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A robust decision-making framework for evaluating and ranking agricultural spraying UAVs based on multiple performance criteria

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Abstract: In selecting the suitable UAV for agricultural spraying, it is necessary to consider simultaneously the payload capacity, field productivity, endurance, spraying capacity, energy capacity, range of operation, weight, and charging requirement. In this paper, the authors have presented a multi-attribute decision analysis technique to rank alternative spraying UAVs based on a common set of criteria. The AHP method was used to evaluate the weights of criteria through reciprocal pairwise comparison, and then, the criterion weights are utilized to calculate the ranking orders of three spraying UAV alternatives using TOPSIS, MABAC, and ARAS methods. From AHP result, it can be seen that the weights of payload capacity, work efficiency, endurance time, and spraying flow performance are higher than other criteria. As a consequence, the results obtained from the above three ranking methods have been completely coincided and showed that the order of UAV alternatives are D-T5 > D-T4 > D-T2A. It shows that the decision is not affected by the choice of computational logic. In addition, sensitivity analysis on payload capacity and work efficiency criteria was performed, and there was no change in ranking order in considered intervals. Hence, the results revealed that D-T5 is superior alternative compared with other two alternatives in terms of capacity, efficiency, spray capability, and operational range while D-T4 and D-T2A are ranked in second and third positions, respectively. The study offers a transparent and technically consistent decision procedure for UAV selection in precision agriculture and related equipment-selection problems.

Keywords: Agricultural UAV, AHP, TOPSIS, MABAC, ARAS, precision agriculture, multi-criteria decision-making

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1. Introduction

Precision agriculture has revolutionized field management techniques, integrating the use of sensors, automation, geospatial data, and quantitative decision-making. Monitoring, mapping, spraying, disaster assessment, logistics, and other field activities are currently done using UAVs because they offer fast access, versatility of use, and high-resolution imagery [1–4]. In crop spraying, UAVs help avoid the exposure of operators to pesticides, give better access to difficult-to-reach areas, and enable a more precise pesticide and fertilizers application when proper equipment is chosen for specific operational conditions [3,5,6].

The increasing number of available agricultural spraying UAVs makes the equipment selection harder, as commercial machines vary greatly in terms of payload capacity, work efficiency, flight duration, flow rate of spray, capacity of the tank, battery capacity, spray width, transmission range, weight of the vehicle, and charge time. All these characteristics are heterogeneous in scale and orientation; hence, increased payload capacity can lead to better coverage per single flight, while higher weight can make the equipment less convenient for field operations. Improved range gives more operational possibilities to UAVs, while quick charge means lower downtime before the next mission. A decision based on one criterion only would be misleading if the task was to select the equipment with the best overall operating profile.

Multi-criteria decision analysis can be effectively applied to solve such a task, as it transforms heterogeneous criteria into comparable measures and combines them based on explicit weights. AHP is widely used to get the weights of criteria from pairwise comparisons and to validate the consistency of judgement of a decision maker [7–10]. TOPSIS ranks alternatives by their proximity to the positive and negative ideal solutions, MABAC assesses alternatives by the distance to the approximating border area, while ARAS calculates the utility degree of alternatives relative to the ideal one [11–16]. These approaches have been applied in aviation, logistics, emergency services, energy systems, and UAV selection [17–22].

The majority of UAV selection studies are based on one ranking approach. It means that the choice is sensitive to the normalization rule, reference point, or aggregation procedure used in this method. The comparative evaluation of several approaches is helpful because the same alternatives will be assessed using different mathematical approaches. Sensitivity analysis is required as well, because AHP-based weights are judgement-based and different for various decision-makers. The current study aims to address both issues by using a combination of AHP and TOPSIS, MABAC, and ARAS methods and verifying whether changing the two highest criterion weights would lead to the change in the final ranking of alternatives. Figure 1 shows the decision procedure.

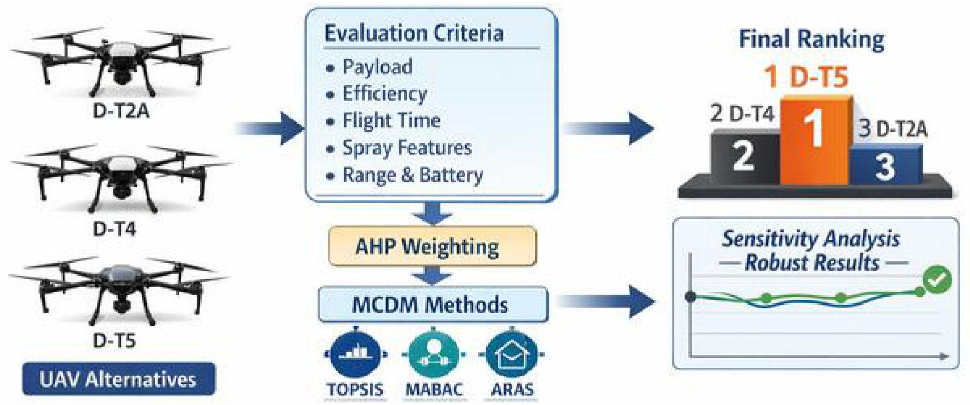


Figure 1. Graphical summary of the UAV selection procedure

Table 1. Representative studies related to UAV selection and multi-attribute decision analysis

