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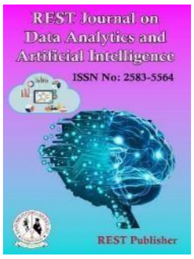

Utilizing Drones and Satellite Imagery in Crop Monitoring and Precision Farming: An Application of the WASPAS Method

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Abstract: *Drones and satellite imagery have revolutionized crop monitoring and precision farming, offering innovative solutions for enhanced agricultural productivity. These technologies enable farmers to collect high-resolution data on crop health, soil conditions, and resource management. Drones provide real-time, localized insights, allowing for precise interventions, while satellite imagery offers extensive coverage and long-term trend analysis. By integrating these advanced technologies, farmers can monitor their fields more efficiently, reduce costs, and contribute to sustainable farming practices, ultimately ensuring food security in an increasingly challenging agricultural landscape. The significance of drones and satellite imagery in crop monitoring and precision farming lies in their potential to enhance agricultural efficiency and sustainability. They facilitate early detection of issues such as pests, diseases, and nutrient deficiencies, reducing waste and minimizing environmental impact. Furthermore, the integration of these tools supports precision agriculture practices, which are crucial for adapting to climate change and meeting the growing global food demand. Ultimately, their application promotes sustainable farming and contributes to food security. The methodology for utilizing drones and satellite imagery in crop monitoring and precision farming involves several key steps. First, high-resolution satellite images are obtained to assess the overall health and variability of crops across large areas. Drones are deployed for targeted monitoring, capturing detailed images and data at a finer scale. Data processing and analysis use advanced algorithms to extract insights, such as NDVI (Normalized Difference Vegetation Index) for assessing plant health. The findings inform precision interventions, such as variable rate irrigation or fertilization. Continuous monitoring allows for adaptive management, ensuring timely responses to emerging issues and optimizing agricultural practices. Alternative taken as Drone A, Drone B, Satelite A, Satelite B, Drone+Satelite. Evaluation preference taken as Cost Efficiency (USD/ha), Data Accuracy (%), Timeliness of Data, Coverage Area (ha). Drone A getting first place of the table and satellite B is getting last place of the table.*

Keywords: *Cost Efficiency (USD/ha), Data Accuracy (%), Timeliness of Data, Coverage Area (ha)*

1. INTRODUCTION

In the rapidly evolving field of agriculture, the integration of technology is transforming traditional farming practices into precision agriculture a method that enhances crop yield, optimizes resource use, and minimizes environmental impact.[1] Among the most significant advancements in this realm are drones and satellite imagery, which provide farmers and agronomists with powerful tools for crop monitoring and management. This introduction explores the role of these technologies in modern farming, their benefits, challenges, and the future of agricultural practices.[2] Satellite imagery, on the other hand, involves capturing images of the Earth's surface from space. Satellites orbit the Earth at different altitudes, providing wide coverage and consistent data collection over time. Both drones and satellite imagery offer unique advantages for crop monitoring, enabling farmers to assess crop health, soil conditions, and environmental factors.[3] Drones and satellites are equipped with multispectral and hyper spectral cameras that capture data beyond the visible spectrum. This capability allows farmers to assess plant health by measuring parameters such as chlorophyll levels and moisture content. For example, drone surveys can reveal variations in soil moisture, allowing for targeted irrigation that conserves water and improves crop yields.[4] Similarly, satellite data can help determine the optimal timing and amount of fertilizers to apply, reducing waste and environmental impact.

