International Journal of IJTM Technology & Modeling

INTERNATIONAL JOURNAL OF TECHNOLOGY AND MODELING
Volume 4 Issue 3 Year 2025 Pages 128 - 146
e–ISSN 2964-6847
Url: https://ijtm.my.id

Unmanned Aerial Vehicles (UAVs) for Pest and Disease Detection in Rice Cultivation: A Systematic Review

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Abstract: This paper presents a systematic review of the use of Unmanned Aerial Vehicles (UAVs) for pest and disease detection in rice cultivation, a critical challenge in maintaining yield stability and reducing chemical overuse in global food systems. The study aims to synthesize current approaches, technologies, and algorithms employed in UAV-based monitoring of rice pests and diseases, while identifying research gaps and future directions for precision rice farming. Following PRISMA-inspired guidelines, a Systematic Literature Review (SLR) was conducted across major scientific databases (Scopus, Web of Science, IEEE Xplore, and ScienceDirect) using predefined keyword combinations related to UAVs, rice, pest/disease detection, and remote sensing. Inclusion criteria focused on peer-reviewed studies that explicitly employed aerial platforms for detecting biotic stress in rice, while review papers, non-rice crops, and purely simulation-based works were excluded. The findings highlight three dominant technology dimensions: sensing modalities, with RGB and multispectral imagery being most prevalent, followed by hyperspectral and thermal sensors; analytical methods, ranging from traditional vegetation indices and thresholding to advanced machine learning and deep learning models; and operational considerations, including flight altitude, spatial resolution, and temporal frequency of data acquisition. The review contributes by proposing a conceptual framework linking sensor choice, image processing pipelines, and pest/disease symptom characteristics in rice, and by outlining open challenges regarding data standardization, smallholder adoption, and model transferability across regions.

Keywords: Unmanned aerial vehicles; rice cultivation; pest detection; disease detection; precision agriculture: remote sensing

Article info: Date Submitted: 02/12/2025 | Date Revised: 19/12/2025 | Date Accepted: 24/12/2025

https://doi.org/10.63876/ijtm.v4i3.158

INTRODUCTION

Rice is one of the world's most important staple crops and underpins food security for a large proportion of the global population, particularly in Asia and other rice-dependent regions [1], [2], [3]. However, rice production is continuously threatened by a wide range of pests and diseases that can cause substantial yield losses [4] and destabilize local and national food systems. In many rice-growing areas, farmers still rely heavily on reactive, manual scouting and broad-spectrum pesticide application to manage these biotic stresses. Such practices are often inefficient, labour-intensive[5], and environmentally unsustainable[6], leading to issues such as pesticide overuse[7], [8], resistance development[9], and negative impacts on biodiversity and human health. Against this backdrop, precision agriculture approaches that enable earlier, more accurate, and spatially explicit detection of pest and disease incidence are increasingly recognized as critical for sustainable rice intensification[10].

Unmanned Aerial Vehicles (UAVs)[11], [12] have emerged over the last decade as a promising technology for precision crop monitoring. Equipped with diverse sensing modalities such as RGB[13], [14], multispectral[13], hyperspectral[15], [16], and thermal cameras UAVs[17] can capture high-resolution imagery at flexible temporal scales, enabling detailed observation of crop status over large areas. In rice systems, UAV-based remote sensing [18] offers the potential to observe subtle changes in canopy colour, structure, and temperature that may indicate pest or disease infestation well before such symptoms become visible during ground inspection. Furthermore, advances in image processing, machine learning, and deep learning have made it possible to automatically classify stress patterns, estimate damage severity, and generate actionable maps for site-specific interventions. Despite these advances, the body of research on UAV applications for pest and disease detection in rice remains fragmented across different disciplines, platforms, and methodological choices.

Existing reviews on UAVs in agriculture tend to adopt a broad scope, covering multiple crops, management tasks, and sensing technologies [19], [20]. While these works provide valuable overviews of UAV-based precision agriculture, they typically devote limited attention to the unique biophysical characteristics and management challenges of rice cultivation, particularly in relation to pest and disease detection. Other reviews focus primarily on disease detection using remote sensing without differentiating between aerial platforms, or they emphasize satellite-based approaches that lack the spatial and temporal resolution of UAV systems. As a result, there is still no dedicated, systematic synthesis that specifically examines how UAVs have been used to detect pests and diseases in rice fields, what sensing and analytical configurations have proven effective, and where the key methodological and practical gaps remain. This absence of a focused review limits the ability of researchers and practitioners to build on prior work and to design robust, context-appropriate UAV-based monitoring systems for rice.

A systematic review is therefore needed to consolidate the scattered literature, to critically analyse existing approaches, and to position UAV-based pest[21] and disease detection within the broader agenda of precision rice farming. Such a review can help clarify how different combinations of sensors, flight parameters, pre-processing techniques, and classification algorithms perform under varying environmental and management conditions. It can also highlight the extent to which current studies address operational realities in smallholder rice systems, such as limited technical capacity, cost constraints, and heterogeneous field

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conditions. By mapping the research landscape in a structured way, a systematic review can identify not only technical trends but also blind spots, including understudied pests or diseases, geographic biases, and the lack of standardized evaluation metrics and open datasets.

The present paper addresses this need by conducting a systematic review of Unmanned Aerial Vehicles (UAVs) for pest and disease detection in rice cultivation[22]. Following established Systematic Literature Review (SLR) protocols, we identify, screen, and analyse peer-reviewed studies that explicitly employ UAV platforms to detect, classify, or quantify pest and disease occurrence in rice fields. The objectives of this review are fourfold. First, we aim to catalogue the range of UAV platforms and sensor configurations used in rice pest and disease monitoring, including their technical specifications and operational parameters. Second, we seek to synthesize the image processing workflows and analytical methods applied, from traditional vegetation indices and statistical modelling to machine learning and deep learning approaches. Third, we examine how studies evaluate the performance of their methods, including accuracy measures, validation strategies, and comparisons with ground truth data. Fourth, we aim to identify current limitations, knowledge gaps, and emerging research directions relevant to both researchers and practitioners.