Methodological focus	Research focus	Reference
Fuzzy ANP and Choquet integral	Aircraft procurement evaluation using fuzzy preference information	[17]
Mathematical programming and clustering	Route planning for UAV operations in disaster zones	[23]
MCDM review	Classification of decision-making applications in the aviation industry	[18]
UAV disaster-management review	Assessment of UAV capabilities and applications in disaster management	[24]
Interval-valued fuzzy TOPSIS	Last-mile delivery drone selection using multiple operational criteria	[19]
DEMATEL, fuzzy ANP, and AHP	Identification of dominant factors and sustainable value requirements for civilian-use drones	[25,26]
Game theory and emergency logistics	Planning support for natural-disaster response and humanitarian operations	[27,28]
AHP and TOPSIS	Drone and aircraft selection under technical and economic constraints	[20,29]
PROMETHEE, TOPSIS, AHP, and related models	Cargo-drone and firefighting-drone selection for emergency intervention	[30,31]
Bayesian network, MABAC, and logistics models	UAV performance assessment and drone selection for logistics, medical supplies, and flood response	[21,32,33]
Decision models for sustainable logistics	Last-mile logistics and drone-delivery studies in complex urban contexts	[34,35]
LOPCOW, VIKOR, TOPSIS, and AHP	Agricultural UAV selection and scheduling for precision-agriculture applications	[22,36]

What sets apart this paper from others is the internally consistent incorporation of AHP weighting into ranking of UAVs for agricultural spraying by means of three different ranking techniques. The contributions of this paper include the following. First, the alternatives are evaluated with a set of criteria representing such factors as spraying capacity, field productivity, endurance, energy supply, range, and supporting conditions. Second, the final rank of alternatives is verified by TOPSIS, MABAC, and ARAS techniques instead of depending on one ranking. Third, the robustness of the ranking results is checked by changing the values of the most impactful weights.

2. Methodology

The decision problem involves three UAV alternatives represented by A_i, where $i = 1, 2, 3$, and ten criteria represented by C_j, where $j = 1, 2, \ldots, 10$. The decision matrix has the form $X = [x_{ij}]$, where x_{ij} is the value of performance of alternative A_i in criterion C_j. Criteria C1–C8 are considered as the benefit criteria since the higher value increases the operational capabilities. Criteria C9 and C10 are considered as the cost criteria because the lighter vehicle weight and the shorter charging time are required. The weight vector has the form $w = (w_1, w_2, \ldots, w_{10})$, where $w_j \geq 0$ and $\sum_{j=1}^{10} w_j = 1$.

2.1. AHP weighting

AHP converts reciprocal pairwise comparisons into a priority vector. Let $P = [p_{jk}]$ be the pairwise comparison matrix. The entries satisfy $p_{jk} = 1/p_{kj}$ and $p_{jj} = 1$. The priority vector is calculated from the principal eigenvector of P:

$$Pw = \lambda_{\max} w, \qquad \sum_{j=1}^{n} w_j = 1. \tag{1}$$

The internal consistency of the pairwise comparisons is evaluated through the consistency index and consistency ratio:

$$CI = \frac{\lambda_{\max} - n}{n - 1}, \qquad CR = \frac{CI}{RI}, \tag{2}$$

where RI is the random index corresponding to the matrix size. A value of $CR < 0.10$ is generally accepted as sufficiently consistent for decision analysis [7–10].

2.2. Ranking methods

TOPSIS first applies vector normalization:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \tag{3}$$

and then obtains the weighted normalized matrix

$$v_{ij} = w_j r_{ij}. \tag{4}$$

For benefit criteria, the positive ideal value is $v_j^+ = \max_i v_{ij}$ and the negative ideal value is $v_j^- = \min_i v_{ij}$. For cost criteria, these definitions are reversed. The separation measures and closeness coefficient are

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, \qquad S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}, \tag{5}$$

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}. \tag{6}$$

A larger C_i indicates a better alternative [11–13].

MABAC uses linear normalization. For benefit criteria,

$$n_{ij} = \frac{x_{ij} - x_j^-}{x_j^+ - x_j^-}, \tag{7}$$

and for cost criteria,

$$n_{ij} = \frac{x_j^+ - x_{ij}}{x_j^+ - x_j^-}, \tag{8}$$

where x_j^+ and x_j^- are the best and worst criterion values. If all alternatives have the same value for a criterion, the normalized value is set to zero because the criterion does not discriminate among alternatives. The weighted matrix is

$$v_{ij} = w_j(n_{ij} + 1). \tag{9}$$

The border approximation area is calculated by the geometric mean

$$g_j = \left(\prod_{i=1}^{m} v_{ij}\right)^{1/m}, \tag{10}$$

and the final MABAC score is

$$S_i = \sum_{j=1}^{n} (v_{ij} - g_j). \tag{11}$$

A larger S_i indicates a stronger alternative [14,37,38].