Drones and satellite imagery can assist in estimating crop yields by analyzing growth patterns and biomass levels. This information is crucial for planning harvests and managing supply chains effectively. [5]Accurate yield forecasts also enable farmers to make better decisions regarding market timing and pricing. High-resolution aerial imagery allows for the creation of detailed maps of fields, including topography, soil types, and crop distributions. These maps are invaluable for planning planting strategies, crop rotations, and resource allocation, ensuring that every part of the field is utilized efficiently.[6] The sheer volume of data generated by drones and satellites can be overwhelming. Farmers require expertise in data analysis to interpret the information effectively. Without proper training or support, the potential of these technologies may not be fully realized. [7]The use of drones in agriculture is subject to regulations that vary by region. Farmers must navigate laws concerning airspace, privacy, and data usage, which can complicate their adoption of drone technology. Both drones and satellites are affected by weather conditions. Cloud cover can obstruct satellite imaging, while adverse weather can limit drone flight. Farmers must consider these factors when planning their monitoring activities. The future of drones and satellite imagery in crop monitoring and precision farming is promising.[8] Additionally, the development of more affordable and user-friendly drone technologies will empower more farmers, particularly smallholders, to adopt precision farming practices. As awareness grows about sustainable agriculture and the need for efficient resource management, the adoption of these technologies will likely become more widespread.[9] Drones and satellite imagery represent a transformative force in modern agriculture, providing farmers with the tools needed to monitor crop health, optimize resource use, and enhance overall productivity. As the agricultural sector faces increasing pressure to produce more food sustainably, the role of precision farming will only become more critical. The journey toward fully realizing the potential of drones and satellite imagery is ongoing, but the benefits they offer are clear, heralding a new era in agricultural practices.[10]

2. MATERIAL AND METHOD

Alternative:

1. **Drone A:** Drone A offers a balance of cost efficiency (150 USD/ha), high data accuracy (85%), moderate timeliness (6 days), and a coverage area of 50 hectares, making it suitable for precise, small-scale operations.

2. **Drone B:** Drone B offers a cost-effective solution at 120 USD/ha, with 80% data accuracy. It provides 8 hours of timeliness and covers an area of 40 hectares, suitable for moderate-scale tasks.

3. **Satelite A:** Satellite A is highly cost-efficient at 100 USD/ha, offering 75% data accuracy. It delivers data within 4 hours and covers a large area of 200 hectares, ideal for extensive coverage needs.

4. **Satelite B:** Satellite B is a cost-efficient option at 90 USD/ha, offering 70% data accuracy. It provides timely data within 5 hours and covers a large area of 180 hectares, ideal for extensive monitoring.

5. **Drone+Satelite:** The Drone + Satellite option combines both technologies, delivering high data accuracy (90%), extensive coverage (300 hectares), and fast data collection (10 hours), though at a higher cost of 200 USD/ha.

Evaluation preference:

1. **Cost Efficiency (USD/ha):** Cost Efficiency (USD/ha) measures the expense of monitoring or surveying per hectare. Lower costs, like 90 USD/ha for Satellite B, are more efficient, while higher costs, such as 200 USD/ha for combined systems, indicate greater investment.

2. **Data Accuracy (%):** Data Accuracy (%) reflects the precision of the information collected. Higher accuracy, like 90% for the Drone + Satellite combination, ensures more reliable data, while lower accuracy, such as 70% for Satellite B, may result in less precision.

3. **Timeliness of Data:** Timeliness of data refers to how promptly data is collected, processed, and made available for decision-making. Timely data ensures relevance, accuracy, and usefulness in dynamic environments, aiding informed actions.

4. **Coverage Area(ha):** Coverage area, measured in hectares (ha), refers to the total land area covered or affected by a specific activity, project, or study. It is commonly used in agriculture, forestry, and environmental planning.

WASPAS (Weighted Aggregated Sum Product Assessment) method: In decision-making processes, particularly in complex environments such as project management, resource allocation, and strategic planning, decision-makers often face multiple criteria that must be considered simultaneously. Traditional methods like WSM and WPM have their strengths but also limitations. [11]WSM treats all criteria linearly and assumes independence among them, while WPM can sometimes be less intuitive for some decision-makers. The WASPAS method was developed to leverage the advantages of both approaches while mitigating their drawbacks.[12] In MCDM problems, alternatives are assessed based on various criteria, each of which may have different units of measurement and varying levels of importance. The WASPAS method facilitates this by assigning weights to each criterion, allowing for a more nuanced evaluation of alternatives.[13] WASPAS has been successfully applied in various domains, such as project selection, supplier evaluation, environmental impact assessment, and resource allocation. Its adaptability to different contexts makes it a valuable tool for decision-makers facing complex scenarios with multiple competing criteria.[14] In summary, the WASPAS method offers a systematic approach to multi-criteria decision-making, blending the strengths of both additive and multiplicative methods. By carefully weighing criteria and evaluating alternatives, it enables informed and effective decision-making across various fields.[15] The WASPAS method represents a powerful tool in multi-criteria decision-making, allowing for a nuanced evaluation of alternatives based on a diverse set of criteria. By blending the weighted sum and weighted product approaches, WASPAS addresses some of the inherent limitations of traditional methods while providing a structured, transparent framework for decision-making.[16] Its versatility makes it applicable across various fields, enabling decision-makers to make informed choices that consider both quantitative and qualitative factors. However, users should remain mindful of the method's limitations and strive for careful implementation to achieve optimal results.[17]

