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Use of Drones In Crop Health Monitoring: A Comprehensive Review (2014–2025)

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Abstract

Drones (unmanned aerial vehicles, UAVs) have rapidly transitioned from experimental tools to dependable, field-scale systems for crop health monitoring. By delivering on-demand, centimeter-level imagery and thermal/structural measurements, UAVs enable early diagnosis of nutrient limitations, water stress, pest and disease outbreaks, and stand establishment issues. This review synthesizes the state of the art in UAV platforms and sensors (RGB, multispectral, hyperspectral, thermal, LiDAR), radiometric and geometric workflows, vegetation indices and biophysical proxies, and analytics using machine learning and deep learning. Practical agronomic applications—nutrient management, irrigation scheduling, weed mapping, variable-rate prescriptions, lodging assessment, and yield forecasting—are evaluated alongside economics, environmental benefits, and operational constraints. We also discuss policy and capacity considerations for large-scale deployment, with emphasis on emerging markets. Finally, we outline future directions in multimodal sensor fusion, 3D/temporal retrievals, edge autonomy, and foundation AI models for robust, field-ready decision support.

Keywords: UAV; drone; precision agriculture; crop health; NDVI; red-edge; thermal imaging; hyperspectral; LiDAR; CWSI; deep learning; edge AI; variable-rate; phenotyping; radiometric calibration; regulation

1.Introduction

Rising climate variability, input costs, and labor constraints have pushed crop monitoring toward **high-resolution, high-frequency** sensing. UAVs bridge the gap between ground scouting and satellites by supplying **on-demand, centimeter-scale** observations that capture subtle canopy and thermal signals indicative of emerging stress (Guebsi et al., 2024; Zhang et al., 2025; Unde et al., 2025). Sensor miniaturization and reliable flight control have democratized access, while multispectral/red-edge and thermal payloads convert images into **quantitative agronomy** through indices such as NDVI, GNDVI, NDRE, and EVI (Hunt et al., 2013; Tucker, 1979; Huete et al., 2002).

Analytics have evolved from thresholding to **deep learning** pipelines that integrate spectral, textural, and structural cues for detection, grading, and prescription mapping—often accelerated by **edge AI** for near real-time advisories (Radočaj et al., 2025; Upadhyay et al., 2025; Ashurov et al., 2024). Despite this progress, endurance limits, illumination variability, radiometric drift, domain shift across fields/seasons, and regulatory requirements remain practical hurdles (Aasen et al., 2015; Brook et al., 2019; Government of India, 2021).

2. UAV Platforms and Payloads

Platforms. Multirotors offer precise, low-altitude mapping for small–medium fields; fixed-wing systems cover larger acreages efficiently; VTOL hybrids combine runway-free operations with longer range (Zhang et al., 2025; Unde et al., 2025).

Payloads.

- **RGB**: high-resolution texture for stand counts, canopy cover, emergence, lodging (Louargant et al., 2018).
- **Multispectral (Blue/Green/Red/Red-edge/NIR)**: chlorophyll/N proxies and vigor mapping via NDVI, GNDVI, NDRE, EVI (Hunt et al., 2013).
- **Thermal (8–14 µm)**: canopy temperature and **CWSI** for irrigation scheduling and heat-stress diagnostics (Berni et al., 2009; Ndlovu et al., 2024; Jackson et al., 1981).
- **Hyperspectral**: narrow-band retrievals of pigments and water content; powerful but calibration- and data-heavy (Aasen et al., 2018; Pandley et al., 2020).
- **LiDAR / SfM-CHM**: canopy height/structure for biomass, lodging, and yield features (Wallace et al., 2016).

