

Review

From Sensing to Intervention: A Critical Review of Agricultural Drones for Precision Agriculture, Data-Driven Decision Making, and Sustainable Intensification

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Abstract

Unmanned aerial vehicles (UAVs) are increasingly employed in precision agronomy to support high-resolution monitoring and management of crops; however, the extent to which UAV-derived data can be translated into reliable, scalable, and decision-ready applications remains inconsistent. This review addresses this gap by critically synthesising the recent literature with a specific focus on the end-to-end data pipeline, from acquisition planning and pre-processing to data fusion, analytics readiness, and operational decision support. A systematic analysis of peer-reviewed studies published over the last five years was conducted to evaluate core agronomic applications, including crop health monitoring, precision irrigation, soil and field variability assessment, spraying, and yield prediction, with particular attention to indicators used, validation strategies, and reported agronomic outcomes. The findings indicate that monitoring and diagnostic applications are the most mature and consistently validated, whereas interventional uses and absolute yield prediction remain strongly context-dependent and constrained by operational, methodological, and regulatory factors. Across applications, pipeline robustness, uncertainty management, and reproducibility emerge as more critical determinants of agronomic value than sensor resolution alone. The review further identifies key barriers to scaling, including technical limitations, skills requirements, data integration challenges, and regulatory constraints, and outlines an innovation roadmap distinguishing currently deployable solutions from emerging developments over the next three to five years. Overall, this work provides a decision-oriented framework to support more transparent, validated, and sustainable integration of UAV technologies into modern agricultural systems.

Keywords: precision agriculture; machine learning; data fusion; edge computing



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1. Introduction

Unmanned aerial vehicles (UAVs) have emerged as a cornerstone of precision agronomy, providing unprecedented spatial and temporal resolution for monitoring crops, soils, and field conditions [1]. Enabled by advances in lightweight sensor technologies, navigation systems, and data analytics, agricultural drones have rapidly transitioned from experimental platforms to operational tools capable of supporting a broad range of agronomic decisions [2]. The rapid expansion of UAV applications in precision agronomy is evidenced by a

significant upward trend in peer-reviewed publications and global adoption rates, shifting the discourse from general digital agriculture to specific, data-driven interventions [3,4].

In recent years, UAV-based remote sensing has expanded beyond basic crop observation towards more complex, data-driven applications, including early stress detection, variable-rate irrigation, targeted spraying, and yield forecasting. The deployment of multispectral, hyperspectral, and thermal sensors enables the extraction of agronomically relevant indicators related to plant health, water status, and nutrient dynamics at spatial resolutions that often surpass those of satellite platforms [5]. Consequently, agricultural drones are increasingly regarded as a key technological pillar of digital and climate-smart farming systems.

Agrawal et al. [6] emphasise that the transformative potential of agricultural drones resides not only in data acquisition but in their integration with artificial intelligence (AI), machine learning (ML), and decision-support systems. In this context, AI technologies applied in UAV-based agronomy can be broadly classified into traditional machine learning methods (e.g., regression models, support vector machines, random forests) and deep learning approaches (e.g., convolutional and recurrent neural networks), as well as into supervised and unsupervised learning paradigms depending on data availability and modelling objectives. This evolution has shifted research focus from isolated UAV applications towards end-to-end analytical pipelines, encompassing data pre-processing, feature extraction, predictive modelling, and actionable agronomic recommendations. Nevertheless, reported performance levels and agronomic benefits vary substantially across studies, reflecting differences in experimental design, spatial scale, sensor calibration, and validation protocols [7,8].

Beyond technological performance, several authors have highlighted that the widespread adoption of UAV technologies in agriculture is constrained by multiple non-trivial factors. Technical limitations related to battery life, payload capacity, weather dependency, and data management complexity continue to restrict large-scale deployment, particularly in commercial farming environments [9,10]. In parallel, economic barriers, limited digital literacy, and challenges associated with data ownership and interoperability further complicate operational integration into existing farm management systems [11].

Regulatory and legal considerations constitute an additional layer of complexity in the implementation of agricultural drones. From a global perspective, aviation regulations—although varying across jurisdictions such as the European Union and the United States—generally impose constraints on flight altitude, beyond-visual-line-of-sight operations, and autonomous missions, significantly influencing the feasibility of advanced UAV applications such as swarm-based monitoring and precision spraying [12]. Ethical and data-governance concerns related to privacy, transparency, and accountability further underscore the need for a comprehensive assessment that extends beyond purely technical performance metrics.

Although the scientific literature includes a growing number of review articles addressing UAV platforms, sensor technologies, or specific agronomic applications, most existing syntheses remain fragmented. They frequently focus on individual components of the UAV ecosystem without systematically linking sensing technologies, data analytics, validation strategies, regulatory constraints, and farm-level decision-making processes [13]. As a result, there is still a lack of integrative perspectives capable of clarifying how drone-derived data are translated into reliable interventions and measurable agronomic outcomes under real-world conditions [14].

Against this background, the present review aims to provide a critical and integrative synthesis of recent advances in agricultural drone technologies, explicitly tracing the pathway from sensing to intervention in precision agronomy. By combining evidence on UAV platforms and sensors, data-processing pipelines, AI-driven analytics, core agronomic

applications, and the technical, economic, and regulatory barriers shaping adoption, this work moves beyond descriptive accounts and proposes a structured framework to support both future research and the informed implementation of UAV-based solutions for sustainable agricultural intensification.

Consequently, agricultural drones are increasingly recognised as a key technological component of digital and climate-smart farming systems. The rapid expansion of UAV applications in precision agronomy is reflected in the growing number of peer-reviewed publications and global adoption trends, shifting the discourse from general digital agriculture towards more specific, data-driven interventions. In this context, the review adopts a structured analytical approach, distinguishing between traditional machine learning (ML) and deep learning (DL) methods, as well as between supervised and unsupervised learning paradigms. Furthermore, the analysis is conducted from a global perspective, integrating evidence from the European Union, the United States, and emerging agricultural systems, with the aim of bridging the gap between data acquisition and farm-level decision-making.

To ensure transparency in the literature selection process, a structured review methodology was applied. Relevant studies were identified through searches in major academic databases, including Scopus, Web of Science, and Google Scholar. The search focused on peer-reviewed publications from the last five years, using combinations of keywords such as “UAV”, “precision agriculture”, “data pipeline”, and “decision support systems”. The initial search yielded approximately 450 records, which were screened based on title and abstract relevance. Following this process, 180 studies were selected for full-text evaluation, and 153 articles were ultimately included in the final analysis. Studies were excluded if they lacked clear agronomic validation, focused solely on platform hardware without integration into data-processing workflows, or were not published in peer-reviewed journals.

2. UAV Platforms and Onboard Technologies

2.1. UAV Platform Types in Agricultural Applications

The selection of a UAV platform is a decision-driven process where aerodynamic properties and endurance profiles must align with specific mission requirements [15,16]. While fixed-wing UAVs offer superior efficiency and coverage for regional surveys or large-scale mapping, their operational utility is often constrained by the requirement for assisted launch/recovery systems and an inability to perform stationary hovering [17]. Conversely, multirotor platforms provide the maneuverability necessary for high-resolution scouting and plot-level phenotyping, though their limited flight endurance and payload capacity remain significant bottlenecks for extensive commercial operations [18]. Hybrid and VTOL (Vertical Take-Off and Landing) configurations have emerged to bridge these gaps, combining long-range efficiency with tactical flexibility [19,20]. However, the increased system complexity and higher maintenance costs associated with hybrid designs currently limit their widespread integration into routine agricultural workflows [21,22]. For a detailed comparison of these platforms in relation to specific sensors and use-case trade-offs, refer to Table 1.

Table 1. Characteristics, applications, and trade-offs of UAV platforms and sensors in precision agronomy.

UAV Platform/ Sensor	Typical Payload Capacity	Suitable Applications	Operational Context	Key Trade-Offs
Fixed wing	1–5 kg	Large-area crop mapping, baseline variability assessment.	Large and homogeneous fields; limited need for site- specific inspection.	High endurance and area coverage; limited manoeuvrability; inability to hover.

Table 1. Cont.

UAV Platform/ Sensor	Typical Payload Capacity	Suitable Applications	Operational Context	Key Trade-Offs
Multicopter	2–20 kg	Close-range scouting, plot-level phenotyping, targeted stress detection.	Small to medium fields; need for high spatial detail and local interventions.	High spatial resolution and flexibility; limited flight time and coverage.
Hybrid/VTOL	2–10 kg	Mixed-scale missions combining mapping and local inspection.	Heterogeneous landscapes; combined survey and intervention planning.	Flexible deployment and improved endurance; increased system complexity and cost.
Spraying/ Intervention	10–50 kg	Variable-rate application of pesticides, fertilizers, or seeds.	Target-specific treatment; high-intensity operational tasks.	High payload capacity; high battery/fuel consumption; complex regulatory compliance.
RGB Sensor	N/A	Canopy cover estimation, plant counting, SfM-based height proxies.	Visual assessment and structural analysis under stable illumination.	Low cost; very high spatial resolution; limited biochemical information.
Multispectral	N/A	Vegetation indices, nutrient and water stress mapping.	Management zone delineation and input optimisation.	Strong agronomic relevance; requires rigorous radiometric calibration.
Hyperspectral	N/A	Detailed biochemical and physiological characterisation.	Experimental studies and high-value crops.	High diagnostic potential; high cost; large data volumes; complex workflows.
Thermal Sensor	N/A	Crop water status assessment, irrigation scheduling.	Time-sensitive monitoring under controlled conditions.	Direct canopy temperature measurements; sensitivity to atmospheric effects.
Radar (SAR)	N/A	Soil moisture mapping, biomass structure assessment, flood monitoring.	All-weather and day/night monitoring; partial penetration through vegetation and soil surface layers	Sensitivity to surface roughness and vegetation cover; complex signal processing; higher system and calibration requirements.

2.2. Onboard Sensor Technologies for Agricultural UAVs

The effectiveness of UAV-based agronomic assessments is intrinsically linked to the characteristics of onboard sensor systems, which deploy RGB, multispectral, hyperspectral, thermal, and LiDAR payloads to capture diverse spectral, structural, and temporal information [22,23]. While RGB cameras remain a cost-effective solution for structural analysis, plant counting, and Structure-from-Motion (SfM)-based three-dimensional reconstructions, their utility is frequently constrained by limited spectral depth and high sensitivity to illumination variability [24–27].

Despite their widespread use, RGB-based UAV assessments are subject to several methodological constraints that may affect data reliability. Radiometric inconsistencies, driven by variations in illumination conditions, necessitate the application of radiometric correction workflows to ensure spectral comparability across multi-temporal acqui-

sitions [23]. In addition, Structure-from-Motion (SfM) processing is sensitive to image overlap, viewing geometry, and surface texture, which may introduce reconstruction errors, particularly in low-texture or highly homogeneous crop canopies [28]. Furthermore, shadow effects in high-density vegetation can distort reflectance values and obscure structural details, potentially biasing vegetation indices and canopy metrics [29].

Multispectral sensors address some of these limitations by enabling the calculation of vegetation indices for improved assessment of crop vigour and stress conditions. However, their operational reliability depends on rigorous radiometric calibration to ensure data consistency across varying flight altitudes, sensor configurations, and illumination conditions [26,30].

In this context, the use of reflectance panels is essential for standardising surface reflectance measurements and ensuring cross-flight comparability [31]. Furthermore, bidirectional reflectance distribution function (BRDF) effects can introduce angular-dependent variability in reflectance values, particularly in heterogeneous crop canopies [32]. These factors are critical for maintaining consistency across acquisitions performed under different illumination conditions and observation geometries [31,32].

LiDAR sensors provide high-resolution three-dimensional information on canopy structure, terrain morphology, and biomass distribution, making them particularly valuable for applications requiring structural characterisation, digital elevation modelling, and volumetric analysis of vegetation [33]. Their ability to directly capture spatial geometry complements passive optical sensing and enhances the accuracy of structural and biophysical assessments.