Step 1 The decision matrix X which shows the performances of different alternatives with respect to various criteria is formed.

$$D = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & x \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \qquad (1)$$

Weight vector may be expressed as

$$w_j = [w_1 \quad \cdots \quad w_n], \qquad (2)$$

where $,\sum_{j=1}^{n}(w_1 \ \cdots \ w_n) = 1$

Step 2: The decision matrix is normalized. Beneficial and non-beneficial criteria are normalized

$$n_{ij} = \begin{cases} \frac{x_{ij}}{max.x_{ij}} \mid j \in B \\ \frac{min.x_{ij}}{x_{ij}} \mid j \in C \end{cases} \qquad (3)$$

Where $n_{ij}$is the normalized value of i^{th} alternative for the j^{th}section $max. x_{ij}$ and $min. x_{ij}$ are the maximum and minimum value of x_{ij} in the jth column for benefit (B) and cost criteria (C) respectively

Step 3. Weighted normalized decision matrix by WSM method is calculated as follows:

$$w_{ij} = w_i n_{ij} \qquad (4)$$

Step 4. Weighted normalized Decision Matrix

$$W_{n_{ij}} = (n_{ij})^{w_j} \qquad (5)$$

Step 5: Preference score for the given alternative, based on WSM, is calculated as follows:

$$S_i^{WSM} = \sum_{j=1}^{n} w_j n_{ij} \qquad (6)$$

Step 6: Preference score for the given alternative, based on WSM, is calculated as follows:

$$S_i^{WPM} = \prod_{j=1}^{n} (n_{ij})^{w_j} \qquad (7)$$

Step 7: Preference score for WASPAS method is calculated using equation (6) and (7),

$$S_i^{WASPAS} = \lambda\, S_i^{WSM} + (1 - \lambda\,) S_i^{WPM}$$

$$S_i^{WASPAS} = \lambda \sum_{j=1}^{n} w_j n_{ij} + (1 - \lambda\,) \prod_{j=1}^{n} (n_{ij})^{w_j}$$

Where λ is between 0 and 1.

Finally, the alternatives are ranked based on the S_i^{WASPAS} values. The best alternative has the highest S_i^{WASPAS} value. If the value of λ is 0, WASPAS method is transformed to WPM and if λ is 1, it becomes WSM.

3. RESULT AND DISCUSSION

TABLE 1. The drones and satellite imagery in crop monitoring

	Cost Efficiency(USD/ha)	Data Accuracy (%)	Timeliness of Data	Coverage Area(ha)
Drone A	150	85	6	50
Drone B	120	80	8	40
Satelite A	100	75	4	200
Satelite B	90	70	5	180
Drone+Satelite	200	90	10	300

The table presents key performance metrics for various alternatives based on four criteria: Cost Efficiency (USD/ha), Data Accuracy (%), Timeliness of Data, and Coverage Area (ha). Drone A incurs a cost of 150 USD/ha with high accuracy (85%) and moderate coverage (50 ha). Drone B is more cost-effective at 120 USD/ha, with slightly lower accuracy (80%) and less coverage (40 ha). Satellite A offers the lowest cost (100 USD/ha) but lower accuracy (75%), while Satellite B is similarly priced. The Drone + Satellite option, though the most expensive at 200 USD/ha, provides the highest accuracy (90%) and coverage (300 ha), making it a comprehensive solution.

