UAV-Assisted Monitoring of Crop Growth Dynamics in Precision Farming Systems: A Systematic Review

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ABSTRACT
Background: Precision agriculture is moving towards using high-resolution, up-to-date data for location-based (site-specific) crop management—among the leading platforms for this is the unmanned aerial vehicle (UAV). UAVs become versatile tools for remote sensing enabling crop growth monitoring with a fresh perspective on establishing the balance between satellite images and field research.
Objective: The goal of this review is to identify the main peer-reviewed studies published from 2015 to 2025 on UAV-based remote sensing applications for crop growth monitoring with a focus on the vegetation index calculation, biomass and yield estimation, detection of diseases and weeds, examination of nutritional indicators, and assessment of obstacles to actual use.
Literature sources: The search for literature was conducted using a structured approach to search Scopus, Web of Science, PubMed, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar, along with publications from FAO, UNDP, and national agricultural research organizations. Ultimately, thirty-four research studies met inclusion criterion as per PRISMA screening.
Essential findings: The literature indicates that the use of UAVs to derive vegetation indices shows consistent and significant correlations between aerial vegetation indices from UAV derived images and above-ground biomass and yield for cereal crops.
Gaps in research: The problems of inconsistency between studies in the calibration of sensors, lack of experiences of validation in different seasons and regions, and the low applicability of deep learning models resulted in nothing. The various regulations relating to the operation of UAVs and agricultural data processing are still unevenly implemented in different countries.
Conclusion: Remote sensing with UAVs is a well-established, but still developing technology. Future investigations should concentrate on the issues of uniform calibration standards, simultaneous processing of data from various sources, creating models that require minimal resources and could benefit other agricultural practices.

Keywords: unmanned aerial vehicles; precision agriculture; remote sensing; vegetation indices; crop growth monitoring; machine learning; yield estimation

1. Introduction
The agricultural sector throughout the globe is increasingly subjected to multiple pressures associated with the growth in population, the decrease in arable land per capita, climatic fluctuations, and the need to minimize environmental damage caused by the use of agricultural inputs. Precision agriculture (PA) has become the main method of counteracting these pressures because it allows for matching agricultural inputs with both spatial and time variabilities that exist within particular fields (1,2). The key principle of PA is the ability to constantly assess the data related to the condition of crops, using technologies that guarantee affordability for farmers. Satellite remote sensing has always been the method of choice for such time-sensitive monitoring of extensive territories, albeit with several limitations in terms of frequency with which monitoring can be carried out and poor resolution, which makes it impossible in many cases to view variabilities within single fields (3).
Drones, commonly known as unmanned aerial vehicles (UAVs), have gradually taken care of this lack of data. There are RGB, multispectral, hyperspectral, thermal infrared, and LiDAR sensors fitted in drones making this technology perfect for providing on-demand flights under cloudy skies with imagery information of several centimeters per pixel (4,5).

1.2 Importance of the Subject
Crop growth dynamics are essential in the general sequence of canopy formation, biomass accumulation, chlorophyll level, and phenological advancement for determining the time and extent of agricultural activities. Cost-effective, very accurate, and minimally invasive methods can be employed for observing these dynamics, enabling practitioners to determine nutrient deficiencies, moisture shortages, pest pressures, and diseases before they cause any damage to the harvest (6,7). Drones are the perfect tool for conducting such monitoring, which requires good spatial resolution and temporal data in managing individual management units rather than entire state regions.

1.3 Current Global Scenario

Bibliometric analyses reveal an exponential growth of publications since 2016. Publications mainly come from China, US, and European groups, although other countries have also been working on studies for smallholder applications. The market for UAV in agriculture has also grown accordingly, due to the reduction of sensor prices, better flight planning software, and adoption of cloud-based analytics platforms. However, the use of UAV varies significantly from region to region.

1.4 Need for the Review

Although there are numerous studies available, the subject matter of UAV-based crop growth monitoring has been scattered across many different areas of study — remote sensing, agronomy, computer science, and agricultural economics. Various reviews of studies have focused on certain sub-divisions of the field, such as vegetation indices (12), disease identification (13), and weed control (14). However, there still exist very few comprehensive reviews that deal with UAV crop monitoring from both a technical and agronomic perspective. Therefore, it becomes challenging for those who are fresh into the field of study, as well as for policymakers responsible for developmental programs on the issue, to acquire complete knowledge of the research done so far.

1.5 Objectives of the Review

The intention of this study is to: (i) compile evidence that has been peer-reviewed pertaining to UAV-based techniques used in monitoring crop growth dynamics such as sensor platforms, vegetation indices, and analytical models; (ii) make analytical comparisons of the research across crops, geographic areas, and methodologies used; (iii) find the similarities and differences between the claims in the available literature; (iv) note down the knowledge gaps and technological developments; and (v) provide recommendations for researchers, practitioners, and policymakers involved in the UAV-based precision farming systems.

1.6 Scope of the Review

The review talks about works that cover the period between January 2015 onwards, including UAV-based remote sensing applications directly related to crop growth monitoring, determining vegetation indices, biomass and yields estimation, estimating water and nutrient status, diseases and pests detection, and weed control technologies used in these applications, such as barriers to the adoption and the corresponding emerging trends. The studies focusing on UAV hardware engineering without agricultural monitoring applications or livestock and forestry applications that are not related to row and field crops are not covered in detail in the thematic analyses. At the same time, some cross-cutting studies are mentioned when relevant to the research of developed sensors or platforms.