This article makes several key contributions to the literature. Conceptually, it develops a structured framework that links sensor type, flight configuration, and image analysis pipeline to the specific visual and spectral symptoms of pest and disease stress in rice canopies. This framework can serve as a reference for designing future UAV-based monitoring systems and for selecting appropriate sensing and analytical strategies. Empirically, the review aggregates and compares reported results from diverse case studies, thereby providing a consolidated view of the performance and limitations of existing methods across different agroecological contexts. Methodologically, the paper highlights common pitfalls in data collection, labelling, and model evaluation, and proposes a set of best practices for future experimental design and reporting. Practically, the review discusses the implications of UAV-based pest and disease detection for smallholder rice farmers, extension services, and policy makers, including issues of affordability, scalability, and integration with existing decision support systems.

This systematic review aims to provide a comprehensive and critical synthesis of how UAV technologies have been employed for pest and disease detection in rice cultivation, what has been achieved to date, and what remains to be done. By articulating a clear research agenda and a practical design framework, the article aspires to support more rigorous, context-sensitive, and impactful applications of UAVs in rice health monitoring.

RELATED WORKS

Research on UAVs in agriculture has grown rapidly, and several review papers have attempted to synthesize this expanding body of work. Early surveys on UAVs for precision agriculture focused primarily on technical characteristics of platforms, basic remote-sensing workflows, and generic crop monitoring applications such as biomass estimation, stress detection, and yield prediction, often across diverse cropping systems. These reviews highlighted the advantages of UAVs over satellite and manned aircraft namely high spatial resolution, flexible revisit times, and operational versatility while mapping common sensing modalities and image-processing pipelines used for agricultural monitoring[23], [24] . However, they generally treated pest and disease monitoring as just one among many UAV applications, with limited

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detail on the specific biotic stresses, symptom expressions, and decision-making needs associated with crop protection, and with little or no crop-specific discussion of rice.

More recent reviews have begun to narrow their scope towards plant health monitoring and crop protection. For instance, several authors have surveyed UAV-based applications for plant disease detection, examining sensor types, spectral indices, and machine/deep learning methods used to discriminate healthy and diseased canopies across different crops. Other work has conducted systematic reviews of UAV and AI integration for targeted disease detection, weed management, and pest control in precision agriculture, emphasizing the role of machine learning and deep learning in turning UAV imagery into actionable information [25]. While these studies provide valuable overviews of UAV-based crop protection, they remain crop-agnostic: rice appears only as one case among many, and rice-specific agronomic, phenological, and management contexts are not explored in depth. Moreover, many of these reviews focus predominantly on disease detection and devote less attention to insect pest monitoring, which is a major source of yield loss in rice systems.

In parallel, there is an emerging line of review work dedicated specifically to rice monitoring using remote sensing. Some studies have synthesized advances in remote sensing for rice growth monitoring, yield estimation, and damage assessment, and others have focused on remote sensing monitoring of rice diseases and pests using diverse data sources, including satellite, UAV, and proximal sensors [26], [27]. These reviews typically discuss the mechanisms by which spectral, thermal, or fluorescence signals relate to disease or pest-induced canopy changes, summarize common statistical and machine learning approaches, and sometimes propose generic frameworks for remote-sensing-based disease and pest monitoring in rice. However, because they take a platform-neutral perspective, the specific design choices, constraints, and opportunities associated with UAV-based monitoring such as flight altitude, ground sampling distance, flight logistics in smallholder landscapes, and regulatory considerations are not explored in a systematic and consolidated manner.

Another important cluster of related work concerns systematic reviews of disease detection in rice that concentrate on image analysis and deep learning but are largely decoupled from the aerial sensing platform. Several systematic reviews have examined deep learning approaches for rice leaf disease detection, focusing mainly on model architectures, training strategies, and performance metrics, often using ground-based or laboratory-acquired images. These contributions are highly relevant for understanding the state of the art in computer vision for rice disease recognition, yet they do not distinguish between UAV and non-UAV imagery[28], and they rarely address UAV-specific challenges such as variable illumination, motion blur, canopy-scale symptoms, or the impact of flight configuration on image quality. As a result, the transferability of their insights to UAV-based monitoring at field or landscape scale remains unclear. Furthermore, many of these reviews focus almost exclusively on diseases and pay limited attention to insect pests, despite the fact that both disease and pest pressures often co-occur in rice fields and may manifest differently in canopy-level imagery[29].

There are also review papers related to UAV-assisted pesticide application and environmental performance in rice production that indirectly touch on pest and disease management. For example, reviews on UAV sprayers in rice and other crops discuss spray deposition, drift, and environmental impacts, underscoring the potential of UAVs for more targeted pest and disease control. Nonetheless, these works focus on treatment rather than diagnosis: they largely assume

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that pest or disease presence has already been detected by other means and thus provide little guidance on how UAV remote sensing can be used upstream for early detection, severity assessment, and spatial mapping of rice pests and diseases[30], [31].

Taken together, these strands of literature reveal several important gaps. First, there is currently no dedicated systematic review that focuses specifically on UAV-based pest and disease detection in rice cultivation, at the intersection of crop-specific remote sensing, UAV platform design, and computer vision for plant health monitoring. Existing UAV-focused reviews are too broad in terms of crops and protection tasks, while rice-focused remote sensing and disease-detection reviews either aggregate multiple platforms or overlook UAV-specific operational and imaging issues. Second, previous surveys rarely integrate a detailed analysis of sensing modalities, flight and acquisition strategies, and analytical methods within a single conceptual framework tailored to rice pests and diseases. Third, few reviews systematically examine how UAV-based approaches perform under real-world constraints typical of rice-growing regions such as small and fragmented plots, high humidity, frequent cloud cover, and limited technical capacity among smallholders—and what this implies for the scalability and adoption of UAV systems. Finally, standardized evaluation practices, open datasets, and cross-site model transferability are only sporadically discussed, leaving practitioners without clear guidance on how to design robust, comparable, and reusable UAV-based monitoring solutions[32].