ARAS adds an optimal alternative A_0 to the decision matrix. For benefit criteria, normalization is given by

$$r_{ij} = \frac{x_{ij}}{\sum\limits_{i=0}^{m} x_{ij}}, \tag{12}$$

and for cost criteria it is given by

$$r_{ij} = \frac{1/x_{ij}}{\sum\limits_{i=0}^{m} 1/x_{ij}}. \tag{13}$$

The weighted matrix, optimality function, and utility degree are

$$v_{ij} = w_j r_{ij}, \qquad S_i = \sum_{j=1}^{n} v_{ij}, \qquad K_i = \frac{S_i}{S_0}. \tag{14}$$

A larger K_i indicates a utility degree closer to the ideal alternative [15,16,39,40].

Table 2. Summary of the applied multi-attribute decision methods

Method	Main role in this study	Main output
AHP	Derives criterion weights from reciprocal pairwise comparisons and checks consistency through CR.	Weight vector w_j for the ten criteria.
TOPSIS	Measures each UAV according to its distance from the positive and negative ideal weighted profiles.	Closeness coefficient C_i.
MABAC	Compares each UAV with the border approximation area for every criterion.	Overall distance score S_i.
ARAS	Compares each UAV with an explicitly defined optimal alternative.	Utility degree K_i.

2.3. Sensitivity analysis

The sensitivity analysis is performed to evaluate how the ranking would be changed by changing the two dominating weights. Payload capacity and work efficiency are varied one after another. During each variation, the selected weight is kept at the test value, and other weights are normalized to maintain the same total sum as one. Then TOPSIS proximity coefficients are recalculated with the new set of weights. This approach allows us to check the dependence of the final ranking on a narrow weight combination.

3. Results and discussion

This section describes the AHP weights, ranking results of TOPSIS, MABAC, and ARAS, and sensitivity analysis. The interpretation of the scores in relation to agricultural spraying is stressed rather than the numerical calculations.

3.1. Decision matrix and AHP results

Technical specifications used for the decision matrix are shown in Table 3. UAVs D-T4 and D-T5 have the biggest payload capacity and tank volume; D-T5 has the biggest work efficiency, spraying width and transmission range; D-T2A has the biggest flight time and smallest vehicle weight. This variety of trade-offs proves the need to use a multi-criteria decision method since none of UAVs is clearly dominant over all the criteria.

The result of pairwise comparisons of the AHP method is given in Table 4. The matrix gives preference to those criteria which define UAV productivity and mission capability. The calculated value of $\lambda_{\max}$ equals 10.491, resulting in $CI = 0.0545$ and $CR = 0.0366$ with $RI = 1.49$. The consistency ratio being less than 0.10 indicates appropriate pairwise comparisons.

Table 3. Technical specifications of the agricultural spraying UAV alternatives

Code	Criterion	Type	Unit	D-T2A	D-T4	D-T5
C1	Payload capacity	Benefit	kg	10	20	20
C2	Work efficiency	Benefit	m^2/min	800	1500	2200
C3	Flight time	Benefit	min	20	14	15
C4	Spray flow rate	Benefit	L/min	1.6	2.0	2.0
C5	Tank capacity	Benefit	L	10	20	20
C6	Battery capacity	Benefit	Wh	222	488	488
C7	Spray width	Benefit	m	4	5	6
C8	Transmission range	Benefit	km	1	1	2
C9	UAV weight	Cost	kg	12.5	14	23
C10	Charging time	Cost	h	1.25	1.25	1.25

Table 4. AHP pairwise comparison matrix for the criteria

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	1	2	3	4	3	5	5	6	7	7
C2	1/2	1	2	3	2	4	4	5	6	6
C3	1/3	1/2	1	2	2	3	3	4	5	5
C4	1/4	1/3	1/2	1	2	3	3	4	5	5
C5	1/3	1/2	1/2	1/2	1	2	2	3	4	4
C6	1/5	1/4	1/3	1/3	1/2	1	2	3	4	4
C7	1/5	1/4	1/3	1/3	1/2	1/2	1	2	3	3
C8	1/6	1/5	1/4	1/4	1/3	1/3	1/2	1	2	2
C9	1/7	1/6	1/5	1/5	1/4	1/4	1/3	1/2	1	2
C10	1/7	1/6	1/5	1/5	1/4	1/4	1/3	1/2	1/2	1

Weights calculated from AHP technique are represented in Figure 2 and Table 5. The criterion with the highest weight is payload capacity, which is followed by work efficiency, duration of the flight, and spray-flow rate. The sum of weights for all four criteria represents more than 70% of all weights. This outcome corresponds to the spraying process because the practical utility of the drone is highly influenced by its payload capacity, work efficiency, duration of operation, and spray-flow rate.