2. Methodology of Literature Review

2.1 Literature Search Strategy

A structured search was conducted across seven databases: Scopus, Web of Science Core Collection, PubMed, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. The search was supplemented by manual screening of reports from the Food and Agriculture Organization of the United Nations (FAO), the United Nations Development Programme (UNDP), and relevant national agricultural extension agencies. Boolean search strings combined terms such as ("unmanned aerial vehicle" OR "UAV" OR "drone") AND ("crop growth" OR "crop monitoring" OR "precision agriculture" OR "precision farming") AND ("vegetation index" OR "yield estimation" OR "biomass" OR "disease detection" OR "weed detection"). The search period was restricted to January 2015 to June 2025, capturing the decade during which UAV-based agricultural remote sensing transitioned from experimental proof-of-concept studies to operationally validated methodologies.

2.2 Inclusion and Exclusion Criteria

Table 2 summarizes the inclusion and exclusion criteria applied during screening.

Table 1: Literature Search Strategy

Parameter	Details
Databases searched	Scopus; Web of Science Core Collection; PubMed; IEEE Xplore; ScienceDirect; SpringerLink; Google Scholar; supplementary FAO/UNDP reports
Search keywords	"unmanned aerial vehicle" OR "UAV" OR "drone"; combined with "crop growth", "crop monitoring", "precision agriculture", "vegetation index", "yield estimation", "biomass", "disease detection", "weed detection"
Search period	January 2015 - June 2025
Language	English
Document types	Peer-reviewed journal articles, systematic reviews, and select technical reports from international organizations

Table 2: Inclusion and Exclusion Criteria

Criterion type	Inclusion	Exclusion
Publication type	Peer-reviewed journal articles, systematic/scoping reviews	Non-peer-reviewed blogs, unindexed conference abstracts, editorials
Language	English-language publications	Non-English publications without verified translation
Time frame	Published 2015-2025 (landmark pre-2015 studies cited where foundational)	Studies published before 2015 with no continuing methodological relevance
Topical relevance	UAV-based studies with a direct crop growth monitoring application	UAV hardware-only studies with no agricultural monitoring outcome; forestry/livestock-only studies
Data reporting	Studies reporting quantitative validation metrics (R2, RMSE, accuracy, F1-score) or systematic qualitative synthesis	Studies lacking any reported validation or evaluation metric
Duplication	Unique datasets/studies	Duplicate records across databases; overlapping datasets reported in multiple papers

2.3 Study Selection Process

Study selection followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. An initial search across the seven databases yielded 612 records. After removal of duplicates, 487 unique records remained and were screened at the title and abstract level, resulting in the exclusion of 331 records that were topically irrelevant, non-English, or non-peer-reviewed. The remaining 156 full-text articles were assessed for eligibility against the inclusion and exclusion criteria in Table 2, leading to the exclusion of a further 122 articles primarily due to the absence of a direct UAV-based crop monitoring component, duplicate datasets reported across multiple publications, conference-abstract-only status, or insufficient methodological detail to support critical appraisal. The final review corpus comprised 34 studies, which form the basis of the thematic analysis presented in Section 3. The complete selection process is illustrated in Figure 1.