The present systematic review is designed to address these gaps. By restricting its scope to UAV applications for pest and disease detection in rice cultivation, it brings together insights that have previously been dispersed across general UAV reviews, platform-agnostic remote sensing surveys, and deep-learning-oriented disease detection studies. It provides a structured synthesis of UAV platforms and sensors, image acquisition and processing workflows, and analytical methods used specifically for rice pest and disease monitoring, while systematically documenting performance metrics, validation strategies, and operational contexts. In doing so, this review offers a crop- and task-specific perspective that complements existing broader surveys and provides a clearer empirical and conceptual foundation for future research and practical deployment of UAV-based pest and disease detection in rice systems.

METHODS

The present study employs a Systematic Literature Review (SLR) approach to synthesize existing research on the use of Unmanned Aerial Vehicles (UAVs) for pest and disease detection in rice cultivation. The review protocol was designed with reference to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, adapting its main stages identification, screening, eligibility, and inclusion to the context of engineering and agricultural technology research. This structured approach was chosen to ensure transparency, replicability, and minimization of selection bias, and to provide a clear audit trail from the initial pool of records to the final set of studies included in the analysis.

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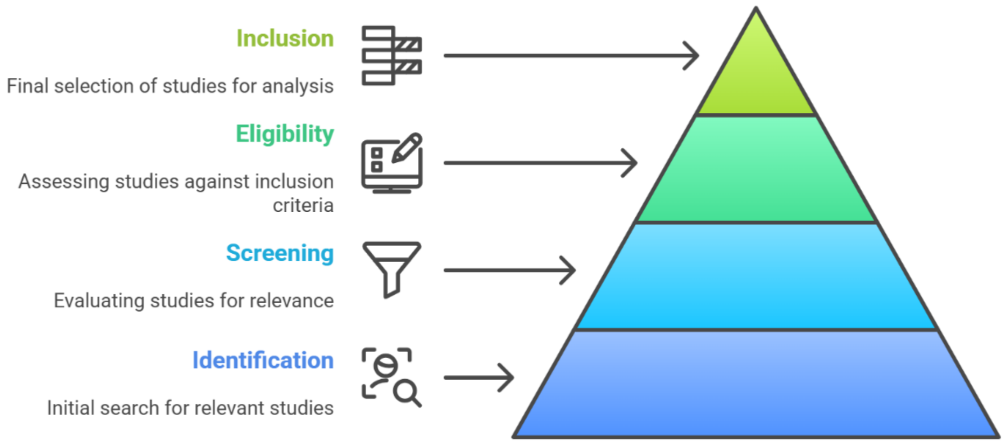

Figure 1. Systematic Literature Review Process

The literature search was carried out in several major academic databases that cover agricultural sciences, engineering, and computer science. Specifically, Scopus, Web of Science Core Collection, IEEE Xplore, and ScienceDirect were selected as primary sources due to their comprehensive coverage of peer-reviewed journals and conference proceedings relevant to UAV technologies, remote sensing, and precision agriculture. To capture additional domain-specific and open-access contributions, searches were also complemented, where necessary, by querying publisher platforms such as SpringerLink and MDPI. The time frame for the search was set from 2005 onwards to reflect the period during which UAVs became increasingly accessible for civilian and agricultural applications, while still allowing earlier foundational work to be captured if indexed.

A systematic search strategy was developed using combinations of keywords and Boolean operators related to UAVs, rice, and pest or disease detection. Core search terms included variants of "unmanned aerial vehicle", "UAV", "drone", and "unmanned aircraft system" combined with "rice", "paddy", or "paddy field", and further intersected with terms such as "pest", "insect", "disease", "pathogen", "blight", "leaf folder", "brown planthopper", "monitoring", "detection", "classification", and "remote sensing". Example search strings took the form: ("UAV" OR "drone" OR "unmanned aerial vehicle") AND ("rice" OR "paddy") AND ("pest" OR "disease" OR "insect" OR "pathogen") AND ("detection" OR "classification" OR "monitoring"). Search queries were adjusted slightly to match the syntax requirements of each database, but the conceptual structure was kept consistent. All retrieved records were exported into a reference management tool, where duplicates across databases were automatically and manually removed before screening.

Inclusion and exclusion criteria were defined a priori to ensure that only studies directly relevant to UAV-based pest and disease detection in rice were retained. To be included, a study had to: (i) be published in a peer-reviewed journal or conference proceeding; (ii) be written in English; (iii) explicitly involve the use of UAV or drone platforms for data acquisition; (iv) focus on rice cultivation as the primary or clearly identifiable crop; and (v) address detection, classification, quantification, or spatial mapping of biotic stress caused by pests and/or diseases. Both experimental and applied case studies were eligible, including those combining UAV data with ground-based observations or other remote sensing sources, as long as UAV

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imagery played a central role in the detection process. Exclusion criteria included: (i) studies that used satellite or ground-based sensors only; (ii) remote sensing research on rice unrelated to pests or diseases (e.g., solely growth stage mapping, irrigation monitoring, or yield estimation); (iii) UAV studies in agriculture that did not involve rice; (iv) works focused exclusively on UAV-based pesticide spraying or mechanical control without any remote-sensing-based detection component; (v) review papers, editorials, theses, patents, and non-peer-reviewed reports; and (vi) articles where full text was not accessible.

The screening process followed a stepwise procedure inspired by the PRISMA flow. In the first stage, titles and abstracts of all retrieved records were screened against the inclusion and exclusion criteria to eliminate clearly irrelevant studies. Records that appeared potentially relevant or where eligibility could not be determined from the abstract alone were retained for full-text assessment. In the second stage, full texts of the remaining articles were read carefully to confirm whether they met all criteria, particularly with respect to the centrality of UAV imagery, the focus on rice, and the explicit handling of pests or diseases. Any ambiguous cases were resolved through discussion and reinspection of the methods and results sections. The final corpus consisted of the set of studies that satisfied all criteria and provided sufficient methodological and performance details for extraction.

