

An Integrated MCDM Framework for UAV Platform Selection in Early Forest Fire Detection Missions

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Abstract: Forest fires are among the most significant threats to ecosystems, biodiversity, and environmental sustainability; therefore, early fire detection is a critical component of effective forest fire management. Traditional fire detection methods, including ground patrols, fire observation towers, and satellite imagery, often fail to provide both adequate spatial coverage and the temporal resolution required for timely detection. In this context, Unmanned Aerial Vehicles (UAVs) have emerged as an effective solution for wildfire monitoring due to their operational flexibility, real-time data transmission capabilities, and ability to support various firefighting tasks, including search and rescue, fire surveillance, and containment operations. However, selecting a suitable UAV for early-stage fire detection is a challenging decision, as stakeholders are faced with multiple options based on technological and operational considerations, rather than a single one. This study presents a comprehensive Multi-Criteria Decision-Making (MCDM) model to identify the most suitable commercially available UAV platforms for early forest fire detection. The proposed method integrates objective and subjective evaluation approaches by combining the Criteria Importance Through Intercriteria Correlation (CRITIC) and Weighted Aggregated Sum Product Assessment (WASPAS) methods with the Best-Worst Method (BWM) and Multi-Objective Optimization by Ratio Analysis plus the Full Multiplicative Form (MULTIMOORA). UAV alternatives were evaluated using key criteria, including flight endurance, payload capacity, operational range, sensor capability, and cost. According to the CRITIC-WASPAS approach, alternative A2 achieved the highest ranking, followed by A6 and A5. In contrast, the BWM-MULTIMOORA approach identified A6 and A5 as the two best-performing alternatives, while A4 was ranked last by both integrated approaches. Overall, the findings demonstrate that the proposed hybrid MCDM framework provides a reliable decision-support tool for UAV selection and can support more effective wildfire monitoring, early fire detection, and disaster management strategies.

Keywords: Unmanned aerial vehicles (UAVs), forest fire early detection, MCDM, CRITIC, WASPAS, BWM, MULTIMOORA, UAV platform selection.

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Orman Yangınlarının Erken Tespitinde İHA Platform Seçimi için Bütünleşik Bir Çok Kriterli Karar Verme (ÇKKV) Yaklaşımı



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Özet: Orman yangınları, ekosistemler, biyoçeşitlilik ve çevresel sürdürülebilirlik için en önemli tehditler arasındadır; bu nedenle, yangının erken tespiti, etkili orman yangını yönetiminin kritik bir bileşenidir. Yer devriyeleri, yangın gözetleme kuleleri ve uydu görüntüleme gibi geleneksel yangın tespit yöntemleri, çoğu zaman zamanında tespit için gerekli olan yeterli mekânsal kapsama alanı ve zamansal çözünürlüğü birlikte sağlayamamaktadır. Bu bağlamda, İnsansız Hava Araçları (İHA'lar), operasyonel esneklikleri, gerçek zamanlı veri aktarım kapasiteleri ve arama-kurtarma, yangın gözetimi ile müdahale operasyonları gibi çeşitli yangınla mücadele görevlerini destekleyebilme yetenekleri nedeniyle orman yangını izlemede etkili bir çözüm olarak öne çıkmaktadır. Bununla birlikte, erken aşama yangın tespiti için uygun bir İHA'nın seçilmesi, paydaşların teknolojik ve operasyonel değerlendirmelere dayalı olarak tek bir seçenekten ziyade çok sayıda alternatifle karşı karşıya kalması nedeniyle zorlu bir karar problemi teşkil etmektedir. Bu çalışmada, erken orman yangını tespiti için ticari olarak temin edilebilen en uygun İHA platformlarının belirlenmesine yönelik kapsamlı bir Çok Kriterli Karar Verme (ÇKKV) modeli sunulmaktadır. Önerilen yöntem, Kriterler Arası İlişki Yoluyla Kriter Önem Derecesi (CRITIC) ve Ağırlıklı Toplam Çarpım Değerlendirmesi (WASPAS) yöntemlerini, En İyi-En Kötü Yöntemi (BWM) ve Tam Çarpımsal Form ile Çok Amaçlı Optimizasyon Oran Analizi (MULTIMOORA) yöntemleriyle birleştirilerek nesnel ve öznel değerlendirme yaklaşımlarını bütünleştirmektedir. İHA alternatifleri; uçuş dayanıklılığı, yük taşıma kapasitesi, operasyonel menzil, sensör yeteneği ve maliyet gibi temel kriterler dikkate alınarak değerlendirilmiştir. CRITIC-WASPAS yaklaşımına göre, A2 alternatifi en yüksek sıralamayı elde etmiş, bunu sırasıyla A6 ve A5 alternatifleri izlemiştir. Buna karşılık, BWM-MULTIMOORA yaklaşımı, A6 ve A5 alternatiflerini en iyi performans gösteren iki alternatif olarak belirlemiştir; A4 alternatifi ise her iki bütünleşik yaklaşım tarafından da son sırada değerlendirilmiştir. Genel olarak elde edilen bulgular, önerilen hibrit ÇKKV çerçevesinin İHA seçimi için güvenilir bir karar destek aracı sunduğunu ve daha etkin orman yangını izleme, erken yangın tespiti ile afet yönetimi stratejilerinin geliştirilmesine katkı sağlayabileceğini ortaya koymaktadır.

Anahtar Kelimeler: İnsansız hava araçları (İHA'lar), orman yangını erken algılama, ÇKKV, CRITIC, WASPAS, BWM, MULTIMOORA, İHA seçimi.

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1. Introduction

Forests and grasslands are some of the most important life-supporting ecosystems on Earth. Not only do they provide natural resources such as timber and food, but they also regulate the climate, sustain biodiversity, and support essential ecological processes. Unfortunately, these ecosystems are increasingly affected by various environmental stressors, resulting in declining ecosystem health and reduced recovery capacity. Although climate change remains the primary driver of ecosystem degradation, forest fires are another major factor contributing to significant ecological damage (Mahmudnia et al., 2022). Forest fires are extremely dangerous to animals, plants, and the functioning of the forest ecosystem as a whole.

In fact, large-scale fires can inflict major environmental destruction, cause economic losses, and their impacts may persist in ecosystems for extended periods. As a result, spotting a fire at its very first stage, and quickly suppressing it, are very important steps in preventing small fire incidents from escalating into large-scale events and get out of control. To be successful in early detection, a lot of different monitoring methods have been invented like ground-based patrols, watchtower observations, automated fire detection systems, aircraft patrols, and satellite-based monitoring (Yu, 2024). Nevertheless, quite a few of these methods have faced significant limitations in terms of response time, operational cost, spatial coverage, and accessibility in remote areas.

Today, Unmanned Aerial Vehicles (UAVs), or drones, have become one of the most influential technological solutions not only for environmental monitoring but also disaster management. Unmanned Aerial Vehicles (UAVs) are aircraft capable of operating without an onboard pilot, either through remote control or autonomous onboard systems. Originally developed for military applications, UAVs have been widely adopted in civilian fields, including precision agriculture, environmental monitoring, infrastructure inspection, logistics, and emergency response operations (Lin et al., 2025; Ausonio et al., 2021). Their rapid deployability, relatively low operational costs, and ability to access hazardous or difficult-to-reach areas make them particularly well suited for real-time monitoring applications.

Due to these advantages, drones are being used more in the management of forest fires. UAVs, with their thermal cameras, multispectral sensors, and high-resolution imaging systems, can identify potential fire sources at the very beginning and send live data to the firefighting crews. This capability enables faster response times and improves situational awareness during wildfires. Furthermore, UAVs can significantly support search and rescue operations, track fire spread, and generate accurate maps of affected areas, all of which are essential for planning effective fire containment strategies. In the context of aerial surveillance, UAV-based monitoring not only reduces the exposure of human pilots to hazardous conditions but also provides a more cost-effective and flexible approach to wildfire monitoring (Manoj & Valliyammai, 2023).

Unmanned aerial vehicles (UAVs) have become increasingly popular for monitoring nature and fighting fires, but there are still many issues in deciding whether to use UAVs in a wildfire suppression mission. Technically, UAV aircraft vary greatly in terms of factors such as flight times, maximum payload capacity, operating distance, number and type of sensors installed, and price. Therefore, selecting an optimal UAV to conduct a fire detection operation is a truly complex multi-criteria decision-making problem. It can be said that various multi-criteria decision-making (MCDM) techniques have been used in studies on UAV selection across various sectors. However, the topic of UAVs for early detection of wildfires remains an insufficiently researched area. Even worse, most researches seem to go no further than subjective or objective weighting methods; in other words, weighting is not discussed at all in the context of decision-making.

Therefore, this research aims to fill this gap and present an innovative Multi-Criteria Decision Making (MCDM) system that combines the CRITIC and WASPAS methods, BWM, and

Multi-Objective Optimization with Ratio Analysis (Multi-MOORA). By including both objectively and subjectively weighted methods, the new setup offers a fresh perspective on the evaluation of UAV options. Furthermore, by showcasing various alternatives, this study introduces a novel approach to UAV selection. In short, the results help users make decisions about selecting the best UAV to achieve the desired level of operational efficiency and support a better wildfire early warning system.

The remainder of this study is structured as follows: Section 2 presents the literature of UAV selection and applications. Section 3 outlines the methodological framework in detail, together with the CRITIC, WASPAS, BWM and MULTIMOORA methods. Section 4 provides the application of the study. Finally, Section 5 concludes the study with key findings, policy implications, and directions for future research.

2. Literature Review

UAVs, or drones, have recently become a major focus of attention due to their ability to perform in confined environments, high efficiency, and wide range of applications in both civil and military sectors. UAV innovations are widely used in areas such as environmental monitoring, disaster relief, agricultural logistics, and oil and gas. With the rapid increase in UAV applications and the development of the low-altitude economy, the demand for effective design, operation, and selection of UAV platforms has also increased. Furthermore, UAVs are becoming a vital tool in controlling forest fires by providing live video sharing, image and audio communication, and the ability to transmit real-time information to authorized public safety agencies (Gao, 2025; Gao, 2026; Lin et al., 2025; Mei et al., 2025).

