International Journal of Agriculture, Environment and Biotechnology
Citation: *IJAEB*: **19**(03): 121-130, September 2026
DOI: 10.30954/0974-1712.03.2026.3

ASSOCIATION FOR AGRICULTURE ENVIRONMENT AND BIOTECHNOLOGY

RESEARCH PAPER

Evaluating the Multi-Dimensional Sustainability Trade-offs of Autonomous Agricultural Systems: An AHP-TOPSIS Decision Model for Precision UAV Spraying in India

Livert Mudzingenyama and Mahesh Vinayak Hadole*

Department of Agricultural Engineering, Vignan's Foundation for Science, Technology and Research, Guntur, Andhra Pradesh, India

*Corresponding author: maheshhadole21@gmail.com (**ORCID ID:** 0000-0002-3464-9030)

Paper No. 1245 **Received:** 07-08-2026 **Revised:** 25-08-2026 **Accepted:** 02-09-2026

ABSTRACT

Autonomous agricultural technologies are gaining more and more traction to enhance the efficiency of resources and precision of operation; however, their sustainability needs to be assessed going beyond their technical performance, and taking into consideration the environmental, economic, social and governance trade-offs. This study designed an integrated Analytic Hierarchy Process –Technique for Order Preference by Similarity to Ideal Solution (AHP –TOPSIS) model to evaluate the three crop protection technologies in India namely, autonomous unmanned aerial vehicle (UAV) spraying, tractor mounted boom spraying and conventional backpack spraying. Secondary empirical data were used to assess the status of fourteen indicators for the four domains of environmental, economic, social, technical and governance. The environmental dimension (0.3523) was given the highest priority, followed by the economic dimension (0.2408), technical dimension (0.1723), social dimension (0.1173) and governance dimension (0.1173). The spraying using UAV showed the best efficiency in terms of field capacity (3.03 ha h^{-1}), application efficiency (95%) and pesticide usage (1.84 kg ha^{-1}), as well as the best benefit–cost ratio (2.45). The UAV spraying option was ranked best with a closeness coefficient (C_i) of 0.6996 and the tractor-mounted boom was ranked second with a C_i value of 0.4555, while conventional backpack spraying was ranked third with a C_i value of 0.3090. While there are environmental and operational benefits to UAVs, there are trade-offs with regard to smallholder access, regulatory compliance, technical skills and cyber security. The results prove that increased agricultural autonomy is not necessarily synonymous with full sustainability. The framework suggested here offers a clear decision support mechanism to consider 'resource efficiency', 'socio-economic', and 'governance' issues and has the potential to assist responsible use of autonomous agro-chemical technologies in India.

HIGHLIGHTS

- An integrated AHP–TOPSIS framework evaluated agricultural spraying technologies across five sustainability dimensions and 14 indicators.
- UAV spraying ranked highest (C_i = 0.6996), demonstrating strong resource-use efficiency and operational performance.
- UAVs offer substantial sustainability benefits, but smallholder access, regulatory compliance, technical skills and cybersecurity remain important adoption trade-offs.

Keywords: Agriculture 5.0, AHP–TOPSIS, autonomous agriculture, multi-criteria decision analysis, precision spraying, sustainability and unmanned aerial vehicle

The world's agriculture faces double challenge of feeding more people while using fewer natural resources and causing less environmental damage. About 1.2 billion people now reside in agricultural

How to cite this article: Mudzingenyama, L. and Hadole, M.V. (2026). Evaluating the Multi-Dimensional Sustainability Trade-offs of Autonomous Agricultural Systems: An AHP-TOPSIS Decision Model for Precision UAV Spraying in India. *Int. J. Ag. Env. Biotech.*, **19**(03): 121-130.

Source of Support: None; **Conflict of Interest:** None

regions where water stress is high, and agriculture accounts for around 72% of global freshwater withdrawals, while climate change is raising the likelihood of water scarcity and the demand for water by crops. Energy, agrochemicals and labour-intensive field operations are also still required in conventional production systems, posing production cost, pesticide exposure, environmental contamination, and resource-use efficiency issues (Maitra *et al*. 2026). All these pressures have driven the shift from traditional mechanization to precision and digitally enabled agriculture, where artificial intelligence (AI), Internet of Things (IoT), robotics and autonomous machines and unmanned aerial vehicles (UAVs) are increasingly part of the farming process. Agriculture 5.0 builds on this transition, focusing more on smart, connected and more and more independent systems, while at the same time remaining human-centered, resilient and sustainable agricultural development as a basic goal (Abdul Razak *et al*. 2024; Ray *et al*. 2026; Guchhait *et al*. 2026; Rishitha *et al*. 2026).