Advanced diagnostics, such as early disease detection and biochemical characterisation, are supported by hyperspectral sensors, which offer detailed spectral signatures across a wide range of wavelengths. However, their integration into commercial agricultural workflows remains limited due to high acquisition costs, large data volumes, and the lack of standardised processing pipelines [34]. Similarly, thermal sensors provide direct proxies for crop water status and irrigation requirements, but require careful integration with environmental and physiological parameters to account for atmospheric effects and emissivity variations [35]. In this context, the interpretation of thermal imagery requires consideration of the temperature difference between the canopy and the surrounding air (ΔT), which serves as a key indicator of plant water stress. Indices such as the Crop Water Stress Index (CWSI) are widely used to normalise canopy temperature measurements and account for environmental variability. Furthermore, it is important to distinguish between radiometric and non-radiometric thermal sensors, as only radiometric systems provide calibrated temperature data suitable for quantitative analysis. Accurate thermal assessment also depends on the integration of ground-based meteorological measurements, including air temperature, relative humidity, and solar radiation, which are essential for image correction, calibration, and reliable irrigation decision support [36].

Beyond optical and thermal systems, UAV-based radar technologies, particularly Synthetic Aperture Radar (SAR), represent an emerging sensing modality in precision agriculture [37,38]. As an active sensing system operating in the microwave domain, SAR is largely independent of solar illumination and can acquire data under cloudy or low-light conditions. Furthermore, depending on the frequency band, radar signals can partially penetrate vegetation canopies and interact with soil and plant structures, providing complementary information to optical sensors [39]. These characteristics make radar particularly valuable for applications requiring reliable, all-weather data acquisition and enhanced structural and dielectric information.

2.3. Platform–Sensor Configurations and Operational Trade-Offs

The choice of UAV platform and sensor combination represents a trade-off between spatial resolution, coverage, endurance, operational complexity, and cost. No single configuration is universally optimal for all agronomic applications; instead, platform–sensor selection must be aligned with specific management objectives, field conditions, and logistical constraints [40].

To facilitate comparison and support informed decision-making, Table 1 summarises typical UAV platform–sensor configurations used in agricultural applications and highlights their most suitable use cases alongside key operational trade-offs.

2.4. Implications for Precision Agronomy

The diversity of UAV platforms and sensor technologies underscores the need for application-driven system selection in precision agronomy. Agricultural decision-making increasingly relies on high-resolution spatial and temporal data streams, yet these streams are only valuable if they are reliable, reproducible, and directly interpretable in agronomic terms. In this regard, the practical value of UAV systems depends on the extent to which aerial data can be integrated into field-level management processes that produce consistent outcomes across different seasons, environments and scales [12].

Extant literature highlights that, although UAV-based sensing provides unprecedented levels of detail, data quality and consistency remain a major challenge when observational conditions vary. For instance, multispectral and hyperspectral remote sensing deliver valuable vegetation indices and biochemical proxies, but the interpretation of these signals can be confounded by illumination changes, atmospheric effects and sensor calibration differences between platforms [41]. This variability impairs not only the accuracy of the derived indicators, but also their comparability across surveys and studies, which in turn hampers the translation of UAV-derived data into reliable agronomic recommendations.

Many studies emphasise that robust calibration protocols and standardised workflows are essential to ensure that UAV-based measurements can support reproducible decision support. Without such protocols, differences in flight altitude, sensor configuration, and data processing pipelines can produce conflicting results even for the same crop and field conditions. Indeed, the lack of methodological standardisation is frequently identified as a barrier in the transition from experimental research to operational agronomy [42].

Large-scale bibliometric analyses indicate that research on drones in agriculture has expanded rapidly in recent years, with a particular focus on integrating UAV data with machine learning and internet of things (IoT) frameworks to support real-time analytics and predictive modelling [43]. While this reflects the strong potential of data-driven approaches, the dominance of simulation and model-based studies over field-validated work underscores a critical gap: the validation of UAV analytics under practical agronomic conditions. Field trials remain unevenly distributed geographically and methodologically, which complicates efforts to generalise findings to diverse cropping systems and environmental contexts [44,45].

Furthermore, the integration of UAV data into decision support systems requires not only high-quality measurements, but also interoperable data architectures that can reconcile aerial observations with other agronomic data sources such as soil sensors or weather stations. Research on combined use of UAVs and wireless sensor networks (WSNs) highlights this need for data harmonisation across heterogeneous collection systems, illustrating that alpine and arid environments present distinctive challenges that must be considered when developing agronomic recommendations [46].

Taken together, these insights imply that the true impact of UAV technologies on precision agronomy can only be realised through systematic workflows that prioritise data

integrity, reproducibility and contextual relevance. In order to build trust among researchers and practitioners alike, future work should emphasise standardised calibration, cross-study comparability, and integrated analyses that link aerial data with farm management outcomes. Only through such concerted efforts can UAV-derived information reliably inform agricultural interventions that enhance sustainability and productivity in dynamic field environments [42].

3. Data Pipeline: From Acquisition to Decision Support

3.1. The Critical Role of the End-to-End Data Pipeline in Decision-Grade Agronomy

In UAV-enabled precision agronomy, the operational value of aerial platforms rarely depends on image acquisition alone; rather, it is determined by the extent to which raw observations can be transformed into traceable, reproducible, and agronomically actionable information. While advances in UAV hardware and sensor technologies have substantially increased spatial and temporal resolution, such improvements do not automatically translate into better agronomic decisions. Instead, the decisive factor is the presence of an end-to-end data pipeline capable of systematically converting heterogeneous raw data into decision-ready outputs that are robust across space, time, and management contexts [47].

Xing, Liu, and Wang [47] emphasise that the scalability of UAV-based decision support systems is fundamentally constrained by data-processing complexity and the lack of harmonisation across data sources rather than by sensor limitations alone. As UAV deployments expand from experimental plots to commercial farming systems, the volume, velocity, and heterogeneity of data increase rapidly, exposing weaknesses in workflows that were originally designed for small-scale studies. Under such conditions, the absence of structured pipelines can lead to inconsistent outputs, limited transferability of models, and reduced confidence among end users.

An effective UAV data pipeline must explicitly address multiple sources of uncertainty introduced throughout the acquisition and processing chain. Variability in illumination conditions, platform motion, sensor drift, and georeferencing accuracy can each introduce systematic biases that propagate into derived vegetation indices, biophysical estimates, or classification outputs [48]. Moreover, modelling assumptions embedded in machine learning or empirical inversion approaches further compound uncertainty if they are not transparently documented and validated. Without rigorous management of these factors, high-resolution UAV products risk becoming high-resolution noise, offering visually compelling maps that cannot be reliably compared across dates, fields, or management zones [26,49].

Beyond technical correctness, the data pipeline also plays a central role in enabling reproducibility and comparability—two criteria that are increasingly emphasised in both scientific evaluation and practical deployment. Agronomic decision-making often relies on temporal change detection, benchmarking across fields, or the delineation of management zones, all of which require consistent data processing and stable reference frames. Pipelines that lack standardised pre-processing, calibration, and validation procedures may yield results that are internally consistent within a single campaign but unreliable when extended across seasons or transferred to different agro-ecological contexts [15].

From an agronomic perspective, the ultimate purpose of UAV-derived data is not observation but intervention, as aerial information only gains value when it informs concrete management decisions at field level. Ahmed and Shakoor [50] emphasise that decision support systems must effectively bridge the gap between analytical outputs and actionable practices, including variable-rate input application, targeted field scouting, and irrigation scheduling. Achieving this transition requires data pipelines that integrate uncertainty-aware analytics, contextual agronomic knowledge, and clearly defined performance metrics,

thereby ensuring that recommendations are both interpretable and operationally feasible. In this context, the data pipeline emerges as the central mediator between sensing technologies and actionable agronomy, determining whether UAV systems function merely as experimental tools or as reliable components of scalable precision farming strategies [51].

Taken together, these considerations underscore that the true differentiator in UAV-enabled precision agronomy is not the sophistication of individual sensors or platforms, but the coherence, transparency, and robustness of the data pipeline that links acquisition to decision support. Reviews that focus exclusively on sensing technologies risk overlooking this critical dimension, whereas pipeline-oriented perspectives provide a more realistic basis for evaluating the readiness of UAV systems to support sustainable and scalable agricultural interventions [47].

The systematic progression of this end-to-end framework, encompassing sensing readiness, hierarchical data fusion, and the transition to actionable agronomic interventions, is conceptually illustrated in Figure 1.

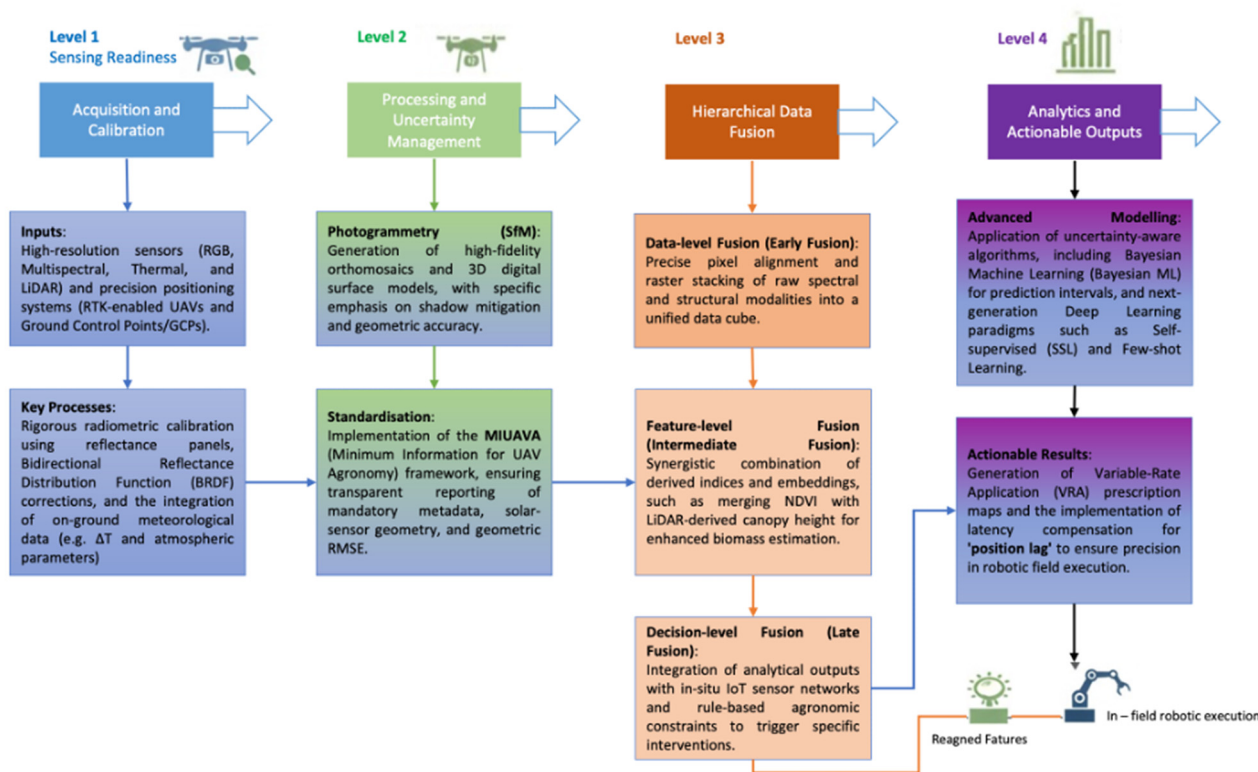


Figure 1. The End-to-End Data Pipeline for Decision-Grade Agronomy.

The schematic illustrates the hierarchical progression from initial data acquisition to actionable field interventions. Level 1 establishes sensing readiness through rigorous radiometric calibration and the integration of on-ground meteorological context. Level 2 focuses on uncertainty management and reproducibility via the MIUAVA (Minimum Information for UAV Agronomy) framework. Level 3 details the hierarchical data fusion levels—Data, Feature, and Decision—enabling the synergistic use of multi-modal signals such as LiDAR-derived structure and multispectral indices. Finally, Level 4 outlines the transition to actionable outputs using uncertainty-aware modelling (Bayesian ML) and next-generation AI (SSL, Few-shot), including latency compensation for 'position lag' to ensure precision in robotic execution.

3.2. Acquisition Planning and Quality Assurance

Effective UAV-based decision support in precision agronomy begins at the acquisition stage, where mission design must be explicitly aligned with the downstream agronomic objective. The same crop and field may require substantially different acquisition strategies depending on whether the primary task is baseline spatial variability mapping, early disease detection, or irrigation scheduling. Consequently, acquisition planning cannot be treated as a generic technical step, but rather as a decision-driven process that conditions the validity of all subsequent analyses [52].