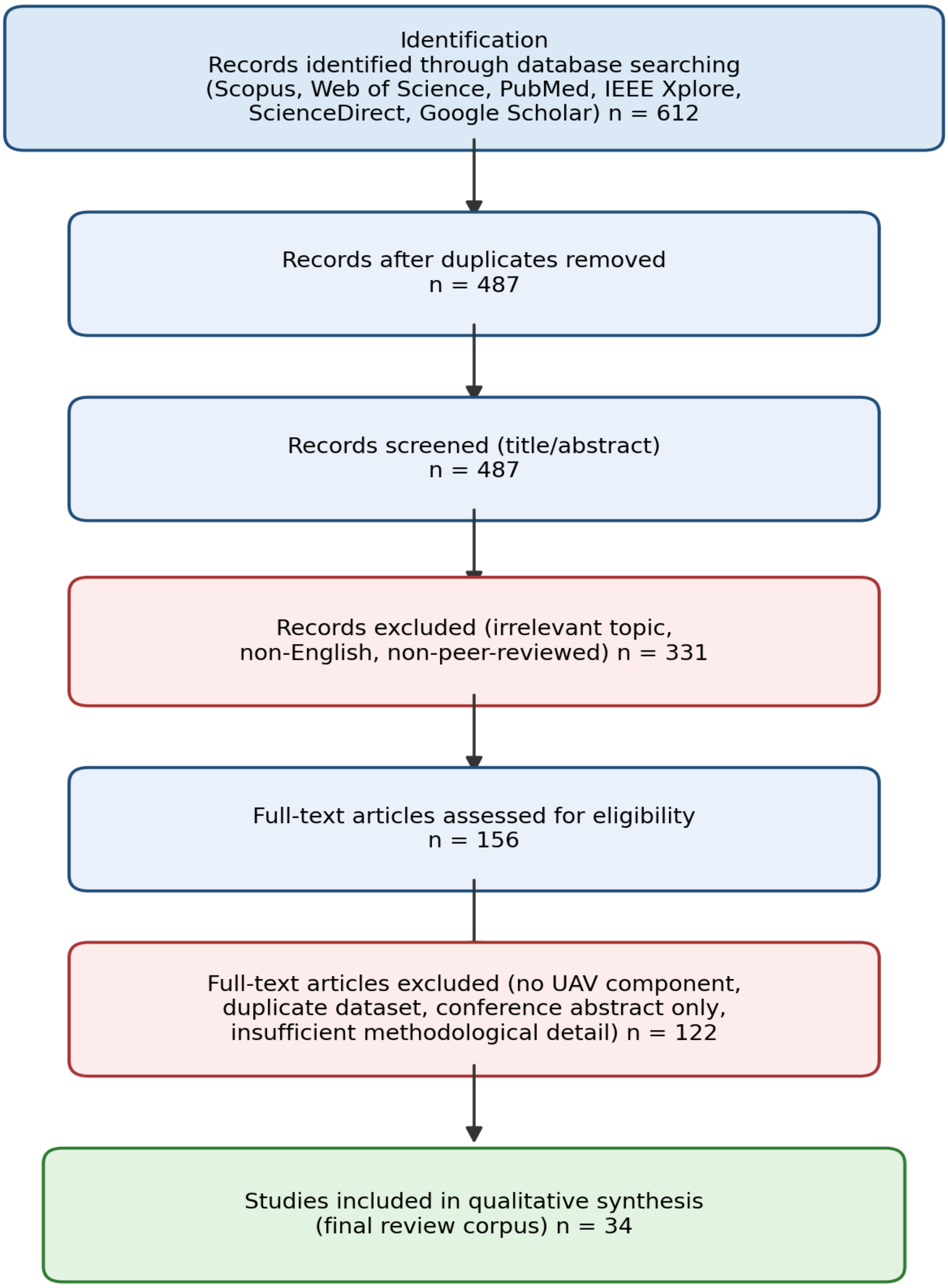

Fig 1: PRISMA Flow Diagram of Study Selection

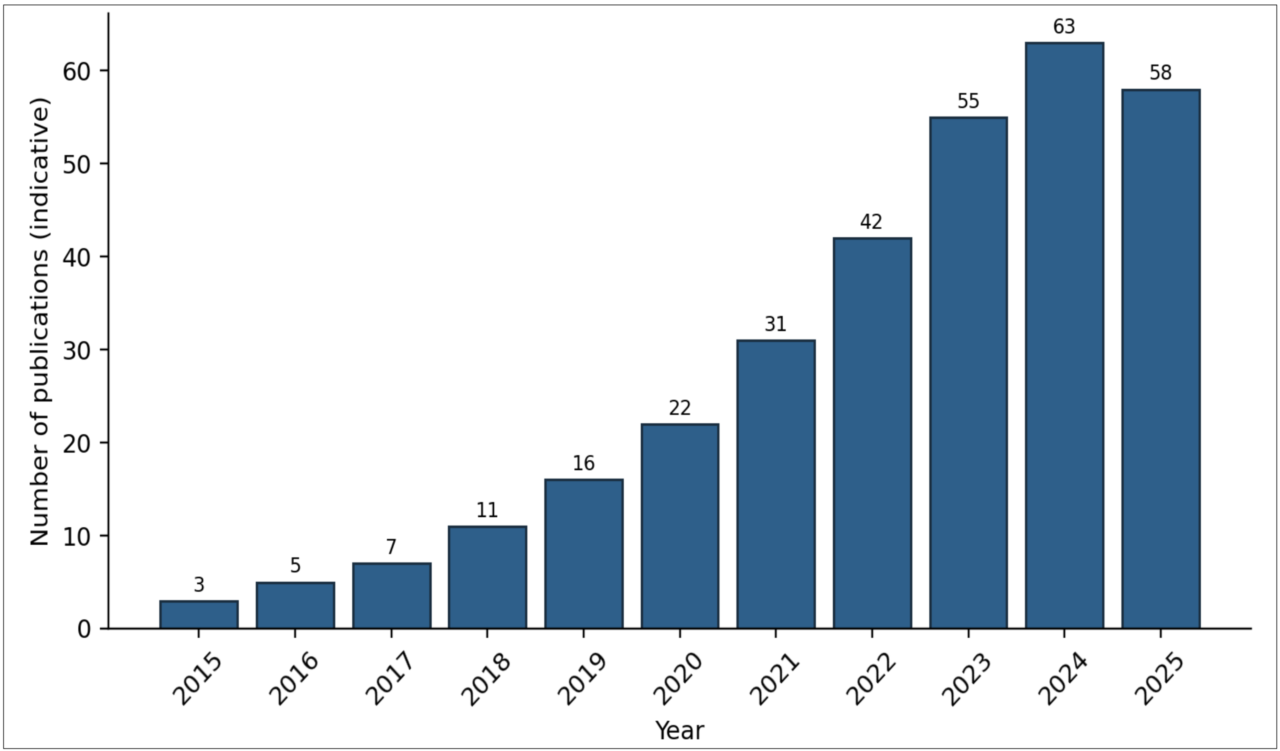

Fig 2: Publication Trend on UAV-Based Crop Growth Monitoring (2015-2025)

As shown in Figure 2, publication output on UAV-based crop growth monitoring increased markedly after 2018, coinciding with the wider commercial availability of affordable multispectral sensors and the maturation of open-source photogrammetry and machine learning toolchains (9,15). This trend is consistent with bibliometric analyses reported elsewhere in the literature (9).