Of these new technologies, UAVs offer a great potential for the application of pesticides and other inputs in crop protection, especially in terms of timely and spatially targeted application, and a minimisation of direct contact with harmful products by humans. UAV spraying can be used at lower spraying volumes, can increase field capacity and can allow for timely operations when conditions may prohibit the use of traditional equipment. These benefits are more significant in India where agriculture production has to cater to resource scarcity, escalation in operational cost and labour deficiency, and also the fragmented nature of farm holdings. The Indian Council of Agricultural Research (ICAR) has thus encouraged the use of agricultural drones through field demonstrations and capacity building programmes, with Agri-Drone procurement of 263 drones in 193 institutions, including ICAR institutes, agricultural universities and Krishi Vigyan Kendras (Singh and Singh, 2025). The ICAR Field demonstrations have also reinforced the advantages of application cost reduction and lowered usage of chemicals, lower operator exposure, and significantly higher work efficiency as compared with hand spraying. The developments suggest autonomous and semi-autonomous technologies are likely to gain significance in precision crop protection in Indian agriculture.

Even so, technological performance – while important – does not necessarily lead to greater overall sustainability. ASs can lower water, pesticide, energy and labour inputs, and can also add high capital investments, specialized skills, reliance on digital infrastructure, regulations, and new issues around cybersecurity, data ownership, and technological exclusion. Recent evidence in India indicates that some of the key challenges in the adoption of agricultural drones include high initial investment, low technical knowledge and training, and small land holdings. Financial accessibility, infrastructure, farmer perception, regulatory compliance, and training, are still constraints on large-scale deployment in India. Agriculture 5.0 is not just a move towards increased automation but also a socio-technical shift where environmental sustainability is being traded-off with economic access, social impact, and technology reliability, and responsible governance (Bhat *et al*. 2024). Cybersecurity, privacy, standardization, and effective legal and regulatory systems have thus become important challenges related to inter-connected agricultural technologies (Sokołowska and Olczyk, 2026).

To assess these competing impacts, an analytical method is needed that is able to capture the impact of a range of sustainability indicators rather than a single engineering or economic measure (Maheswari *et al*. 2025). Such a framework can be offered by Multi-Criteria Decision Analysis (MCDA), which takes into account environmental, economic, social, technical and institutional criteria. In a systematic comparison of holistic approaches to assessing agricultural sustainability, Valizadeh and Hayati (2025) emphasized the importance of multidimensional frameworks and MCDA for incorporating various sustainability criteria. The Analytic Hierarchy Process (AHP) gives a systematic method to assign relative priorities to decision criteria while the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) identifies the alternatives based on their relative closeness to an ideal multidimensional solution. Therefore, their integration is ideally suited for the assessment of agricultural technologies where a higher level of performance in one dimension comes with a different one in the other.

Although research on agricultural UAVs and autonomous technologies has continued to increase, studies have largely addressed these technologies individually, either from the perspective of technical performance or resource-use efficiency/barriers, and have not explicitly integrated the aspects of environmental, economic, social, technical and governance. This means that the need arises to conduct a system-level evaluation of the potential for increased agricultural autonomy to increase overall sustainability, or to create new socio-technical trade-offs. For this reason, the present study constructed the five-dimensional AHP–TOPSIS sustainability assessment framework and used it to the UAV spraying, tractor-mounted boom spraying and conventional backpack spraying in India. The objective of the study was to create sustainability indicators in the form of SDGs, prioritize them with AHP, compare the multidimensional performance of the three spraying technologies and rank them with TOPSIS and identify key sustainability trade-offs. The framework serves as a structured approach to evaluate the potential to balance the advantage of autonomous crop protection in terms of resource-efficiency against the requirements of economic accessibility, social inclusiveness, technical reliability and responsible governance.

MATERIALS AND METHODS

Study Design and Analytical Framework

The study took the Multi-Criteria Decision Analysis (MCDA) approach with secondary data, to assess the multidimensional sustainability of crop-protection technologies of varying degrees of agricultural autonomy in India. Three technological options were evaluated: UAV-based spraying, mechanized spraying (tractor-mounted boom) and manual spraying (backpack). The field studies conducted in India and peer-reviewed field studies, publications and reports from ICAR and relevant regulatory and technical documents have been used to compile empirical performance data. An integrated Analytic Hierarchy Process (AHP) – Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was then adopted where the AHP was applied to find out the relative weightage of sustainability dimensions and TOPSIS fused the criteria to prioritize the three alternatives. These hybrid AHP–TOPSIS methods are used to address agricultural decision problems since they incorporate systematic weighting of the criteria and distance-based assessment of competing options.

Selection and Classification of Sustainability Indicators

A 5-dimensional sustainability framework of environmental, economic, social, technical and governance dimensions was established. The 14 indicators were chosen because they were relevant to an autonomous system for crop protection and for which there was comparable empirical data. The three dimensions of the environment were energy consumption (E1), water consumption (E2) and pesticide use (E3); the three dimensions of the economy were operational cost (EC1), productivity/yield (EC3) and benefit–cost ratio (EC4); and the three dimensions of the social were labour requirement (S1), occupational safety (S3) and smallholder suitability (S4). The technical dimension included field capacity (T1), application efficiency (T2) and operational reliability (T5), while the governance dimension included regulatory compliance (G1) and the cybersecurity risk (G5). These indicators were assigned to either be a benefit indicator (best to have a higher value) or a cost indicator (best to have a lower value). The indicators were also associated with the applicable United Nations Sustainable Development Goals to determine its wider implications for sustainability.