Although UAV-assisted wildfire detection gained popularity lately, the existing literature show that the selection and deployment of UAVs for early detection still remain unsystematic. Most of the recent researches have been focusing on isolated sub-problems like swarm-based coordination and optimization algorithm, fire risk-based path planning, or image-based fire recognition with deep learning techniques. For instance, the UAV swarm methods are mainly aimed at collaborative detection and optimization of path, even though the platform's capability aspects such as robustness, sensor configuration, or communication ability have been rarely considered for the impact on early detection performance. Similarly, the fire risk mapping and coverage optimization have been done in path planning, but the researchers use the UAV capabilities as given without discussing the UAV selection criteria under very different operational constraints. By contrast, vision-based methods mainly aim at improving the fire recognition accuracy from UAV images but still ignore the potential impacts of UAV type, flight parameters, and sensor payload selection on the data quality in early-stage fire detection (Xu et al., 2022; Yan & Chen, 2024; Zhang et al., 2022). Therefore, an integrated decision-making framework is still needed to systematically evaluate and select UAVs according to the specific requirements of early wildfire detection missions.

Recently, several studies (e.g., Wang et al., 2025; Mei et al., 2025) have explored various aspects of UAV operational improvement, including navigation, energy efficiency, and task allocation. For instance, Wang et al. (2025) focused on enabling UAVs to independently navigate through complex 3D environments by combining reinforcement learning with LiDAR sensing. In contrast, Mei et al. (2025) have taken the problem of maximizing drone-collected data with sensor deployment in the presence of battery limitations while still assuring the safe return to the base station. Another critical research area in UAV operations is efficient energy management.

Another important research direction involves the integration of UAVs with advanced computational architectures, such as Mobile Edge Computing (MEC). In disaster scenarios, including forest fires and other natural hazards, UAV networks face significant challenges due to limited onboard computational resources and energy constraints. To overcome these limitations, Priya et al. (2024) proposed a Multi-Agent Deep Policy Model (MADPM) to improve task offloading and power management in UAV networks. Their results

demonstrated significant improvements in computational efficiency and energy utilization, highlighting the effectiveness of intelligent task offloading in UAV-based emergency response systems.

In addition to technical aspects, several studies have applied MCDM techniques to address UAV selection and evaluation problems. As an example, Rishabh and Das (2025) developed a Decomposed Fuzzy-based Non-Linear AHP along with CRITIC weighting and MULTIMOORA ranking to select the best UAVs for smart farming. Likewise, Li et al. (2022) established a Multi-Attribute Group Decision-Making system that merges the BWM with a 2-Dimensional Linguistic Heuristic Fuzzy Variable based MULTIMOORA technique to select sustainable UAV suppliers for the infrastructure monitoring purposes.

Several studies have investigated UAV selection problems using hybrid MCDM techniques. For example, Gao (2025) proposed a hybrid decision-making framework integrating BWM and MULTIMOORA to evaluate UAV alternatives in the industrial sector while considering uncertainty in expert judgments. In another study, Sirin (2023) addressed the problem of engine selection for rotary-wing UAV systems through a hybrid approach combining Fuzzy BWM and the MAIRCA ranking technique.

A summary of the representative studies from the literature is presented in Table 1. The studies listed in the table employ various MCDM methods, including the Fuzzy Weighted Zero Inconsistency (FWZIC), WASPAS, Actor-Critic (AC), State-Space Twin Delayed Deep Deterministic Policy Gradient (SS-TD3), Multi-Agent Deep Policy Model (MADPM), Deep Q-Network (DQN) / Implicit Quantile Network (IQN) using LiDAR, Double-Fuzzy Nonlinear AHP (DFNL-AHP), CRITIC, MULTIMOORA, 2-Dimensional Linguistic Intuitionistic Fuzzy Variable (2DLIFV)-based MULTIMOORA, and BWM.

Table 1. Summary of Previous Studies on UAV Selection and Applications.

Author	Purpose	Method
Gao (2026)	To identify and prioritize barriers to UAV adoption in agriculture.	FWZIC, WASPAS
Mei et al. (2025)	To maximize UAV-based sensor data collection under limited battery energy while ensuring a safe return.	Actor-CRITIC, SS-TD3
Priya et al. (2024)	Improve task offloading and power management in energy-constrained UAV networks for emergency applications.	MADPM, Actor-CRITIC
Wang et al. (2025)	Ensure safe and adaptive UAV navigation in 3D environments.	Actor-CRITIC, DIQN/IQN using LiDAR
Rishabh and Das (2025)	Select optimal UAVs for smart agriculture.	DFNL-AHP, CRITIC, MULTIMOORA
C. Li et al. (2022)	Select sustainable UAV suppliers for applications like power line inspection.	2DLIFV-based MULTIMOORA, BWM
Gao (2025)	Selecting the most suitable UAVs for industrial applications under uncertain expert evaluations.	Dual Hesitant Fuzzy BWM, MULTIMOORA
Lin et al. (2025)	In unmanned aerial vehicle design, noise reduction and the promotion of sustainability are achieved by aligning the design with user needs.	Fuzzy BWM
Sirin (2023)	Selecting the most suitable engines for rotary-wing UAVs.	Fuzzy BWM, MAIRCA

Despite the growing number of studies applying MCDM methods for UAV evaluation and selection, the existing literature has primarily focused on application areas such as agriculture, industrial inspection, infrastructure monitoring, and UAV component design. However, limited attention has been paid to the selection of UAV platforms for early forest fire detection missions. Furthermore, most existing studies rely on either objective or subjective weighting approaches, while integrated frameworks that simultaneously incorporate both evaluation perspectives remain limited. In addition, the combination of objective and subjective weighting methods with robust ranking techniques in this context has not been sufficiently explored. Therefore, this study proposes an integrated MCDM model by combining the CRITIC and WASPAS methods with BWM and MULTIMOORA. The proposed

approach enables a comprehensive evaluation of UAV alternatives by integrating data-driven and expert-based weighting mechanisms, thereby providing an effective decision-support tool for selecting the most suitable UAV platform for early forest fire detection missions. Accordingly, this study aims to address the identified research gap in the literature.

3. Methodology

In this study, we combine various multi-criteria decision-making methods to evaluate and compare the ability of unmanned aerial vehicles (UAVs) to detect early signs of forest fires. In addition to combining objective and subjective weighting techniques, our structure also incorporates two independent ranking methods to obtain more reliable decision-making results. The methodology of the study consists of two main stages for evaluation purposes.

In the first stage, objective weighting and ranking can be performed through the CRITIC and WASPAS methods. CRITIC extracts the objective weights of the criteria based on the statistical properties of the decision matrix, such as standard deviation and inter-criteria correlation. Then, the results obtained from this process are used as input to WASPAS to rank the UAV options according to their performance scores.

The second step involves the subjective evaluation phase using the BWM-MULTIMOORA approach. Through BWM, criterion weights are determined based on expert opinions. First, two criteria are selected that experts consider most and least important, then all pairwise comparisons are made between these criteria. These weights are then used in the MULTIMOORA process to identify and rank alternatives using three types of criteria: the ratio system, the reference point approach, and the full multiplicative form. The model incorporates objective and subjective weighting methods to make the evaluation results more reliable. In reality, CRITIC assigns weights to criteria without any human input, meaning it cannot capture the decision-maker's subjective preferences. Conversely, the BWM procedure allows for the reflection of expert opinions and the decision-maker's preferences. By applying two different ranking procedures (WASPAS and MULTIMOORA), you can compare the results of these methods from two different perspectives to determine which rankings are consistent. The primary reason for choosing the CRITIC-WASPAS and BWM-MULTIMOORA methods is how they complement each other in Multi-Criteria Decision Making (MCDM) processes. While weighting using criterion conflicts can result in a highly objective weighting scheme through the contrast and conflict between criteria considered by the CRITIC approach, the BWM weighting method provides consistent and much more limited pairwise comparisons by incorporating expert opinions.

Regarding the ranking phase, the WASPAS method improves ranking reliability by combining the advantages of the weighted sum model and the weighted product model, whereas the MULTIMOORA method provides a comprehensive evaluation by integrating ratio analysis, the reference point approach, and the full multiplicative form. Therefore, the combined application of these methods enables a more reliable, consistent, and comprehensive evaluation compared with a single MCDM approach.

Accordingly, the methodological framework of the study is structured into the following two main stages:

Stage 1: Objective evaluation

- Determination of criteria weights using the CRITIC method
- Ranking of UAV alternatives using the WASPAS method

Stage 2: Subjective evaluation

- Determination of criteria weights using the BWM method
- Ranking of UAV alternatives using the MULTIMOORA method

Finally, the ranking results obtained from both approaches are compared to evaluate the consistency and robustness of the decision outcomes. The overall methodological structure of the study is illustrated in the research flowchart presented in Figure 1.

3.1 Research Framework

The research design of this study consists of a series of steps. First, the study will investigate both potential UAV options and relevant decision criteria through a comprehensive review of the existing literature and the collection of expert opinions. The decision matrix of the study will be constructed by summing the performance values of each alternative against the selected criteria. The first step will involve identifying UAV alternatives through a systematic literature review, followed by expert interviews and discussions. The CRITIC method will be used to objectively determine the weights of the criteria based on the statistical properties and correlation model of the decision matrix. Then, these weights will be used in the WASPAS method to rank the UAVs.

In the second phase, expert judgments are integrated into the decision-making process through the BWM approach. Based on pairwise comparisons between the most and least important criteria, subjective criteria weights are determined. These weights are then used in the MULTIMOORA method to evaluate and rank the UAV alternatives through its different assessment mechanisms. Finally, the ranking results obtained from the two evaluation phases are compared to assess the consistency and robustness of the proposed methodology.