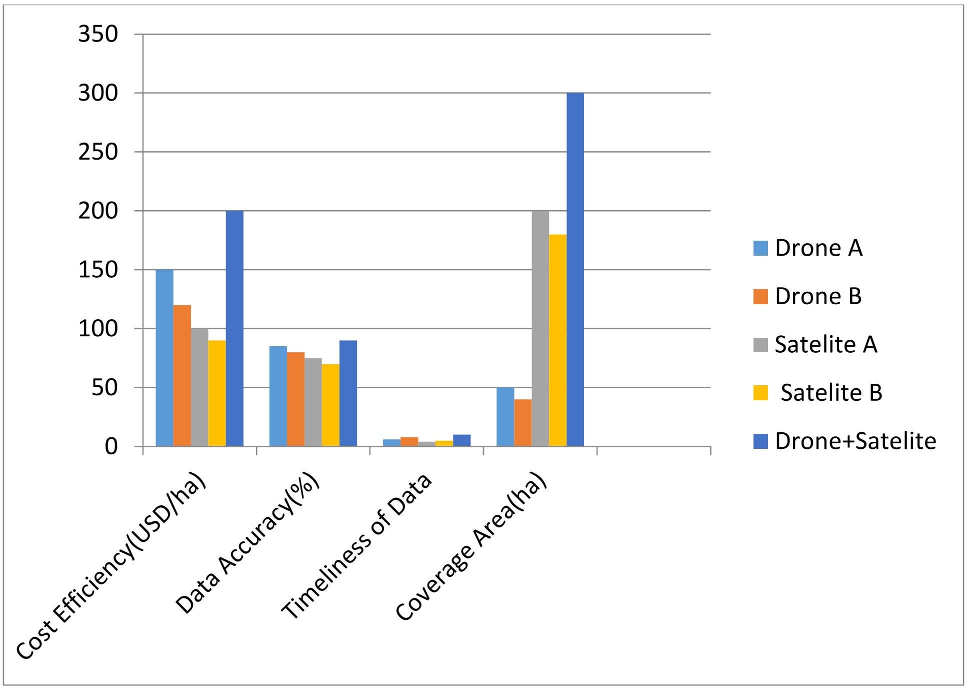

FIGURE 1. The drones and satellite imagery in crop monitoring

The chart presents key performance metrics for various alternatives based on four criteria: Cost Efficiency (USD/ha), Data Accuracy (%), Timeliness of Data, and Coverage Area (ha). Drone A incurs a cost of 150 USD/ha with high accuracy (85%) and moderate coverage (50 ha). Drone B is more cost-effective at 120 USD/ha, with slightly lower accuracy (80%) and less coverage (40 ha). Satellite A offers the lowest cost (100 USD/ha) but lower accuracy (75%), while Satellite B is similarly priced. The Drone + Satellite option, though the most expensive at 200 USD/ha, provides the highest accuracy (90%) and coverage (300 ha), making it a comprehensive solution.

TABLE 2. Performance value

Drone A	0.75000	0.94444	0.66667	0.80000
Drone B	0.60000	0.88889	0.50000	1.00000
Satelite A	0.50000	0.83333	1.00000	0.20000
Satelite B	0.45000	0.77778	0.80000	0.22222
Drone+Satelite	1.00000	1.00000	0.40000	0.13333

The performance value table displays the effectiveness of various alternatives across four criteria, quantified on a scale from 0 to 1, where higher values indicate better performance. Each row corresponds to an alternative: Drone A, Drone B, Satellite A, Satellite B, and Drone + Satellite. For example, Drone A has strong scores in the second criterion (0.94444) and the fourth criterion (0.80000), indicating robust performance. Drone + Satellite achieves the highest score in the first criterion (1.00000), but significantly lower in the last criterion (0.13333). This matrix allows for a detailed comparison of how well each alternative meets the defined criteria.