Construction of the Decision Matrix

A quantitative decision matrix was developed, where each of the three spraying alternatives was listed as a row and the 14 sustainability indicators as the evaluation criteria. The values were energy consumption and water consumption, pesticide requirement, operational cost, crop yield, benefit–cost ratio, labour requirement, occupational safety, smallholder suitability, field capacity, application efficiency, operational reliability, regulatory compliance, and cybersecurity risk for the empirical values used for comparison. This matrix thus involved direct engineering, economic, socio-technical and governance indicators (based on indices). The values used in the manuscript were derived from the cited empirical studies and institutional information, such as Biswas *et al*.

(2025) and Sambaiah *et al*. (2023) chilli crop trials information provided by ICAR.

AHP-Based Weighting of Sustainability Dimensions

In accordance with Saaty (1980) decision making procedure, the eigenvector method of AHP was used to determine the relative importance of five sustainability dimensions. The study used a system approach, and a 5 × 5 reciprocal pairwise comparison matrix was built, stressing more environmental protection and economic viability. The comparison matrix from which the priority vector \(w\) was calculated with the principal eigenvector expresses the relative importance of dimension \(i\) over dimension \(j\). The use of pairwise comparisons allows for the transformation of heterogeneous criteria into normalized relative weights, while still providing a formal test of the consistency of judgments, making AHP suitable for multidimensional agricultural sustainability assessment. The logical consistency of the pairwise comparison matrix was checked by the Consistency Index (CI) and Consistency Ratio (CR):

$$CI = (\lambda\max - n) / (n - 1)$$

$$CR = CI / RI$$

Where λmax is the principal eigenvalue, n is the number of dimensions and *RI* is the corresponding Random Index. For $n = 5$, the manuscript used an *RI* of 1.12. A *CR* below 0.10 was considered acceptable, consistent with established AHP methodology. The resulting dimension weights were environmental = 0.3523, economic = 0.2408, technical = 0.1723, social = 0.1173 and governance = 0.1173. These dimension-level weights were distributed among their respective indicators to obtain the indicator weights subsequently used in TOPSIS.

TOPSIS-Based Multidimensional Sustainability Assessment

The technique of TOPSIS was used to combine the weighted environmental, economic, social, technical and governance indicators and calculate the relative sustainability performance of each technology. This procedure was based on the principle that the best alternative has the shortest distance to positive ideal solution and the highest distance to negative ideal solution, which is already known as a basis in TOPSIS applications for assessing sustainability. Firstly, the original decision matrix was normalized to a dimensionless matrix using vector normalization:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}}$$

where x_{ij} represents the original performance of alternative i for criterion j, and r_{ij} is its normalized value. The weighted normalized decision matrix was then calculated as $v_{ij} = r_{ij} \times w_j$, where w_j represents the corresponding criterion weight.

Positive-ideal A^+ and negative-ideal A^- solutions were subsequently established according to criterion orientation. For benefit criteria, the maximum weighted normalized value represented the positive ideal and the minimum represented the negative ideal; the procedure was reversed for cost criteria. The Euclidean separation distances of each alternative from the positive S_i^+ and negative S_i^- ideal solutions were then calculated. Finally, the relative closeness coefficient was determined as:

$$C_i = S_i^- / (S_i^+ + S_i^-)$$

where C_i ranges from 0 to 1. Higher values indicate greater proximity to the multidimensional positive-ideal sustainability solution. The alternatives were therefore ranked in descending order of C_i.

Integrated Interpretation and Visualization

The final assessment combined the AHP dimension priorities and the TOPSIS technology scores to allow for both the weightage of the dimensions and the overall assessment of sustainability to be interpreted at the same time. To make a better comparison between the five sustainability dimensions and between the three spraying technologies and the AHP weights, the values of closeness coefficients and AHP weights were displayed together in Fig. 1. The closeness coefficients and AHP weights for the three spraying technologies and five sustainability dimensions were presented together in Fig. 1, to make them easier to compare. This integrated representation enabled a rapid identification of the sustainability aspects that were most influential in the

decision made and also provided an understanding of the relative position of autonomous, mechanized and manual crop protection systems. All rankings were seen as relative multidimensional comparisons or relationships that were calculated within the indicator framework, and not as absolute measures of sustainability.