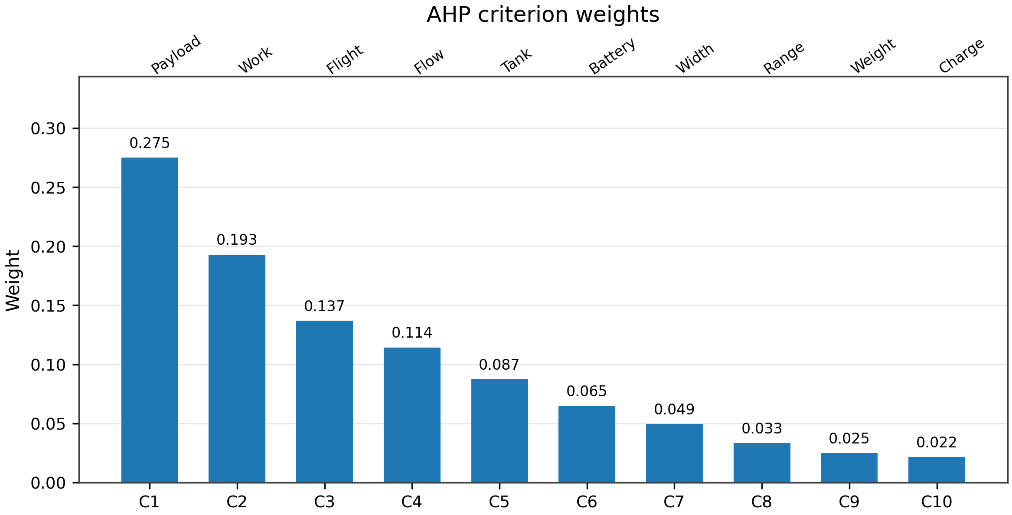


Figure 2. AHP criterion weights

Table 5. AHP criterion weights

Criterion	Description	Weight
C1	Payload capacity	0.275
C2	Work efficiency	0.193
C3	Flight time	0.137
C4	Spray flow rate	0.114
C5	Tank capacity	0.087
C6	Battery capacity	0.065
C7	Spray width	0.049
C8	Transmission range	0.033
C9	UAV weight	0.025
C10	Charging time	0.022
	Total	1.000

The small importance of criteria of the vehicle weight and charging time does not mean that these criteria are unimportant. On the contrary, this means that within the current set of alternatives, the decision-makers are more concerned about the field performance of UAVs rather than support constraints. Charging time criterion has the smallest discriminating power since all three UAVs are equal on this criterion.

3.2. Results of TOPSIS analysis

The vector-normalized matrix is presented in Figure 3. UAV D-T5 shows good results in terms of work efficiency, spray width, and transmission range; D-T2A has the best result in terms of flight time and good raw value of the criterion of vehicle weight. As C9 is the cost criterion, the impact of this criterion should be considered within the solution process of finding an ideal solution.

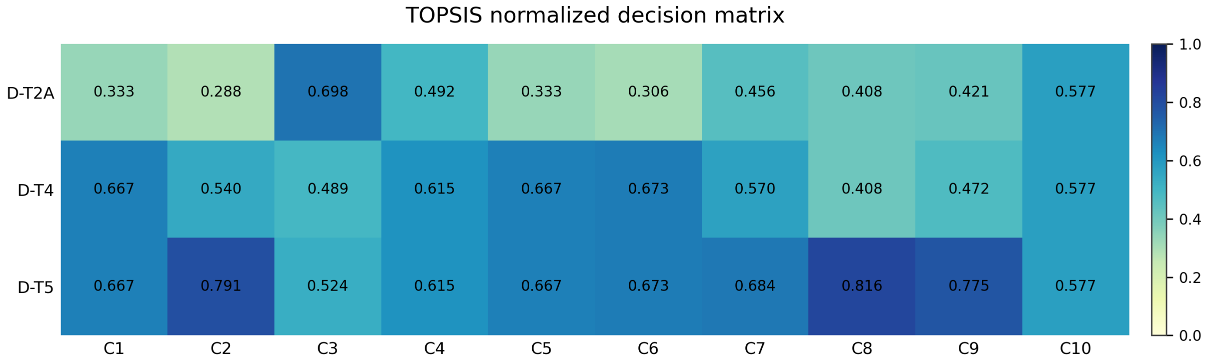


Figure 3. TOPSIS normalized decision matrix

As we can see from Figure 4, after applying the AHP weights, the differences in payload capacity and work efficiency are the most influential factors in separation measures. Even though D-T2A has the best flight time, this does not help to overcome its disadvantages such as low payload capacity, tank capacity, battery capacity, and work efficiency.