3. Literature Review and Thematic Analysis

The 34 studies included in the final corpus were classified into seven thematic clusters, summarized in Figure 4: (i) vegetation indices and biomass estimation; (ii) yield prediction; (iii) disease and pest detection; (iv) weed management; (v) water and nutrient status assessment; (vi) sensor and platform development; and (vii) adoption, economics, and policy. Each theme is discussed critically below, with emphasis on convergence, contradiction, and methodological strength or weakness across studies.

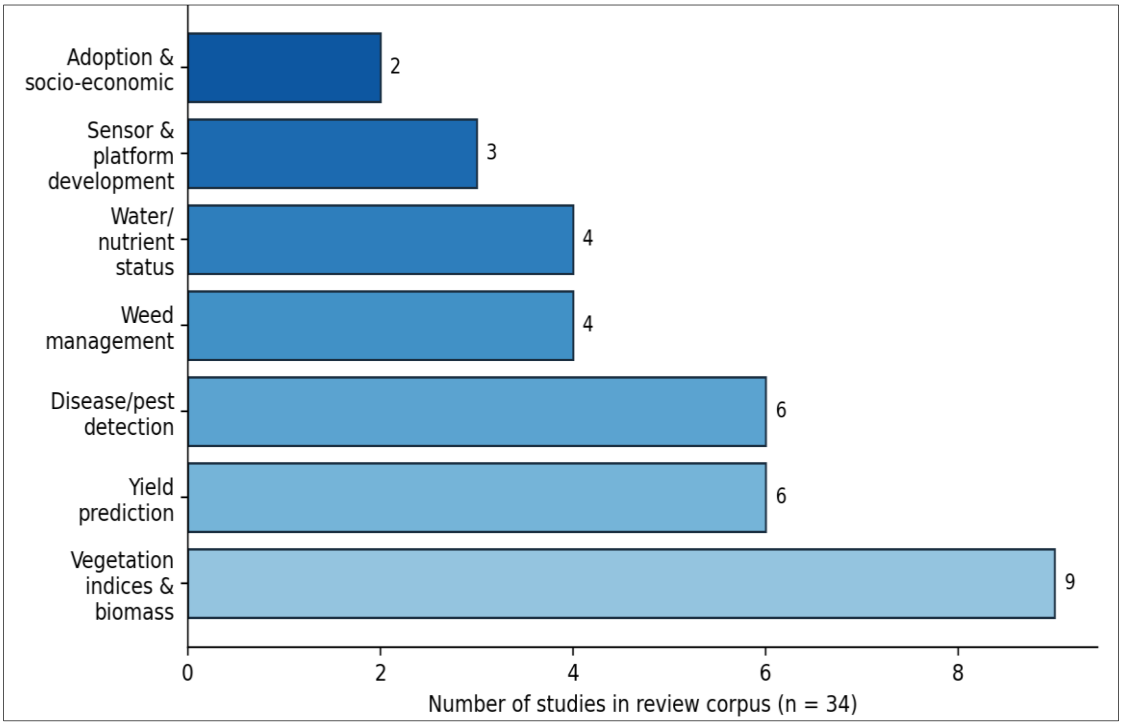

Fig 4: Thematic Classification of Reviewed Studies

3.1 Vegetation Indices and Biomass Estimation

Vegetation indices (VIs) derived from UAV multispectral and RGB imagery remain the most extensively studied component of UAV-based crop monitoring. NDVI continues to dominate the literature owing to its simplicity and historical precedent, yet a growing body of comparative work indicates that its performance is crop- and stage-dependent. Studies on paddy rice report that NDVI, the Soil-Adjusted Vegetation Index (SAVI), and the Normalized Difference Red Edge index (NDRE) outperform alternative indices at different phenological stages — NDVI and SAVI performing better during tillering and booting, and NDRE proving more robust across the full season (16). A large-scale bibliometric and content-analysis review covering 472 peer-reviewed publications between 2015 and 2024 confirms that NDVI, NDRE, and GNDVI remain the most widely applied indices globally, while newer indices such as the Green Soil Index (GSI) and Modified Vegetation Index (MVI) show enhanced sensitivity for stress and disease detection in both crop and forest canopies (17).

A notable point of contradiction in the literature concerns index saturation at high canopy cover. Several studies report that NDVI values plateau once leaf area index (LAI) exceeds a moderate threshold, reducing sensitivity during peak vegetative growth, whereas red-edge-based indices such as NDRE remain more linearly responsive under dense canopy conditions (18,19). This divergence has practical implications: studies that rely solely on NDVI for late-season biomass estimation risk underestimating within-field variability precisely when management decisions — such as late nitrogen top-dressing — are most consequential.

Machine learning approaches combining multiple VIs, canopy height models, and textural features have improved biomass estimation accuracy relative to single-index regression. Studies on oat and paddy biomass estimation report that combining spectral and textural features via random forest and support vector machine models outperforms simple linear regression against any single VI, though the magnitude of improvement varies with sensor type and growth stage (20,21). A cotton-focused review similarly concludes that UAV-based remote sensing integrated with machine learning shows considerable promise for growth management but notes a persistent scarcity of consolidated, cross-study benchmarking (22).