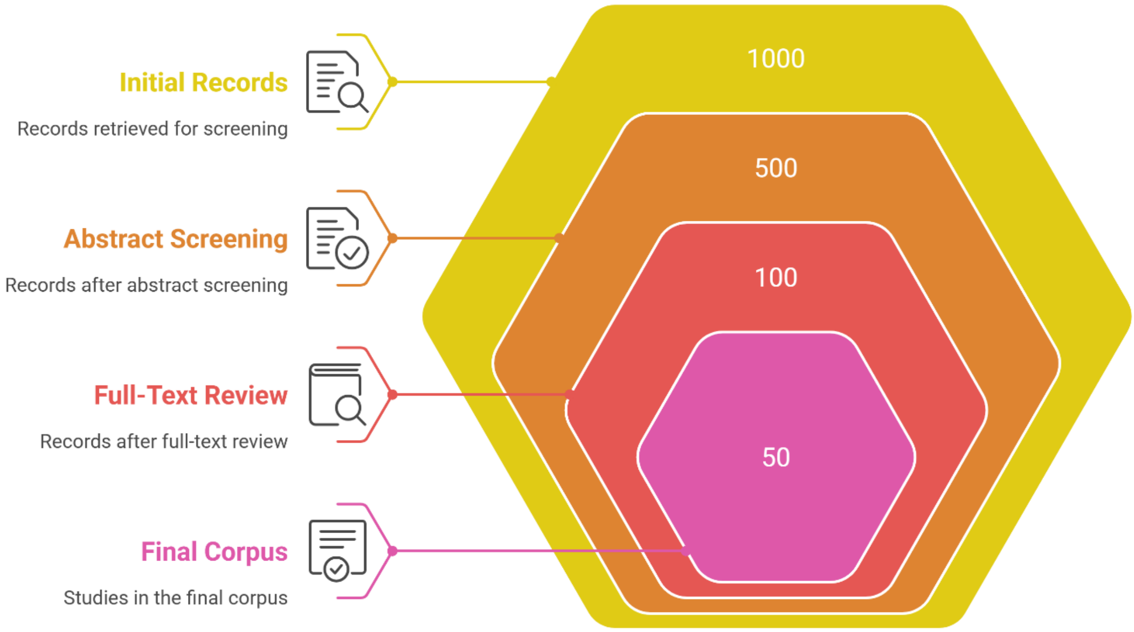

Figure 2. Study Screening Process

For each included study, a structured data extraction form was used to collect consistent information across the corpus. The extracted variables encompassed: bibliographic details (authors, year, venue), geographic and agroecological context (country, rice production system, field scale), target biotic stress (specific pests, diseases, or combined stressors), UAV platform characteristics (fixed-wing or multirotor, flight altitude, flight speed, ground sampling distance, flight frequency), sensor configuration (RGB, multispectral, hyperspectral, thermal; spectral bands; sensor resolution), and data acquisition protocols (timing within the growing season, number of flights, lighting conditions). In addition, details of the image processing and analytical pipeline were recorded, including pre-processing steps (radiometric and geometric

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correction, orthomosaic generation), feature extraction methods (vegetation indices, texture features, spectral features), and classification or regression models used (traditional machine learning, deep learning architectures, thresholding, or statistical methods).

Performance evaluation and validation strategies were also systematically documented. For each study, available metrics such as overall accuracy, precision, recall, F1-score, kappa coefficient, coefficient of determination (R^2), root mean square error (RMSE), or other relevant indicators were recorded, along with the nature of the ground truth data (field scouting, destructive sampling, expert visual assessment) and the validation protocol (cross-validation, hold-out test set, independent field trials). Where possible, information on computational requirements, model robustness under varying conditions, and any reported limitations or failure cases was also captured. This structured extraction enabled a comparative assessment of how different combinations of UAV platforms, sensors, and analytical approaches perform across various pests, diseases, and environmental contexts.