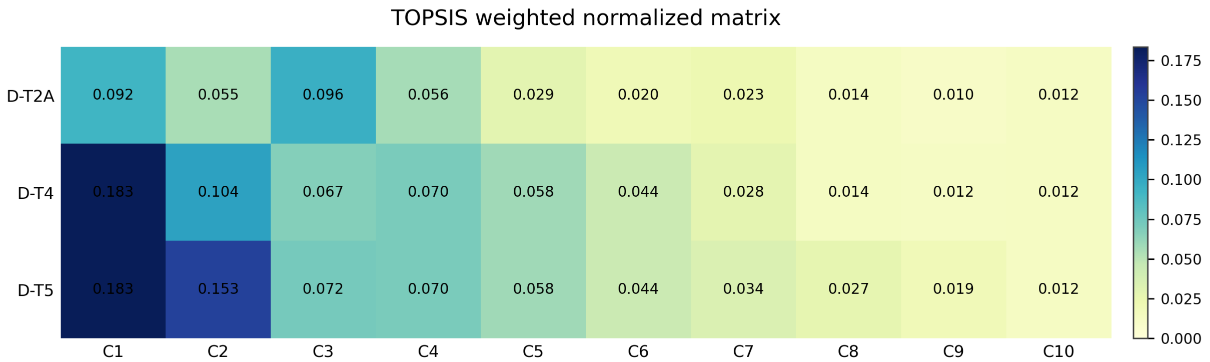


Figure 4. TOPSIS weighted normalized decision matrix

Ideal and negative ideal values are represented in Table 6. In case of the cost criteria, the positive ideal is the smallest weighted value. It is especially important for criterion C9, since D-T2A has the smallest vehicle weight, but D-T5 has the biggest one. Identical charging time makes C10 a nondiscriminating criterion in TOPSIS calculation.

Table 6. TOPSIS positive and negative ideal solutions

Criterion	Type	Positive ideal v_j^+	Negative ideal v_j^-
C1	Benefit	0.183	0.092
C2	Benefit	0.153	0.055
C3	Benefit	0.096	0.067
C4	Benefit	0.070	0.056
C5	Benefit	0.058	0.029
C6	Benefit	0.044	0.020
C7	Benefit	0.034	0.023
C8	Benefit	0.027	0.014
C9	Cost	0.010	0.019
C10	Cost	0.012	0.012

Closeness coefficients and separation measures are presented in Table 7. Among the designs, D-T5 has the largest closeness coefficient; D-T4 ranks the second; D-T2A ranks the third. D-T5 design does not demonstrate superiority in all criteria compared to others, however, it is closer to the positive ideal solution since it has high load, high productivity, good energy capability and largest distance.

Table 7. TOPSIS separation measures and closeness coefficients

Alternative	S_i^+	S_i^-	C_i	Rank
D-T2A	0.141	0.030	0.176	3
D-T4	0.058	0.112	0.657	2
D-T5	0.025	0.141	0.847	1

The TOPSIS ranking is therefore

$$\text{D-T5} > \text{D-T4} > \text{D-T2A}. \tag{15}$$

This order indicates that the best spraying UAV for agriculture is the one which retains an excellent aggregate performance in the criteria that are of highest importance with regard to benefits, without having a high cost criteria penalty.

3.3. MABAC Results

Table 8 presents the normalized matrix for MABAC. The drone with the designation D-T5 has the best score in payload capacity, work efficiency, spray flow, tank capacity, battery capacity, spray width, and transmission range. The drone with the designation D-T2A has the best score in flight time and vehicle weight. The normalized values make the trade-off explicit before the border approximation area is calculated.

Table 8. MABAC normalized decision matrix

Criterion	D-T2A	D-T4	D-T5
C1	0.000	1.000	1.000
C2	0.000	0.500	1.000
C3	1.000	0.000	0.167
C4	0.000	1.000	1.000
C5	0.000	1.000	1.000
C6	0.000	1.000	1.000
C7	0.000	0.500	1.000
C8	0.000	0.000	1.000
C9	1.000	0.857	0.000
C10	0.000	0.000	0.000

The weighted MABAC matrix presented in Table 9 shows that the higher the weight of the AHP criteria, the more impact these criteria make on the distance. The superiority of the D-T5 option can be seen in C1 and C2, whereas the D-T2A alternative is dominated by C3 and C9.

Table 9. MABAC weighted decision matrix

Criterion	D-T2A	D-T4	D-T5
C1	0.275	0.550	0.550
C2	0.193	0.289	0.386
C3	0.274	0.137	0.160
C4	0.114	0.228	0.228
C5	0.087	0.174	0.174
C6	0.065	0.130	0.130
C7	0.049	0.074	0.099
C8	0.033	0.033	0.066
C9	0.050	0.046	0.025
C10	0.022	0.022	0.022

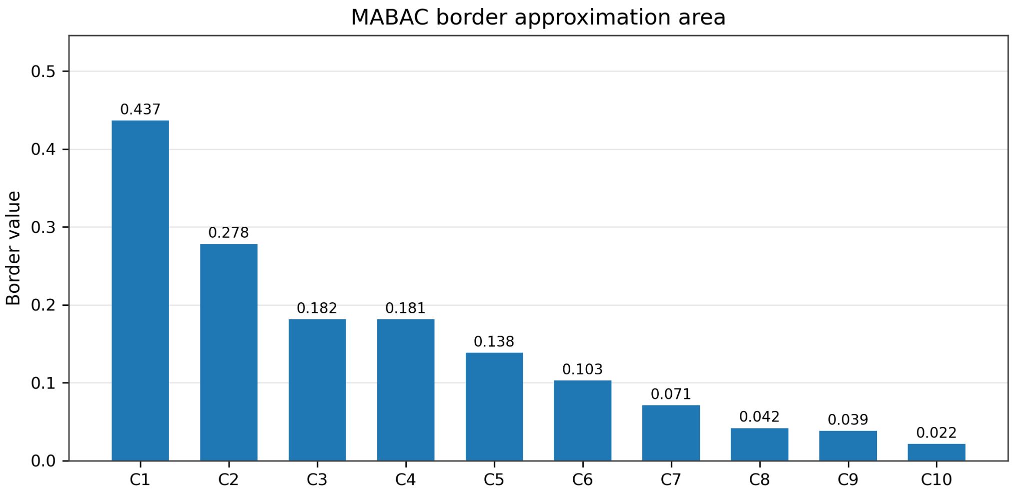


Figure 5. MABAC border approximation area values

The largest border approximation area in Figure 5 belongs to C1 and C2. Thus, C1 and C2 are the most critical criteria to define the strong and weak alternatives. Criteria that have minor or equal values like the charging time criterion cannot influence the MABAC ordering much.