3.2 Objective Weighting: CRITIC

The CRITIC method is an objective weighting technique and one of the most widely used approaches in MCDM-based decision-making problems for determining the relative importance of evaluation criteria based on the information contained in the decision matrix. Unlike subjective weighting methods that rely solely on expert judgments, the CRITIC method determines criteria weights based on the statistical characteristics of the dataset. More specifically, it considers both the degree of variation in criterion values and the conflict among criteria. Degree of variation is the measure of how different the criterion values are, this is measured using standard deviation, while the amount of disagreement between different criteria is measured by their correlation coefficients (Anjum et al., 2024; Q. Li, 2025; Novotn et al., 2022; Rashmitha et al., 2024; Reyes-Norambuena et al., 2025; Srivastava et al., 2024). According to the CRITIC principle, criteria with higher contrast intensity and lower correlation with other criteria provide more information and consequently receive greater weights. This characteristic enables CRITIC to determine the relative importance of criteria objectively without relying on subjective judgments.

Assume that m alternatives are evaluated with respect to n criteria. The performance of each alternative under each criterion is represented in the decision matrix $X = [x_{ij}]$, where x_{ij} denotes the performance value of alternative i with respect to criterion j .

The CRITIC method can be implemented through the following steps (Anjum et al., 2024; Q. Li, 2025; Novotná et al., 2022; Rashmitha et al., 2024; Reyes-Norambuena et al., 2025; Srivastava et al., 2024).

Step 1: Normalization of the Decision Matrix

Since the criteria can be measured in different units, the decision matrix must first be normalized. Larger values for benefit criteria indicate better performance, while smaller values are preferred for cost criteria. Equation 1 presents the equation used for the benefit criterion. Equation 2 presents the equation used for the cost criterion:

$$r_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \quad (1)$$

$$r_{ij} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}} \quad (2)$$

Step 2: Calculation of Standard Deviations

The standard deviation of each criterion is calculated using Equation 3 to measure the distribution of the normalized values:

$$\sigma_j = \sqrt{\frac{1}{m} \sum_{i=1}^m (r_{ij} - \bar{r}_j)^2} \quad (3)$$

Step 3: Calculation of Correlation Coefficients

The correlation coefficients between criteria are calculated in order to determine the degree of conflict between them. The correlation matrix $R = [r_{jk}]$ contains the correlation coefficients between criteria j and k .

Step 4: Calculation of the Information Measure

Equation 4 is calculated by combining the amount of information provided by each criterion, its variability, and its correlation with other criteria:

$$H_j = \sigma_j \sum_{k=1}^n (1 - r_{jk}) \quad (4)$$

Step 5: Determination of Criteria Weights

Finally, the objective weight of each criterion is obtained in Equation 5 by normalizing the information measures:

$$w_j = \frac{H_j}{\sum_{j=1}^n H_j} \quad (5)$$

3.3 Ranking Method: WASPAS

The WASPAS method is a MCDM technique introduced by Zavadskas et al. (2012) that combines the principles of two classical models: the Weighted Sum Model (WSM) and the Weighted Product Model (WPM). By integrating additive and multiplicative aggregation mechanisms, the WASPAS method improves the reliability and stability of alternative rankings in complex decision problems (Anjum et al., 2024; Q. Li, 2025; Novotná et al., 2022; Rashmitha et al., 2024; Reyes-Norambuena et al., 2025; Srivastava et al., 2024).

The fundamental idea of the WASPAS method is to evaluate alternatives using both aggregation models simultaneously and then combine the results through a coefficient parameter. This hybrid evaluation mechanism allows decision-makers to capture different aspects of alternative performance.

Assume that x_{ij} represents the performance value of alternative i under criterion j and w_j denotes the weight of criterion j .

The WASPAS method consists of the following steps (Anjum et al., 2024; Q. Li, 2025; Novotná et al., 2022; Rashmitha et al., 2024; Reyes-Norambuena et al., 2025; Srivastava et al., 2024).

Step 1: Normalization of the Decision Matrix

To eliminate the effects of different measurement scales, the decision matrix is normalized. Equation 6 is used for benefit criteria and Equation 7 is used for cost criteria:

$$\bar{x}_{ij} = \frac{x_{ij}}{\max_i x_{ij}} \quad (6)$$

$$\bar{x}_{ij} = \frac{\min_i x_{ij}}{x_{ij}} \quad (7)$$

Step 2: Calculation of the Weighted Sum Model

The first performance metric is obtained using the weighted sum model (Equation 8):

$$Q_i^1 = \sum_{j=1}^n \bar{x}_{ij} w_j \quad (8)$$

Step 3: Calculation of the Weighted Product Model

The second performance metric is calculated using the weighted product model (Equation 9):

$$Q_i^2 = \prod_{j=1}^n (\bar{x}_{ij})^{w_j}. \quad (9)$$

Step 4: Determination of the Final WASPAS Score

The final performance score for each alternative is obtained by combining the results of the WSM and WPM models (Equation 10):

$$Q_i = \lambda Q_i^1 + (1 - \lambda) Q_i^2 \quad (10)$$

where λ represents a coefficient that determines the relative importance of the two models and typically varies between 0 and 1. When $\lambda = 1$, the model becomes equivalent to the weighted sum model, whereas $\lambda = 0$ corresponds to the weighted product model (Novotná et al., 2022).

Step 5: Ranking of Alternatives

The alternatives are ranked according to their final Q_i values. The alternative with the highest score is considered the most suitable alternative within the evaluation framework.

3.4 Subjective Weighting: Best–Worst Method (BWM)

In the second stage of the proposed framework, the subjective weights of the evaluation criteria are determined using the BWM. BWM is an MCDM weighting technique developed to determine reliable criteria weights while requiring fewer pairwise comparisons and achieving higher consistency compared with traditional approaches such as the Analytic Hierarchy Process (AHP). The method is based on identifying the most important (best) and least important (worst) criteria and then evaluating the relative preferences of these criteria with respect to the remaining criteria (Gao, 2025; Khiavi et al., 2023; C. Li et al., 2022; T. Li & Fei, 2025; Roshanravan et al., 2025; Srdjevic et al., 2022; Wei et al., 2023).

Compared with conventional pairwise comparison techniques, BWM requires fewer comparisons, thereby reducing the cognitive burden on decision-makers while maintaining a high level of consistency in the obtained criteria weights.

Assume that a decision problem involves a set of criteria $C = \{C_1, C_2, \dots, C_n\}$. The BWM procedure for determining subjective criteria weights consists of the following steps (Gao, 2025; Khiavi et al., 2023; C. Li et al., 2022; T. Li & Fei, 2025; Roshanravan et al., 2025; Srdjevic et al., 2022; Wei et al., 2023).

Step 1: Identification of the Best And Worst Criteria

Decision-makers first determine the most important criterion (best criterion C_B) and the least important criterion (worst criterion C_W) among all evaluation criteria based on their experience and judgment.

Step 2: Construction of the Best-to-Others Preference Vector

Decision-makers evaluate the preference of the best criterion over each of the other criteria according to Equation 11, using a predefined preference scale. These evaluations form the best-to-others vector:

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn}) \quad (11)$$

Step 3: Construction of the Others-To-Worst Preference Vector

Similarly, the degree to which each criterion is preferred over the worst criterion is evaluated according to Equation 12, creating the others-to-worst vector:

$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW}) \quad (12)$$

Step 4: Determination of Optimal Criteria Weights

The optimal weights for the criteria are obtained by minimizing the maximum absolute deviation between the pairwise comparison ratios and the corresponding weight ratios. This leads to the optimization model in Equation 13, 14, 15:

$$\text{Min } \xi$$

$$\left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi \quad (13)$$

$$\left| \frac{w_j}{w_W} - a_{jW} \right| \leq \xi \quad (14)$$

$$\sum_{j=1}^n w_j = 1, w_j \geq 0 \quad (15)$$

where w_j represents the weight of criterion C_j , while w_B and w_W denote the weights of the best and worst criteria, respectively. Solving this optimization model yields the optimal weight vector $W = (w_1, w_2, \dots, w_n)$.

In the proposed study, BWM is applied to capture expert judgments regarding the relative importance of the evaluation criteria. The obtained subjective weights complement the objective weights derived from the CRITIC method in the first stage, thereby providing a more comprehensive weighting structure for the integrated decision-making framework.

3.5 Ranking Method: MULTIMOORA

After determining the subjective weights of the criteria using the BWM, the alternatives are evaluated and ranked through the MULTIMOORA approach. MULTIMOORA is an integrated MCDM method that combines three complementary evaluation mechanisms: the ratio system, the reference point approach, and the full multiplicative form. By combining these three components, MULTIMOORA provides stable and reliable ranking results in complex decision environments (Cheema et al., 2025; Gao, 2025; C. Li et al., 2022).

Let $A = \{A_1, A_2, \dots, A_m\}$ represent the set of alternatives and $C = \{C_1, C_2, \dots, C_n\}$ denote the set of evaluation criteria. The performance values of alternatives with respect to the evaluation criteria constitute the decision matrix in Equation 16:

$$X = [x_{ij}]_{m \times n} \quad (16)$$

where x_{ij} indicates the performance value of alternative A_i with respect to criterion C_j .

The MULTIMOORA procedure consists of the following three components (Cheema et al., 2025; Gao, 2025; C. Li et al., 2022).

Ratio System

In the ratio system, the decision matrix is first normalized to eliminate the influence of different measurement scales. The normalized value is calculated as shown in Equation 17:

$$x_{ij}^* = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (17)$$

After normalization, the overall performance score of each alternative is calculated by summing the weighted normalized values. Values for the benefit criteria given in Equation 18 are maximized, while those for the Cost criteria are minimized:

$$y_i = \sum_{j \in B} w_j x_{ij}^* - \sum_{j \in C} w_j x_{ij}^* \quad (18)$$

where B and C represent the sets of benefit and cost criteria, respectively. Alternatives are ranked according to the obtained performance scores.