RESULTS AND DISCUSSION

The multidimensional indicator framework for assessing autonomous agricultural systems' sustainability is given in (Table 1). The framework consists of 14 indicators across five sustainability dimensions: environmental, economic, social, technical and governance. The environmental dimension comprises of energy consumption (E1), water consumption (E2) and pesticide use (E3) which is all considered cost dimensions; a reduction in the use of such resources and chemicals is desirable. The economic dimension includes operational cost (EC1) as one of the cost criteria, and productivity/yield (EC3) and benefit–cost ratio (EC4) as benefit criteria. The technical performance is expressed by field capacity (T1), application efficiency (T2), and operational reliability (T5); social sustainability is expressed by labour requirement (S1), occupational safety (S3) and smallholder suitability (S4). Governance is added to regulatory compliance (G1) and cybersecurity risk (G5) to take the assessment beyond traditional environmental and economic assessments. The indicators are also related to Sustainable Development Goals (SDGs) 2, 3, 6, 7, 8, 9, 10, 12, 13, 15 and 16, and can serve as a framework for the following evaluation of the alternative spraying technologies using AHP–TOPSIS.

The five dimensions used in (Table 1) are based on a structure that has become more widespread, the assessment of autonomous agricultural technologies as integrated socio-technical systems, not just for operational efficiency. In recent years, the evidence has suggested the use of multidimensional approaches, because technological advances in the efficiency of resource use may occur in parallel to economic, social and institutional constraints. In a systematic evaluation of agricultural sustainability frameworks, Yuan *et al*. (2025) showed the specific value of MCDA techniques for incorporating different environmental, economic, social, and procedural criteria, and pointed out that sustainability assessments must not be based on a single dimension.

The current implementation of energy and water use, plus pesticide use, is particularly significant for precision spraying, and the UAV technologies being introduced are expected to enhance input targeting and use efficiency of these resources. Meanwhile, the social and governance-related indicators are relevant as they are not all about technology performance; in order to make technology successful, the social and

Table 1: Sustainability dimensions, indicators, criteria types and Sustainable Development Goal linkages used for evaluating autonomous agricultural systems

Dimension	Indicator Code	Indicator Name	Unit	Type	SDG Linkage
Environmental	E1	Energy consumption	kWh/ha	Cost	SDG 7, 13
Environmental	E2	Water consumption	L/ha	Cost	SDG 6, 12
Environmental	E3	Pesticide use	kg/ha	Cost	SDG 2, 12, 15
Economic	EC1	Operational cost	₹/ha	Cost	SDG 8, 12
Economic	EC3	Productivity / Yield	kg/ha	Benefit	SDG 2
Economic	EC4	Benefit-cost ratio	Ratio	Benefit	SDG 2, 8
Social	S1	Labour requirement	Persons	Cost	SDG 8
Social	S3	Occupational safety	% exp. red.	Benefit	SDG 3, 8
Social	S4	Smallholder suitability	Index (0-100)	Benefit	SDG 1, 10
Technical	T1	Field capacity	ha/h	Benefit	SDG 8, 9
Technical	T2	Application efficiency	%	Benefit	SDG 12
Technical	T5	Operational reliability	%	Benefit	SDG 9
Governance	G1	Regulatory compliance	Index (0-100)	Benefit	SDG 16
Governance	G5	Cybersecurity risk	Index (0-100)	Cost	SDG 9, 16

governance measures need to be considered as well. Dhivya *et al*. (2024) found that the use of agricultural drones can enhance the efficiency of agriculture, save labour and optimize agrochemical usage, but they also noted the technological expertise gap, small farm size and high cost as major adoption barriers. In parallel, farmer-level evidence revealed that other factors such as training, infrastructure, maintenance, connectivity, and appropriate policy support are key factors to consider for broader agricultural drone adoption (Murugan *et al*. 2024). By explicitly incorporating the governance aspects of regulatory compliance and Cybersecurity risk, the current framework is made stronger of the interconnected digital systems used in Agriculture 5.0, where transparency, trust and responsible technology deployment are becoming crucial (Razak *et al*. 2024). Together these indicators offer a more comprehensive framework for determining if environmental and technical improvements are realized without imposing unacceptable costs or risks on farmers, labour systems or governance.

This decision matrix in (Table 2) showed significant differences in the performance of the environmental, economic, social, technical and governance aspects across the three crop-protection technologies. UAV spraying showed the lowest energy consumption (20.20 kWh ha^{-1}), water requirement (25 L ha^{-1}), pesticide use (1.84 kg ha^{-1}) and operational cost (₹ 3,750 ha^{-1}), compared with conventional backpack spraying (44.20 kWh ha^{-1}, 500 L ha^{-1}, 3.12 kg ha^{-1} and ₹ 5,450 ha^{-1}, respectively) and tractor-mounted boom spraying (35.00 kWh ha^{-1}, 375 L ha^{-1}, 2.50 kg ha^{-1} and ₹ 4,200 ha^{-1}, respectively). The spraying with the UAV also showed the best yield (4,675 kg ha^{-1}), benefit–cost ratio (2.45), occupational safety index (90), field capacity (3.03 ha h^{-1}) and application efficiency (95%) and only one person was needed for operating the machine. Conventional backpack spraying had the highest scores for smallholder suitability (95), operational reliability (95%) and regulatory compliance (99), and the lowest score for cybersecurity risk (5), and did not perform well in resource consumption, labour requirement and field capacity. Spraying with tractor mounted booms tended to fall between the extremes on most factors. The individual weights assigned to the indicators showed that the indicators related to the environment had the highest weights (0.1174 each), followed by those related to economy, governance, technical and social indicators (0.0803, 0.0587, 0.0574 and 0.0391, respectively), meaning that the decision matrix reflected both the resource-efficiency benefit and the socio-technical constraints of greater agricultural autonomy.