The values of MABAC scores are presented in Table 10. D-T5 and D-T4 belong to the border approximation area, but D-T2A does not because its score is negative. It means that the poor performance of D-T2A on criteria with large weights makes it a weak alternative.

Table 10. MABAC scores and ranking

Alternative	Score S_i	Rank
D-T2A	-0.330	3
D-T4	0.192	2
D-T5	0.348	1

The MABAC ranking is

$$\text{D-T5} > \text{D-T4} > \text{D-T2A}. \tag{16}$$

The consistency of results from MABAC and TOPSIS increases credibility of the decision making because the two approaches apply to criteria in a different way. Namely, TOPSIS uses ideal and negative ideal points as references, whereas MABAC uses border values according to criteria.

3.4. ARAS results

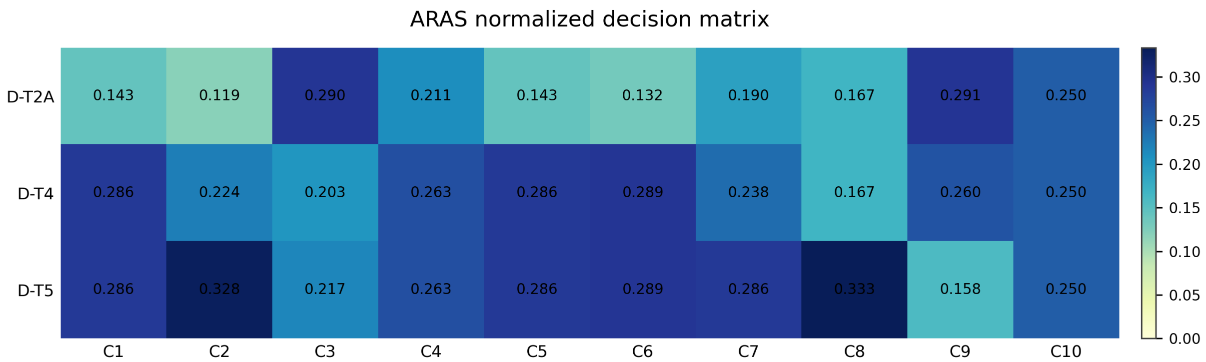
ARAS analysis applies the optimal alternative A_0 along with the three UAV alternatives. Table 11 shows the decision matrix in question. The optimal row consists of the best values for all benefit criteria and the worst values for all cost criteria.

Table 11. ARAS decision matrix including the optimal alternative

Criterion	A_0	D-T2A	D-T4	D-T5
C1	20	10	20	20
C2	2200	800	1500	2200
C3	20	20	14	15
C4	2.0	1.6	2.0	2.0
C5	20	10	20	20
C6	488	222	488	488
C7	6	4	5	6
C8	2	1	1	2
C9	12.5	12.5	14	23
C10	1.25	1.25	1.25	1.25

Table 12 contains the normalized ARAS values for the alternatives. Once more, D-T5 performs the best with respect to work efficiency, spray width, and transmission range, and D-T2A has an edge in flight time and vehicle weight. Normalization of ARAS values allows for comparing them with the optimal row directly.

Table 12. Normalized ARAS decision matrix



The weighted normalized ARAS scores are presented in Table 13. D-T5 is the best performer in terms of the weighted dominance criteria scores, especially those for C1 and C2, while the cost-based deduction by C9 is not large due to its smaller AHP weight.

Table 13. ARAS weighted normalized matrix for the UAV alternatives

Criterion	Weight	D-T2A	D-T4	D-T5
C1	0.275	0.039	0.079	0.079
C2	0.193	0.023	0.043	0.063
C3	0.137	0.040	0.028	0.030
C4	0.114	0.024	0.030	0.030
C5	0.087	0.012	0.025	0.025
C6	0.065	0.009	0.019	0.019
C7	0.049	0.009	0.012	0.014
C8	0.033	0.006	0.006	0.011
C9	0.025	0.007	0.006	0.004
C10	0.022	0.005	0.005	0.005

The results obtained for ARAS optimality and utility can be seen in Table 14. D-T5 scores the highest level of utility, then comes D-T4 and D-T2A. Hence, the result from ARAS shows that D-T5 is the most ideal of all alternatives.