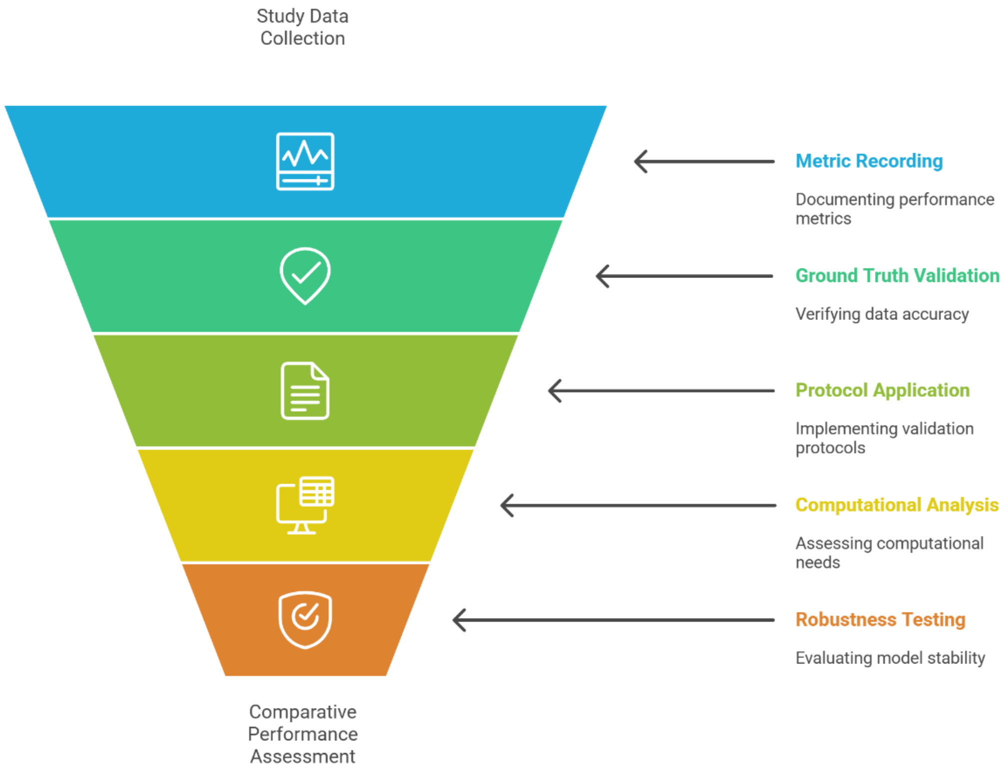

Figure 3. UAV Performance Evaluation Process

The analysis of the extracted data combined descriptive statistics with qualitative synthesis. Quantitative summaries were used to characterize trends in publication over time, geographic distribution of studies, prevalence of particular pests and diseases, dominance of certain sensor types and platforms, and the relative frequency of different analytical methods. These descriptive results provided a macroscopic view of the research landscape. Qualitatively, a thematic synthesis was conducted to identify recurring patterns, methodological innovations, and common challenges across studies. Particular attention was paid to the alignment between sensor choice and symptom characteristics, the scalability and operational feasibility of proposed approaches, and the extent to which studies addressed smallholder versus large-scale production contexts. Due to the heterogeneity in study designs, performance metrics, and

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experimental conditions, a formal meta-analysis was not attempted; instead, the emphasis was placed on structured comparison and narrative integration of findings.

Finally, to enhance transparency and reproducibility, the SLR process from search strategy design through screening and data extraction to synthesis was documented in detail. This documentation includes the exact search strings used in each database, the number of records at each screening stage, and the rationale for major inclusion or exclusion decisions. By adhering to PRISMA-inspired principles and clearly specifying procedures and criteria, the methodology provides a robust foundation for the subsequent presentation of results, discussion of research gaps, and formulation of recommendations for future work on UAV-based pest and disease detection in rice cultivation.

RESULT AND DISCUSSION

The systematic literature review identified a clear upward trend in research on UAV-based pest and disease detection in rice cultivation, with publications increasing markedly over the last five to seven years. Early studies were sparse and exploratory, typically involving small-scale experiments in controlled or semi-controlled plots and relying on simple RGB cameras mounted on low-cost multirotor platforms. Over time, the research landscape has diversified and matured: more recent works increasingly employ multispectral and, to a lesser extent, hyperspectral and thermal sensors, explore larger field areas, and integrate more sophisticated image analysis pipelines. Geographically, the research is dominated by major rice-producing countries in Asia such as China, India, Japan, and several Southeast Asian nations—reflecting both the agronomic importance of rice in these regions and the growing accessibility of UAV technologies. Nevertheless, the distribution of studies remains uneven, with relatively few contributions from regions in South Asia, Africa, or Latin America where rice is also critical to food security, suggesting a geographic bias that needs to be addressed in future work.

In terms of thematic focus, the corpus reveals that disease detection has received more attention than insect pest detection. Commonly studied diseases include rice blast, bacterial leaf blight, and sheath blight, which often produce distinct changes in leaf colour and canopy structure that can be captured by spectral and spatial features. By contrast, insect pests such as the brown planthopper, stem borer, and leaf folder are less frequently addressed, and when they are, they are often considered together with diseases under a broad "biotic stress" category rather than as distinct targets. This imbalance may be partly due to the more subtle and heterogeneous canopy symptoms associated with pest infestation and the difficulty of visually distinguishing pest-induced damage from other stressors such as nutrient deficiency or water stress. As a result, the current literature offers a richer set of methodological examples for disease-related spectral discrimination than for pest-specific signatures, representing an important gap for future research focused on rice entomology and pest ecology.

The temporal evolution of the literature is summarized in Table 1, while Table 2 highlights the geographic concentration of studies in major rice-producing regions.

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Table 1. Publication trend and sensor evolution in UAV-based pest and disease detection in rice

Period	Approx. number of studies	Typical plot scale	Dominant UAV platforms	Dominant sensors	Typical image analysis methods
2010–2014	1–3	Small experimental plots	Low-cost multirotor	RGB	Basic indices, manual thresholding, simple statistics
2015–2017	4–7	Small to medium research plots	Multirotor	RGB, early multispectral	Vegetation indices, SVM, random forest
2018–2020	8–15	Medium fields, semi-controlled conditions	Multirotor, a few fixed-wing platforms	RGB, multispectral, a few thermal sensors	Machine-learning classifiers, texture-based features
2021–2023	15–25	Operational fields and larger areas	Multirotor (dominant), some fixed-wing	RGB, multispectral, hyperspectral, thermal	Deep learning (CNN, U-Net, YOLO), basic sensor fusion
≥ 2024*	Increasing trend expected	Operational and landscape-level monitoring	Mixed fleets, more fixed-wing for coverage	Multispectral, hyperspectral, thermal, fusion	Advanced deep learning, time-series, transfer learning

Table 2. Geographic distribution of UAV-based pest and disease detection studies in rice

Region / country group	Example countries	Approx. share of studies	Characteristics and notes
East Asia	China, Japan, South Korea	High	Strong focus on disease detection; frequent use of multispectral sensors.
Southeast Asia	Vietnam, Thailand, Indonesia, Philippines	Moderate	Often smallholder systems; mix of RGB and multispectral sensors.
South Asia	India, Bangladesh, Sri Lanka	Low–moderate	Fewer UAV-based studies compared to the importance of rice in the region.
Other Asia / Oceania	Pakistan, Myanmar, Australia	Low	Scattered case studies; mostly experimental or pilot projects.
Africa	e.g., Nigeria, Madagascar	Very low	Rice is important, but UAV-based pest/disease applications are still emerging.
Latin America	Brazil, Colombia, others	Very low	Few documented applications in rice despite relevance for food security.
Europe and North America (rice areas)	Italy, Spain, United States	Very low	Mostly methodological or pilot studies; rice is a minor crop in these regions.