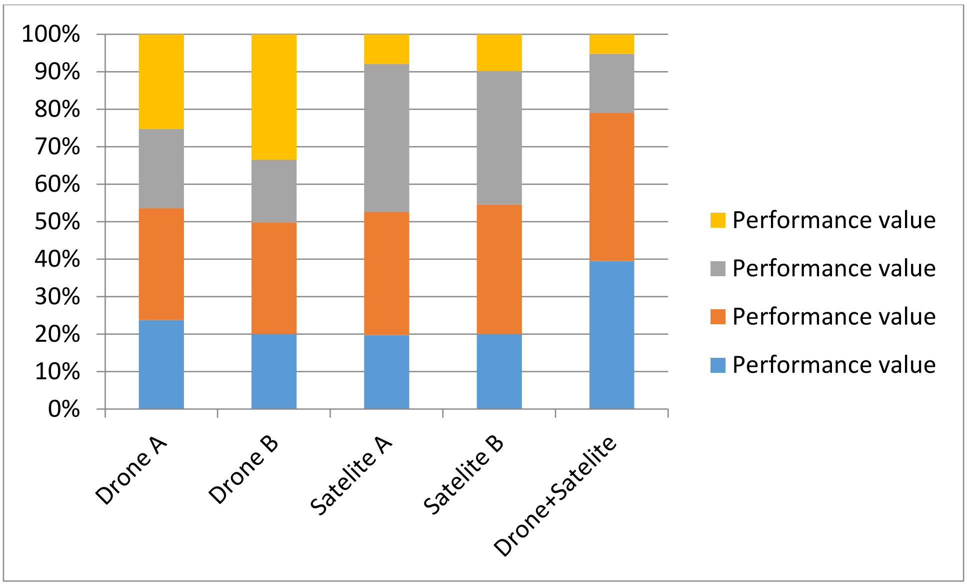

FIGURE 2. Performance value

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TABLE 3. Weight

Drone A	0.25	0.25	0.25	0.25
Drone B	0.25	0.25	0.25	0.25
Satelite A	0.25	0.25	0.25	0.25
Satelite B	0.25	0.25	0.25	0.25
Drone+Satelite	0.25	0.25	0.25	0.25

The weights assigned in this table indicate equal importance for each of the four criteria across all alternatives: Drone A, Drone B, Satellite A, Satellite B, and Drone + Satellite. Each criterion is given a weight of 0.25, reflecting a uniform approach to evaluation, where no criterion is prioritized over another. This balanced weighting ensures that all alternatives are assessed fairly, based on the same standard. The equal distribution of weights simplifies the decision-making process by emphasizing that each criterion contributes equally to the overall performance scores, allowing for a straightforward comparison of alternatives.

TABLE 4. Weighted normalized decision matrix (WSM)

Drone A	0.18750	0.23611	0.16667	0.20000
Drone B	0.15000	0.22222	0.12500	0.25000
Satelite A	0.12500	0.20833	0.25000	0.05000
Satelite B	0.11250	0.19444	0.20000	0.05556
Drone+Satelite	0.25000	0.25000	0.10000	0.03333

The weighted normalized decision matrix (WSM) displays the performance scores of various alternatives across four criteria, indicating their relative effectiveness. Each row corresponds to an alternative Drone A, Drone B, Satellite A, Satellite B, and Drone + Satellite while each column represents a specific criterion. The values indicate the weighted performance, with higher values signifying better performance. For example, Drone A has the highest score in the second criterion (0.23611) and overall scores, making it a strong choice. Drone +

Satellite performs relatively well in the first criterion (0.25000), but its scores in other criteria are lower, indicating variability in effectiveness.

TABLE 5. Weighted normalized decision matrix (WPM)

Drone A	0.93060	0.98581	0.90360	0.94574
Drone B	0.88011	0.97098	0.84090	1.00000
Satelite A	0.84090	0.95544	1.00000	0.66874
Satelite B	0.81904	0.93910	0.94574	0.68659
Drone+Satelite	1.00000	1.00000	0.79527	0.60428

The weighted normalized decision matrix (WPM) presents the performance of various alternatives across four criteria, reflecting their relative effectiveness. Each row corresponds to an alternative Drone A, Drone B, Satellite A, Satellite B, and Drone + Satellite while each column represents a specific criterion. The values range from 0 to 1, with 1 indicating the best performance for that criterion. For instance, Drone A shows high scores across most criteria, particularly in the second criterion (0.98581). Drone + Satellite scores the highest in the first criterion (1.00000), but performs lower in the last two. This matrix enables a comparative assessment of alternatives based on multiple criteria.

TABLE 6. Preference Score (WSM&WPM)

	Preference Score (WSM)	Preference Score (WPM)
Drone A	0.79028	0.78399
Drone B	0.74722	0.71861
Satelite A	0.63333	0.53728
Satelite B	0.56250	0.49944
Drone+Satelite	0.63333	0.48056

The table presents preference scores for various alternatives calculated using two methods: the Weighted Sum Model (WSM) and the Weighted Product Model (WPM). Drone A has the highest scores in both methods, with 0.79028 (WSM) and 0.78399 (WPM), indicating its strong overall performance. Drone B follows with scores of 0.74722 (WSM) and 0.71861 (WPM), showing it is also a solid choice. Satellite A scores 0.63333 (WSM) and 0.53728 (WPM), reflecting moderate preference. Satellite B and Drone + Satellite have lower scores, indicating they are less favorable options in this evaluation.