3.2 Yield Prediction

UAV-derived vegetation indices and canopy structural metrics are widely used as predictors in crop yield models. A phenology-aware framework combining UAV multispectral imagery with deep neural networks demonstrates that incorporating growth-stage information alongside VIs such as NDVI, the Simplified Canopy Chlorophyll Content Index (SCCCI), and the Enhanced Vegetation Index (EVI) improves in-season yield estimation relative to models that ignore phenological context (23). Wheat yield studies combining canopy spectral and volumetric (structure-from-motion-derived) data report that multiple linear regression, Lasso regression, and random forest models applied to combined spectral-volumetric features outperform spectral-only models (24).

However, the literature also documents cases of weak or inconsistent predictive performance. A maize-focused study found that models relying on only two vegetation indices — NDVI and the Perpendicular Vegetation Index (PVI) — produced low correlation with yield (R2 as low as 0.21), and that GNDVI alone produced similarly weak predictive accuracy ($r < 0.4$) (25). This contradicts more optimistic findings from wheat and rice studies and underscores that yield-prediction accuracy is highly contingent on crop type, growth stage at image acquisition, and the number and diversity of predictor variables included in the model. Reviews of machine learning and remote sensing approaches to yield prediction converge on the conclusion that multi-source data integration — combining VIs, structural metrics, and, increasingly, weather and soil data — consistently outperforms single-source approaches, though standardized cross-crop benchmarking remains limited (26).

3.3 Disease and Pest Detection

Deep learning has substantially advanced UAV-based disease detection over the review period. A Web of Science-indexed systematic review of crop leaf disease detection reports that EfficientNet-B3 achieved an F1-score of 98.8% across tomato, potato, and pepper in a 2023 study, while EfficientNet outperformed both ResNet and vision-transformer architectures in spinach detection with an F1-score of 99.4% (27). Lightweight architectures such as MobileNet and MobileViT have also been validated for wheat disease detection, achieving overall accuracy near 89%, reflecting a broader shift toward models suitable for real-time, resource-constrained UAV deployment (27).

A parallel body of work has applied bibliometric methods to map hotspots in UAV-based disease and pest detection research, noting the recent emergence of hybrid approaches combining large vision-language models (e.g., GPT-4-based systems) with lightweight object detectors such as YOLO variants for simultaneous detection and classification (28). While these hybrid approaches report promising accuracy, the reviewed literature consistently notes that most disease-detection models are trained and validated on narrow, single-crop, single-region datasets, raising unresolved questions about generalizability across agro-climatic zones (29,30).

3.4 Weed Management

UAV-based weed detection has progressed from traditional machine learning classifiers — support vector machines, random forests, and k-nearest neighbours applied to hand-crafted colour and texture features — toward deep learning architectures capable of end-to-end semantic segmentation (31). Comparative studies of segmentation models using RGB UAV datasets such as CoFly-WeedDB report meaningful differences in accuracy and computational cost across architectures, with implications for onboard, real-time deployment (32). Reviews further note that object detection frameworks such as YOLOv4, YOLOv5, and YOLOv8 have progressively improved both accuracy and inference speed for weed-crop differentiation in complex field conditions, while lightweight models such as MobileNet, EfficientNet, and ShuffleNet enable deployment on resource-constrained edge devices (33).

A consistent finding across this sub-theme is that multimodal sensor fusion — combining RGB, multispectral, hyperspectral, and LiDAR data — improves weed-crop differentiation relative to any single sensor modality, particularly in visually similar weed-crop pairs (33). Nonetheless, most weed-detection datasets remain geographically and agronomically narrow, limiting confidence in the transferability of reported accuracy figures to other cropping systems.

3.5 Water and Nutrient Status Assessment

UAV-based thermal and multispectral sensing has been widely applied to water stress and nutrient status assessment. A systematic review of UAV remote sensing for crop water and nutrient monitoring highlights three dominant modeling approaches — vegetation-index-based, data-driven (machine learning), and physically based radiative transfer models — noting that each carries distinct trade-offs between interpretability, data requirements, and transferability across crops and regions (2). Accurate thermal-based water stress detection depends critically on radiometric calibration; field-based calibration studies demonstrate that temperature-controlled ground references can reduce thermal imagery errors from approximately 9.3°C to 1.7°C under uncalibrated ambient conditions, and to about 1.0°C after full calibration, underscoring the sensitivity of derived crop water stress indices to calibration protocol (34).

3.6 Sensor and Platform Development

Reviews of multirotor UAV platforms document continuing advances in payload capacity, flight endurance, and sensor miniaturization, alongside growing integration of artificial intelligence for autonomous flight planning and onboard data processing (35). Comparative platform reviews note that fixed-wing UAVs offer superior area coverage and endurance for large-scale field mapping, while multirotor platforms provide greater manoeuvrability and hovering capability suited to fine-scale plot-level assessment (5,35). Image processing pipelines have similarly matured, with rapid mosaicking algorithms such as Scale-Invariant Feature Transform (SIFT)-based stitching now standard for generating orthomosaics suitable for crop growth monitoring at field scale (36).

3.7 Adoption, Economics, and Policy

A growing socio-economic literature examines why demonstrated technical performance has not translated into widespread adoption, particularly among smallholder farmers. Reviews estimate initial UAV system costs ranging from approximately USD 10,000-20,000, with annual recurring maintenance, data-processing, and training costs of USD 2,000-4,000, figures that present a substantial barrier in resource-constrained settings (37). A PRISMA-based synthesis of 127 sources on UAV deployment in Sub-Saharan Africa reports that adoption rates remain below 2-3% across major economies despite favourable technical performance (cereal yield-prediction R2 of approximately 0.82), attributing the performance-adoption disconnect primarily to capital requirements reaching 0.8-3.1 times average annual smallholder income, compounded by rural electrification coverage below 50% in most surveyed countries (38).