Reference Point Approach

The reference point approach evaluates alternatives based on their distance from the ideal reference point. First, the best value for each criterion is determined as a reference point. Equation 19 is used for the benefit criterion, and Equation 20 is used for the cost criterion:

$$r_j = \max_i x_{ij}^* \quad (19)$$

$$r_j = \min_i x_{ij}^* \quad (20)$$

The deviation of each alternative from the reference point is calculated using the Chebyshev metric given in Equation 21:

$$D_i = \max_j |w_j (r_j - x_{ij}^*)| \quad (21)$$

Full Multiplicative Form

The full multiplicative form evaluates alternatives by considering the multiplicative aggregation of criteria values. The overall benefit of each alternative is calculated using Equation 22:

$$U_i = \frac{\prod_{j \in B} (x_{ij})^{w_j}}{\prod_{j \in C} (x_{ij})^{w_j}} \quad (22)$$

where benefit criteria are included in the numerator and cost criteria in the denominator. A higher value of U_i indicates better performance of the corresponding alternative.

Final Ranking

The final ranking of alternatives is obtained by integrating the results of the three components of MULTIMOORA. By combining the outcomes of the ratio system, reference point approach, and full multiplicative form, the method provides a more comprehensive and reliable decision-making process. This integrated evaluation capability makes MULTIMOORA suitable for addressing complex MCDM problems (Cheema et al., 2025; Gao, 2025; C. Li et al., 2022).

In this study, the MULTIMOORA method is employed in the second stage of the proposed framework to rank the UAV alternatives using the subjective criteria weights derived from the BWM. The integration of BWM and MULTIMOORA enables expert judgments to be incorporated into the evaluation process while providing robust and consistent ranking results.

3.6 Integrated Decision Framework

Decision-making is a challenging process, often conducted within a specific framework. This study proposes a decision-making framework that combines objective and subjective evaluation methods for assessing alternatives. In the first step, the CRITIC method is used to calculate the objective weights of the criteria based on the intensity of opposition and the level of conflict between the evaluation criteria. These weights represent the intrinsic information carried by the decision data, and subjective judgments are minimized during the weighting phase. Then, the WASPAS method is used to combine the features of the Weighted Sum Model and the Weighted Product Model to simultaneously produce a balanced and stable preliminary ranking of alternatives through performance evaluation.

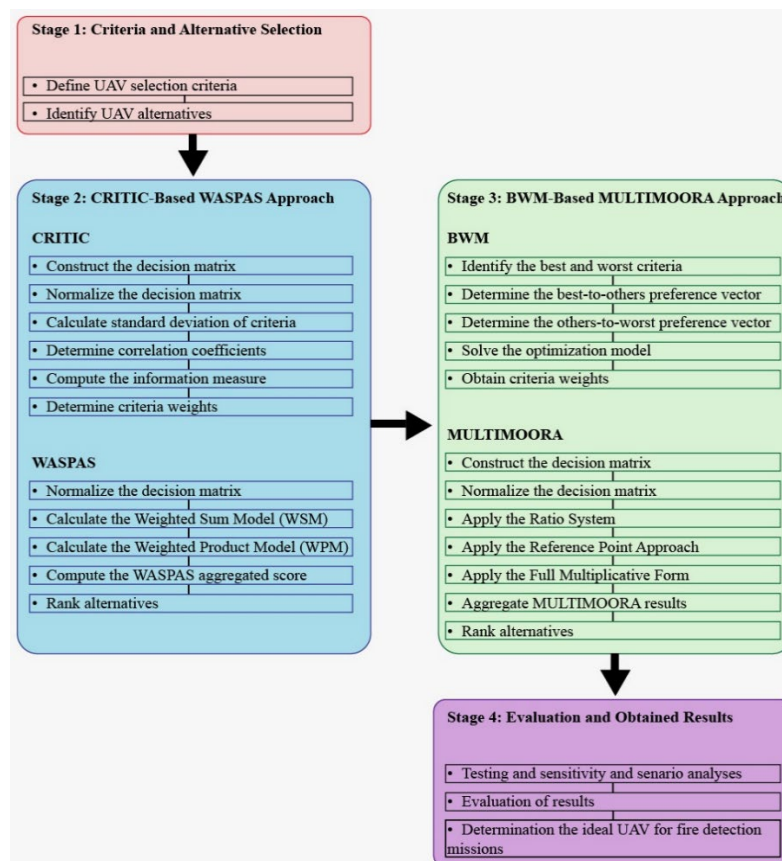


Figure 1. Flowchart of the proposed method.

In the second step, BWM is used to capture expert knowledge in a pairwise comparison method to define subjective criterion weights. The subjective criterion weights obtained from BWM represent the strategic priorities and contextual preferences of decision-makers that other data-driven weighting methods might overlook. Finally, the performance of the alternatives is evaluated using the MULTIMOORA method with these subjectivity weights. The MULTIMOORA method combines the ratio system, the reference point method, and the exact multiplication form to obtain a complete and accurate ranking of alternatives.

By integrating the CRITIC–WASPAS and BWM–MULTIMOORA methods within a single framework, the proposed approach benefits from both objective, data-driven analysis and expert-based subjective evaluation. This hybrid model enhances the reliability and robustness of the decision-making process while reducing the limitations associated with relying on a single weighting or ranking technique. Consequently, the integrated framework provides a systematic and comprehensive evaluation approach for complex MCDM problems.

Figure 1 illustrates the overall research framework and methodological flow of the study.

4. Application and Results

4.1 Problem Structure and Decision Matrix

This study addresses the challenging problem of selecting the most suitable UAV platform for early-stage forest fire detection missions. Such operations require rapid situational awareness, wide-area surveillance capability, and continuous operation to support effective fire monitoring. These missions demand a combination of long endurance, extensive coverage, reliable sensing capabilities, environmental adaptability, and cost-effectiveness. Therefore, six UAV platforms representing different operational classes were shortlisted as potential candidates: A1 DJI Matrice 300 RTK, A2 DJI Mavic 3 Enterprise, A3 senseFly eBee X, A4 Parrot Anafi USA, A5 WingtraOne GEN II, and A6 Quantum Systems Trinity F90+. These alternatives were selected because each represents a distinct category of UAV solutions used for surveillance, mapping, and autonomous monitoring applications, including multirotor, fixed-wing, and Vertical Take-Off and Landing (VTOL) configurations. The evaluation framework was developed by selecting twelve criteria grouped into four main categories: operational performance, sensing and detection capability, operational robustness, and economic factors. Specifically, the selected criteria include flight endurance time (C1), operational range (C2), flight speed (C3), maximum take-off weight-MTOW- (C4), thermal camera capability (C5), optical camera resolution (C6), fire detection capability (C7), wind resistance (C8), operational altitude (C9), environmental robustness (C10), acquisition cost (C11), and maintenance cost (C12). Among these criteria, C1–C10 are considered benefit-type criteria, whereas C11 and C12 are classified as cost-type criteria. Flight endurance time is the maximum time a UAV can continuously operate in flight without refueling or recharging. The selected criteria aim to capture multiple aspects of early forest fire detection missions, where successful operations depend not only on flight performance and sensing capabilities but also on the long-term economic feasibility and practicality of the UAV platform.

The empirical decision matrix was developed based on expert opinion, and three experts from a Turkish company operating in the field of autonomous unmanned aerial vehicle (UAV) systems were invited to the meeting. The selection of experts was based particularly on their professional experience in different types of autonomous mission systems, payload integration, and mission performance evaluation. Their expertise in specific areas was considered because, since some criteria could not be fully and accurately determined solely by technical specifications, it was necessary to evaluate the potential of various UAVs in early detection of forest fires through their own assessments. Examples of such criteria include fire detection capability, environmental resilience, and maintenance

considerations; these are primarily assessed based on field experience, knowledge of system integration, and operational requirements at the mission level.

Based on the responses of three experts to our three-round survey, we first evaluated and ranked six UAV alternatives under twelve criteria of this framework. Then we created the decision matrix. The collected data can be summarized in two ways: firstly, the participants'/experts' assessments of the platforms' suitability/match for real-world tasks; secondly, the actual platform characteristics that can be measured on a scale. In this way, we increase the practical and real-world validity of the study because this analysis is based entirely on the knowledge of field professionals, not on secondhand technical data. To be even clearer and more transparent, the Decision Matrix is a major integration of operational knowledge and technical platform evaluation that is highly aligned with the requirements of wildfire early warning operations.

The decision matrix used in this study was created by combining both objective (measurable) data and expert judgment-based evaluations. The method of obtaining data for the criteria is explained in detail below.

First, the criteria were divided into two main groups:

Objective criteria: Technical and numerical data such as C1 (flight endurance time), C2 (range), C3 (flight speed), C4 (MTOW), C6 (camera performance), C8 (wind resistance), C9 (operational altitude), C11 (acquisition cost), and C12 (maintenance cost) were obtained directly from manufacturer technical documents, catalogs, and publicly available data sources. Expert opinions were used to evaluate these criteria and improve the reliability of the collected data (Triantaphyllou, 2000).

Expert judgment-based criteria: Criteria such as C5 (thermal camera capability), C7 (fire detection capability), and C10 (environmental robustness) were evaluated based on expert judgments because they cannot be adequately represented through directly measurable or standardized data. Particularly in early forest fire detection applications, these performance-related indicators require domain knowledge, field experience, and technical expertise for reliable assessment.

Expert evaluations were obtained through a structured survey conducted with three experts from a company operating in the field of autonomous unmanned systems in Turkey. The experts were selected based on their professional experience in UAV system design, autonomous mission planning, payload integration, and operational performance analysis. Each expert had at least five years of professional experience in the relevant field.