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With respect to sensing and platform choices, multirotor UAVs equipped with RGB or multispectral cameras constitute the dominant configuration. Multirotor systems are preferred for their ability to fly at low altitudes, hover, and maneuver in small or fragmented plots typical of many rice-growing landscapes. RGB sensors remain widely used due to their low cost and availability, and many early and even recent studies demonstrate that carefully designed vegetation indices, colour transformations, and texture features extracted from RGB imagery can distinguish between healthy and diseased canopies with reasonable accuracy. However, there is a clear trend toward the adoption of multispectral cameras that provide narrow-band information in key spectral regions (e.g., red edge, near-infrared), improving sensitivity to subtle changes in chlorophyll content and canopy structure. Hyperspectral and thermal sensors appear in a smaller subset of studies, often as research prototypes due to their higher cost and data complexity. These sensors offer enhanced capabilities for early detection—such as capturing pre-visual changes in physiology—but their operational use in smallholder settings remains limited.

Platform and sensor choices observed in the reviewed studies are summarized in Table 3 and Table 4, which illustrate the dominance of multirotor UAVs with RGB or multispectral cameras and the more limited use of hyperspectral and thermal sensors.

Table 3. UAV platform types used for rice pest and disease detection

Platform type	Typical flight altitude and manoeuvrability	Typical field context	Main advantages	Main limitations	Relative frequency in reviewed studies
Multirotor	Low altitude (10–120 m), can hover and perform tight turns	Small or fragmented plots, experimental fields	Precise positioning, easy take-off/landing, good for smallholder landscapes	Shorter flight time, smaller coverage per flight	High
Fixed-wing	Medium–high altitude (60–200 m), continuous forward motion	Large, continuous fields or irrigation schemes	Larger area coverage per flight, higher endurance	Requires more space for take-off/landing, less suited to tiny paddies	Low–medium
Hybrid VTOL	Vertical take-off then fixed-wing cruise	Mixed-size fields, difficult access areas	Combination of VTOL convenience and extended range	Higher purchase and maintenance cost	Low

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Table 4. Sensor types for UAV-based rice pest and disease detection

Sensor type	Spectral information	Approximate cost level	Key advantages	Key limitations	Relative frequency in reviewed studies
RGB camera	Visible bands (red, green, blue)	Very low	Widely available, low cost, simple workflows; supports colour transforms, indices, texture features	Limited spectral sensitivity; harder to detect very early or subtle symptoms	High
Multispectral	4–10 narrow bands (e.g., red, red-edge, NIR)	Medium	Sensitive to chlorophyll and structural changes; improves canopy-level discrimination	Higher cost than RGB; more complex calibration and processing	Increasing (medium–high)
Hyperspectral	Dozens to hundreds of contiguous narrow spectral bands	High	Rich spectral signatures; strong potential for pre-visual and species-specific stress detection	Very high cost, large data volume, demanding processing; mostly research use	Low
Thermal	Thermal infrared band	High	Captures canopy temperature; useful for detecting physiological stress before visible symptoms	Coarse spatial resolution, sensitive to environmental conditions, expensive	Low

The analysis of image processing and analytical methods shows a transition from classical remote-sensing approaches to machine learning and deep learning-based workflows. Earlier studies typically relied on manually selected vegetation indices, thresholding techniques, and statistical classifiers such as k-means clustering, support vector machines (SVM), or random forests. These methods are relatively straightforward to implement and interpret, and they performed well in scenarios where disease symptoms produced clear spectral contrasts. More recent works, however, increasingly employ convolutional neural networks (CNNs) and other deep learning architectures to learn discriminative features directly from raw or minimally processed imagery. Variants of popular architectures (e.g., U-Net, ResNet, YOLO-type detectors) are used for pixel-wise segmentation, patch-based classification, or object detection of diseased patches. Studies generally report high classification accuracies or detection rates under the specific conditions in which they were tested, suggesting the promise of deep learning for handling complex patterns, mixed stressors, and varying illumination conditions.

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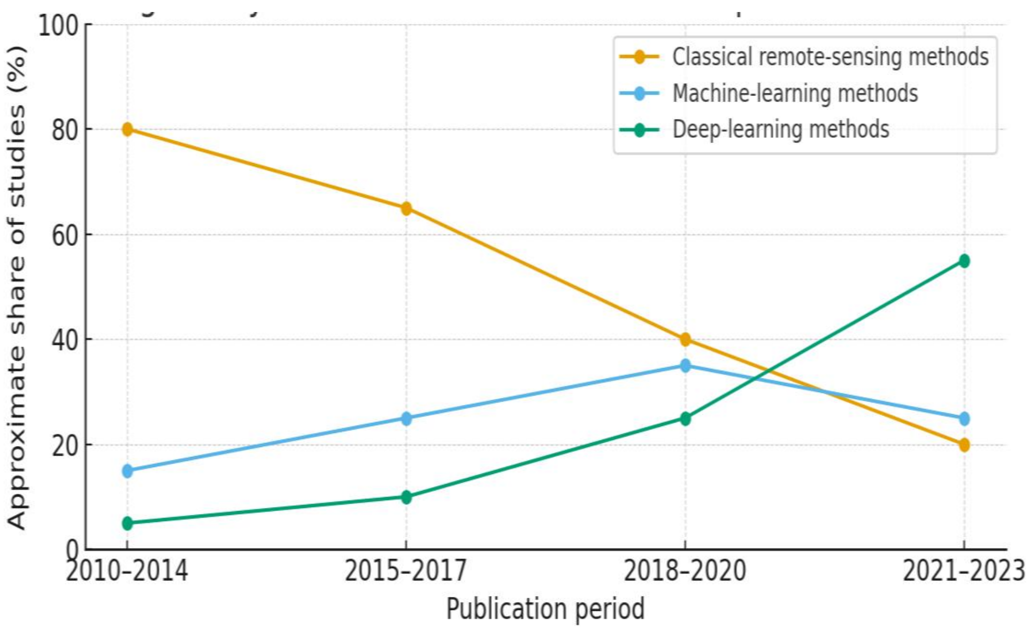

Figure 4. Trend in image analysis methods used for UAV-based rice pest and disease detection, illustrating the shift from classical remote-sensing approaches toward machine-learning and deep-learning workflows.