The efficiency of resource use and operational performance of UAV spraying shown in (Table 2) is in line with recent empirical studies that

Table 2: Decision matrix and indicator weights for sustainability assessment of alternative crop-protection technologies

Indicator	Dimension	UAV (Autonomous)	Conventional Backpack	Tractor-mounted Boom	Indicator Weight
E1_Energy (kWh/ha)	Env	20.20	44.20	35.00	0.1174
E2_Water (L/ha)	Env	25.00	500.00	375.00	0.1174
E3_Pesticide (kg/ha)	Env	1.84	3.12	2.50	0.1174
EC1_OpCost (₹/ha)	Econ	3750.00	5450.00	4200.00	0.0803
EC3_Yield (kg/ha)	Econ	4675.00	4500.00	4600.00	0.0803
EC4_BCRatio (ratio)	Econ	2.45	1.85	2.10	0.0803
S1_LabourReq (pers.)	Soc	1.00	5.00	2.00	0.0391
S3_Safety (index)	Soc	90.00	10.00	50.00	0.0391
S4_Suitability (idx)	Soc	70.00	95.00	40.00	0.0391
T1_Capacity (ha/h)	Tech	3.03	0.10	1.50	0.0574
T2_Efficiency (%)	Tech	95.00	65.00	80.00	0.0574
T5_Reliability (%)	Tech	85.00	95.00	90.00	0.0574
G1_Compliance (idx)	Gov	90.00	99.00	95.00	0.0587
G5_CyberRisk (idx)	Gov	80.00	5.00	15.00	0.0587

have found that low-volume aerial spraying can significantly reduce water use, pesticide use and energy consumption while delivering effective crop protection. A recent Indian assessment indicates that water use reduced by 67.9%, pesticide use reduced by 41.0% and energy use reduced by 54.3% when the UAV was used to spray pesticides compared to the conventional approach, reinforcing the environmental benefits (1–3) in the current decision matrix. Similarly, the field trials conducted in India showed that application of herbicide using drones in greengram reduced spray fluid consumption by 88% with same weed control efficiency and increased yield compared to manual spraying and improved incremental economic returns compared to manual spraying in groundnut at 25 L ha^{-1} spray fluid. The high capacities of field capacity and application efficiency achieved by UAVs also appear technically achievable, as evidenced by a recent field assessment of a hybrid UAV that achieved an operational efficiency of 4.11 ha h^{-1}, effective droplet deposition, and very little droplet drift. Despite this, the lower suitability of small farmers for UAV and the increased cyber security threat it poses puts forward the need for technical efficiency to prove the overall sustainability of UAV technology. However, the low smallholder suitability and high cyber security risk posed by UAV technology highlight the technical inefficiency to prove sustainability. Yadav *et al*. (2023) on their part revealed that initial investment costs, small land holdings, technical skills, and availability are also major barriers for Indian farmers to adopt drones on a larger scale. As such, the contrasting indicator values in (Table 2) illustrate a fundamental sustainability trade-off between UAV spraying and conventional spraying systems: UAV spraying offers significant environmental, economic and operational benefits, while conventional spraying offers benefits in terms of accessibility, reliability and reduced digital-governance risk. This multidimensional contrast is the justification for the next step of using AHP–TOPSIS instead of just assessing the technologies based on resource savings or operational performance.

The TOPSIS analysis clearly distinguished the three crop-protection technologies according to their multidimensional sustainability performance integrated into one (Table 3). The second position was occupied by tractor-mounted boom spraying (C_i = 0.4555) with the smallest separation from the positive-ideal solution (S* = 0.0830) and the largest separation from the negative-ideal solution (S− = 0.0695). The closeness coefficient (C_i = 0.3090) is the lowest and the distance from positive-ideal solution (S* = 0.1271) is the highest among the three methods, hence the third rank is given to conventional backpack spraying. Therefore, it is concluded that the integrated AHP–TOPSIS assessment showed that UAV spraying was the best sustainability profile of the options tested, whereas tractor mounted spraying was an intermediate option and conventional backpack spraying had the lowest overall sustainability profile.