Yang et al. [15] underline that mission parameters such as spatial resolution, temporal frequency, and spectral configuration must be selected in accordance with the biophysical processes being monitored. For instance, applications focused on canopy structure or plant density may prioritise very high spatial resolution obtained through RGB imagery, whereas nutrient or water stress assessment typically requires multispectral or thermal data acquired under more stringent radiometric conditions. Failure to align acquisition parameters with the agronomic question often leads to datasets that are technically sound but analytically inadequate for decision support.

From a geometric perspective, ground sampling distance (GSD), image overlap, and flight speed collectively determine the spatial fidelity and robustness of derived products such as orthomosaics and digital surface models [49]. High overlap ratios and stable flight trajectories improve feature matching and reduce reconstruction artefacts, but they also increase flight time and data volume. These trade-offs must be carefully managed, particularly in commercial settings where operational efficiency and cost constraints limit the feasibility of overly conservative acquisition designs [29].

Radiometric quality assurance represents one of the most critical—and frequently underestimated—components of UAV acquisition planning. Multispectral and hyperspectral analyses are highly sensitive to variations in illumination conditions, solar angle, atmospheric scattering, and sensor response. Zhu et al. [53] demonstrate that changes in flight altitude, time of day, and irradiance can significantly alter reflectance values and vegetation indices, even when the same sensor and field are used. Such variability directly propagates into biophysical inversion models and stress indicators, undermining comparability across dates and sites if not properly corrected.

Sharma et al. [54] further highlight that factors such as sensor viewing angle and bidirectional reflectance effects can introduce systematic biases in water stress indicators derived from thermal and multispectral imagery. These effects are particularly problematic for irrigation scheduling, where small errors in canopy temperature or index values may lead to suboptimal management decisions. As a result, acquisition protocols increasingly emphasise consistent solar geometry, stable atmospheric conditions, and the use of calibration targets or downwelling light sensors as integral components of quality assurance.

Beyond individual flights, reproducibility across campaigns is a central requirement for precision agronomy applications that rely on temporal analysis or benchmarking. Daniels et al. [49] argue that inconsistent acquisition and calibration practices are among the primary reasons why UAV-derived products often perform well in isolated experiments but fail to generalise across seasons or locations. Standardised acquisition workflows, combined with transparent reporting of mission parameters and calibration procedures, are therefore essential to ensure that UAV data can support longitudinal monitoring and transferable decision models.

In operational contexts, acquisition planning must also account for practical constraints such as weather variability, wind conditions, and regulatory limitations on flight timing and altitude. These constraints often necessitate compromises between ideal data quality and feasible deployment, reinforcing the importance of adaptive mission design that balances

agronomic requirements with real-world limitations [50]. Integrating quality assurance considerations at the planning stage reduces the need for aggressive post hoc corrections and increases confidence in downstream analytics.

Taken together, these findings indicate that acquisition planning and quality assurance are not peripheral technical considerations but foundational elements of UAV-enabled precision agronomy. Robust, decision-oriented acquisition strategies underpin the reliability, reproducibility, and agronomic relevance of UAV-derived data, directly influencing whether such systems can transition from experimental demonstrations to dependable components of precision farming workflows [55,56].

3.3. Pre-Processing and Uncertainty Management

Pre-processing constitutes a critical transition stage between UAV data acquisition and analytical modelling, as it determines whether raw observations can be transformed into consistent, analysis-ready datasets suitable for decision support. In precision agronomy, pre-processing workflows must address both systematic errors introduced during acquisition and random variability arising from environmental and operational factors. Without rigorous pre-processing, downstream analytics may amplify artefacts rather than agronomically meaningful signals, thereby compromising the reliability of UAV-based recommendations.

Pádua et al. [28] emphasise that UAV data pre-processing should be viewed as a multi-layered quality control process rather than a single corrective step. Typical workflows include image quality screening, geometric correction and alignment, radiometric normalisation, and the handling of missing or corrupted data. Each of these stages contributes to reducing uncertainty propagation and improving the robustness of derived products such as vegetation indices, canopy height models, or thermal maps.

From a geometric standpoint, accurate image alignment and orthomosaic generation are fundamental for spatial consistency, particularly when multi-temporal analyses are required. Errors in georeferencing or bundle adjustment can result in spatial misalignment that is mistakenly interpreted as crop change or stress dynamics. Colomina and Molina highlight that even small positional inaccuracies can significantly affect plot-level analyses, a concern that remains highly relevant in contemporary UAV-based agronomy where spatial resolution continues to increase. To mitigate these uncertainties, advanced positioning techniques such as Real-Time Kinematic (RTK) GNSS are increasingly employed in UAV platforms to improve geolocation accuracy to the centimetre level. In addition, the use of Ground Control Points (GCPs) remains a common practice for enhancing geometric correction and ensuring spatial consistency across datasets [57,58]. However, the selection and density of GCPs involve important trade-offs between accuracy, operational complexity, and processing time. While higher GCP density can improve positional accuracy, it also increases field deployment effort, whereas RTK-enabled systems can reduce—but not entirely eliminate—the need for extensive ground control, particularly in high-precision agronomic applications [59,60].

Radiometric pre-processing plays an equally decisive role, especially for applications relying on spectral reflectance or index-based indicators. Aasen et al. [61] demonstrate that uncorrected variations in illumination and sensor response can dominate vegetation index variability, masking true biophysical differences between plants or management zones. More recent studies confirm that radiometric normalisation across flights is essential for ensuring temporal comparability, particularly when UAV data are used for monitoring crop development or evaluating management interventions [28].

Noise reduction and the treatment of missing values represent additional challenges in UAV data pipelines. High-resolution imagery is inherently susceptible to noise arising from sensor limitations, atmospheric effects, and motion-induced artefacts. Tmušić

et al. [62] show that filtering and smoothing techniques must be carefully selected to avoid over-smoothing, which can remove subtle but agronomically relevant patterns. Similarly, gaps caused by occlusions, flight interruptions, or sensor malfunctions require explicit handling strategies, as naïve interpolation may introduce artificial spatial structures that bias subsequent modelling.

Beyond individual correction steps, uncertainty management has emerged as a key requirement for UAV-enabled decision support. Candiago et al. [63] argue that most UAV-based agricultural studies report point estimates without adequately characterising uncertainty, limiting their usefulness for risk-aware decision-making. Although uncertainty quantification is still underrepresented in operational workflows, recent contributions advocate for the propagation of uncertainty through pre-processing and modelling stages, enabling more transparent interpretation of UAV-derived outputs [28]. In this context, recent studies have explored the integration of uncertainty-aware modelling approaches, including Bayesian machine learning frameworks, variance-based methods, and the use of prediction intervals to quantify model confidence. For example, Bayesian approaches enable the explicit representation of uncertainty in model parameters and predictions, while ensemble and variance-based techniques provide insights into prediction stability across different model configurations. The incorporation of prediction intervals further supports risk-aware decision-making by quantifying the range of possible outcomes rather than relying solely on point estimates. These approaches have been increasingly applied in UAV-based crop classification, yield prediction, and stress detection, improving the robustness and interpretability of agronomic analyses [64–66].

Importantly, pre-processing choices are not neutral with respect to downstream analytics. Feature extraction, machine learning model performance, and decision thresholds are all sensitive to the quality and consistency of input data. As noted by Tosin et al. [67], inconsistencies introduced during pre-processing can lead to model overfitting in experimental settings and poor generalisation under real-world conditions. Consequently, pre-processing and uncertainty management should be explicitly documented and treated as integral components of UAV-based analytical pipelines rather than implicit technical preliminaries.

Taken together, these considerations underscore that effective pre-processing and uncertainty management are prerequisites for transforming UAV imagery into decision-ready agronomic information. By reducing artefacts, enhancing comparability, and making uncertainty explicit, robust pre-processing workflows strengthen the credibility of UAV-derived analytics and support their integration into operational precision agriculture systems.

3.4. Data Fusion and Analytics Readiness

Data fusion is increasingly recognised as a prerequisite for moving UAV remote sensing from descriptive mapping to decision-grade analytics, because single-modality datasets rarely capture the full set of agronomically relevant processes (e.g., canopy structure, biochemical status, and water/energy balance) at the same time. In practice, fusion aims to reconcile complementary strengths and weaknesses across sensors (RGB/multispectral/thermal/LiDAR), platforms (UAV vs satellite), and in situ/IoT streams (soil moisture, weather, irrigation logs), thereby improving robustness, transferability, and actionability of downstream models [68,69].

Xing et al. [70] argue that UAV decision support becomes scalable only when UAV data are integrated with other data streams in a harmonised pipeline (e.g., satellite for temporal continuity and coverage; IoT for ground truth context), rather than treated as a stand-alone “high-resolution” layer. This is particularly relevant in commercial settings, where UAV campaigns may be intermittent (weather, labour, regulation), and decision-making often requires temporal continuity that UAV-only monitoring may not reliably provide.

3.4.1. Schematic Progression of Data Fusion Levels in Agronomic Pipelines

To bridge the gap between multi-sensor acquisition and actionable interventions, fusion must be conceptualized as a structured hierarchy that manages uncertainty across different analytical stages [41,71].

This conceptual workflow is illustrated in Figure 2, which presents the hierarchical organisation of multi-sensor data fusion and the propagation of uncertainty across the UAV-based agronomic pipeline.

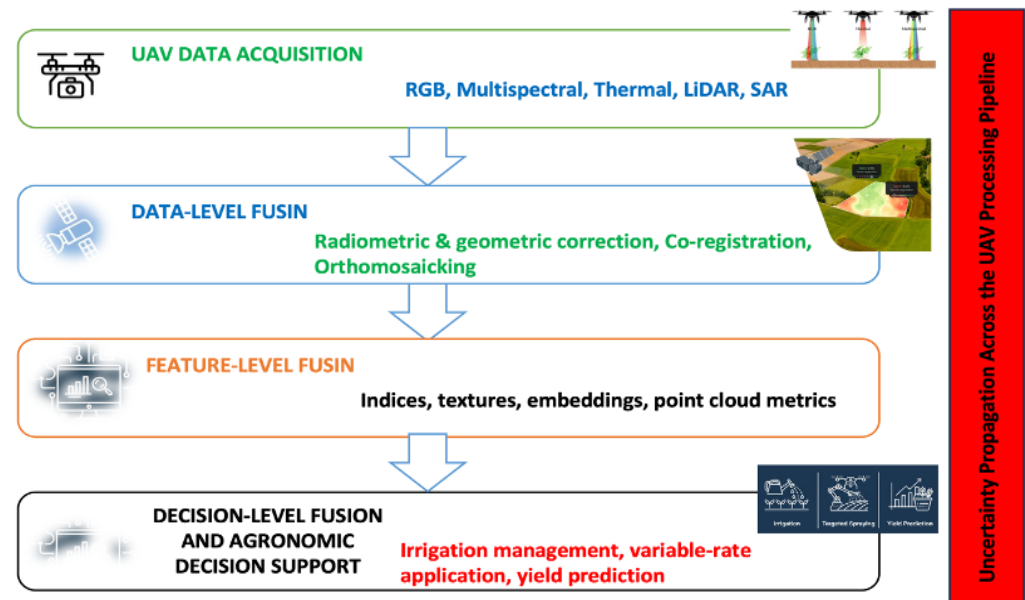


Figure 2. Schematic representation of multi-sensor data fusion levels and uncertainty propagation in UAV-based agronomic pipelines, from data acquisition and pre-processing to feature extraction and decision support.

In agronomic terms, this progression follows three distinct levels of integration:

- **Data-level Fusion (Early Fusion):** This initial stage involves the spatial co-registration of raw raster layers (e.g., stacking thermal, multispectral, and RGB bands) into a unified data cube prior to any feature extraction. This ensures that structural and physiological signals are perfectly aligned at the pixel level.
- **Feature-level Fusion (Intermediate Fusion):** This level integrates independent variables or learned embeddings extracted from multiple modalities. For example, combining explicit canopy structure metrics (from LiDAR) with spectral indices (from multispectral sensors) allows for more robust biomass or yield modeling than single-modality approaches.
- **Decision-level Fusion (Late Fusion):** Governed by multi-criteria logic, this final stage ensembles predictions from multiple models or combines analytical outputs with rule-based agronomic constraints. A practical application includes irrigation scheduling, where a management action (e.g., a spraying or irrigation trigger) is only initiated when independent signals—such as canopy temperature (ΔT), vegetation condition, and ground-based meteorological logs—converge to cross-validate a detected stress event [72,73].

