.518	0.493
Alt4	0.513	0.461

Table 13. Weighted normalized matrix.

Weighted normalized	C1	C2
Alt1	0.301	0.210
Alt2	0.259	0.228
Alt3	0.301	0.207
Alt4	0.298	0.194

Table 14. Final rank.

	Yj	Rank
Alt1	0.091	3
Alt2	0.031	4
Alt3	0.094	2
Alt4	0.104	1

Level C1: For the first level of the tree DMs express their opinion using Table 2 to get Table 15. Then, use Eq. (2) to aggregate the DMs in Table 16. Use Eq. (5) to get crisp numbers as shown in Table 17. Calculate the normalized decision matrix using Eq. (12) to get Table 18. Calculate the weight normalized matrix by multiplying the weight by the normalized matrix to get Table 19. Calculate the Yj using Eq. (13), then rank as shown in Table 20.

Table 15. Decision matrix for C1 level.

DMs	Altn	C11	C12	C13
DM1	Alt1	VG	MG	B
	Alt2	G	B	MG
	Alt3	MG	M	B
	Alt4	VG	MG	VG
DM2	Alt1	MB	VG	VG
	Alt2	G	M	M
	Alt3	VG	MG	VB
	Alt4	VG	VG	MB
DM2	Alt1	VG	VG	G
	Alt2	MB	MB	MG
	Alt3	MG	MG	VB
	Alt4	VG	MB	MG

Table 16. Aggregate matrix.

	C11	C12	C13
Alt1	((0.650,0.619,0.650), (0.002,0.001,0.0004), (0.0004, 0.0005,0.0005))	((0.653,0.629,0.650), (0.0007, 0.0005,0.0002), (0.00008, 0.0002,0.0001))	((0.589,0.588,0.591), (0.003,0.005,0.003), (0.0008,0.002,0.002))
Alt2	((0.552, 0.544, 0.593), (0.004, 0.005,0.009), (0.002,0.002,0.008))	((0.393,0.351,0.358), (0.033,0.039,0.060), (0.026,0.030,0.059))	((0.485,0.420,0.458), (0.005,0.003,0.010), (0.001,0.008,0.003))
Alt3	((0.603,0.539, 0.571), (0.001,0.0008,0.001), (0.0002,0.001,0.0004))	((0.485,0.420,0.458), (0.005,0.003,0.010), (0.001,0.008,0.003))	((0.245,0.245,0.099), (0.070,0.160,0.193), (0.034,0.160,0.106))
Alt4	((0.664,0.657,0.664), (0.0003,0.0003,0.00004), (0.00004,0.00004,0.00004))	((0.588,0.510,0.571), (0.003,0.002,0.002), (0.0008,0.001,0.002))	((0.588,0.510,0.571), (0.003,0.002,0.002), (0.0008,0.001,0.002))

Table 17. Crisp numbers.

	C11	C12	C13
Alt1	0.8776	0.8799	0.8611
Alt2	0.8497	0.7614	0.8118
Alt3	0.8538	0.8118	0.6493
Alt4	0.8867	0.8471	0.8471

Table 18. Normalized matrix.

	C11	C12	C13
Alt1	0.506	0.532	0.540
Alt2	0.490	0.461	0.509
Alt3	0.492	0.491	0.407
Alt4	0.511	0.513	0.532

Table 19. Weighted normalized matrix.

Weight normalized	C11 +	C12 -	C13 +
Alt1	0.155	0.091	0.055
Alt2	0.150	0.079	0.052
Alt3	0.151	0.084	0.041
Alt4	0.157	0.088	0.054

Table 20. Final rank.

	Yj	Rank
Alt1	0.118995	3
Alt2	0.123189	1
Alt3	0.108346	4
Alt4	0.12311	2

Level C2: For the first level of the tree DMs express their opinion using Table 2 to get Table 21. Then, use Eq. (2) to aggregate the DMs in Table 22. Use Eq. (5) to get crisp numbers as shown in Table 23. Calculate the normalized decision matrix using Eq. (12) to get Table 24. Calculate the weight normalized matrix by multiplying the weight by the normalized matrix to get Table 25. Calculate the Yj using Eq. (13) then, rank as shown in Table 26.

Table 21. Decision matrix for Cl Level.