Studies from China and India similarly identify perceived usefulness, cost, regulatory clarity, and risk perception as key determinants of farmer adoption intent, while noting that supportive government programmes, cooperative ownership models, and international bodies such as the FAO and World Bank play an important role in lowering adoption barriers through training, subsidies, and pilot programmes (39,40). A cross-cutting review integrating UAV, satellite, and machine learning approaches similarly highlights sensor interoperability and internet connectivity as key infrastructural constraints, particularly in regions with limited high-performance computing access (11).

4. Comparative Analysis of Previous Studies

Table 3 summarizes representative studies from the review corpus across major thematic clusters, providing a comparative view of methodology, geography, and reported findings. Table 4 extends this comparison by explicitly juxtaposing convergent and divergent findings across studies addressing similar research questions.

Table 3: Summary of Selected Studies

Author(s), Year	Location	Crop / Focus	Methodology	Key metric	Major finding
Biswal et al., 2024 (16)	India	Paddy rice biomass	UAV multispectral VIs + linear/ML regression	R2 (VI-AGB)	NDVI, SAVI, NDRE outperform others at specific growth stages
Ferreira et al., 2025 (17)	Global (bibliometric)	472 studies, crops & forests	Bibliometric + content analysis	Publication counts	NDVI, NDRE, GNDVI dominant; novel indices (GSI, MVI) emerging
Liu et al., 2024 (24)	China	Wheat yield	UAV canopy spectral + volumetric data, MLR/Lasso/RF	R2, RMSE	Combined spectral-volumetric models outperform spectral-only
Anonymous review, 2024 (25)	South Africa	Maize yield	UAV VIs (NDVI, PVI, GNDVI) + regression	R2, r	Weak correlation using limited VI sets (R2 as low as 0.21)
Systematic review, 2025 (27)	Multi-country (WoS review)	Crop leaf disease (multi-crop)	CNN/EfficientNet/MobileViT comparison	F1-score	EfficientNet-B3 achieved F1 = 98.8% across tomato, potato, pepper
Comparative study, 2023 (32)	Multi-country	Weed detection (RGB UAV)	Semantic segmentation model comparison	Accuracy/IoU	Model choice significantly affects accuracy-speed trade-off
Calibration study (34)	USA	Thermal imagery calibration	Ground-reference calibration protocol	Temperature error (°C)	Calibration reduced error from 9.3°C to 1.0°C
Multirotor UAV review, 2025 (37)	Global / developing regions	Cross-crop, platform review	Narrative + comparative review	Cost (USD)	High capital cost ($10,000-20,000) constrains smallholder adoption
Sub-Saharan Africa synthesis, 2026 (38)	Sub-Saharan Africa	Cross-crop adoption	PRISMA meta-analysis, 127 sources	Adoption rate (%)	Adoption below 2-3% despite R2 = 0.82 yield-model performance

Table 4: Comparative Analysis of Previous Research: Convergence and Divergence

Research question	Convergent findings	Divergent / contested findings
Which vegetation index best predicts biomass/yield?	NDVI, NDRE, and GNDVI are consistently among the top-performing indices across multiple crops (16,17)	NDVI saturates at high LAI and performs inconsistently across crops; some maize studies report R2 as low as 0.21 using limited VI sets (18,19,25)
Do deep learning models generalize across regions/crops?	Deep learning (CNN, YOLO-family) consistently outperforms traditional ML for disease/weed detection within-dataset (27,31,32)	Most models are trained and validated on narrow, single-region datasets; cross-region generalizability remains largely untested (29,30)
Is UAV monitoring economically viable for smallholders?	UAV-derived monitoring demonstrates strong technical performance across studies (R2 > 0.8 in several yield models) (38)	High capital and infrastructure costs mean technical performance does not translate into adoption; adoption-performance disconnect is well documented (37,38,41)
Does sensor/data fusion improve accuracy?	Fusion of multiple sensor modalities (RGB + multispectral + LiDAR) improves detection/estimation accuracy relative to single sensors (11,33)	Standardized fusion protocols are lacking; radiometric and geometric harmonization across platforms remains methodologically inconsistent (2,11)

5. Research Gaps and Emerging Trends Synthesis of the reviewed literature reveals seven interlinked categories of unresolved issues, mapped in Figure 5 and summarized in Table 5.