3.4.2. UAV–Satellite Fusion for Scale and Temporal Continuity

UAV–satellite fusion is commonly justified by complementary resolution: UAVs provide ultra-high spatial detail, while satellites provide repeat coverage and broader spatial context. When combined appropriately, this can reduce the “scale gap” between

plot-level observations and field-/region-level management decisions, and it can improve monitoring continuity when UAV flights are constrained. A recent ISPRS contribution reports improved crop monitoring performance when fusing UAV and satellite imagery, framing fusion as both a methodological and operational enabler for decision support [74].

However, analytics readiness requires acknowledging that UAV–satellite fusion is rarely straightforward: differences in viewing geometry, atmospheric effects, spectral response functions, and revisit timing introduce harmonisation burdens that can dominate model uncertainty if not handled explicitly. For review purposes, it is therefore important to evaluate fusion studies not only on headline accuracy metrics, but also on the clarity of co-registration steps, temporal alignment strategy, and validation design across sites and seasons [41,47].

3.4.3. Multimodal UAV Fusion (RGB/Multispectral/Thermal/LiDAR) for Agronomic Inference

Within UAV-only ecosystems, multimodal fusion is increasingly used to connect structural and physiological signals. LiDAR provides explicit canopy structure (height, roughness, 3D metrics) that can complement multispectral indicators of chlorophyll or vigour, which is particularly valuable when yield/biomass models require both morphology and biochemical proxies [71].

Recent empirical studies demonstrate that fusing UAV LiDAR with multispectral measurements can improve yield estimation and strengthen mechanistic interpretability by linking remote sensing signals to intermediate biophysical variables (e.g., plant height, chlorophyll) [63]. These improvements are also reflected in quantitative performance gains, with multi-sensor approaches reporting higher R^2 values and reduced prediction errors compared to single-sensor models [75,76].

For instance, multi-feature fusion models integrating structural (e.g., plant height) and biochemical (e.g., chlorophyll content) variables have been shown to outperform single-source models, highlighting the complementary nature of LiDAR and multispectral data [77].

However, these improvements are often context-dependent, and their statistical significance and robustness may vary across datasets, crop types, and environmental conditions. In particular, several studies indicate that while data fusion enhances within-sample accuracy, model transferability across different varieties or growing conditions remains a challenge, requiring further validation and domain adaptation strategies.

Similarly, LiDAR–multispectral fusion has been applied to above-ground biomass estimation in complex environments, where structural heterogeneity can confound purely spectral approaches. Such studies reinforce that fusion improves performance most consistently when it reduces a known limitation of a single modality (e.g., structure-driven variance not captured by reflectance alone), rather than when modalities are combined opportunistically [78].

Thermal–multispectral fusion is especially prominent in water-stress monitoring, because thermal signals relate directly to canopy temperature (and thus transpiration constraints), while multispectral signals capture vegetation condition and stress responses that may lag thermal changes. A recent field study using multispectral and thermal features with a model-updating strategy illustrates how multi-feature fusion can improve robustness of crop water status estimation across seasons, a critical step for operational analytics readiness [79].

3.4.4. Analytics Readiness: Validation, Generalisation, and Decision-Compatibility

Analytics readiness is achieved when fused products can be reliably converted into management actions under real operational constraints. This requires (a) validation beyond a single site or season, (b) clear reporting of data harmonisation steps, (c) sensitivity

analysis to acquisition variability, and (d) metrics aligned to the agronomic decision (e.g., stress class accuracy for irrigation triggers; RMSE/MAE for quantitative traits such as biomass). Reviews of deep-learning applications in UAV imagery consistently emphasise that performance claims are highly dependent on dataset characteristics and validation protocols, and that transferability across environments remains a key barrier [43,53].

An emerging trend in multimodal data fusion is the growing emphasis on explainable and interpretable modelling approaches aimed at enhancing the transparency and practical acceptance of UAV-based analytics. Recent studies have combined feature selection and explainability techniques with fused data inputs to elucidate the variables that most strongly influence stress classification outcomes, signalling a shift away from purely “black-box” performance metrics towards models that better align with agronomic decision-making requirements [80].

To provide a structured synthesis of how data fusion is implemented and evaluated in the recent literature, Table 2 summarises representative agronomic tasks, data combinations, fusion strategies, algorithm families, evaluation metrics, and an indicative level of readiness for operational deployment.

Table 2. Data fusion strategies and analytics readiness for UAV-enabled precision agronomy.

Task (Decision Context)	Data Sources (Typical)	Fusion Level (Data/Feature/Decision)	Algorithms Reported in Recent Studies/Reviews	Common Metrics	Indicative Readiness (Operational) *
Crop water-stress diagnosis/irrigation scheduling	UAV thermal + multispectral ± weather/IoT	Feature- or decision-level	ML regression/classification; model updating; hybrid rule + ML	RMSE/MAE (continuous); Accuracy/F1 (classes)	Medium (field-ready in constrained contexts)
Yield estimation (crop-specific)	UAV LiDAR + multispectral (sometimes RGB)	Feature-level	Multimodal regression; ensemble models; intermediate-variable modelling	RMSE/R ² ; error by growth stage/zone	Medium (promising; depends on site transferability)
Biomass estimation in heterogeneous vegetation	UAV LiDAR + multispectral	Feature-level	Regression/ensemble learning; structural + spectral modelling	RMSE/R ² ; stability across terrain	Medium (strong in research; scaling depends on data costs)
Multi-scale crop monitoring (continuity + coverage)	UAV multispectral/RGB + satellite (multi-date)	Data- or feature-level	Spatiotemporal fusion; harmonisation + ML	Accuracy/F1 (classification); RMSE (biophysical)	Medium–low (methodologically mature, operationally complex)
Disease/pest surveillance for targeted scouting	UAV RGB/multispectral ± contextual layers	Feature- or decision-level	Deep learning (detection/segmentation) + ensembles	Accuracy; Precision/Recall; F1; mAP	Medium (often plot-level; deployment needs generalisation)
Farm-scale “smart” decision support (resource optimisation)	UAV + IoT (soil moisture, weather) + management logs	Decision-level	DSS integration; hybrid analytics; edge/cloud workflows	Task-dependent; latency; robustness; user interpretability	Low–medium (integration bottlenecks dominate)

* Indicative readiness reflects synthesis of reported validation scope, integration demands, and operational constraints in the recent literature, not an official TRL certification.

3.5. Knowledge Gaps and Challenges in UAV-Based Data Pipelines

Despite substantial technological progress in UAV platforms, sensors, and analytics, several critical knowledge gaps continue to limit the operational deployment of UAV-based decision support systems in precision agronomy. These gaps are not primarily technological, but methodological and systemic, reflecting misalignments between data generation, analytical modelling, and real-world agronomic decision-making [6,81].

One of the most persistent challenges concerns the lack of standardised data pipelines across studies and operational contexts. While numerous workflows have been proposed for UAV data acquisition, pre-processing, and analysis, there is little consensus regarding

best practices that ensure reproducibility and comparability across sites, seasons, and crop types. As highlighted by Tmušić et al. [71], variations in acquisition protocols, calibration procedures, and pre-processing choices often lead to results that are difficult to generalise beyond individual case studies, limiting their value for large-scale adoption.

A second major gap relates to uncertainty quantification and propagation throughout the data pipeline. Most UAV-based agronomic studies report deterministic outputs—such as stress maps, yield predictions, or classification accuracies—without explicitly accounting for uncertainty arising from acquisition conditions, sensor noise, or model assumptions. Pádua et al. [28] note that this absence of uncertainty-aware reporting hampers risk-sensitive decision-making, particularly in management contexts where incorrect recommendations may lead to economic losses or environmental impacts. To address this limitation, recent methodological advances in remote sensing advocate the integration of uncertainty-aware modelling frameworks throughout the UAV data pipeline. Probabilistic machine learning approaches, including Bayesian inference methods, enable the explicit quantification of predictive uncertainty by modelling parameter distributions rather than point estimates [82,83].

In parallel, ensemble learning techniques such as random forest ensembles, model averaging, or bootstrap aggregation, provide a practical means of capturing model variance and improving robustness under heterogeneous field conditions [64]. These approaches allow uncertainty to be propagated from data acquisition through to final predictions, thereby supporting more transparent and risk-aware agronomic decision-making [84].

Furthermore, the use of prediction intervals and confidence bounds is increasingly recommended to complement deterministic outputs, enabling practitioners to assess the reliability of UAV-derived recommendations under varying environmental and operational conditions [85].

The transferability of analytical models represents another unresolved challenge. Many machine learning and deep learning approaches demonstrate high performance under controlled experimental conditions but exhibit substantial performance degradation when applied to new fields, seasons, or crop varieties. Zhu et al. [53] emphasise that overfitting to site-specific conditions remains a major barrier to operational analytics readiness, especially when training datasets are limited in diversity or insufficiently documented.

Interoperability between UAV-derived data and other agricultural information systems also remains limited. Although data fusion with satellite imagery, IoT sensors, and farm management systems is increasingly advocated, practical implementations often face challenges related to data harmonisation, temporal alignment, and incompatible data standards. Xing et al. [70] argue that without interoperable architectures, UAV analytics risk remaining isolated technical solutions rather than integrated components of digital agriculture ecosystems.

A further gap concerns the alignment of analytical outputs with agronomic decision frameworks. Many studies focus on maximising predictive accuracy without considering whether the resulting outputs are interpretable, actionable, or aligned with operational decision thresholds. As noted by Choi et al. [80], the growing interest in explainable modelling reflects recognition that trust, transparency, and usability are as critical as statistical performance for the adoption of UAV-based decision support tools.

Finally, economic and organisational constraints are frequently underrepresented in methodological discussions. The cost of repeated UAV deployments, data processing infrastructure, and skilled personnel can limit adoption, particularly for small and medium-sized farms. Reviews increasingly acknowledge that scalable precision agronomy requires not only technical robustness but also economically viable and organisationally feasible data pipelines [43,86].

Taken together, these gaps indicate that future progress in UAV-enabled precision agronomy will depend less on incremental improvements in sensing technologies and more on the development of standardised, uncertainty-aware, interoperable, and decision-oriented data pipelines. Addressing these challenges is essential for transitioning UAV applications from experimental demonstrations to reliable tools that support sustainable and data-driven agricultural management.

4. Core Agronomic Applications of UAVs: Evidence-Based Assessment

UAV-enabled precision agronomy is best evaluated through the lens of decision utility: whether UAV-derived indicators consistently translate into agronomic actions that improve productivity, resource efficiency, or risk management under real field constraints. Recent synthesis papers emphasise that application maturity varies markedly between use cases, with the strongest evidence typically reported for monitoring/diagnostics and water management, while interventional applications (spraying/seeding) remain more context- and regulation-dependent [6,41].

4.1. Monitoring and Health Assessment

Monitoring crop condition is the most widely reported UAV application, spanning early stress detection, disease/pest surveillance, nutrient-status proxies, and within-field variability mapping. Common indicator families include (a) multispectral vegetation indices such as NDVI/NDRE and related red-edge metrics for canopy vigour and chlorophyll proxies, (b) RGB-derived texture and structural features for canopy heterogeneity, and (c) task-specific spectral features used in ML pipelines for disease or pest identification. However, despite their widespread use, vegetation indices such as NDVI and NDRE present well-documented limitations that must be considered in agronomic interpretation. In dense canopies characterised by high leaf area index (LAI), NDVI tends to saturate, reducing its sensitivity to further increases in biomass or chlorophyll content. As a result, its ability to discriminate between moderate and high vigour conditions becomes limited [87,88].

In addition, during early growth stages, reflectance signals are strongly influenced by background soil properties, including soil moisture, colour, and roughness. These background effects can introduce variability unrelated to plant physiological status, potentially biasing vegetation index values and leading to misinterpretation of crop condition if not properly accounted for [89].

Anam et al. [90] synthesise recent UAV+AI developments for targeted management (disease detection, weed management, pest control), showing that UAV imagery is typically coupled with supervised learning (including deep learning for detection/segmentation) to support rapid scouting and prioritisation of interventions. In agronomic terms, the reported outcomes are most commonly framed as improved timeliness of detection and better spatial targeting of field inspections, rather than direct yield gains—reflecting the fact that many studies validate against expert labels or plot-level observations rather than long-term performance endpoints.