The improved TOPSIS closeness coefficient of UAV spraying is mainly related to its good performance on the highly weighted criteria, such as the environmental aspects (low energy, water and pesticide consumption) and technical aspects (high field capacity and application efficiency). This interpretation aligns with the recent Indian evidence provided by Ramteke *et al*. (2026), who reported that spraying using UAVs was found to have less water consumption (67.9%), pesticide consumption (41.0%) and energy consumption (54.3%) relative to conventional spraying methods, with greater operational efficiency. In another study, Safaeinejad *et al*. (2025) found that conventional spraying is 2.43

Table 3: TOPSIS ranking of alternative crop-protection technologies based on multidimensional sustainability performance

Rank	Alternative Technology	Separation S*	Separation S^-	Closeness Coefficient (C_i)
1	UAV Spraying (Autonomous)	0.0547	0.1275	0.6996
2	Tractor-mounted Boom Spraying	0.0830	0.0695	0.4555
3	Conventional Backpack Spraying (Manual)	0.1271	0.0568	0.3090

times more energy-intensive than drone spraying and results in significantly higher global warming potential with pesticide usage, reinforcing the environmental benefit of UAV spraying. More recent field-based research also shows that optimizing UAV flight paths and spray parameters can increase spray efficiency and decrease chemical usage and operating time (Bayrak and Olu, 2025). However, a value of 0.6996 for C_i instead of a value close to 1 shows that in every sustainability criterion UAV technology is not dominant. The present decision matrix shows that UAVs have setbacks with respect to smallholder suitability, regulatory considerations and operational reliability and cybersecurity risk. Other barriers to agricultural drone adoption mentioned in manuscript include technical training, the complexity of operation, and scalability. Hence, the TOPSIS ranking should be viewed as a multi-dimensional result of sustainability and not purely technologically efficient, highlighting that the sustainability benefit of autonomous spraying is dependent on a combination of: environmental performance, economic accessibility, technical capacity and governance-related risks.

The five sustainability dimensions and the three crop-protection technologies are integrated in Fig. 1, where the priority weights assigned to the five sustainability dimensions are also represented as their AHP-derived weights. Fig. 1 is an integrated view of the five sustainability dimensions and the three crop-protection technologies, while their priority weights derived from the AHP are also presented. The environmental dimension was the most prioritized (0.3523) followed by the economic dimension (0.2408), technical dimension (0.1723), social dimension (0.1173) and governance dimension (0.1173), meaning that the environmental dimension and the economic dimension together represented a significant part of the overall sustainability assessment. The TOPSIS analysis clearly distinguished the technological alternatives, where spraying with UAV achieved the highest closeness coefficient (C_i = 0.6996), followed by spraying from a tractor-mounted boom (C_i = 0.4555), and spraying from a backpack (C_i = 0.3090). Therefore, overlaying the two visualizations shows that the benefits in the highly weighted environmental dimension, such as lower energy, water and pesticide use, and positive technical and economic performance, were key factors in the higher aggregate performance of UAV spraying. However, its coefficient was still less than 1, as benefits in using the resource were offset by comparatively lower performance in selected social and governance indicators, such as suitability for smallholders, cybersecurity risk.

The integrated pattern shown in Fig. 1 illustrates the need to consider agricultural automation from a multi-dimensional sustainability perspective, not just

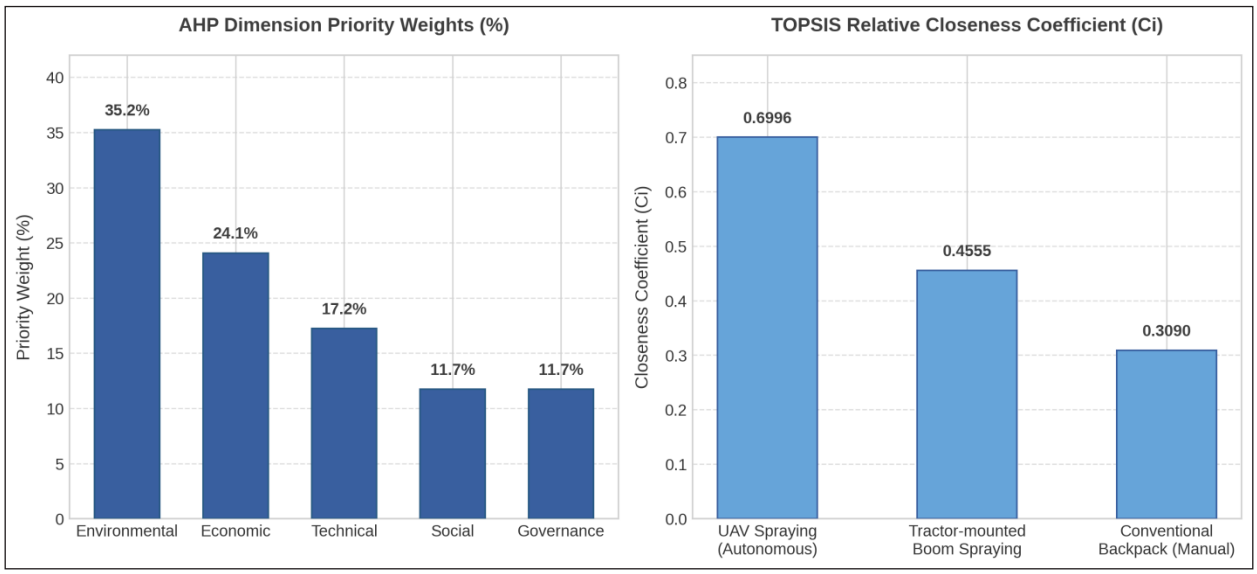


Fig. 1: Integrated AHP–TOPSIS assessment of multidimensional sustainability: **(a)** AHP-derived priority weights for environmental, economic, technical, social and governance dimensions; and **(b)** TOPSIS relative closeness coefficients (C_i) for UAV, tractor-mounted boom and conventional backpack spraying systems