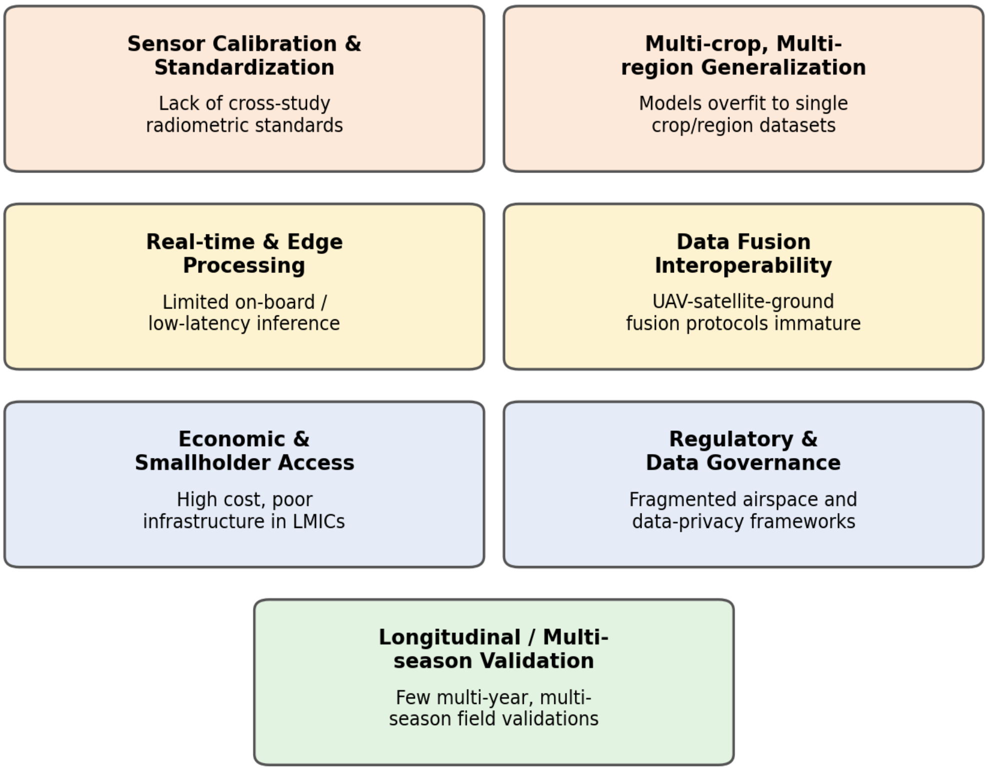

Fig 5: Research Gap Mapping Across the UAV Crop-Monitoring Pipeline

Table 5: Research Gaps Identified

Gap category	Description	Representative sources
Sensor calibration & standardization	Absence of cross-study radiometric and geometric calibration standards limits comparability of VI values and derived biomass/yield models across studies	[2, 34]
Cross-crop / cross-region generalization	Deep learning models for disease and weed detection are predominantly trained and validated on narrow, single-crop or single-region datasets	[27, 29, 30]
Real-time / edge processing	Limited progress on lightweight, onboard inference suitable for real-time in-flight decision-making, despite advances in mobile-optimized architectures	[27, 32, 33]
Data fusion interoperability	UAV-satellite-ground sensor fusion protocols remain methodologically inconsistent, with variable preprocessing and harmonization approaches	[2, 11]
Economic & smallholder access	High capital and recurring costs, combined with infrastructural deficits (electrification, connectivity), constrain adoption in low- and middle-income countries	[37, 38, 41]

Regulatory & data governance	Airspace regulation, pilot licensing, and agricultural data governance frameworks remain fragmented across jurisdictions	[39, 40]
Longitudinal / multi-season validation	Few studies validate models across multiple growing seasons or years, limiting confidence in long-term robustness	[16, 24]

5.1 Emerging Trends

Alongside these gaps, the literature points to several emerging trends that are likely to shape the next phase of research (Table 6, Figure 6). These include the development of swarm and cooperative UAV systems for large-area coverage, growing interest in edge-deployable, lightweight deep learning architectures, integration of UAV data with satellite and Internet of Things (IoT) ground-sensor networks within unified decision-support platforms, and increasing attention to policy-integrated deployment models designed explicitly for smallholder contexts (11,38,41).

Table 6: Emerging Trends in the Field

Trend	Description	Sources
Swarm / cooperative UAV sensing	Multiple coordinated UAVs covering larger areas with reduced per-flight cost and improved temporal frequency	(35,37)
Edge AI / onboard inference	Lightweight CNN architectures (MobileNet, EfficientNet, ShuffleNet) enabling near real-time detection without cloud dependency	(27,32,33)
UAV-satellite-IoT data fusion	Integrated platforms combining UAV imagery with satellite time series and ground IoT sensors for continuous monitoring	(2,11)
Transfer and few-shot learning	Models designed to generalize across crops/regions with limited labelled data, reducing dependence on large single-site datasets	(29,30)
Policy-integrated deployment	Cooperative ownership, subsidy, and drone-as-a-service models designed to extend UAV benefits to smallholder farmers	(38,39,40)