Nevertheless, the evidence base also highlights recurring methodological limits that condition reliability: (a) generalisation across sites/seasons (domain shift), (b) confounding by illumination and background soil in sparse canopies, and (c) incomplete ground-truthing (e.g., physiological confirmation of stress vs. purely spectral classification). These limitations are repeatedly identified as barriers to operational decision support, particularly where the intended action has economic or environmental risk [41].

4.2. Precision Irrigation and Water Management

UAVs are increasingly employed to support irrigation decision-making, as canopy temperature and spectral indicators provide spatially explicit proxies for crop water status. The primary advantage of aerial platforms lies in their ability to capture high-resolution thermal imagery, enabling the derivation of the Crop Water Stress Index (CWSI)—a normalised indicator that accounts for both atmospheric demand and plant physiological response [91]. A fundamental analytical step in this process is the estimation of ΔT (the temperature difference between the canopy and the surrounding air), which serves as a direct proxy for transpiration cooling efficiency.

Reported agronomic outcomes in the literature consistently indicate improvements in water-use efficiency (WUE) and enhanced spatial targeting of variable-rate irrigation. Quantitative evidence suggests that UAV-supported irrigation management can lead to WUE improvements typically ranging between 10% and 30%, depending on crop type, environmental conditions, and irrigation strategy. For example, studies integrating UAV-derived thermal indicators with precision irrigation systems report water savings of approximately 15–25% without significant yield penalties, and in some cases yield increases of 5–15% due to improved stress mitigation and optimised water allocation [92–94]. However, the magnitude of these benefits remains highly context-dependent and is influenced by baseline irrigation efficiency, soil properties, and climatic variability.

Despite these advances, achieving operational decision-readiness requires more than standalone thermal data acquisition [95]. Evidence consistently demonstrates that irrigation decision-support frameworks are not robust when thermal products are used in isolation. To mitigate atmospheric variability and ensure accurate temperature retrieval, the integration of ground-based meteorological measurements (e.g., vapour pressure deficit, solar radiation, air temperature) is essential for calibration. In addition, the use of radiometric thermal sensors is critical, as non-radiometric systems do not provide calibrated temperature outputs required for quantitative analysis and cross-temporal comparability [96].

From a methodological perspective, the reliability of UAV-derived water stress metrics remains sensitive to several factors, including (a) flight timing relative to solar geometry, (b) rapid atmospheric fluctuations during data acquisition, and (c) canopy structure, particularly in row crops where soil background and partial canopy cover can introduce bias in thermal signals. Recent studies emphasise that the transition from experimental UAV-based irrigation monitoring to operational scheduling depends on standardised acquisition protocols and the integration of UAV data with in situ sensor networks, rather than reliance on single-flight diagnostics [97].

In addition, the integration of UAV data with satellite observations—although increasingly promoted for scaling analysis—introduces several non-trivial challenges. Temporal misalignment between high-frequency UAV acquisitions and lower revisit rates of satellite platforms can lead to inconsistencies in crop condition assessment. Furthermore, substantial differences in spatial resolution (centimetre-level for UAVs versus metre-level for satellites such as Sentinel-2) complicate data fusion and may result in information loss or scale-induced bias. The fusion process itself can propagate and amplify uncertainty, particularly when combining datasets with different radiometric properties, viewing geometries, and atmospheric correction levels. As a result, while UAV–satellite integration can enhance spatial coverage and temporal continuity, it requires careful harmonisation strategies and uncertainty-aware modelling to ensure reliable agronomic interpretation [98–100].

4.3. Soil and Field Analysis

UAV-based soil and field analysis primarily targets the characterisation of spatial variability to support management zoning and soil property inference, particularly under

bare-soil conditions. Typical inputs include high-resolution RGB and multispectral mosaics, terrain derivatives from photogrammetric models (DSM/DTM), and ancillary data such as management history. Biney et al. [101] demonstrated that bare-soil UAV imagery, when combined with auxiliary datasets, can support high-accuracy mapping of soil organic carbon (SOC). Subsequent work has utilised machine-learning methods (e.g., PLS, RF, SVM) to refine these predictions, emphasizing that performance remains conditional on sampling strategy and soil surface representativeness [102].

However, a fundamental limitation of UAV-based SOC estimation lies in the fact that optical sensors capture reflectance information from only the uppermost soil layer (typically a few millimetres to centimetres), whereas SOC measurements are conventionally defined over deeper soil profiles (e.g., 0–30 cm). This depth mismatch introduces uncertainty in the interpretation of UAV-derived estimates, as surface conditions (e.g., moisture, roughness, residue cover) may not be representative of subsurface carbon content. Consequently, UAV-based SOC mapping should be interpreted as a proxy of surface organic matter rather than a direct substitute for standard laboratory measurements, and requires careful calibration with in situ soil sampling and validation datasets [103,104].

The integration of radar technology also addresses a significant gap in high-resolution soil moisture monitoring. While optical and thermal sensors typically infer water status indirectly through surface reflectance or canopy temperature, radar backscatter is sensitive to the dielectric properties of soil, which are strongly influenced by moisture content [105]. Several studies have demonstrated that SAR-based observations can capture spatial variability in soil moisture, even under conditions of moderate vegetation cover or variable illumination [106,107]. However, retrieval accuracy is influenced by surface roughness, vegetation structure, and radar frequency, requiring careful calibration and model-based interpretation [108–110].

4.4. *Spraying and Seeding*

Interventional UAV applications (spraying and, less consistently, seeding) are high-visibility topics but require careful evidence framing because outcomes depend on platform capability, nozzle/boom configuration, meteorology (wind, turbulence), and regulation. In addition to platform and operational constraints, the effectiveness of UAV-based spraying is fundamentally governed by droplet generation and transport dynamics. Key technical parameters include droplet size distribution, commonly expressed as volume median diameter (VMD), nozzle type and operating pressure, flight height, and forward speed. These factors directly influence deposition efficiency, canopy penetration, and off-target drift [111,112].

Droplet spectrum classification provides a framework for characterising spray quality and drift potential. Fine droplets increase coverage but are more prone to drift, whereas coarse droplets reduce drift at the expense of uniformity. Consequently, the optimisation of droplet size represents a critical trade-off between efficacy and environmental safety [111,112].

It is important to note that UAV sprayers often employ rotary atomisers or centrifugal nozzles, which differ fundamentally from conventional hydraulic nozzles in their droplet generation mechanisms. Rotary systems produce droplets through centrifugal forces, allowing more precise control of droplet size distribution and often generating narrower spectra compared to pressure-based hydraulic nozzles [111].

As a result, droplet characteristics such as volume median diameter (VMD), uniformity, and drift potential can differ substantially between these technologies. Rotary atomisers typically enable the production of finer and more uniform droplets at lower pressures, which can enhance coverage but may also increase susceptibility to drift under certain

environmental conditions. Conversely, hydraulic nozzles tend to produce broader droplet spectra, with greater variability in deposition patterns.

These differences have direct implications for spray efficiency, canopy penetration, and environmental risk, and should be explicitly considered when evaluating UAV-based spraying performance and comparing results across studies.

Furthermore, spray drift dynamics are strongly affected by atmospheric conditions (e.g., wind speed, turbulence, temperature gradients) and canopy structure, making real-time adaptation essential for reliable field application. Recent studies emphasise that UAV spraying performance must be analysed within the broader framework of atomisation physics and fluid–canopy interactions, rather than solely in terms of platform capability [113].

García-Munguía et al. [114] systematically assess whether integrating precision technologies into spraying drones improves application accuracy relative to standard approaches, reviewing a large body of studies (2019–2024). The synthesis highlights that improvements are typically linked to better control of droplet deposition and targeting, but also that field variability, canopy structure, and environmental conditions can limit repeatability and complicate cross-study comparison.

Beyond reviews, recent field studies illustrate how sensing-driven control strategies can support variable-rate spraying. Chen et al. [115] propose orchard variable-rate spraying based on canopy volume derived from UAV LiDAR, aiming to address canopy heterogeneity that undermines uniform application. This type of approach is particularly relevant in orchards/vineyards where 3D structure strongly influences deposition efficiency, and where “one-rate-fits-all” spraying leads to over-application in sparse zones and under-coverage in dense canopies [116].

However, the relationship between LiDAR-derived canopy volume and optimal spray volume is not necessarily linear, as deposition efficiency is influenced by canopy density, leaf area distribution, and airflow dynamics within the canopy. In particular, spray penetration into inner canopy layers remains a critical challenge, especially in high-density orchard systems where outer foliage may intercept a substantial proportion of droplets [117,118].

Moreover, many UAV-based variable-rate spraying studies primarily evaluate performance using deposition metrics (e.g., coverage uniformity or droplet distribution), while fewer studies assess biological efficacy outcomes such as disease reduction or pest control effectiveness [119,120]. This distinction is important, as improved deposition does not always translate into agronomic benefit. Consequently, further research is required to establish robust links between canopy structural metrics, spray distribution, and biological response under field conditions [121].

For fertiliser-related variable-rate application, Guan et al. [56] examine UAV-based nitrogen management strategies linked to crop status mapping, illustrating how the sensing-to-action loop can be operationalised. Reported outcomes indicate improvements in nitrogen use efficiency (NUE) and yield under specific conditions, although the magnitude of these gains varies depending on crop type, baseline fertilisation practices, and environmental factors.

However, evidence regarding the statistical significance and temporal stability of these improvements remains limited, as relatively few studies assess performance across multiple growing seasons or heterogeneous field conditions. In particular, while short-term gains in NUE and yield are often reported, their consistency and transferability across sites remain insufficiently validated.

From an operational perspective, UAV-based variable-rate fertilisation is also constrained by platform limitations, including restricted payload capacity, limited flight endurance, and the need for frequent refilling cycles. These logistical constraints can affect field efficiency, application uniformity, and economic feasibility, especially in large-scale farming

systems. Consequently, the practical deployment of UAV-based fertilisation requires careful consideration of both agronomic performance and operational scalability [114,116].

4.5. Yield Prediction and Harvest Planning

Yield prediction is a high-impact application because it directly supports harvest planning and logistical decisions; however, it is also among the most methodologically demanding due to phenological variability, cultivar differences, and the requirement for robust ground-truth data. Importantly, yield forecasting operates at multiple spatial scales—plot, field, and farm level—each associated with different sources of variability and uncertainty [41].

At the plot scale, models are typically calibrated using manually measured yields, providing high accuracy but limited spatial representativeness. At the field and farm scales, yield monitor data collected during harvesting are more commonly used; however, these datasets introduce additional uncertainty due to calibration errors, time lags, and sensitivity to grain flow dynamics and moisture content. As a result, model performance may vary significantly depending on the scale of aggregation and the quality of reference data.

Inputs for yield prediction commonly include multi-temporal vegetation indices, canopy height and structural proxies, and machine learning models linking remotely sensed features to yield outcomes. However, the reliability of these models is strongly influenced by the accuracy of the ground-truth data used for calibration. In particular, errors associated with yield monitor measurements can propagate through the modelling pipeline, affecting both training and validation stages and potentially leading to over-optimistic performance estimates if not properly accounted for [122].

These considerations highlight that yield prediction should not be treated as a single modelling task, but rather as a scale-dependent problem requiring explicit attention to data sources, calibration procedures, and uncertainty propagation [123].

Zhou et al. [110] evaluate UAV-based multispectral approaches for yield prediction and explicitly compare feature-based versus image-based modelling strategies, illustrating that model performance and the optimal timing for early prediction depend on crop variety and growth stage. This evidence reinforces a key review conclusion: yield prediction is not a single problem, but a family of crop- and context-dependent modelling tasks that require careful protocol design.

Earlier, Herzig et al. [124] compare RGB and multispectral UAV sensors for yield prediction in barley across environments and repeated flights, emphasising that sensor choice and modelling strategy influence both performance and the practical feasibility of multi-temporal monitoring. Such work strengthens the evidence that yield models must be validated across environments to claim operational readiness.

Regarding harvest planning (beyond yield), UAV imaging is increasingly used for maturity/ripeness classification and counting in horticultural contexts. While this is crop-specific, it is relevant to “harvest readiness” decisions and demonstrates the broader scope of UAV analytics for operational planning [125].