its technological performance. The relatively high environmental weighting is especially applicable as the recent Indian field assessment demonstrated spraying with the UAV can save around 70% water, 40% pesticide and 50% CO_2 emissions over conventional spraying, while also being more efficient in terms of operation. However, recent reviews also show that the UAV-driven variable-rate spraying can save resources and environmental effects by the more precise delivery of agrochemicals, yet technical and regulatory limitations must be taken into account (Taseer and Han, 2024). The high representation of environmental and economic aspects in the AHP part is also methodologically in accordance to the findings of Arulnathan *et al*. (2025) that the MCDA method is very suitable for the sustainability assessment of agriculture, in which the sustainability criteria can be heterogeneous and integrated into a unified decision framework. However, it is important to remember that the advantages of UAV spraying in terms of aggregate position should not mask the socio-technical trade-offs. Avhale *et al*. (2025) noted that the use of agricultural drones helped save labour and input costs, boost operational efficiency, but the high upfront costs, small land holdings, lack of technical skills among farmers, and the limited availability of drones hindered their broader adoption in India. Therefore, Fig. 1 supports the main finding of the study that while higher levels of agricultural self-reliance are likely to lead to higher levels of sustainability, the environmental and operational advantages of UAV systems must also be coupled with economic, regulatory and institutional access mechanisms, capacity development, and digital-governance protection measures to deliver inclusive and balanced deployment.

CONCLUSION

The present study shows that the sustainability of autonomous agricultural technologies must be assessed in an integrated way that goes beyond just the technical efficiency and involves the consideration of environmental, economic, social and governance factors. The five dimensional AHP–TOPSIS framework with 14 sustainability indicators was found to be very suitable to differentiate autonomous UAV spraying, tractor-mounted boom spraying and conventional backpack spraying. The environmental dimension (0.3523) was deemed to be the most crucial followed by economic (0.2408), technical (0.1723), social (0.1173) and governance (0.1173) dimensions. The energy consumption for UAV spraying was significantly lower at 20.20 kWh ha^{-1}, water consumption was 25 L ha^{-1}, pesticide consumption was 1.84 kg ha^{-1}, field capacity was 3.03 ha h^{-1}, application efficiency of 95%, and benefit–cost ratio of 2.45. Therefore, the TOPSIS closeness coefficient (C_i = 0.6996) of UAV spraying was the highest among tractor-mounted boom (0.4555) and conventional backpack spraying (0.3090).

However, the results also show that the increased autonomy does not necessarily guarantee full sustainability. Environmental and operational benefits were observed but there were drawbacks in terms of smallholder access, regulation, technology and cyber security risk of UAV spraying. Thus, capacity building, proper regulatory and data-governance structures, and a shared-service model like Custom Hiring Centres or Farmer Producer Organizations need to be promoted to ensure better access to smallholders. The AHP–TOPSIS framework proposed in the study offers a clear and comprehensible decision-making support tool to reconcile the issues of resource efficiency with social-economic and governance aspects. Future research is needed for validation of framework from primary field data, farmer-based and expert-based weighting, lifecycle assessment of UAV systems, evaluations of various agro-climatic and farming conditions.

GENERATIVE AI DECLARATION

The author(s) confirm that there was no use of artificial intelligence (AI)-assisted technology for assisting in the writing or editing of the manuscript, and no images were manipulated using AI. The authors developed and verified all scientific content, data analysis, interpretation of results, and conclusions. The authors take full responsibility for the accuracy, integrity, and originality of the work presented, and no AI tool was listed as an author.

REFERENCES

Arulnathan, V., Heidari, M.D., Doyon, M., Li, E. and Pelletier, N. 2020. Farm-level decision support tools: A review of methodological choices and their consistency with

principles of sustainability assessment. *Journal of Cleaner Production*, **256**: 120410.

Avhale, V.R., Senthil Kumar, G., Kumaraperumal, R., Prabukumar, G., Bharathi, C., Sathya Priya, R. and Pazhanivelan, S. 2025. AgriDrones: A holistic review on the integration of drones in Indian agriculture. *Agricultural Research*, **14**(1): 34–46.

Bayrak, T. and Olu, M. 2025. Applications of artificial intelligence in smart agriculture: Plant health, drone technology, and digital communication. *Journal of Agricultural Production*, **6**(3): 157–166.