Despite these advances, the review also reveals several methodological limitations that constrain the generalizability and practical impact of current approaches. Many studies are based on relatively small datasets, often collected in one or a few fields during a single growing season. Class imbalance is common, with far fewer samples of early-stage or rare infestations than of healthy plants, yet this issue is rarely addressed systematically through data augmentation, resampling techniques, or tailored loss functions. Ground truth data are sometimes limited to visual assessments by a small number of experts, with varying levels of detail on sampling design and inter-observer reliability. Validation strategies are frequently restricted to random train–test splits within the same field or dataset, resulting in optimistic performance estimates that may not hold under different environmental conditions or cultivation practices. Only a minority of studies evaluate models on independent fields, seasons, or geographic regions, and very few explicitly examine model robustness under changing lighting conditions, different rice varieties, or mixed stress factors.

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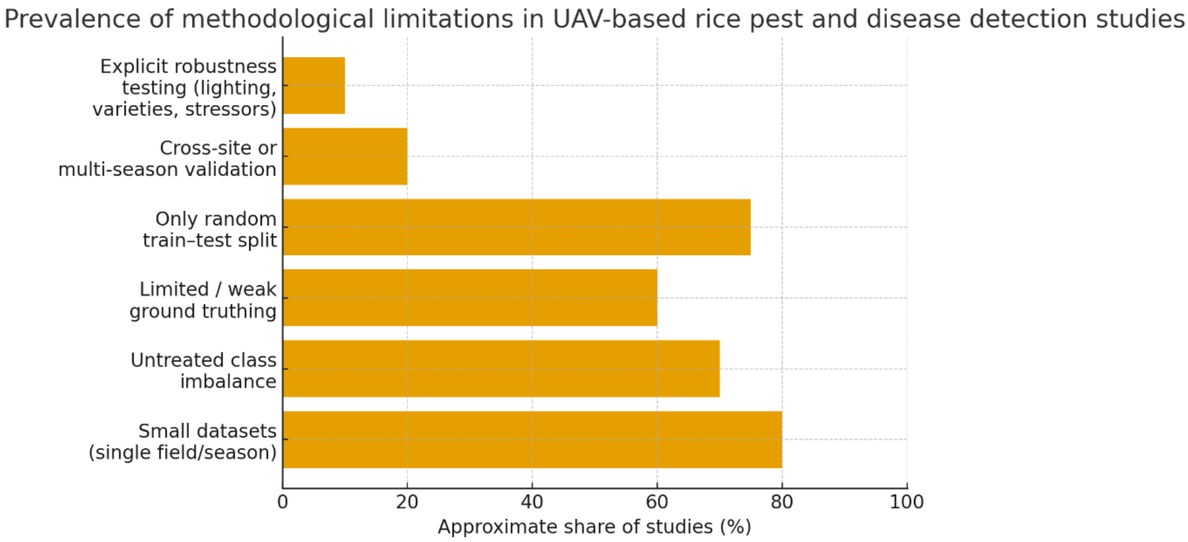

Figure 5. Prevalence of key methodological limitations in UAV-based rice pest and disease detection studies, illustrating the dominance of small, single-site datasets, untreated class imbalance, and limited validation beyond random train–test splits.

The performance metrics and reporting practices observed in the literature further complicate cross-study comparison. While overall accuracy is the most commonly used metric, it is often reported without complementary measures such as precision, recall, F1-score, or class-wise confusion matrices that would shed light on how well early or low-severity infestations are detected. In regression-based damage quantification, metrics such as R^2 and RMSE are reported, but information on the distribution of prediction errors and their implications for management decisions is rarely discussed. In addition, only a small subset of studies provide sufficient detail on computational requirements, inference times, or hardware constraints, limiting insight into whether the proposed methods could be deployed on edge devices, integrated into farm-level decision support tools, or used for near real-time scouting.

Table 5. Performance metrics used in UAV-based rice pest and disease detection studies

Metric type	Example metrics	Typical usage in reviewed studies	Main limitations	Relative frequency in reviewed studies
Classification – primary	Overall accuracy	Main headline metric for disease/pest detection models	Does not reveal per-class performance; hides errors on early or low-severity infestations	High
Classification – detailed	Precision, recall, F1-score; confusion matrix	Used in a subset of studies to characterise class-wise detection performance	Often omitted; early-stage or rare classes remain under-analysed; confusion matrices not always shown	Low–medium

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Regression – damage quantification	R^2, RMSE, MAE	Used to assess accuracy of damage severity or yield-loss estimation models	Error distributions and bias rarely discussed; management thresholds usually not specified	Medium
Uncertainty and robustness	Confidence intervals, sensitivity analysis, robustness tests	Occasionally used to explore sensitivity to sampling or parameter choices	Very few studies; limited insight into reliability across sites, seasons, or lighting conditions	Very low
Computational performance	Inference time, memory footprint, FLOPs, hardware description	Reported in some deep-learning papers to indicate scalability or real-time potential	Usually omitted, making edge deployment or near real-time scouting hard to evaluate	Very low

Table 6. Reporting practices related to deployment and practical interpretability