Across these studies, several limitations recur consistently, including (a) limited transferability across years and management regimes, (b) strong sensitivity to acquisition timing and crop phenology, and (c) high demands for ground-truth data, such as calibrated yield monitors and extensive harvest sampling. Consequently, the available evidence indicates that UAV-based yield prediction is most robust when framed as relative variability mapping and early warning, unless supported by rigorous multi-site and multi-year validation [124].

To provide a structured and comparable synthesis of evidence across application domains, Table 3 summarises typical indicators, reported agronomic outcomes, validation

metrics, and the agronomic context in which results are most defensible, alongside recurring methodological constraints.

Table 3. Evidence-based synthesis of core UAV agronomic applications: indicators, outcomes, validation, and context.

Application Domain	Typical UAV Data & Indicators	Reported Agronomic Outcomes (Evidence Framing)	Validation Approaches & Metrics Commonly Reported	Agronomic Context Where Evidence Is Strongest	Recurring Limitations/Failure Modes	Representative Recent Sources
Monitoring & health assessment	Multispectral VIs (NDVI/NDRE); RGB texture/structure; DL features for detection	Earlier detection and targeted scouting; improved spatial targeting of interventions	Accuracy/F1/mAP (classification/detection); agreement with field scoring	Plot–field scale; crops with visible canopy signals; repeatable acquisitions	Domain shift; illumination/soil background confounding; limited physiological ground truth	[6,75,90]
Precision irrigation & water management	Thermal canopy temperature; CWSI; multispectral condition indices; contextual weather/soil moisture	Improved water-use efficiency; spatially targeted irrigation scheduling	RMSE/MAE vs field measures; classification accuracy for stress levels; cross-date consistency	Irrigated systems; stable met windows; integration with in situ data	Timing/atmosphere sensitivity; canopy architecture effects; need for calibration & context	[94,95,109]
Soil/field analysis	Bare-soil multispectral/RGB; terrain derivatives; ML soil-property models	Fine-scale variability mapping; targeted soil sampling support; SOC mapping under controlled conditions	RMSE/R ² for soil properties; external validation with soil samples	Bare-soil windows; consistent surface condition; adequate sampling density	Surface moisture/residue confounding; limited transferability across fields	[101,102]
Spraying (intervention)	Canopy maps/3D structure (RGB/LiDAR); prescription maps; variable-rate logic	Reduced over-application; improved targeting (context dependent)	Deposition/coverage metrics; operational performance indicators	Orchards/vineyards; heterogeneous canopy structures; controlled wind conditions	Payload/endurance constraints; wind drift; regulation; repeatability issues	[114–116]
Variable-rate fertiliser (intervention)	Crop status mapping (often multispectral); VRA execution by drone	More tailored application; improved efficiency (often crop/goal specific)	Outcome-specific field metrics; consistency across zones	Field-scale trials with integrated workflow	Map accuracy and timing; integration burden; economics	[56]
Yield prediction & harvest planning	Multi-temporal VIs; canopy height proxies; ML regression; maturity classification (horticulture)	Relative yield zoning; earlier forecasting; harvest planning signals	RMSE/R ² ; cross-year validation; variety-specific assessment	Crop-specific; multi-temporal designs; sufficient harvest ground truth	Phenology sensitivity; limited generalisation; ground-truth intensity	[110,124,125]

Monitoring and irrigation exhibit the highest operational readiness and scalability, whereas spraying and yield prediction remain constrained by high uncertainty and lower validation robustness.

To provide a structured and comparable synthesis of evidence across application domains, Table 3 and Figure 3 summarise typical indicators, reported agronomic outcomes, validation metrics, and operational constraints across core UAV applications.

The figure summarises key dimensions influencing operational deployment, including data complexity, validation robustness, readiness level, uncertainty, scalability, and agronomic impact. Monitoring and irrigation applications demonstrate higher maturity and scalability, while soil analysis, spraying, and yield prediction remain more constrained

by uncertainty, validation limitations, and operational complexity. Colour coding reflects relative levels across studies synthesised in this review.

Application	Data complexity	Validation	Readiness	Uncertainty	Scalability	Impact
MONITORING 🌱	Low-Medium	Medium	High	Medium	High	Medium
IRRIGATION 💧	Medium	Medium	Medium-High	High	Medium	High
SOIL 🟫	Medium	Low-Medium	Low	High	Low	Low
SPRAYING 🚒	High	Low	Medium	High	Low	High
YIELD 📊	High	Medium	Medium	High	Medium	Medium

Low	Low-Medium	Medium	Medium-High	High
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Figure 3. Comparative synthesis of core UAV agronomic applications.

5. Performance, Validation, and Reproducibility in UAV-Based Agronomy

The performance of UAV-enabled agronomic applications cannot be credibly assessed without rigorous validation and transparent reporting of uncertainty and reproducibility. While numerous studies report high predictive accuracy or strong correlations between UAV-derived indicators and agronomic variables, these results are often context-specific and difficult to generalise. Consequently, validation design and reproducibility have emerged as critical criteria for evaluating whether UAV-based analytics are suitable for operational deployment rather than experimental demonstration [126].

5.1. Validation Strategies for UAV-Derived Agronomic Data

Validation of UAV-based agronomic products typically relies on comparisons with ground truth data, including field measurements, destructive sampling, sensor networks, or harvest records. Common validation strategies include point-based comparisons (e.g., leaf chlorophyll, canopy temperature), plot-level aggregation, and field-scale yield or biomass assessment.

Haghighattalab et al. [127] emphasise that the spatial scale of validation must be consistent with the intended agronomic decision. For instance, plot-level validation may be sufficient for experimental trials but inadequate for field-scale management decisions, where spatial aggregation and sampling density strongly influence reported performance metrics. Inconsistencies between UAV pixel resolution and ground sampling design can lead to inflated accuracy estimates that do not translate into operational reliability.

Recent work has highlighted the value of multi-source validation, combining UAV data with satellite imagery and proximal sensing to reveal systematic biases not evident from single-source validation [128,129]. However, the primary bottleneck for these validation frameworks remains the high cost and labor-intensive nature of acquiring high-quality ground-truth labels. To address this challenge, the field is shifting toward advanced AI paradigms such as Self-supervised Learning (SSL) and Few-shot Learning. SSL allows models to learn robust agricultural features from large, unlabeled spectral datasets, which can then be fine-tuned with minimal annotated samples for specific crop varieties or local conditions. This evolution reduces the dependence on massive ground-truth datasets and accelerates the deployment of reliable decision-support models across diverse geographical regions.

5.2. Performance Metrics and Their Agronomic Interpretation

Performance in UAV-based studies is commonly reported using statistical metrics such as coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and classification accuracy or F1-score. While these metrics provide a standard for technical comparison, their agronomic utility is often limited if they are not explicitly linked to field-level decision thresholds [130]. High statistical performance, as measured by R^2 or RMSE, does not necessarily imply practical usefulness in a farming context, particularly if the inherent prediction errors exceed the sensitivity required for critical management interventions, such as specific irrigation triggers or fertilizer rate adjustments.

To address this gap, the recent literature advocates for aligning performance metrics with operational decision contexts. For example, reporting classification performance for stress severity categories (e.g., low, medium, high stress) can be more agronomically relevant for targeted scouting than reporting continuous vegetation indices alone [131]. Furthermore, the performance of UAV-derived biophysical estimates is highly sensitive to acquisition timing and phenological stage. Research has shown that accuracy often peaks during specific growth stages and may decline significantly outside these optimal windows. Consequently, robust validation requires reporting performance across multiple dates and environmental conditions to ensure that the derived information remains reliable for longitudinal monitoring and season-wide decision support.

Biases in spectral indices can significantly distort management outcomes. For instance, a systematic error of ± 0.1 in the Crop Water Stress Index (CWSI) can shift the decision threshold for irrigation, potentially leading to a 20% reduction in water-use efficiency or unnecessary crop water stress. Similarly, an NDVI bias of 15% during peak growth stages can result in miscalculated nitrogen application rates, impacting final yield by up to 10%.

5.3. Sources of Error and Uncertainty in Precision Agronomy

The reliability of UAV-enabled decision support is fundamentally challenged by multiple sources of error that propagate throughout the data pipeline, from initial acquisition to final modeling [132]. These uncertainties are rarely isolated, but rather interact in complex ways, affecting the transition from experimental observation to operational intervention.

5.3.1. Technical and Sensor-Level Limitations

Technical errors are often rooted in the physical acquisition geometry and sensor characteristics.

- *Geometric and resolution effects:* Acquisition altitude and viewing geometry are dominant contributors to variability in vegetation indices, especially in heterogeneous canopies where the background soil signal can confound plant-level reflectance. While acquisition altitude remains a primary factor, the precision of spatial products is increasingly dependent on the use of Real-Time Kinematic (RTK) UAV positioning or the strategic placement of Ground Control Points (GCPs). The trade-off between GCP density and operational efficiency is a critical determinant of centimetric accuracy in precision agronomy applications.
- *Sensor noise and radiometric inconsistency:* Motion blur and radiometric inconsistencies introduced by changing illumination during a single flight create spatial artifacts that can be misinterpreted as agronomic signals. For thermal sensors, emissivity assumptions and atmospheric scattering add layers of uncertainty that complicate absolute temperature retrieval for irrigation scheduling.

5.3.2. Data Processing and Methodological Challenges

Beyond the hardware, the methods used to transform raw imagery into actionable data introduce significant modeling-related uncertainties.

- *Machine learning overfitting:* Models trained on limited or site-specific datasets frequently exhibit substantial performance degradation when deployed under real-world conditions [133]. Moreover, the scientific literature is shifting from purely deterministic results toward uncertainty-sensitive models, such as Bayesian Machine Learning (Bayesian ML), which allow for the estimation of prediction intervals and variance, providing a more realistic assessment of model reliability under field conditions. In addition, dataset size and feature dimensionality represent critical but often underreported factors influencing model reliability. UAV-based agronomic studies frequently operate under a “high-dimensional, low-sample-size” regime, where the number of input features (e.g., spectral bands, texture metrics, multi-temporal indices) exceeds the number of ground-truth samples. This imbalance (features $\gg$ samples) increases the risk of overfitting and limits model generalisation unless appropriate dimensionality reduction or feature selection techniques are applied.

Furthermore, improper model evaluation practices can lead to overly optimistic performance estimates.

In particular, hyperparameter tuning conducted without nested cross-validation introduces information leakage between training and validation steps, resulting in biased accuracy metrics. Despite being a well-established requirement in machine learning, nested cross-validation is still rarely implemented in UAV-based agronomic studies, which raises concerns regarding the robustness and reproducibility of reported results.

- *Lack of reporting standards:* A major obstacle to reproducibility is the inadequate reporting of training–validation splits and feature selection procedures in many UAV-based studies. This transparency gap makes it difficult to assess whether reported accuracy reflects robust methodology or favorable experimental circumstances.

To bridge this gap, we propose the adoption of a “Minimum Information for UAV Agronomy” (MIUAVA) framework. This implementable solution requires researchers to report mandatory metadata, including: (a) sensor-to-sun geometry, (b) specific radiometric calibration protocols, and (c) geometric RMSE. Such a framework ensures that data pipelines remain interoperable and results can be robustly compared across different experimental contexts.

5.3.3. Operational Constraints Under Real-World Conditions

Uncertainty management must also account for non-trivial operational factors that influence data integrity.

- *Environmental variability:* Wind conditions and sudden changes in cloud cover during mission execution can alter irradiance levels, necessitating aggressive post hoc corrections that may introduce further artifacts.
- *Scale mismatch:* Inconsistencies between ultra-high UAV pixel resolution and coarser ground-truth sampling density can lead to inflated performance metrics that do not translate into operational reliability. To address this, agricultural data pipelines should implement hierarchical upscaling methods and spectral-based stratified sampling strategies. By utilizing the high-resolution UAV imagery to guide the placement of ground sensors in areas of maximum spectral variability (e.g., using a Latin Hypercube Sampling approach), researchers can ensure that point-based validation data are statistically representative of the larger UAV pixel footprint, thereby minimizing scale-dependent biases in yield and biomass models.

5.4. Reproducibility and Reporting Standards

Reproducibility is increasingly recognised as a prerequisite for scientific credibility and operational adoption. However, many UAV-based agronomic studies lack sufficient methodological detail to enable independent replication.

Kattenborn et al. [130] and Maxwell et al. [133] both emphasise the importance of standardised reporting, including detailed documentation of flight parameters, sensor calibration procedures, pre-processing workflows, and modelling choices. Without such transparency, it is difficult to assess whether reported performance reflects robust methodology or favourable experimental conditions.