DMs	Altn	C21	C22	C23
DM1	Alt1	VG	VB	VG
	Alt2	G	G	G
	Alt3	MG	G	MG
	Alt4	VG	MG	VG
DM2	Alt1	VG	MG	G
	Alt2	G	VB	MG
	Alt3	MG	G	VG
	Alt4	VB	MB	VG
DM2	Alt1	VG	VG	VG
	Alt2	M	M	M
	Alt3	B	MG	G
	Alt4	M	G	VG

Table 22. Aggregate matrix.

	C21	C22	C23
Alt1	((0.664,0.657,0.664),(0.0003,0.0003,0.00004), (0.00004,0.00004,0.00004))	((0.545,0.490,0.501), (0.004,0.004,0.004), (0.0008,0.003,0.002))	((0.656,0.648,0.659), (0.0005,0.0007,0.0002), (0.00008,0.0001,0.0002))
Alt2	((0.535,0.566,0.593), (0.003,0.006,0.010), (0.001,0.003,0.006))	((0.415,0.444,0.453), (0.013,0.024,0.035), (0.005,0.016,0.021))	((0.511,0.499,0.533), (0.004,0.005,0.010), (0.001,0.005,0.005))
Alt3	((0.475,0.393,0.358), (0.007,0.006,0.017), (0.002,0.016,0.005))	((0.569, 0.566,0.593), (0.002,0.002,0.005), (0.0004,0.002,0.002))	((0.617,0.599,0.623), (0.001,0.001,0.001), (0.0001,0.0006,0.0005))
Alt4	((0.491,0.490,0.501), (0.009,0.012,0.007), (0.003,0.005,0.005))	((0.530,0.466,0.533), (0.005,0.003,0.009), (0.002,0.004,0.006))	((0.664,0.657,0.664), (0.0003,0.0003,0.00004), (0.00004,0.00004,0.00004))

Table 23. Crisp numbers.

	C21	C22	C23
Alt1	0.8867	0.8334	0.8840
Alt2	0.8518	0.8002	0.8335
Alt3	0.7953	0.8564	0.8694
Alt4	0.8262	0.8299	0.8867

Table 24. Normalized matrix.

	C21	C22	C23
Alt1	0.527	0.502	0.509
Alt2	0.507	0.482	0.480
Alt3	0.473	0.516	0.500
Alt4	0.491	0.510	0.510

Table 25. Weighted normalized matrix.

Weight normalized	C21 -	C22 +	C23 +
Alt1	0.102	0.070	0.044
Alt2	0.098	0.067	0.042
Alt3	0.091	0.072	0.044
Alt4	0.095	0.071	0.044

Table 26. Final rank.

	Yj	Rank
Alt1	0.012753	3
Alt2	0.011431	4
Alt3	0.024453	1
Alt4	0.019538	2

5 | Conclusions

UAVs (Unmanned Aerial Vehicles) are increasingly playing a significant role in climate change research, mitigation, and adaptation efforts. UAVs equipped with cameras and other sensors are used to monitor changes in ecosystems such as forests, wetlands, and coastal areas. They can assess vegetation health, land cover changes, biodiversity, and carbon sequestration rates. This information is crucial for understanding the impact of climate change on ecosystems and developing conservation strategies. UAVs equipped with cameras and other sensors are used to monitor changes in ecosystems such as forests, wetlands, and coastal areas. They can assess vegetation health, land cover changes, biodiversity, and carbon sequestration rates. This information is crucial for understanding the impact of climate change on ecosystems and developing conservation strategies. UAVs are deployed in disaster-prone areas to assess damage and support disaster response efforts. In the context of climate change, UAVs can be used to survey areas affected by extreme weather events such as hurricanes, floods, and wildfires. They provide real-time aerial imagery and data to emergency responders, helping them prioritize rescue and relief operations and assess infrastructure damage. UAVs equipped with sensors capable of measuring carbon dioxide ($CO2$) and other greenhouse gases are used to estimate carbon fluxes in terrestrial ecosystems. By flying over forests, croplands, and other vegetation-covered areas, UAVs can quantify carbon uptake and release rates, contributing to carbon accounting efforts and climate change mitigation strategies. UAVs provide observational data that improve weather forecasting models and climate simulations. They can collect localized atmospheric data in regions where traditional observations are sparse, enhancing the accuracy of weather predictions and climate projections. UAVs also help validate satellite data and ground-based observations, improving the overall reliability of climate models.

In this study, we introduce a new hybrid method that combines between SWARA method and MOORA method using Type-2 Neutrosophic Numbers under TreeSoft Set for evaluating UAVs.

In the future, we will estimate the performance of UAVs by using different multi-criteria decision analysis techniques and compare their results.

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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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