Table 14. ARAS optimality values, utility degrees, and ranking

Alternative	S_i	K_i	Rank
D-T2A	0.175	0.596	3
D-T4	0.252	0.861	2
D-T5	0.280	0.955	1

The ARAS ranking is

$$\text{D-T5} > \text{D-T4} > \text{D-T2A}. \tag{17}$$

Such a concordance between TOPSIS and MABAC is significant since the ARAS method is based on the ideal alternative within the decision matrix instead of using a distance criterion based on the ideal points or border approximation area.

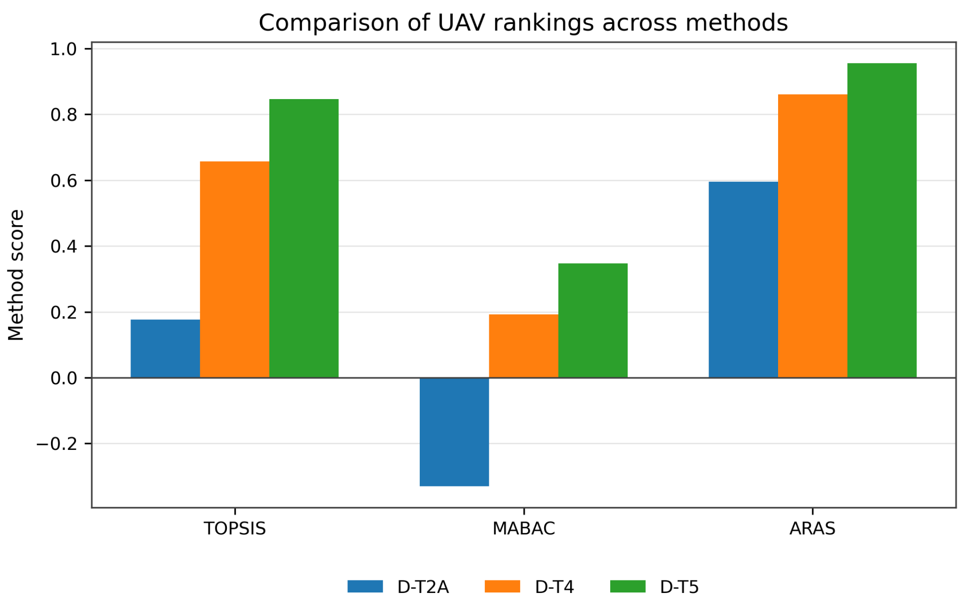


Figure 6. Comparison of UAV ranking scores between TOPSIS, MABAC, and ARAS

3.5. Comparison of ranking methods

All three ranking methods provide identical ordering, which can be seen in Figure 6 and Table 15. It should not be possible to make any direct comparison between the scores from the different methods due to a difference in their scales. The rank order, however, is directly comparable and is identical for all methods.

Table 15. Cross-method comparison of UAV ranking results

Alternative	TOPSIS C_i	MABAC S_i	ARAS K_i	Overall rank
D-T2A	0.176	-0.330	0.596	3
D-T4	0.657	0.192	0.861	2
D-T5	0.847	0.348	0.955	1

D-T5 is considered since it holds all favorable characteristics in terms of productivity along with great capacity and range. D-T4 could be chosen as an alternative solution since it holds equal payload, tank capacity, and battery capacity but is inferior to D-T5 with regard to work efficiency and range. D-T2A can be regarded as the last one among the solutions since it is characterized by low payload, tank capacity, battery capacity, and work efficiency. It is positive in terms of flight time and vehicle weight.

3.6. Sensitivity analysis

Figures 7 and 8 show the results of sensitivity analysis. If the weight of payload capacity varies from 0.15 to 0.35, then D-T5 stays first, D-T4 stays second, and D-T2A stays third. The closeness coefficients change gradually, but no rank reversal occurs.

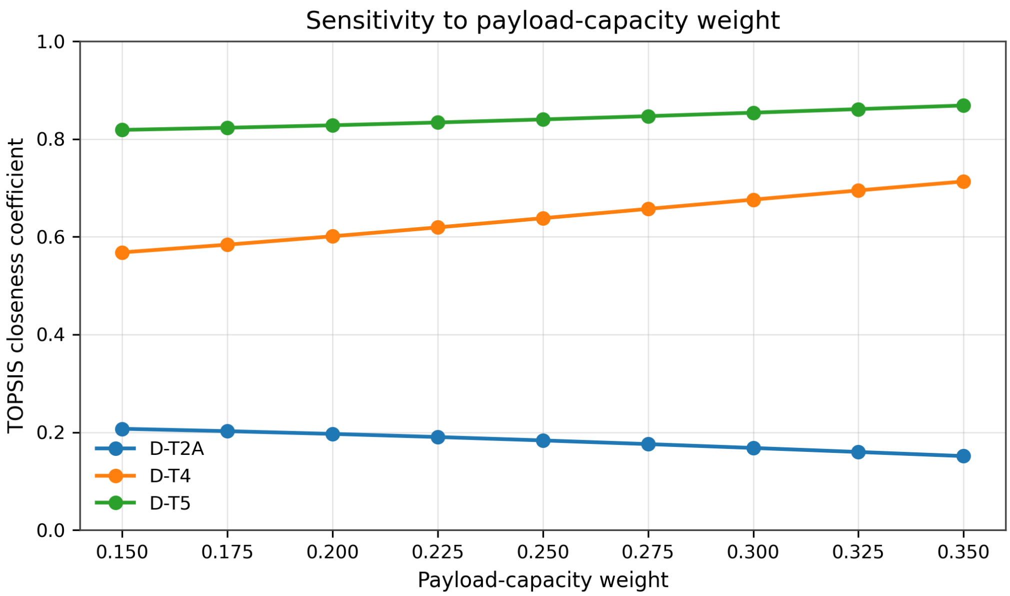


Figure 7. Sensitivity of TOPSIS closeness coefficients to the payload-capacity weight