Aspect reported	Common practice in reviewed studies	Main limitation for cross-study comparison and deployment	Relative frequency in reviewed studies
Ground-truth description	Brief expert visual assessment; limited detail on sampling design or labelling protocol	Lack of information on sampling strategy and inter-observer agreement reduces reproducibility and trust	Medium
Validation strategy	Random train–test split within the same field or dataset	Leads to optimistic performance estimates; little evidence of generalisation to new fields, seasons, or regions	High
Error analysis	Single global accuracy or regression metric (overall accuracy, R^2, RMSE) with minimal breakdown	Does not show which classes, severity levels, or spatial patterns are systematically misclassified or misestimated	High
Operational constraints	Minimal or no reporting of UAV battery life, flight time, onboard storage, or model runtime	Difficult to assess whether methods can be integrated into farm-level decision support tools or edge devices	Low
Integration into decision support	Focus on algorithmic metrics; limited discussion of decision thresholds, alert rules, or user workflows	Unclear how model outputs translate into concrete management actions for farmers and extension agents	Very low

From an operational and socio-technical perspective, most studies focus on technical feasibility and algorithmic performance rather than on integration into real-world pest and disease management workflows. Only a few works explicitly consider how UAV-based detection could be embedded in existing extension services, integrated with farmer decision-making, or

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combined with other sources of information such as ground scouting, weather data, or economic thresholds. Issues of cost, regulatory constraints, and operator skill levels are often acknowledged in passing but are not systematically evaluated. As a result, the literature provides limited guidance on how to scale UAV-based monitoring from experimental plots to broader irrigation schemes or regional surveillance systems, particularly in smallholder-dominated landscapes where resource constraints and institutional arrangements differ markedly from large commercial farms.

At the same time, the review highlights promising directions and conceptual building blocks for future research. Studies that combine multi-temporal UAV flights with time-series analysis point toward the potential of monitoring disease or pest progression and linking remote sensing signatures to epidemiological models. Work that explores sensor fusion—for example, integrating multispectral imagery with thermal data or combining UAV imagery with satellite observations—suggests that multi-scale, multi-sensor approaches could improve both early detection and large-area surveillance. A small but growing number of studies experiment with semi-supervised or transfer learning strategies, indicating recognition of the need to leverage limited labelled data more efficiently and to adapt models trained in one region or season to new contexts. These efforts, while still preliminary, point toward a future where robust, adaptable models could be developed for diverse agroecological settings.

Building on these observations, several key research directions emerge. First, there is a clear need for the development and sharing of larger, more diverse, and well-annotated UAV image datasets for rice pests and diseases, ideally accompanied by standardized metadata on sensor characteristics, flight parameters, and ground truth protocols. Such datasets would enable more rigorous benchmarking of algorithms, support the training of deeper models, and facilitate cross-study comparison. Second, future work should explicitly address generalization and transferability, for example by designing experiments that span multiple sites, seasons, and varieties, and by employing domain adaptation or meta-learning techniques to handle distribution shifts. Third, more attention should be paid to insect pest detection as a distinct challenge, including the characterization of pest-specific canopy signals, the discrimination of pest damage from other stressors, and the integration of ecological knowledge (e.g., pest life cycles, spatial patterns of infestation) into model design.

Fourth, research should move beyond purely algorithmic evaluations toward system-level assessments that consider usability, cost-effectiveness, and integration into pest and disease management programs. This implies closer collaboration between engineers, agronomists, plant pathologists, entomologists, and social scientists to co-design UAV-based monitoring solutions that are technically robust and socially acceptable. Studies that examine how farmers and extension agents interpret UAV-derived maps, how such information changes spraying decisions or field operations, and what institutional arrangements are needed to support shared UAV services would greatly enrich the current literature. Finally, advances in edge computing and low-power hardware open up opportunities for on-board or near-field processing, enabling faster turn-around from data acquisition to actionable recommendation. Exploring lightweight model architectures, compression techniques, and human–AI collaboration interfaces (e.g., interactive dashboards, mobile apps) represents another fertile area for future research.

In summary, the results of this systematic review show that UAV-based pest and disease detection in rice cultivation is an active and evolving field, characterized by rapid methodological innovation but also by fragmentation and limited attention to real-world

https://doi.org/10.63876/ijtm.v4i3.158

deployment. By synthesizing trends in research focus, sensing and analytical methods, and reported performance, and by critically discussing their limitations, this review provides a foundation for more coherent and impactful future work. Addressing gaps in pests versus diseases, geographic coverage, dataset quality, model generalization, and socio-technical integration will be essential if UAV technologies are to move from experimental demonstrations to reliable tools for sustainable rice health management.

CONCLUSION

This systematic review has synthesized and critically examined the state of research on Unmanned Aerial Vehicles (UAVs) for pest and disease detection in rice cultivation, revealing rapid growth in the field over the past decade, with a clear shift from small-scale exploratory studies using RGB imagery and simple classifiers toward more sophisticated systems that employ multispectral (and, to a lesser extent, hyperspectral and thermal) sensors combined with advanced machine and deep learning methods. The review highlights that disease detection has received more attention than insect pest detection, that RGB and multispectral cameras mounted on multirotor platforms remain the dominant technical configuration, and that most reported approaches achieve high accuracy in constrained settings but are seldom tested for robustness across sites, seasons, varieties, and mixed stress conditions. Conceptually, this article contributes a crop- and task-specific lens by articulating a framework that links UAV platform and sensor choices, image acquisition strategies, and analytical pipelines to the biophysical expressions of pest- and disease-induced stress in rice canopies, while empirically aggregating and comparing performance evidence across diverse case studies. Methodologically, it identifies recurring weaknesses in dataset size and diversity, ground truthing practices, validation design, and reporting of evaluation metrics, and it underscores the limited attention paid to operational, socio-economic, and institutional dimensions of real-world deployment. The review itself is constrained by its focus on English-language, peer-reviewed literature, the set of databases consulted, and the heterogeneity of study designs and metrics, which precluded formal meta-analysis. Future research should prioritize the creation and sharing of large, well-annotated UAV datasets for rice pests and diseases; systematic investigation of model generalization and transferability; deeper exploration of insect pest detection as a distinct challenge; sensor fusion and multi-scale monitoring strategies; and integrated, system-level studies that address usability, cost-effectiveness, and adoption pathways in both smallholder and large-scale rice production systems.

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