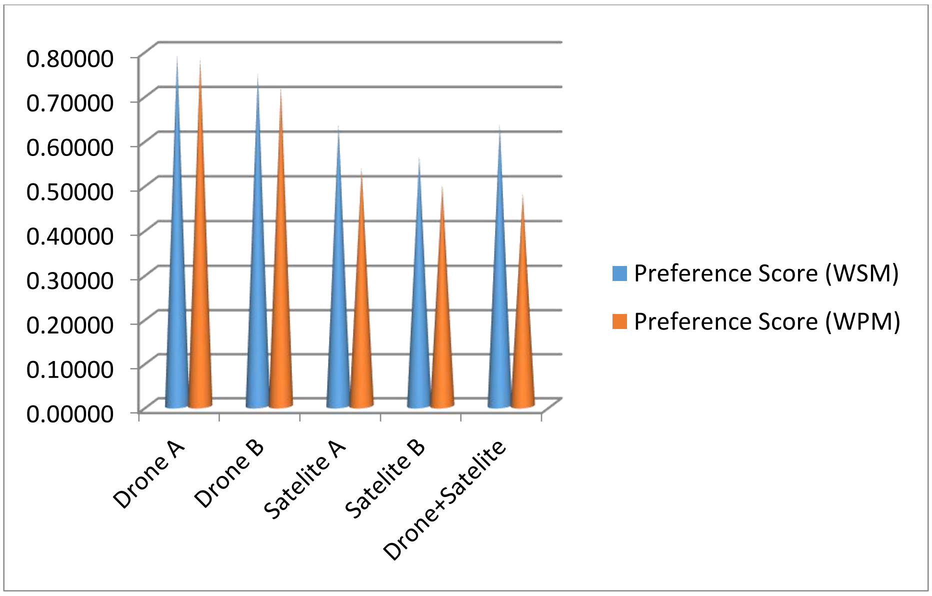

FIGURE 3. Preference Score (WSM&WPM)

The bar chart presents the preference scores for various alternatives evaluated using two methods: the Weighted Sum Model (WSM) and the Weighted Product Model (WPM). Each alternative Drone A, Drone B, Satellite A, Satellite B, and the combined option (Drone + Satellite) is represented along the x-axis. The blue bars indicate the scores from the WSM, while the red bars show the scores from the WPM. The chart highlights how each method assesses the performance of the alternatives, allowing for a visual comparison of the results and illustrating any differences in rankings between the two evaluation approaches.

TABLE 7. WASPAS Coefficient

Drone A	0.78713
Drone B	0.73292
Satelite A	0.58531
Satelite B	0.53097
Drone+Satelite	0.55695

The WASPAS coefficients represent the performance scores of various alternatives assessed using the Weighted Aggregated Sum Product Assessment method. Drone A has the highest coefficient at 0.78713, indicating it is the most favorable option. Drone B follows with a score of 0.73292, also demonstrating strong performance. Satellite A scores 0.58531, showing moderate preference, while Drone + Satellite has a coefficient of 0.55695, suggesting it is less desirable than the top drones. Finally, Satellite B ranks lowest with a score of 0.53097, indicating it is the least preferred option among the alternatives evaluated.