Another sensitivity analysis on work-efficiency weight from 0.10 to 0.30 is conducted, with results displayed in Figure 8. D-T5 remains the best solution throughout the whole range. This is meaningful in practice since work efficiency is an extremely critical criterion in spraying process; it determines the area of sprayed zone per unit of time.

The lack of rank reversals implies that the decision is robust against any plausible changes of the two highest weights. The overall consideration of all ranking techniques and sensitivity analysis leads to the same practical conclusion: D-T5 is the most powerful spraying drone of the considered alternatives, while D-T4 is the second best, and D-T2A is a weaker choice for such tasks.

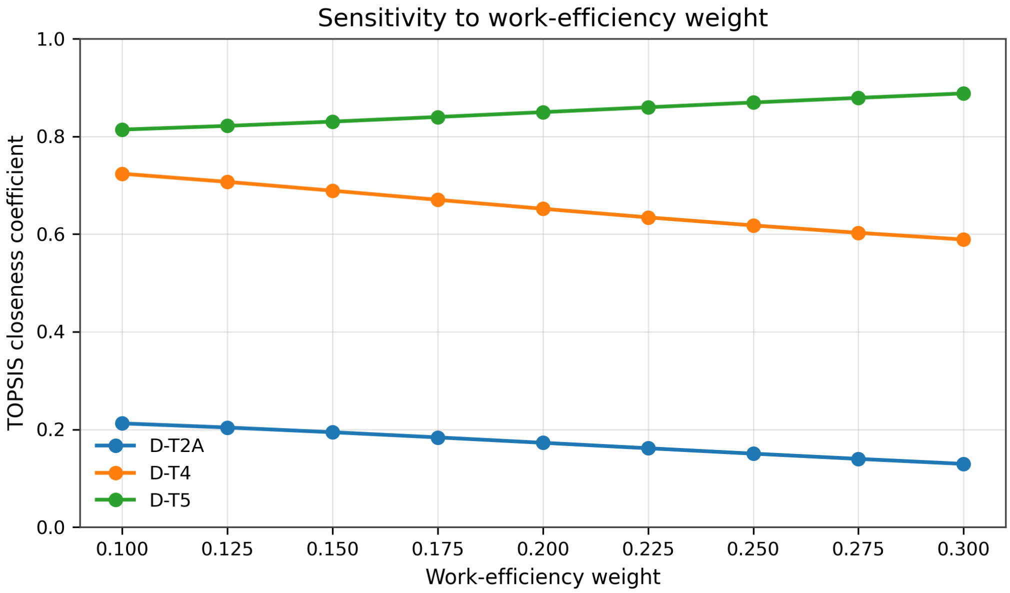


Figure 8. Sensitivity of TOPSIS closeness coefficients to the work-efficiency weight

4. Conclusions

This research attempted to find out if a stable and transparent ranking of agricultural spraying UAVs could be achieved in consideration of multiple criteria. The answer is positive. AHP generated the criterion weight vector consistently, and TOPSIS, MABAC, and ARAS produced the same ranking order: first place was taken by D-T5, the second – by D-T4, and the third - by D-T2A.

From AHP we know that the payload capacity, work efficiency, flight time, and spray-flow rate criteria are the most influential. These criteria are the main ones in agricultural spraying because they define the carrying ability, productivity, continuity of operations, and capability of delivering liquid. Tank capacity, battery capacity, spray width, and transmission range are also essential for the final ranking, and vehicle weight and charging time have less influence on it within the current decision matrix.

The convergence of three separate ranking techniques shows that the superiority of D-T5 is not a consequence of applying one particular ranking technique. The best UAV is D-T5 because it has maximum values of payload and tank capacities, work efficiency, spray width, and transmission range. The UAV D-T4 offers the best balance, while D-T2A is limited by low capacity and efficiency despite its advantages in flight time and vehicle weight.

The results of sensitivity analysis show that the final ranking order does not change under variation of payload capacity and work efficiency weights. It is quite significant since these criteria take a dominating place in the weight vector and are going to be differently weighted by various potential users. Hence, the findings may serve as a reliable basis for purchasing UAVs, forming a fleet, and conducting agricultural spraying.

The major innovation of this research is the development of the consistent decision-making procedure combining AHP weights with rankings of three alternative techniques and providing a ranking stability check via sensitivity analysis. Further research can include additional criteria such as acquisition cost, maintenance cost, field-testing reliability, environmental impact, operator safety, spare parts availability, and uncertain preference information.

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