During the evaluation process, the experts were asked to assess the qualitative criteria of each UAV alternative using a 1–9 scale. The scale was defined as follows:

1–3: low performance

4–6: medium performance

7–9: high performance

This scale is a rating system widely used in decision-making literature and facilitates experts' relative evaluation. Experts were specifically asked to evaluate each criterion within the context of an early detection of forest fires scenario.

The experts' scores were averaged for each criterion and alternative to obtain a single final score, which was then added to the decision matrix. By averaging the individual scores of the three experts, the study obtained a single value representing their combined opinions while limiting the possibility of individual bias. The minimum number of experts used in this study was three because these experts had extensive backgrounds in the theory and practice of the subject. As noted in the literature, conducting research with a group of several experts is an acceptable method if they are the most qualified individuals in a particular field of study and area of expertise. Furthermore, the fact that the experts share the same work environment and solve similar problems was considered an advantage to ensure consistency in the evaluation. Expert opinions were collected individually using a designed questionnaire, and the experts made their own assessments. This method is highly effective

because it eliminates the possibility of a group's influence or bias affecting the decision-making process. This method creates a very high-quality decision support base by ensuring that the final decision matrix is based on both objective technical information and qualitative opinions based on domain knowledge.

First, after constructing the decision matrix, the empirical analysis was performed using a two-stage decision-making framework. In the first stage, the CRITIC method was applied to determine the objective weights of the criteria based on data variability and inter-criteria conflict. These weights were subsequently incorporated into the WASPAS method to obtain an initial ranking of the UAV alternatives. In the second stage, the weighting structure was established using the BWM method to incorporate expert judgments regarding mission-critical criteria, and the resulting weights were then applied in the MULTIMOORA method for alternative ranking. By sequentially integrating objective and subjective weighting approaches, this study aims to develop a comprehensive and analytically reliable framework for selecting the most suitable UAV platform for early-stage forest fire detection.

4.2 Stage I: CRITIC-Based Weighting and WASPAS Evaluation

In the first stage, the raw decision matrix was normalized according to the directional characteristics of the evaluation criteria. Benefit-type criteria were normalized using the benefit criterion normalization formula, whereas cost-type criteria were normalized using the cost criterion normalization formula. Subsequently, the CRITIC method was applied to determine the objective weights of the criteria by considering both the variability of each criterion (measured by standard deviation) and the degree of conflict among the criteria (measured by correlation). Table 2 presents the decision matrix. Table 3 shows the normalization of the decision matrix. Table 4 shows the standard deviation values. The correlation matrix is provided in Table 5. The C_j values, representing the contrast intensity of each criterion, are presented in Table 6. The I_j values, indicating the amount of information contained in each criterion, are given in Table 7. The weights obtained from the CRITIC analysis are presented in Table 8.

Table 2. Decision matrix for CRITIC.

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	55	15	82	2,07	9	20	9	15	5000	9	15000	1200
A2	45	32	75	0.2	8	20	8	12	6000	7	3500	400
A3	90	50	110	1,5	7	24	7	12	4000	8	25000	1500
A4	32	15	55	0.5	8	32	7	10	4500	7	7000	500
A5	59	40	90	1	7	42	8	14	5000	8	20000	1300
A6	90	100	100	1,2	7	24	8	14	5000	9	22000	1400

Table 3. Normalization of the decision matrix.

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.397	0	0.491	1	1	0	1	1	0.5	1	0.466	0.273
A2	0.224	0.2	0.364	0	0.5	0	0.5	0.4	1	0	1	1
A3	1	0.412	1	0.695	0	0.182	0	0.4	0	0.5	0	0
A4	0	0	0	0.161	0.5	0.545	0	0	0.25	0	0.837	0.909
A5	0.466	0.294	0.636	0.428	0	1	0.5	0.8	0.5	0.5	0.233	0.182
A6	1	1	0.818	0.535	0	0.182	0.5	0.8	0.5	1	0.140	0.0910

Table 4. Standard deviation.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
standard deviation	0.373	0.339	0.322	0.330	0.372	0.355	0.343	0.334	0.303	0.408	0.364	0.395

Table 5. Correlation table.

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
C1	1.000	0.807	1.000	0.669	0.077	-0.706	-0.077	-0.067	0.293	-0.043	0.481	-0.595
C2	0.807	1.000	0.669	0.077	-0.706	-0.077	-0.067	0.293	-0.043	0.481	-0.595	-0.541
C3	0.954	0.669	1.000	0.535	-0.597	-0.125	0.032	0.502	-0.308	0.599	-0.880	-0.872
C4	0.508	0.077	0.535	1.000	0.191	-0.224	0.451	0.680	-0.450	0.850	-0.668	-0.776
C5	-0.623	-0.706	-0.597	0.191	1.000	-0.458	0.542	0.089	0.307	0.000	0.603	0.463
C6	-0.192	-0.077	-0.125	-0.224	-0.458	1.000	-0.279	-0.089	-0.229	-0.209	-0.175	-0.103
C7	-0.058	-0.067	0.032	0.451	0.542	-0.279	1.000	0.845	0.566	0.594	0.049	-0.139
C8	0.413	0.293	0.502	0.680	0.089	-0.089	0.845	1.000	0.232	0.853	-0.481	-0.629
C9	-0.382	-0.043	-0.308	-0.450	0.307	-0.229	0.566	0.232	1.000	-0.168	0.606	0.521
C10	0.641	0.481	0.599	0.850	0.000	-0.209	0.594	0.853	-0.168	1.000	-0.690	-0.798
C11	-0.880	-0.595	-0.880	-0.668	0.603	-0.175	0.049	-0.481	0.606	-0.690	1.000	0.981
C12	-0.852	-0.541	-0.872	-0.776	0.463	-0.103	-0.139	-0.629	0.521	-0.798	0.981	1.000

Table 6. C_j values (contrast intensity).

Criteria	C_j
C1	9.16
C2	10.70
C3	10.49
C4	9.83
C5	11.19
C6	13.16
C7	8.46
C8	8.29
C9	10.35
C10	8.85
C11	13.13
C12	13.75

Table 7. I_j values (information measure).

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
I_j	3.420	3.630	3.379	3.245	4.169	4.672	2.908	2.778	3.138	3.611	4.790	5.434

Table 8. CRITIC Weights.

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
w_j	0.075	0.080	0.074	0.071	0.092	0.103	0.064	0.061	0.069	0.079	0.106	0.120

The CRITIC results indicate that the objective importance of the evaluation criteria is not uniformly distributed. The highest objective weights were assigned to maintenance cost (C12 = 0.1203), acquisition cost (C11 = 0.1060), optical camera resolution (C6 = 0.1034), operational range (C2 = 0.0804), and environmental robustness (C10 = 0.0799). In contrast, the lowest weights were obtained for wind resistance (C8 = 0.0615) and fire detection capability (C7 = 0.0644). These findings suggest that, within the analyzed dataset, economic factors and selected technical performance criteria exhibited greater variability and stronger

discriminatory power than the remaining criteria. Consequently, cost-related criteria played a more influential role in the objective weighting process.

The CRITIC-derived weights were subsequently incorporated into the WASPAS method. As is well known, WASPAS combines the weighted sum model and weighted product model through the aggregation coefficient λ . In this application, the standard balanced specification $\lambda = 0.5$ was adopted, thereby assigning equal importance to additive and multiplicative utility structures. The normalized decision matrix is presented in Table 9. The Q_1 values, obtained using the weighted sum model, are given in Table 10. The Q_2 values, calculated based on the weighted product model, are presented in Table 11. The obtained Q_1 , Q_2 , and final Q values reveal a clear differentiation among the six UAV platforms. The final WASPAS scores and rankings are reported in Table 12.

Table 9. Normalized Decision Matrix for WASPAS.

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.611	0.150	0.745	1.000	1.000	0.476	1.000	1.000	0.833	1.000	0.233	0.333
A2	0.500	0.320	0.681	0.096	0.888	0.476	0.888	0.800	1.000	0.777	1.000	1.000
A3	1.000	0.500	1.000	0.724	0.777	0.571	0.777	0.800	0.666	0.888	0.140	0.266
A4	0.355	0.150	0.500	0.241	0.888	0.761	0.777	0.666	0.750	0.777	0.500	0.800
A5	0.655	0.400	0.818	0.483	0.777	1.000	0.888	0.933	0.833	0.888	0.175	0.307
A6	1.000	1.000	0.909	0.579	0.777	0.571	0.888	0.933	0.833	1.000	0.159	0.285

Table 10. Q_1 values (Weighted Sum Model).

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.046	0.012	0.055	0.071	0.092	0.049	0.064	0.061	0.057	0.079	0.024	0.040
A2	0.037	0.025	0.051	0.006	0.082	0.049	0.057	0.049	0.069	0.062	0.106	0.120
A3	0.075	0.040	0.074	0.052	0.071	0.059	0.050	0.049	0.046	0.071	0.014	0.032
A4	0.026	0.012	0.037	0.017	0.082	0.078	0.050	0.041	0.052	0.062	0.053	0.096
A5	0.049	0.032	0.061	0.034	0.071	0.103	0.057	0.057	0.057	0.071	0.018	0.037
A6	0.075	0.080	0.068	0.041	0.071	0.059	0.057	0.057	0.057	0.079	0.016	0.034

Table 11. Q_2 values (Weighted Product Model).

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.963	0.859	0.978	1.000	1.000	0.926	1.000	1.000	0.987	1.000	0.857	0.876
A2	0.949	0.913	0.972	0.845	0.989	0.926	0.992	0.986	1.000	0.980	1.000	1.000
A3	1.000	0.946	1.000	0.977	0.977	0.944	0.984	0.986	0.972	0.991	0.812	0.853
A4	0.925	0.859	0.949	0.903	0.989	0.972	0.984	0.975	0.980	0.980	0.929	0.974
A5	0.969	0.929	0.985	0.949	0.977	1.000	0.992	0.996	0.987	0.991	0.831	0.868
A6	1.000	1.000	0.993	0.962	0.977	0.944	0.992	0.996	0.987	1.000	0.823	0.860

Table 12. CRITIC–WASPAS results for UAV platform selection.