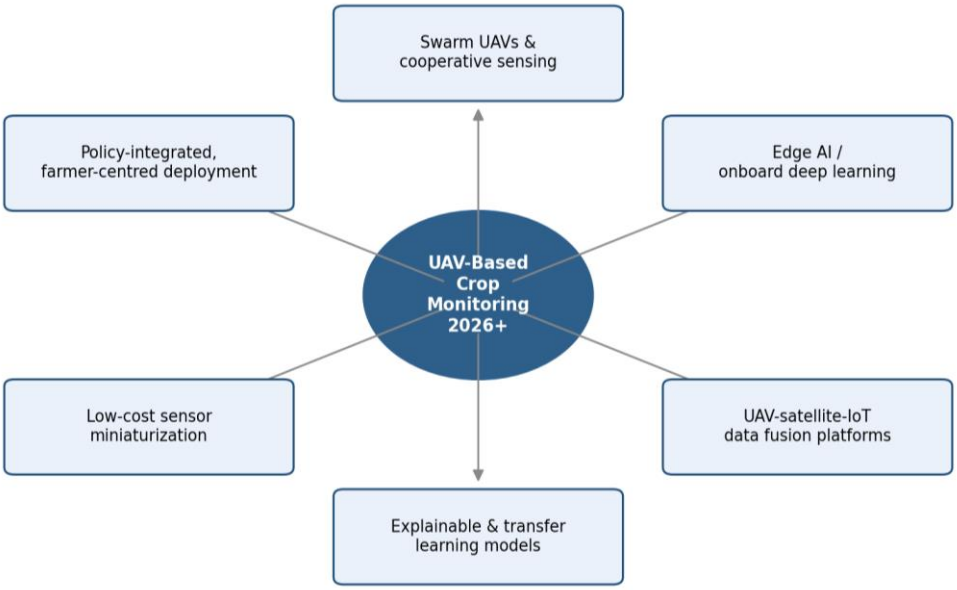

Fig 6: Future Research Directions in UAV-Assisted Crop Growth Monitoring

6. Discussion

Taken together, the reviewed literature demonstrates that UAV-based remote sensing has matured from a largely exploratory technology into a methodologically diverse and increasingly validated component of precision agriculture. The consistency with which NDVI, NDRE, and GNDVI emerge as leading predictors of biomass and yield across independent studies (16,17) provides reasonably strong convergent evidence for their continued use as default indices in operational monitoring systems. At the same time, the well-documented saturation behaviour of NDVI at high leaf area index, and the markedly weaker performance reported in some maize yield studies (18,19,25), indicate that no single index is universally reliable across crops, growth stages, and environmental conditions. This suggests that the field's methodological centre of gravity is shifting appropriately toward multi-index and multi-source modeling approaches, consistent with the improved performance reported when spectral and structural or textural features are combined (20,21,24).

The disease and weed detection literature illustrates a parallel pattern: rapid, well-documented gains in raw classification accuracy through deep learning (27,31,32) sit alongside a persistent and largely unaddressed concern about generalizability. High F1-scores reported within narrow, single-crop datasets do not, by themselves, establish that a given model will perform comparably when deployed in a different agro-climatic zone or against previously unseen disease presentations (29,30). This is not merely a technical limitation; it has direct implications for how much confidence extension agencies and commercial developers should place in vendor claims of "validated" disease-detection accuracy when the validation dataset's provenance is not disclosed.

A further consistent theme concerns the gap between technical performance and real-world adoption. The Sub-Saharan Africa synthesis reporting adoption below 2-3% despite yield-model R2 values around 0.82 (38) exemplifies a broader pattern also visible in Indian and Chinese adoption studies (39,40): the constraints limiting UAV uptake are predominantly economic and infrastructural rather than technical. This has an important implication for how the research agenda should be prioritized. Continued refinement of already well-performing models is likely to yield diminishing returns relative to research directed at reducing hardware and data-processing costs, improving rural connectivity dependencies, and designing cooperative or service-based deployment models suited to smallholder economics (37,38,41).

Methodologically, the review also surfaces a calibration and standardization deficit that cuts across nearly every thematic cluster. Because radiometric calibration materially affects derived index values and thermal-based stress indicators — as demonstrated by the reduction in thermal imagery error from 9.3°C to 1.0°C following calibration (34) — comparisons of reported accuracy figures across studies that do not disclose calibration protocols should be treated with caution. This is a controllable source of literature heterogeneity, and its resolution through community-adopted calibration standards would substantially improve the comparability of future meta-analyses.

Finally, the emergence of data fusion as a recurring theme across vegetation monitoring, water/nutrient assessment, and weed detection sub-literatures (2,11,33) reflects a broader convergence toward integrated, multi-platform monitoring systems. However, the absence of standardized fusion protocols means that current fusion studies, while individually promising, do not yet constitute a coherent, comparable evidence base. This represents one of the most consequential open problems identified in this review, given that fusion-based approaches are widely regarded as the most likely pathway toward monitoring systems that are both accurate and operationally practical at scale.

7. Conclusion

The review examined a total of 34 peer-reviewed studies that were published during the period of 2015 to 2025 focused on UAV monitoring of crop growth. The findings show that UAV-based remote sensing is quite effective, particularly when it comes to the combination of this technology with the methodologies of vegetation indices and machine learning or deep learning models. In addition to that, the UAV technology is able to monitor accumulation of biomass, forecast a possible yield number, detect disease and pest attacks as well as weed pressure at the rate and accuracy that satellites cannot provide. However, on the other hand, the review has shown that there are persistent issues and some interrelated problems like the lack of proper calibration of sensors, the limitations on applicability of models across crops and regions, the inadequateness of technology related to data fusion as well as possibly the most serious drawback – the big difference between measurable results of usage of UAVs and the real-life experience of small farmer managers in developing countries. In the context of this review, the authors have recommended that the researchers place greater emphasis on standardized calibration and reporting protocols, multi-season and multi-region validation strategies, and transfer learning methods that have been explicitly tested for cross-context generalizability. This would help make performance metrics used in diverse studies more comparable. For practitioners and policymakers, it is recommended to invest in collaborative ownership and drone-as-a-service models, targeted infrastructure improvements (rural electrification and connectivity), and establishment of policies that would reduce financial and administrative barriers to equal access to UAV-based technologies for monitoring. Subsequently, future research should focus specifically on lightweight and easy-to-deploy systems that can provide real-time results and offer integration of UAV and IoT technologies.

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