Recent initiatives in the remote sensing community advocate for open datasets, shared code, and benchmark protocols to improve reproducibility and comparability. While these practices are not yet widespread in agronomic UAV research, they represent a clear pathway towards more reliable evidence and faster translation into practice [81].

5.5. Implications for Operational Deployment

From an operational perspective, validation and reproducibility directly influence trust in UAV-based decision support systems. Agronomic decisions often involve economic and environmental trade-offs, and decision-makers require confidence that UAV-derived recommendations are robust under variable conditions.

Haghighattalab et al. [127] argue that validation strategies should therefore be designed not only to maximise statistical performance, but also to characterise uncertainty and failure modes. Such an approach enables risk-aware decision-making and facilitates the integration of UAV analytics into broader farm management systems.

To synthesise current practices and challenges, Table 4 summarises common validation strategies, reported metrics, typical error sources, and implications for reproducibility and operational use.

Table 4. Validation approaches, performance metrics, and reproducibility considerations in UAV-based agronomy.

Aspect	Common Approaches in the Literature	Typical Metrics Reported	Key Limitations	Implications for Reproducibility
Ground-truth validation	Field sampling, destructive measurements, yield monitors	RMSE, MAE, R^2	Scale mismatch; sparse sampling	Results difficult to generalise without standardised protocols
Cross-platform comparison	UAV vs satellite or proximal sensors	Correlation, bias analysis	Sensor differences; temporal misalignment	Requires detailed harmonisation reporting
Temporal validation	Multi-date acquisitions across growth stages	Performance stability over time	Often limited to optimal stages	Single-date validation overestimates robustness
Model validation	Train–test split, cross-validation	Accuracy, F1-score, RMSE	Risk of overfitting; dataset leakage	Poor reproducibility without transparent reporting
Reporting standards	Documentation of flight, processing, modelling	Not consistently applied	Missing metadata; incomplete workflows	Limits independent replication and benchmarking

6. Constraints and Barriers to Scaling UAV-Based Precision Agronomy

Despite the robust scientific evidence supporting UAV applications, routine operational uptake remains limited by a synergistic network of technical, economic, and governance-related constraints [134]. Rather than acting in isolation, these barriers interact to create significant hurdles for scalable adoption, requiring a decision-oriented framework to navigate their relative importance.

6.1. The Interplay Between Technical Limitations and Operational Reliability

From a structural perspective, the intrinsic technical constraints of UAV platforms—such as battery life, payload limitations, and weather dependency—extend beyond simply limiting mission duration; they directly affect the temporal consistency required for reliable agronomic monitoring [135]. In operational terms, UAV-based mapping typically achieves coverage rates on the order of ~5–10 ha per hour, depending on flight altitude, sensor configuration, and image overlap requirements. Consequently, monitoring farms exceeding 100 ha may require multiple flights (often >10 missions), increasing mission planning complexity, data processing demands, and turnaround time.

In contrast, satellite platforms provide regional-scale coverage (thousands to millions of hectares per acquisition), albeit at lower spatial resolution and with revisit constraints (e.g., 5–16 days), while ground-based systems offer high accuracy but limited spatial coverage and operational flexibility. This fundamental trade-off between spatial resolution, coverage capacity, and temporal frequency highlights that UAVs occupy an intermediate niche, combining high-resolution sensing with limited scalability [136,137].

The need for repeated UAV flights over large or fragmented fields further amplifies operational costs and logistical constraints, particularly due to battery recharging, payload limitations, and data handling requirements. These factors can significantly affect cost-effectiveness, especially when compared to conventional ground machinery, which typically achieves higher field throughput under stable conditions [138]. As a result, the economic viability of UAV deployment depends not only on sensing performance but also on workflow integration, farm size, and the degree of automation in data processing and decision support.

Moreover, the high spatial resolution of UAV imagery, while advantageous for detecting fine-scale variability, generates large data volumes that require advanced computational infrastructure, potentially limiting adoption in resource-constrained farming systems. These constraints collectively highlight that UAV-based monitoring systems must be evaluated not only in terms of sensing capability, but also through a systems-level perspective that accounts for operational scalability, cost, and integration within existing farm management practices.

To bridge the gap between sensing and effective intervention, the “perception-decision-execution” loop must address both spatial and physical delivery uncertainties. A critical technical hurdle is the “position lag” inherent in this closed loop; to ensure sub-decimeter application accuracy, advanced latency compensation algorithms are required to synchronize real-time GNSS positioning with physical nozzle reaction times. Furthermore, precision spraying effectiveness is not only a function of spatial accuracy but also of rigorous droplet spectrum control. Adhering to ISO 25358 standards for droplet size classification is vital to mitigate off-target drift and ensure uniform deposition. For instance, transitioning from traditional hydraulic nozzles to centrifugal rotary atomisers (CDA) allows for a more uniform Volume Median Diameter (VMD). This technical optimization enables operators to reduce drift significantly while maintaining effective canopy coverage at substantially lower carrier volumes, thereby partially alleviating the payload and refill frequency constraints typical of interventional UAVs.

6.2. Economic Viability and the Skills Gap: A Barrier to Small-Scale Adoption

The economic feasibility of UAV technology is inextricably linked to the availability of human capital. High initial investments in hardware and specialized software are compounded by recurring costs for skilled personnel capable of bridging the gap between raw data processing and agronomic interpretation [135]. For small and medium-sized farms, this skills gap reinforces a costly dependence on external service providers, further reducing operational flexibility and hindering the long-term digital transformation of the sector. However, the economic outlook follows a non-linear scale dependence. Quantitative analyses suggest that for large-scale operations (>500 ha), the payback period for integrated UAV systems is typically 2–3 years, primarily driven by a 15–20% reduction in chemical input costs and improved yield monitoring. These ROI estimates are based on a baseline scenario of a 500 ha cereal farm, assuming an initial investment of \$15,000–\$20,000 for a combined sensing/spraying fleet, with an operational frequency of 4–6 missions per season. In contrast, for small-holder farms, the input-output ratio remains prohibitive if the technology is acquired individually. To ensure broader adoption, the focus must shift from individual ownership to cooperative-based sharing models or service-as-a-system (SaaS) approaches, which can amortize the high fixed costs of equipment and specialized expertise across multiple users.

6.3. Regulatory Challenges and the Escalation of Compliance Costs

The interaction between regulatory frameworks and economic constraints is a primary determinant of scalability in precision agronomy. Stringent aviation rules, particularly those governing Beyond Visual Line of Sight (BVLOS) operations in the US (FAA) and EU (EASA), impose heavy administrative and safety-case burdens on operators [88,89]. These requirements not only increase compliance costs but also dictate the feasibility of larger-area coverage, effectively making high-frequency monitoring economically unviable under current restricted flight categories.

However, the global regulatory landscape is becoming increasingly fragmented, with major agricultural nations adopting more permissive frameworks to accelerate digital transformation. For instance, China and Brazil have pioneered streamlined certification pathways for high-payload spraying swarms, treating agricultural UAVs as specialized farm machinery rather than traditional aircraft. This has led to a surge in interventionist UAV adoption compared to the EU, where the interplay between aviation safety and chemical application directives (e.g., the Sustainable Use Regulation) remains a bottleneck. Similarly, India has recently decentralized its drone certification process, introducing “E-VTOL corridors” to support rural connectivity and precision spraying, though infrastructure for real-time monitoring remains a challenge. The divergent regulatory philosophies across these major agricultural regions, ranging from risk-averse aviation frameworks to mechanisation-oriented policies, are summarised in Table 5.

The comparative regulatory assessment highlights a substantial divergence in operational philosophy across major agricultural regions. While the European Union and United States emphasise risk-based authorisation and layered certification mechanisms, China adopts a development-oriented model that integrates UAVs directly into agricultural mechanisation strategies. Brazil and India exhibit hybrid or de-centralised approaches, balancing aviation safety with agricultural modernisation objectives. Notably, BVLOS permissions and high-payload spray operations are universally treated as higher-risk categories requiring elevated authorisation, yet the administrative burden and scaling potential differ significantly. These regulatory asymmetries directly influence deployment speed, operational cost structures, and the scalability of precision spraying and intervention-based UAV systems.

Table 5. Comparative regulatory framework for agricultural UAV operations in major agricultural regions.

Region/Country	BVLOS Operations	Spraying Legality	Payload & Scaling Approach	Regulatory Philosophy
European Union (EASA)	Restricted; permitted only under the Specific category with operational authorization and a formal SORA (Specific Operations Risk Assessment).	Legal but subject to aviation safety approval and compliance with environmental and pesticide regulations (including Sustainable Use Regulation requirements).	Risk-based categorization; no explicit fixed payload threshold, but increased payload and swarm deployment elevate the operational risk class and authorization requirements.	Safety-centric framework prioritizing airspace risk management, third-party protection, and chemical drift mitigation.
United States (FAA)	Requires a waiver under Part 107 or an exemption (e.g., Section 44807) for BVLOS operations.	Legal under Part 137 Agricultural Aircraft Operator Certificate (AAOC) in addition to Part 107 remote pilot certification.	Simplified regulatory pathway for UAVs under 25 kg (55 lb); heavier platforms or swarm operations require additional exemptions and airworthiness considerations.	Compliance-intensive framework emphasizing pilot certification, operational waivers, and layered federal oversight.
China	Relatively permissive; streamlined approval processes for agricultural BVLOS operations in designated sectors.	Widely legal and actively promoted; agricultural UAVs are often treated as specialized mechanized farm equipment.	High-payload agricultural swarms (often up to 50 kg or more) are common, supported by centralized and accelerated certification pathways.	Growth-oriented framework integrating UAVs as core agricultural modernization tools with strong state-level support.
Brazil (ANAC)	Evolving framework; BVLOS permitted under specific regional or risk-based authorizations.	Legal under civil drone regulations, with additional operational conditions applicable to agricultural use.	Differentiated operational classes based on weight and risk profile; strong emphasis on operator registration and traceability.	Hybrid regulatory approach balancing aviation safety standards with the need for rapid agricultural mechanization.
India (DGCA)	Default VLOS operations; BVLOS permitted under designated corridors and approved projects, particularly in rural contexts.	Permitted under Drone Rules 2021; requires certified drones, licensed pilots, and approved pesticide use under defined SOPs.	Decentralized certification structure; designated “Green Zones” simplify deployment for small-to-medium agricultural UAVs.	Decentralized empowerment model focused on rural access, simplified certification, and accelerated agricultural adoption.

Consequently, the lack of interoperable data architectures and unresolved governance issues regarding data ownership continue to fragment the global UAV ecosystem, preventing its integration into a unified, scalable precision agriculture framework [136].

7. Regulatory, Legal, and Ethical Considerations

UAV-enabled agronomy operates within regulatory frameworks that are explicitly designed to manage aviation safety risk, and these requirements can materially shape what is feasible in routine agricultural operations (e.g., flight altitude, operational area, line-of-sight constraints, and administrative burdens). In practice, regulatory compliance influences not only where and how often drones can be deployed, but also the economics of UAV services, the viability of BVLOS workflows, and the organisational maturity required for safe and repeatable operations.

7.1. Regulatory Frameworks: FAA and EASA as Risk-Management Systems

In the United States, commercial agricultural UAV operations are typically conducted under the FAA's Small UAS Rule (Part 107) [137], which requires that operations are conducted by a certificated Remote Pilot or under the supervision of one.

In the European Union, EASA's regulatory approach is risk-based and structured around categories that reflect operational risk rather than whether the activity is "commercial" or "recreational". The primary legal framework is established through EU Regulations 2019/947 (operations) [137] and 2019/945 (UAS product requirements) [138].

7.2. Operational Constraints and Permissions: VLOS, BVLOS, and Authorisations

A core practical distinction for agricultural scaling is whether an operation is conducted VLOS (visual line of sight) or BVLOS (beyond visual line of sight). Under FAA Part 107 [137,138], certain operations outside baseline limitations may be possible via an FAA waiver process, which requires the operator to demonstrate an alternative means of compliance that maintains safety.

In the EU/EASA framework, BVLOS typically requires an operational authorisation in the specific category, unless the operation falls under certified category conditions. EASA guidance explicitly notes that BVLOS usually requires authorisation under the conditions in Article 12 of Regulation (EU) 2019/947 [139].