Alternative	UAV platform	Q1	Q2	Q	Rank
A1	DJI Matrice 300 RTK	0.6560	0.5557	0.6058	4
A2	DJI Mavic 3 Enterprise	0.7172	0.6253	0.6712	1
A3	senseFly eBee X	0.6372	0.5516	0.5944	5
A4	Parrot Anafi USA	0.6091	0.5460	0.5776	6
A5	WingtraOne GEN II	0.6520	0.5732	0.6126	3
A6	Quantum Systems Trinity F90+	0.7003	0.6081	0.6542	2

The results of the first-stage evaluation identify A2 (DJI Mavic 3 Enterprise) as the highest-ranked UAV platform, followed by A6 (Quantum Systems Trinity F90+) and A5 (WingtraOne GEN II). The superior performance of A2 can be primarily attributed to its favorable economic profile, particularly with respect to acquisition and maintenance costs, which received the highest objective weights in the CRITIC analysis. Since the CRITIC method assigns greater importance to criteria exhibiting higher variability and lower correlation with other criteria, the relatively low cost of A2 contributed substantially to its overall WASPAS score, despite its comparatively lower payload capacity and flight endurance than the fixed-wing and VTOL alternatives.

A6 ranked second, demonstrating a well-balanced technical profile in terms of flight endurance, operational range, flight speed, environmental robustness, and overall mission suitability. Similarly, A5 achieved a high ranking due to its strong sensing capabilities and balanced operational performance. In contrast, A4 ranked last, mainly because of its relatively limited flight endurance, operational range, flight speed, and payload capacity, despite its comparatively favorable cost profile.

Overall, the CRITIC-WASPAS results indicate that when criterion weights are determined solely from the statistical properties of the decision matrix, UAV platforms that combine strong economic performance with adequate technical capabilities tend to achieve higher overall rankings.

4.3 Stage II: BWM-based Weighting and MULTIMOORA Evaluation

In the BWM implementation, expert assessments were obtained from three field experts. The first step consisted of the experts individually identifying the best (most important) and worst (least important) criteria. All three experts agreed on the best and worst criteria, thus achieving strong consensus. They were then asked to rate the relative importance of the remaining criteria. Because the ratings were very close, the arithmetic mean was used to create a comparison matrix for the BWM model from their assessments.

Table 13. Aggregated Pairwise Comparisons for BWM.

Criteria	Best-to-Others	Others-to-Worst
C1	5	6
C2	5	6
C3	6	7
C4	7	7
C5	3	5
C6	3	5
C7	1	9
C8	4	6
C9	4	6
C10	3	5
C11	6	3
C12	8	1

Subsequently, a weighting structure was derived from the BWM based on the experts' combined assessments. Fire detection capability (C7) was considered the best criterion, while maintenance cost (C12) was considered the worst. This preference model corresponds to the functional needs of wildfire detection missions, where sufficiently early detection of thermal anomalies and detection in the smallest stages of the fire are considered the most important issues. While economic considerations still play a role, the subjective weighting procedure showed that experts placed much greater emphasis on mission-related factors that would improve fire detection. The arithmetic mean of the expert assessments were fractional numbers. Since BWM uses a discrete preference scale from 1 to 9, the decimal point was removed by rounding these values to the nearest integer before generating the pairwise

comparison vectors. The pairwise comparisons obtained by the final aggregation method for use in the model are shown in Table 13.

The optimization model was solved using the BWM optimization model implemented in Excel Solver, where optimal weights were obtained by minimizing maximum deviation (ξ) subject to model constraints. Model consistency was assessed based on the resulting ξ value, with low deviation indicating consistent and reliable comparisons. The optimal criterion weights obtained with BWM are given in Table 14.

Table 14. Optimal Criteria Weights Obtained by BWM.

Criteria	Weight (w_j)
C1	0.03
C2	0.06
C3	0.06
C4	0.06
C5	0.11
C6	0.08
C7	0.21
C8	0.10
C9	0.10
C10	0.11
C11	0.06
C12	0.03

The BWM analysis produced a weighting profile in which fire detection capability (C7) received the highest importance. The resulting criterion weights used in the MULTIMOORA analysis were as follows: C7 = 0.21, C5 = 0.11, C10 = 0.11, C8 = 0.10, C9 = 0.10, C6 = 0.08, C2 = 0.06, C3 = 0.06, C4 = 0.06, C11 = 0.06, C1 = 0.03, and C12 = 0.03. This weighting distribution represents a clear shift from the objective, data-driven weighting structure obtained by the CRITIC method toward an expert-based weighting scheme that prioritizes mission-critical capabilities, particularly fire detection capability, sensing performance, and operational robustness.

Furthermore, although fire detection capability (C7) received the highest weight, the remaining criteria also retained meaningful levels of importance, reflecting the experts' balanced evaluation of the decision problem. The consistency of the weighting structure can be attributed to the high level of consensus among the experts regarding the relative importance of the evaluation criteria. This finding indicates that, despite the prominence of mission-critical criteria, the UAV selection process for early forest fire detection requires the simultaneous consideration of multiple technical, operational, and economic factors.

Based on the BWM-derived weights, the MULTIMOORA analysis was carried out using its three classical components: the ratio system, the reference point approach, and the full multiplicative form. Table 15 presents the normalized decision matrix obtained using vector normalization, in which each element is divided by the square root of the sum of the squared values for the corresponding criterion.

Table 15. Normalized Decision Matrix for MULTIMOORA.

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.343	0.120	0.384	0.680	0.477	0.291	0.467	0.473	0.412	0.457	0.354	0.431
A2	0.280	0.256	0.351	0.066	0.424	0.291	0.415	0.379	0.494	0.355	0.083	0.144
A3	0.561	0.401	0.515	0.493	0.371	0.349	0.363	0.379	0.330	0.406	0.590	0.539
A4	0.199	0.120	0.258	0.164	0.424	0.465	0.363	0.315	0.371	0.355	0.165	0.180
A5	0.368	0.321	0.422	0.329	0.371	0.610	0.415	0.442	0.412	0.406	0.472	0.467
A6	0.561	0.801	0.468	0.394	0.371	0.349	0.415	0.442	0.412	0.457	0.519	0.503

Table 16 presents the weighted normalized decision matrix, where the normalized values are multiplied by the criteria weights derived from the BWM method. This process integrates the relative importance of each criterion into the evaluation of alternatives.

Table 16. Weighted Normalized Decision Matrix for MULTIMOORA.

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.009	0.007	0.025	0.039	0.052	0.023	0.096	0.047	0.041	0.050	0.023	0.015
A2	0.007	0.014	0.022	0.004	0.046	0.023	0.085	0.038	0.049	0.039	0.005	0.005
A3	0.015	0.022	0.033	0.028	0.040	0.028	0.075	0.038	0.033	0.044	0.038	0.018
A4	0.005	0.007	0.016	0.009	0.046	0.037	0.075	0.031	0.037	0.039	0.011	0.006
A5	0.010	0.018	0.027	0.019	0.040	0.049	0.085	0.044	0.041	0.044	0.030	0.016
A6	0.015	0.044	0.030	0.022	0.040	0.028	0.085	0.044	0.041	0.050	0.033	0.017

4.3.1 Ratio System Results

The ratio system values (y_i) indicate that A1 achieved the highest overall performance score, followed by A6 and A5. The full ranking obtained from the ratio system is shown in Table 17.

Table 17. BWM–MULTIMOORA ratio system results.

Alternative	UAV platform	y_i	Rank
A1	DJI Matrice 300 RTK	0.349	1
A2	DJI Mavic 3 Enterprise	0.317	4
A3	senseFly eBee X	0.298	5
A4	Parrot Anafi USA	0.285	6
A5	WingtraOne GEN II	0.329	3
A6	Quantum Systems Trinity F90+	0.348	2

A1's superior performance in the ratio system can be attributed to its long flight endurance, wide operational range, high flight speed, environmental robustness, and strong sensing capabilities. Since the expert-based weighting scheme assigned greater importance to mission-critical criteria, particularly fire detection capability and operational performance, rather than economic considerations alone, A1 emerged as the most suitable UAV platform. Similarly, A6 achieved the second-highest ranking owing to its thermal camera capability, environmental robustness, and well-balanced operational characteristics. In contrast, A2, which ranked first in the CRITIC–WASPAS analysis, dropped to fourth place in the BWM–MULTIMOORA evaluation. This result indicates that A2's primary advantage lies in its economic performance, whereas its mission-oriented capabilities received comparatively lower emphasis under the expert-based weighting structure.

4.3.2 Reference Point Results

Table 18 presents the reference values determined for each criterion based on the weighted normalized decision matrix. For benefit criteria, the maximum values were selected, whereas for cost criteria, the minimum values were considered as reference points.

Table 19 presents the absolute deviations of alternatives from the reference point. The deviations were calculated based on the weighted normalized values to evaluate the closeness of each alternative to the ideal solution.

Table 18. Reference Values (Maximum and Minimum) for Each Criterion.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
max-min (r_i)	0.015	0.044	0.033	0.039	0.052	0.049	0.096	0.047	0.049	0.050	0.005	0.005

Table 19. Absolute Deviations from the Reference Point.

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.006	0.038	0.008	0.000	0.000	0.025	0.000	0.000	0.008	0.000	0.017	0.010
A2	0.007	0.030	0.011	0.035	0.006	0.025	0.011	0.009	0.000	0.011	0.000	0.000
A3	0.000	0.022	0.000	0.011	0.012	0.021	0.021	0.009	0.016	0.006	0.032	0.013
A4	0.009	0.038	0.017	0.029	0.006	0.012	0.021	0.016	0.012	0.011	0.005	0.001
A5	0.005	0.027	0.006	0.020	0.012	0.000	0.011	0.003	0.008	0.006	0.025	0.011
A6	0.000	0.000	0.003	0.016	0.012	0.021	0.011	0.003	0.008	0.000	0.028	0.012

Table 20. BWM–MULTIMOORA reference point results.