Bhatt, R., Hossain, A., Majumder, D., Chandra, M.S., Ghimire, R., Shahzad, M.F., Verma, K.K., Riar, A.S., Rajput, V.D., Oliveira, M.W. and Nisi, A. 2024. Prospects of artificial intelligence for the sustainability of sugarcane production in the modern era of climate change: An overview of related global findings. *Journal of Agriculture and Food Research*, **18**: 101519.

Dhivya, C., Arunkumar, R., Murugan, P.P. and Senthilkumar, M. 2024. Drone technology in agricultural practices: A SWOC analysis. *Journal of Scientific Research and Reports*, **30**(11): 626–635.

Guchhait, D., Sagar, L., Yasasri, L., Maity, B., Divya, B.S., Ray, S., Atapattu, A. and Maitra, S. 2026. Agentic Artificial Intelligence-Based Nutrient Management: A frontier approach for agricultural sustainability. *In:* CRC Press e-Books, pp. 48–54. https://doi.org/10.1201/9781042036325-8

Maheswari, N., Maitra, S., Sairam, M., Ray, S., Sagar, L., DT, S. and Gaikwad, D.J. 2025. Impact of real-time nitrogen management on the performance of maize-cowpea intercropping system. *Crop Research*, **60**(3-4):139-154.

Maitra, S., Santosh, D.T., Jena, J., Behera, S.D., Ray, S., Sairam, M., Palai, J.B., Gaikwad, D.J., Rishitha, S., Gitari, H.I. and Atapattu, A.J. 2026. Understanding plant responses to abiotic stress through systems biology. In *Systems Biology in Crop Improvement*, Academic Press, pp. 59-100. https://doi.org/10.1016/B978-0-443-36457-0.00011-0

Murugan, P.P., Dhivya, C. and Senthilkumar, M. 2024. Farmers awareness and perception of drone technology. *Journal of Experimental Agriculture International*, **46**(10): 426–435.

Ramteke, S.V. 2026. Renewable energy optimization with artificial intelligence. In: *AI and Computational Intelligence for Environmental Sustainability*, pp. 39–62. Elsevier. https://doi.org/10.1016/B978-0-443-48507-7.00014-6

Ray, S., Maitra, S., Maity, B., Reddy, G.S., Somahanthi, A., Sagar, L., Masina, S., Rishitha, S., Guchhait, D. and Hossain, A. 2026. Artificial Intelligence-Based maize yield forecasting using random forest regressor under different nitrogen and Bio-Stimulant management strategies. *In:* CRC Press eBooks pp. 228–233. https://doi.org/10.1201/9781042036325-35

Razak, S.A., Yogarayan, S., Sayeed, M.S. and Derafi, M.I.F.M. 2024. Agriculture 5.0 and explainable AI for smart agriculture: A scoping review. *Emerging Science Journal*, **8**(2): 744–760.

Rishitha, S., Sairam, M., Vanitha, S., Somraj, B., Nanda, S.P., Pradhan, P., Anhuya, J., Sagar, L., Ray, S., Gitati, H.I., Santosh, D., Gaikwad, D.J. and Maitra, S. 2026. Artificial Intelligence-Based Nutrient Management in Cereals: Future directions of smart agriculture. In CRC Press eBooks, pp. 222–227. https://doi.org/10.1201/9781042036325-34

Saaty, T.L. 1980. *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*. McGraw-Hill, New York.

Safaeinejad, M., Ghasemi-Nejad-Raeini, M. and Taki, M. 2025. Reducing energy and environmental footprint in agriculture: A study on drone spraying vs. conventional methods. *PLoS ONE*, **20**(6): e0323779.

Singh, R. and Singh, S. 2025. A review of Indian-based drones in the agriculture sector: Issues, challenges, and solutions. *Sensors*, **25**(15): 4876.

Sokołowska, E. and Olczyk, M. 2026. *The Economics and Finance of the Green Transition: Financial Instruments, Institutional Analysis, and Policy Design*. Taylor and Francis, pp. 222. https://doi.org/10.4324/9781003713784

Taseer, A. and Han, X. 2024. Advancements in variable rate spraying for precise spray requirements in precision agriculture using unmanned aerial spraying systems: A review. *Computers and Electronics in Agriculture*, **219**: 108841.

Valizadeh, N. and Hayati, D. 2025. A systematic review on selection and comparison of holistic agricultural sustainability assessment approaches. *Frontiers in Sustainable Food Systems*, **9**: 1559503.

Yadav, J., Chauhan, U. and Sharma, D. 2023. Importance of drone technology in Indian agriculture, farming. In: *Smart Village Infrastructure and Sustainable Rural Communities*, pp. 35–46. IGI Global Scientific Publishing. https://doi.org/10.4018/978-1-6684-6418-2.ch003

Yuan, W., Zhao, J., Huo, M., Feng, Y. and Xu, S. 2025. Information acquisition and green technology adoption among Chinese farmers: Mediation by perceived usefulness and moderation by digital skills. *Sustainability*, **17**(21): 9712.