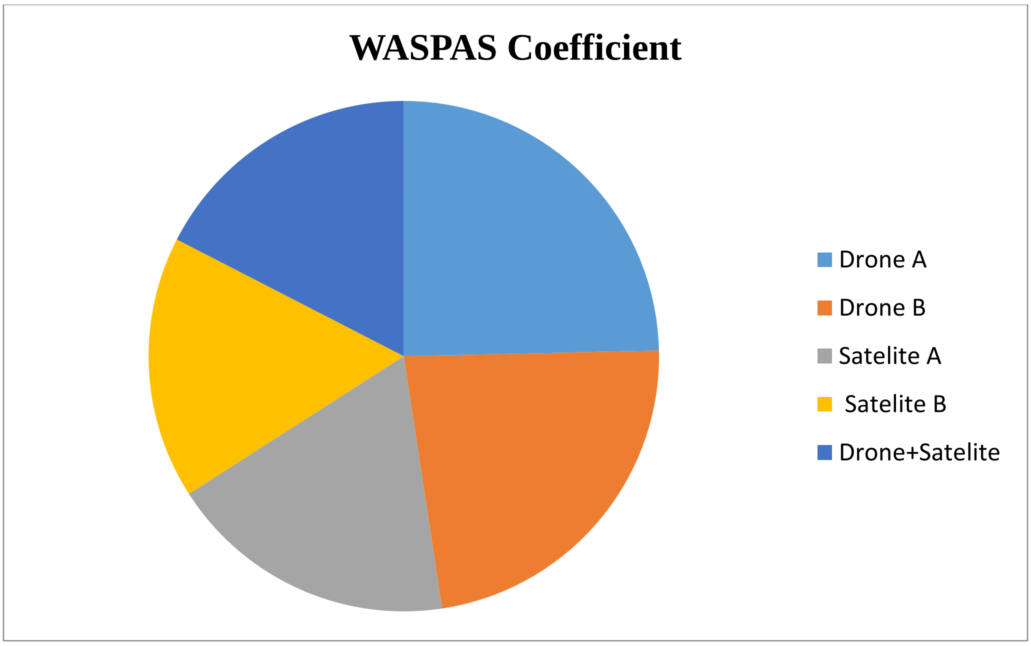

FIGURE 4. WASPAS Coefficient

The pie chart titled "WASPAS Coefficient" illustrates the distribution of scores for various alternatives evaluated using the WASPAS method. Each segment represents different alternatives: Drone A (blue), Drone B (red), Satellite A (green), Satellite B (purple), and a combined option (Drone + Satellite) (cyan). The size of each segment indicates the relative performance or preference of each alternative based on the weighted criteria used in the WASPAS analysis. This visualization aids in understanding which alternatives are favored in the decision-making process, highlighting the strengths of each option in a comparative manner.

TABLE 8. Rank

Drone A	1
Drone B	2
Satellite A	3
Satellite B	5
Drone+Satelite	4

The ranking data outlines the performance of various alternatives based on a multi-criteria evaluation. Drone A is ranked highest (1), indicating it is the most preferred option among the alternatives. Drone B follows closely in second place (2). Satellite A is in the middle with a rank of 3. Drone + Satellite ranks fourth (4), suggesting it offers a combination of features but is less preferred than the top three. Finally, Satellite B is ranked the lowest at 5, indicating it is the least favored option based on the established criteria in the decision-making process.