Alternative	UAV platform	Max deviation	Rank
A1	DJI Matrice 300 RTK	0.0375	5
A2	DJI Mavic 3 Enterprise	0.0349	4
A3	senseFly eBee X	0.0324	3
A4	Parrot Anafi USA	0.0375	5*
A5	WingtraOne GEN II	0.0265	1
A6	Quantum Systems Trinity F90+	0.0279	2

*A1 and A4 have the same reported maximum deviation value in the worksheet and therefore share the same ordinal position in the raw output.

The reference point component produced a similar but not identical ranking order. The results indicate that A5 achieved the best performance, while A6 again obtained the second-highest ranking, followed by A3. The corresponding ranking results are presented in Table 20.

The results of the reference point analysis further support the competitiveness of A5 and A6 under mission-oriented evaluation conditions. A5 outperformed A1 in this assessment, indicating that WingtraOne GEN II is closer to the ideal weighted reference point for several mission-relevant criteria. This finding supports the argument that UAV platforms with stronger sensing capabilities and broader mission coverage potential become more advantageous when the weighting structure is based on operational expertise rather than solely on objective variation patterns.

4.3.3 Full Multiplicative Form Results.

Table 21 presents the results of the full multiplicative form. In this approach, the weighted normalized values of benefit criteria were multiplied for each alternative, and similarly, the values of cost criteria were multiplied separately. The overall performance score was obtained by dividing the product of benefit criteria by the product of cost criteria. The full multiplicative form likewise identified A6 as the best alternative.

Table 22 presents the comparative rankings of alternatives obtained from the three MULTIMOORA approaches.

Table 21. BWM–MULTIMOORA full multiplicative form results.

Alternative	UAV platform	FMF	Rank
A1	DJI Matrice 300 RTK	0.0000000000001857	5
A2	DJI Mavic 3 Enterprise	0.0000000000002173	3
A3	senseFly eBee X	0.0000000000001952	4
A4	Parrot Anafi USA	0.0000000000000465	6
A5	WingtraOne GEN II	0.0000000000002349	2
A6	Quantum Systems Trinity F90+	0.0000000000006482	1

Table 22. Comparative and Final Ranking of Alternatives Based on MULTIMOORA.

Alternative	Ratio	Reference	FMF
A1	1	5	5
A2	4	4	3
A3	5	3	4
A4	6	5	6
A5	3	1	2
A6	2	2	1

This component further highlights the strong performance of A6. The multiplicative utility ratio of A6 compared with the other alternatives indicates that this UAV achieves a clear advantage when the weighted criteria are aggregated through a multiplicative structure. Although A5 also demonstrated competitive performance in this sub-model, its results were not equally consistent across the other MULTIMOORA components, particularly the ratio system and the reference point approach. Therefore, the competitiveness of A5 should be interpreted cautiously rather than considered as definitive evidence of overall superiority.

4.4 Comparative Interpretation of the Two-Stage Results

Comparing the results of the first and second stages reveals a significant technical difference. In the ranking using CRITIC and WASPAS, A2 was identified as the best alternative because objective weighting placed greater weight on those with more information (those with greater differentiation), namely purchase, maintenance, and operating costs. However, BWM and MULTIMOORA yield a result showing that A6 consistently performs among the best alternatives. While A6 ranks second in the ratio system, it ranks first among the others in the full multiplicative part and at the reference point where two first-place alternative are located. The result demonstrates that when comparing different evaluation criteria of the MULTIMOORA method, A6 consistently performs at a high level, rather than being best in only a specific evaluation component.

When analyzed from an operational decision-making perspective, the two-stage system proposed here offers a much broader and deeper perspective compared to a single-method approach. The first stage captures data-driven differentiation among UAV alternatives, while the second stage adds expert-based mission priorities. In early wildfire detection missions where rapid anomaly detection, comprehensive surveillance, long-duration flight, and environmental adaptation are key requirements, the BWM and MULTIMOORA results better align with operational priorities. In this way, within the context of the decision we are discussing, the Quantum Systems Trinity F90+ (A6) can be considered the most suitable UAV alternative for wildfire detection.

Nevertheless, the first-stage results should not be overlooked. The first-place ranking of DJI Mavic 3 Enterprise (A2) in the CRITIC–WASPAS analysis demonstrates its strong cost-effectiveness profile. Consequently, A2 may remain a suitable option for organizations with budget limitations or scenarios where lower acquisition barriers and reduced life-cycle costs are prioritized over extended endurance and advanced mission capabilities. Overall, the findings reveal two distinct decision perspectives: one emphasizing economic accessibility and objective data-driven discrimination, and the other prioritizing mission effectiveness through expert judgment. Considering the critical nature of early forest fire detection operations, the second perspective may be more relevant for applications requiring higher operational capability. Accordingly, this study identifies A6 as the most mission-oriented alternative, while A2 emerges as the most cost-effective option under the objective weighting framework.

4.5 Sensitivity Analysis

4.5.1 Sensitivity Analysis for CRITIC-WASPAS

To evaluate the robustness of the proposed model, a sensitivity analysis was conducted by increasing and decreasing the weights of the most influential criteria (C12 and C11) by 5%. The resulting CRITIC weights under these modified scenarios are presented in Table 23.

The WASPAS results obtained under different weighting scenarios are presented in Table 24. W0 represents the original weights, while W1–W4 correspond to the modified weighting scenarios.

The results demonstrate that the rankings remain unchanged across all weighting scenarios. The results indicate that the rankings remain stable under the considered perturbations

Table 23. The recalculated CRITIC weights.

w_j	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
C12 (+5%)	0.0752	0.0798	0.0743	0.0713	0.0917	0.1027	0.0639	0.0611	0.0690	0.0794	0.1053	0.1263
C11 (+5%)	0.0753	0.0799	0.0744	0.0714	0.0917	0.1028	0.0640	0.0611	0.0691	0.0795	0.1113	0.1196
C12 (-5%)	0.0762	0.0809	0.0753	0.0723	0.0929	0.1041	0.0648	0.0619	0.0699	0.0805	0.1068	0.1143
C11 (-5%)	0.0762	0.0808	0.0752	0.0722	0.0928	0.1040	0.0648	0.0619	0.0699	0.0804	0.1007	0.1210

Table 24. WASPAS results based on modified CRITIC weights.

Alternative	W0	W0 Rank	W1 (C12 %5 +)	W1 Rank	W2 (C11 %5 +)	W2 Rank	W3 (C12 %5 -)	W3 Rank	W4 (C11 %5 -)	W4 Rank
A1	0.6058	4	0.6038	4	0.6031	4	0.6079	4	0.6085	4
A2	0.6712	1	0.6732	1	0.6729	1	0.6693	1	0.6695	1
A3	0.5944	5	0.5918	5	0.5907	5	0.5970	5	0.5981	5
A4	0.5776	6	0.5789	6	0.5771	6	0.5762	6	0.5780	6
A5	0.6126	3	0.6102	3	0.6092	3	0.6150	3	0.6160	3
A6	0.6542	2	0.6512	2	0.6502	2	0.6572	2	0.6582	2

4.5.2 Sensitivity Analysis for BWM-MULTIMOORA

To evaluate the robustness of the BWM-MULTIMOORA model, a sensitivity analysis was conducted by increasing and decreasing the weights of the most significant criteria (C7 and C5) by 5%.

The recalculated BWM weights are presented in Table 25.

The rankings of the alternatives obtained from the MULTIMOORA components under different weighting scenarios are presented in Table 26. Scenario 1: C7 increased by 5%; Scenario 2: C5 increased by 5%; Scenario 3: C7 decreased by 5%; Scenario 4: C5 decreased by 5%.

The results indicate that the rankings remain unchanged across all weighting scenarios and MULTIMOORA components. This stability demonstrates the robustness and consistency of the proposed framework under different weighting conditions. The comparative rankings of the alternatives obtained from the WASPAS and MULTIMOORA methods are presented in Table 27.

Table 25. The recalculated BWM weights.

w_j	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
C7 (+5 %)	0.0256	0.0544	0.0631	0.0560	0.1071	0.0786	0.2158	0.0980	0.0980	0.1071	0.0631	0.0333
C5 (+5 %)	0.0257	0.0548	0.0635	0.0564	0.1139	0.0791	0.2042	0.0987	0.0987	0.1078	0.0635	0.0335
C7 (-5 %)	0.0262	0.0558	0.0647	0.0575	0.1099	0.0807	0.1952	0.1006	0.1006	0.1099	0.0647	0.0341
C5 (-5 %)	0.0261	0.0554	0.0643	0.0571	0.1031	0.0801	0.2067	0.0999	0.0999	0.1092	0.0643	0.0339

Table 26. Rankings of alternatives obtained from MULTIMOORA components under different weighting scenarios.

Alternative	Ratio 0	Ratio 1	Ratio 2	Ratio 3	Ratio 4	Reference	Reference1	Reference2	Reference3	Reference4	FMF	FMF1	FMF2	FMF3	FMF4
A1	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5
A2	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3
A3	5	5	5	5	5	3	3	3	3	3	4	4	4	4	4
A4	6	6	6	6	6	5	5	5	5	5	6	6	6	6	6
A5	3	3	3	3	3	1	1	1	1	1	2	2	2	2	2
A6	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1

Table 27. Comparison of alternative rankings across WASPAS and MULTIMOORA methods.