For agriculture, this distinction matters because BVLOS is often associated with larger-area coverage and reduced labour intensity per hectare, while VLOS operations can increase mission fragmentation and staffing requirements for large or dispersed holdings.

7.3. Remote Identification and Traceability Obligations

Remote identification is increasingly treated as a baseline requirement for accountability and airspace safety. FAA materials state that operators of unmanned aircraft registered or required to be registered must comply with Part 89 Remote ID [138] operating requirements (with the stated compliance date for operators on FAA's RID compliance page).

From an operational standpoint, Remote ID requirements may influence procurement (equipment capability), mission planning (broadcast compliance), and the feasibility of service provision at scale, particularly for organisations operating mixed fleets.

7.4. Risk Assessment and Safety Case Documentation

In the EU, the "specific" category commonly relies on structured operational risk assessment. EASA's AMC/GM documentation indicates that the operational risk assessment required by Article 11 may be conducted using the SORA methodology (as an acceptable means of compliance), while allowing alternative methodologies as well [139].

This has direct implications for agricultural operators and service providers: risk assessment becomes an administrative and technical competency, requiring documentation, training evidence, and operational controls that may not be necessary for small-scale VLOS flights but become essential for more complex operations and BVLOS.

7.5. Legal and Ethical Considerations Beyond Aviation Safety

Although aviation regulations primarily address safety, agricultural UAV deployments also raise broader legal and ethical questions, particularly around privacy, data ownership, and security. EASA guidance explicitly acknowledges that aspects beyond safety—such as security and privacy—should be assessed in addition to operational risk, reinforcing that compliance is not solely an aviation matter but also a governance issue for data-driven agriculture.

In practical terms, high-resolution UAV imagery can inadvertently capture identifiable features (people, vehicles, property) and sensitive farm information, and therefore responsible deployment requires governance measures such as purpose limitation, controlled access to datasets, retention policies, and secure storage—especially when third-party service providers process data.

To clarify how regulatory frameworks shape the feasibility and cost of UAV-enabled agronomy, Table 6 summarises key operational dimensions and their practical implications for agricultural deployment.

Table 6. Comparative overview of FAA and EASA regulatory implications for agricultural UAV operations.

Dimension	FAA (United States)	EASA/EU framework	Practical Implications for Agriculture
Core framework	Part 107 commercial small UAS operations (Remote Pilot certification)	Risk-based regulations under EU 2019/947 & 2019/945	Training, accountability, and compliance planning are non-trivial scaling requirements
Baseline operations	Standard operating rules; deviations may require waivers	“Open”, “Specific”, “Certified” categories based on operational risk	Determines whether routine operations are low-admin (open) or require safety case (specific)
BVLOS pathway	Potential via waiver/authorisation mechanisms (case-by-case)	BVLOS usually requires operational authorisation in “specific” category (unless certified)	BVLOS can reduce labour per hectare but raises compliance cost and documentation burden
Remote ID	Part 89 Remote ID operating requirements (FAA RID compliance guidance)	EU framework emphasises standardised rules and technical requirements under 2019/945 & 2019/947	Fleet procurement, configuration management, and operational checks become scaling factors
Risk assessment	Waivers require showing safe alternative methods	SORA may be used as AMC for Article 11 risk assessment; alternatives allowed	Formal risk documentation and operator competence are key barriers for complex missions
Beyond safety (privacy/security)	Often addressed through broader legal frameworks (not just aviation rules)	EASA AMC/GM explicitly notes assessing security/privacy alongside safety	Data governance (ownership, access, retention, security) becomes essential for trust and adoption

8. Future Trends and Innovation Roadmap

8.1. Why a Roadmap Is Necessary

Future progress in UAV-enabled precision agronomy is increasingly shaped by the convergence of sensing, automation, and digital infrastructure, rather than by incremental improvements in platform hardware alone. Recent systematic synthesis indicates that the principal bottlenecks are shifting towards scalability: dependable end-to-end workflows, interoperability with farm systems, and the ability to operate at the right frequency under real constraints [1].

At the same time, the most impactful innovations are those that reduce the operational gap between data collection and actionable decisions. Yang et al. [15] explicitly frame UAV agronomy as an end-to-end process—from sensor selection and acquisition through pre-processing and modelling to decision support—implying that future advances should be evaluated as pipeline improvements rather than isolated algorithmic gains.

8.2. Autonomy and “Decision-Ready” UAV Systems

A major near-term trend is the transition from operator-intensive deployments towards increasingly autonomous workflows, including automated mission planning, adaptive re-visits, and onboard quality control. While full autonomy remains constrained by safety requirements, incremental autonomy (e.g., automated take-off/landing, terrain following, dynamic route planning) is already improving reliability and repeatability in agricultural operations [1].

However, a critical technical hurdle for interventionist autonomy is the “position lag” inherent in the perception-decision-execution loop. To ensure sub-decimeter application accuracy during high-speed tasks like precision spraying, advanced latency compensation algorithms are required to synchronize real-time GNSS positioning with the physical reaction time of hardware components. Without predictive compensation, the spatial mismatch between target detection and chemical discharge compromises efficacy. Therefore, “decision-ready” systems must evolve from simple mapping to integrated control loops where UAV data drive responsive, real-time interventions.

FAA [140] also anticipates a regulatory and operational trajectory towards routine, scalable BVLOS operations, which would substantially change the feasibility of high-frequency monitoring across large farms and dispersed parcels.

A practical implication is that “autonomy” should be discussed not only as flight automation but also as decision automation, where data products are delivered in formats aligned with agronomic thresholds and operational actions. This requires robust uncertainty-aware pipelines and decision support integration, rather than solely higher-resolution imaging.

8.3. Edge AI and Cloud–Edge–Device Orchestration for Time-Critical Decisions

Another high-impact direction is the move from batch post-processing to near-real-time analytics using edge computing. This is particularly relevant for time-sensitive interventions such as irrigation adjustment, pest control escalation, or targeted scouting after extreme weather events. Yu et al. [141] describe cloud–edge–device collaboration as a strategy that allocates time-critical inference to edge nodes while retaining cloud capacity for heavier modelling and system-wide optimisation.

Gong et al. [142] similarly discuss edge-enabled agriculture scenarios in which UAV observations are combined with high-frequency ground sensor streams to drive responsive control (e.g., variable irrigation), illustrating how UAV data become operationally valuable when integrated into control loops rather than used only for retrospective mapping.

This trajectory implies that future “best practice” will increasingly involve designing UAV analytics for deployment constraints (latency, bandwidth, robustness), including model compression, modular pipelines, and auditability of inference outputs in production environments.

8.4. Multi-Agent and Swarm Concepts for Coverage and Resilience

Multi-UAV coordination (often framed as “swarm” or cooperative UAV systems) is repeatedly proposed as a route to scalable coverage, redundancy, and rapid response. Ahmad [143] summarises current directions in UAV swarm intelligence and UAV-enabled edge computing, suggesting that coordinated systems may address the coverage limitations of single-UAV deployments while distributing sensing and computation.

From an agronomic standpoint, swarm concepts are most compelling where the monitoring frequency must be high (e.g., disease outbreak surveillance, post-storm damage assessment) and where spatial heterogeneity is high enough to justify distributed sensing. However, the practical readiness of swarms remains dependent on airspace integration,

safety case requirements, and system reliability, which means that most near-term deployments are likely to be semi-coordinated fleets rather than fully autonomous swarms.

8.5. Climate-Smart Agronomy and Resilience-Oriented Monitoring

Climate variability is increasing the value of rapid, spatially explicit diagnostics for stress, damage, and resource constraints. UAV pipelines that can deliver rapid assessments of crop water/nutrient status and identify emerging stress patterns are increasingly framed as climate-smart tools because they support adaptive management and potentially reduce wasted inputs [15].

In this context, the most promising innovations are not necessarily new indices but improved integration: combining UAV observations with weather, soil moisture, and management records to support decision support systems that are robust to variable conditions and uncertainty [144].

8.6. What Is Deployable Now Versus the Next 3–5 Years

Regulatory and operational trajectories matter because they determine whether an innovation is deployable outside research conditions. The FAA’s Drone Integration CONOPS [145] explicitly focuses on enabling routine, scalable BVLOS operations over the coming decade. Complementary oversight reporting also indicates rapid growth in approvals for more complex BVLOS operations over recent years, suggesting accelerating institutional capacity for advanced operations. In the UK, the regulator has published a roadmap that targets routine BVLOS operations by 2027.

To make the innovation trajectory explicit and decision-oriented, Table 7 contrasts capabilities that are already deployable at scale with those that are likely to mature over the next 3–5 years, together with the enabling conditions and principal risks.

Table 7. Innovation roadmap for UAV-enabled precision agronomy: deployable now vs next 3–5 years.

Innovation Domain	Deployable Now (Typical)	Next 3–5 Years (Likely)	Key Enablers	Principal Risks/Constraints	Representative Source
Autonomous operations	Automated mission planning; semi-automated workflows; repeatable VLOS missions	Broader BVLOS routine operations; higher autonomy under managed risk	Regulatory evolution; detect-and-avoid; robust ops procedures	Compliance burden; safety case complexity	[145]
Edge AI for near-real-time decisions	Edge-assisted inference for specific tasks; cloud post-processing for heavy models	Edge–cloud orchestration as standard; tighter closed-loop control (e.g., irrigation)	Edge hardware; model compression; reliable connectivity	Latency, bandwidth, and model drift in the field	[141]
Multi-source integration	UAV + basic IoT + weather layers in project-based setups	Interoperable, platform-level integration with farm systems	Standards; APIs; data governance maturity	Fragmentation; vendor lock-in; privacy/security	[144]
Multi-UAV coordination	Coordinated fleet scheduling by operators (limited autonomy)	Increased autonomy in cooperative coverage and resilience	Reliable comms; scheduling algorithms; safety frameworks	Airspace integration; reliability; regulation	[143]
Climate-smart monitoring	End-to-end workflows for water/nutrient monitoring	More resilient, uncertainty-aware DSS integrated with control systems	Validation across seasons; uncertainty reporting	Generalisation across environments; ground-truth cost	[15]

9. Conclusions

This review provides a comprehensive and integrative assessment of UAV-enabled precision agronomy, with a specific focus on the data pipeline—from acquisition and pre-processing to data fusion, analytics readiness, and decision support—and on the conditions under which UAV-derived information becomes agronomically actionable. By synthesising recent evidence across core applications, validation practices, regulatory frameworks, and emerging innovation pathways, the review highlights both the maturity achieved in selected domains and the persistent barriers that limit large-scale operational deployment.

The evidence indicates that monitoring and diagnostic applications, particularly crop health assessment and irrigation support, represent the most mature and defensible use cases. These applications consistently demonstrate value when UAV-derived indicators are aligned with specific decision contexts, supported by appropriate validation, and interpreted alongside contextual information such as weather and soil conditions. In contrast, interventional applications (e.g., spraying and seeding) and absolute yield prediction remain more context-dependent, with performance strongly conditioned by operational constraints, validation design, and regulatory feasibility.

A central conclusion of this review is that the data pipeline, rather than sensor resolution alone, constitutes the primary differentiator between experimental demonstrations and decision-grade UAV systems. Robust acquisition planning, rigorous pre-processing, uncertainty-aware analytics, and transparent validation are essential prerequisites for trust and reproducibility. Studies that neglect these aspects often report optimistic performance metrics that do not translate into reliable agronomic decisions under real-world conditions.

Scalability remains constrained by a combination of technical limitations, economic and skills-related barriers, interoperability challenges, and regulatory requirements. While ongoing regulatory developments—particularly regarding BVLOS operations—are likely to improve feasibility in the medium term, effective scaling will depend equally on organisational capacity, standardised reporting practices, and data governance frameworks that address privacy and trust.

Looking forward, the most impactful innovations are expected to arise from system-level integration rather than isolated technological advances. Incremental autonomy, edge-enabled analytics, multi-source data integration, and climate-smart decision support systems offer clear pathways towards more resilient and responsive agricultural management. However, their successful deployment will require coordinated progress in validation standards, interoperability, and regulatory alignment.

Overall, this review underscores that UAVs have the potential to become reliable components of precision agriculture systems, provided that future research prioritises decision-oriented design, reproducibility, and operational realism. By shifting emphasis from proof-of-concept accuracy towards validated, scalable, and transparent workflows, the research community can accelerate the transition of UAV technologies from experimental tools to dependable enablers of sustainable and data-driven agriculture.

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