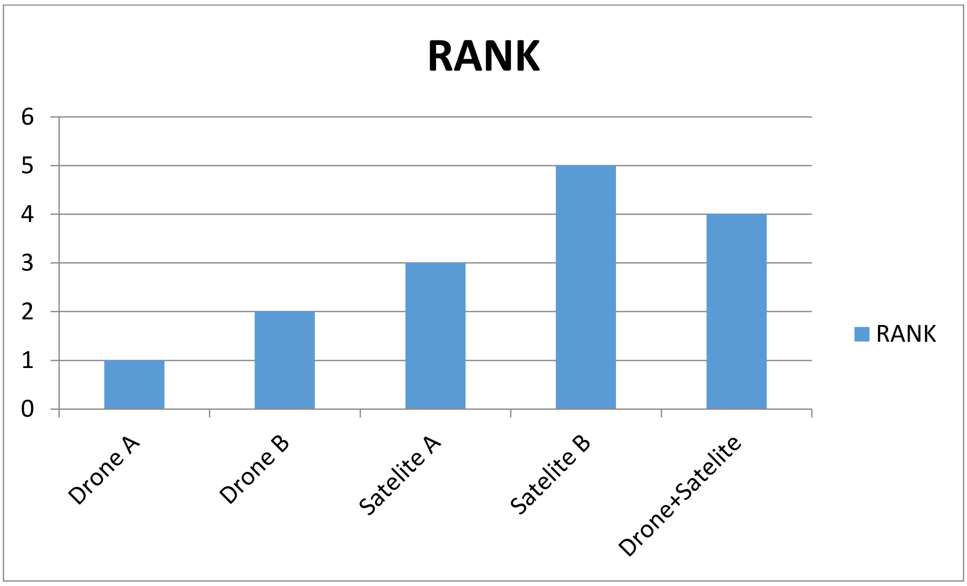

FIGURE 5. Rank

The line graph titled "RANK" displays the ranking of different alternatives based on their performance in a multi-criteria decision-making analysis. Each alternative Drone A, Drone B, Satellite A, Satellite B, and the combined option (Drone + Satellite) is plotted along the x-axis, while the y-axis indicates their respective ranks. The data shows that Drone A and Drone B rank lowest, while Satellite B and the combined option (Drone + Satellite) achieve higher rankings, indicating better overall performance. This visualization helps in quickly identifying which alternatives are preferred based on the established criteria and assessment method.

4. CONCLUSION

In recent years, the integration of drones and satellite imagery into agricultural practices has transformed crop monitoring and precision farming, offering unprecedented opportunities for enhancing productivity, sustainability, and efficiency in the sector. Consequently, modern technologies such as drones and satellite imagery have emerged as vital tools in addressing these challenges. Meanwhile, drones offer high-resolution, localized data that can reveal issues not detectable from satellites, such as specific pest infestations or nutrient deficiencies. This dual approach enhances decision-making by allowing farmers to tailor interventions based on real-time data, ultimately leading to better crop management and increased yields. For instance, farmers can use drone data to implement targeted pesticide applications, reducing chemical use while ensuring effective pest control. By facilitating informed and timely decision-making, drones and satellite imagery significantly contribute to optimizing resource allocation and improving overall farm efficiency. Sustainability is a pressing concern in agriculture, and the use of drones and satellite imagery can significantly contribute to more environmentally friendly practices. By providing precise data on crop health and field conditions, these technologies help reduce chemical inputs, minimize water usage, and lower greenhouse gas emissions associated with farming activities. For example, precision irrigation techniques informed by drone data can lead to more efficient water use, conserving this vital resource in regions facing water scarcity. Moreover, the ability to monitor crop health in real time allows farmers to adopt integrated pest management practices, reducing reliance on chemical pesticides and promoting biodiversity. The integration of drones and satellite imagery with existing farm management systems further enhances their impact on precision farming. By incorporating data from these technologies into comprehensive management platforms, farmers can create detailed farm profiles that inform strategic decision-making. For instance, combining yield data, soil health information, and climatic conditions allows for the development of customized crop management plans tailored to specific fields and conditions. This level of integration facilitates collaboration among stakeholders, including agronomists, consultants, and farmers, promoting knowledge sharing and improving overall farm management practices. Moreover, the data collected can be archived and analyzed over time, allowing farmers to track trends and assess the effectiveness of various interventions.

This historical data is invaluable for planning future crops, identifying long-term changes in soil health, and making informed decisions that contribute to the sustainability and resilience of farming operations. Despite the numerous benefits, the adoption of drones and satellite imagery in crop monitoring and precision farming is not without challenges. One significant hurdle is the initial cost of acquiring drone technology and high-resolution satellite imagery. While prices have decreased over time, the investment required can still be a barrier for smallholder farmers. Additionally, the technical knowledge required to operate drones and analyze the data effectively can be a limiting factor. Farmers must invest in training or seek assistance from agricultural experts to maximize the benefits of these technologies. Regulatory challenges also exist, particularly concerning drone usage. Airspace regulations, privacy concerns, and land rights can complicate the deployment of drone technology. Therefore, it is crucial for stakeholders to work collaboratively to establish clear guidelines and regulations that facilitate safe and responsible drone operations in agriculture. Advancements in drone technology, such as increased flight times, improved sensor capabilities, and automated flight planning, will make it easier for farmers to utilize these tools effectively. As these technologies become more accessible and user-friendly, their adoption is likely to expand, particularly among smallholder farmers in developing regions.

The integration of drones and satellite imagery in crop monitoring and precision farming represents a transformative shift in agricultural practices. By enhancing data collection, enabling real-time monitoring, optimizing resource use, and promoting sustainability, these technologies are poised to address the pressing challenges facing modern agriculture. While there are obstacles to overcome, the benefits they offer in terms of increased productivity, cost-effectiveness, and environmental stewardship make them essential tools for the future of farming.

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