Alternative	WASPAS	RATIO	REFERENCE	FMF
A1	4	1	5	5
A2	1	4	4	3
A3	5	5	3	4
A4	6	6	5	6
A5	3	3	1	2
A6	2	2	2	1

4.6 Main Findings

The key findings of the empirical study can be summarized in three points. First, changing the weighting of the criteria can significantly affect the final list. Second, and most importantly, among all alternatives in the decision matrix, A6 is the option that demonstrates the strongest performance in both task-oriented and expert opinion-based scenarios. This makes it the most optimal solution when considering both operational aspects and expert opinion. Third, A2 is highly preferable when cost-related factors are given more consideration. This shows that in this case, a cost-effective choice would be more appropriate than relying solely on the most task-oriented platform.

The method presented here supports a complete evaluation process for the selection of UAV platforms for early warning systems in forest fires. The rankings generated with the help of the system not only provide you with a list of options but also explain the logic between different rankings when the evaluation based on criterion weightings shifts from a purely objective, data-driven approach to a subjective expert opinion-based evaluation. This type of explainable artificial intelligence (XAI) will greatly benefit public institutions, emergency response planners, and government officials responsible for procurement decisions. These stakeholders must compare the various technical parameters of a product with the financial costs associated with procurement.

The findings further demonstrate that although the rankings vary depending on the weighting approach, the proposed integrated MCDM framework produces consistent and explainable decision outcomes. The sensitivity analysis confirms that the relative positions of the leading alternatives remain stable under different weight variation scenarios, supporting the robustness of the proposed model.

5 Conclusion and Future Remarks

This study introduces a two-stage, innovative multi-criteria decision-making method to evaluate and ultimately select types of unmanned aerial vehicles (UAVs) for early detection of forest fires. The successful completion of this task largely depends on: a) capturing a snapshot of the entire situation at once (without missing crucial details), b) uninterrupted reconnaissance operations (no time loss or risk), and c) maintaining a consistent operational level (no major disruptions in the process) – all these factors are essential for an effective fire

protection strategy. In this study, two MCDM techniques, namely CRITIC-WASPAS and BWM-MULTIMOORA, were combined to develop such a model. This decision-making model is an integration of objective aspects and subjective rankings, i.e., those provided by field experts, which can be expressed with a data matrix. It provides a comprehensive picture of the situation necessary for making a UAV selection.

The empirical results demonstrate that UAV rankings are strongly influenced by the weighting strategy applied in the evaluation process. In the first stage, where criterion importance was determined objectively using CRITIC and alternatives were ranked through WASPAS, DJI Mavic 3 Enterprise (A2) achieved the highest ranking. This finding indicates that when criterion importance is primarily determined by the statistical characteristics of the dataset, economically advantageous alternatives may gain a substantial advantage. In particular, the relatively high importance assigned to acquisition and maintenance costs within the CRITIC weighting structure contributed significantly to A2's superior position in the first-stage evaluation.

On the other hand, the second-stage analysis, where expert-based weights were added via BWM and alternatives were examined using MULTIMOORA, revealed a different preference ranking more aligned with mission requirements. It appears that Quantum Systems Trinity F90+ (A6) was one of the leading options in almost all sections of MULTIMOORA, placing it in an excellent position in the reference point method and full multiplicative form domains. This demonstrates that the A6's performance is quite robust and balanced, considering many aspects of decision-making. In particular, it would make sense to consider the A6 as a very promising alternative in a scenario where fire detection performance, durability, operational range, environmental robustness, and mission continuation after a malfunction are of greater value.

Methodologically, this study contributes to the field by demonstrating the benefit of combining objective and subjective weighting methods within a single MCDM framework. Instead of using only a single evaluation mechanism, the method enhances the readability of the decision-making process for both researchers and practitioners by highlighting the impact of changes in decision-makers' preferences on the final outcome rankings. We believe this feature is particularly useful in public safety and environmental monitoring situations where a constrained budget needs to be matched with a specific operational need and mission performance level.

The described framework provides a suitable guide for companies and other organizations involved with UAVs in wildfire monitoring, emergency preparedness, and aerial surveillance. Fire and emergency department planners should consider the overall capabilities of UAVs rather than focusing solely on the cost of the machine or the technical parameters of the device. Furthermore, UAV procurement policies should be aligned with the unique aspects of the mission environment (detection targets, operational resilience, deployment conditions, operational constraints, etc.). For these reasons, our study supports a clearer, more robust, and mission-oriented evaluation of UAV alternatives.

Nevertheless, this study has several limitations arising from its scope and methodological design. The analysis considered six UAV alternatives evaluated according to twelve criteria, which, although selected to represent the main aspects of early forest fire detection missions, may not fully capture all characteristics of available UAV platforms. Additionally, some criteria, particularly those related to fire detection capability and performance under challenging environmental conditions, required expert-based assessments using qualitative scales. Finally, the obtained results are influenced by the selected MCDM methods, weighting approaches, and evaluation scenarios. Therefore, the findings should be interpreted as context-dependent rather than universally generalizable. Future studies may extend the proposed framework by incorporating additional UAV alternatives, broader expert panels, real operational data, and alternative decision-making methodologies.

There are many ways to expand or improve this study in the future. For example, more and/or larger sets of alternatives could be considered, or new criteria could be added to the decision system for UAV platform selection, such as regulatory compliance, autonomous navigation capability, communication robustness, payload modularity, etc. In addition, conducting sensitivity analyses, using different MCDM methods as a validation step, and performing scenario-based modeling by varying different wildfire risk factors could ensure better stability and reliability of the results. Furthermore, the use of fuzzy, interval-based, or probabilistic extensions of the proposed system could be considered to better reflect the uncertainty arising from expert opinions and operational data.

In summary, the design of a UAV platform for early wildfire warning systems should be a comprehensive decision rather than a purely technical comparison. After analyzing experimental results, methods such as CRITIC-WASPAS and BWM-MULTIMOORA were identified as the most capable techniques in revealing the diversity in accurate characterization and even decision-making processes. If task-oriented criterion values are paramount, the Quantums Systems Trinity F90+ is the most suitable platform for early wildfire detection. Otherwise, considering the price-performance ratio, the DJI Mavic 3 Enterprise might be more cost-effective. Our research provides decision-makers with a robust and fundamental planning procedure for UAV-based wildfire monitoring.

Although the top-ranked alternatives differ between the two approaches (A2 and A6), both methods produce stable and robust rankings, highlighting different performance priorities. From a practical standpoint, the BWM-MULTIMOORA results may better reflect real-world decision-making, as they incorporate expert judgment and multiple evaluation perspectives, whereas the CRITIC-WASPAS approach remains particularly useful for highlighting cost-efficiency and data-driven distinctions among alternatives.

This particular study has neither conducted actual wildfire monitoring field tests nor utilized operational validation of real monitoring data at this stage. However, the proposed system has been developed considering the necessary evaluation criteria and expert opinions, and its robustness to minor changes has been checked through sensitivity analysis. The Unified MCDM approach will likely assist decision-makers in identifying suitable UAV platforms for various operational environments. Furthermore, it could be part of decision support systems used by forestry management and emergency services where characteristics of UAV options such as structure, flight duration, weight capacity, maneuverability, sensors, and cost are determining factors.

Furthermore, the model is flexible and adaptable to different fire scenarios and geographical conditions. For instance, maneuverability and stability may be more critical in mountainous regions, whereas flight time and coverage area may become more important in large-scale forest fires. Similarly, sensor capacity and response time can be prioritized in early fire detection scenarios.

In this regard, the suggested method offers a useful, adaptable, and reliable decision-making instrument to help choose the most appropriate UAV systems in a variety of environmental and operational conditions. In addition, the results show that different UAV platforms could be the choice depending on the exact priorities of the operation. For instance, in case of rapid responses, UAVs with higher speed and sophisticated detection could be the first choice, whereas those with longer endurance and larger coverage would be better suited for monitoring over time. This also demonstrates the practicality and versatility of the developed model.

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Abbreviations:

The following abbreviations are used in this manuscript:

UAVs	Unmanned Aerial Vehicles
MCDM	Multi-Criteria Decision-Making
CRITIC	Criteria Importance Through Intercriteria Correlation
WASPAS	Weighted Aggregated Sum Product Assessment
BWM	Best-Worst Method
MULTIMOORA	Multi-Objective Optimization by Ratio Analysis plus the Full Multiplicative Form
MEC	Mobile Edge Computing
MADPM	Multi-Agent Deep Policy Model
FWZIC	Fuzzy Weighted Zero Inconsistency
AC	Actor–Critic
SS-TD3	State-Space Twin Delayed Deep Deterministic Policy Gradient
DQN	Deep Q-Network
IQN	Implicit Quantile Network
DFNL-AHP	Double-Fuzzy Nonlinear AHP
2DLIFV	2-Dimensional Linguistic Intuitionistic Fuzzy Variable
VTOL	Vertical Take-Off and Landing
XAI	Explainable Artificial Intelligence

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Appendix A. Supplementary Spearman Rank Correlation Analysis

An additional Spearman rank correlation analysis was conducted to further evaluate the consistency between the applied MCDM methods. This supplementary analysis provides additional robustness evidence supporting the main findings. Spearman's rank correlation coefficient was computed between the WASPAS method and the Full Multiplicative Form (FMF) component of the MULTIMOORA method. The analysis revealed a strong positive correlation between the two methods (Spearman's $\rho = 0.7714$), indicating a substantial degree of agreement in the ranking results. The corresponding Spearman rank correlation matrix is presented in Table A1.

Table A1. Spearman rank correlation matrix of MCDM methods

	WASPAS	FMF
WASPAS	1.0000	0.7714
FMF	0.7714	1.0000

The conclusion drawn from the results is that there is a close agreement between the ranking results obtained using the WASPAS and FMF methods, and that there are methodological differences between these two methods, for example, stemming from mathematical formulations, normalization procedures, or the way the results are combined. A strong correlation supporting the validity of the rankings was observed. This also means that these methods are, in a sense, very reliable and their results are different but still useful when used together.