3. Vegetation Indices and Biophysical Proxies

Foundational indices include **NDVI** (Rouse et al., 1974), **GNDVI** (Gitelson et al., 1996), and **EVI** (Huete et al., 2002). Red-edge metrics (e.g., **NDRE**) improve sensitivity in dense canopies and for nitrogen status (Li et al., 2018). Thermal metrics such as **CWSI** quantify water stress and guide irrigation (Jackson et al., 1981; Berni et al., 2009; Deery et al., 2016). Fusing spectral indices with **canopy height models** strengthens biomass and yield inference (Wallace et al., 2016; Madec et al., 2017).

Figure 1. A four-panel multicolored illustration showing drones in crop health monitoring and precision agriculture. Each panel depicts a unique UAV-based function: (A) Vegetation health assessment using optical imagery, (B) Multispectral mapping through digital data transfer, (C) Thermal sensing for water stress detection, and (D) LiDAR or spectral scanning for canopy structure analysis. The image visually merges captions within each section, representing the technological diversity and sustainability focus of drone-assisted smart farming.

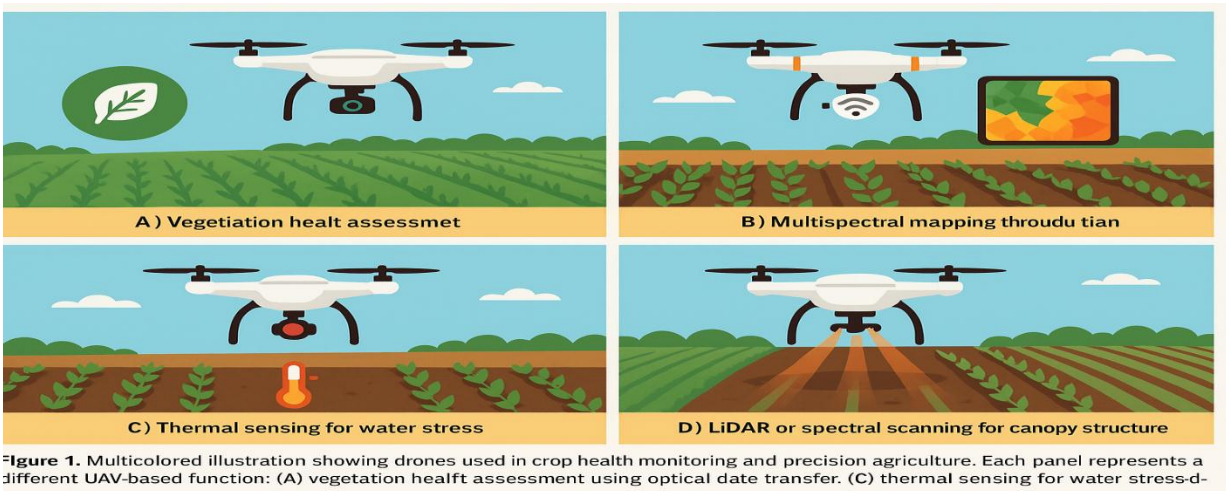

Table 1. Common UAV Sensors, Example Indices, and Core Crop-Health Use-Cases

Sensor	Bands	Typical GSD @120 m	Indices / Features	Primary use-cases
RGB	R,G,B	2–4 cm	VARI, excess-green, canopy cover, texture	stand/emergence counts; lodging; weed patches (Louargant et al., 2018)
Multispectral	B,G,R,RE,NIR	5–10 cm	NDVI, GNDVI, NDRE, EVI	vigor; N status; early disease cues (Hunt et al., 2013; Li et al., 2018)
Thermal LWIR	8–14 µm	8–20 cm	canopy temperature, **CWSI**	irrigation scheduling; heat stress (Berni et al., 2009; Deery et al., 2016)
Hyperspectral	30–150 narrow bands	5–15 cm	pigment/water proxies, red-edge shape	nutrient/disease chemistry (Aasen et al., 2018; Pandley et al., 2020)
LiDAR / SfM-CHM	laser / 3D	5–15 cm height	CHM, gap/roughness metrics	biomass; lodging; yield features (Wallace et al., 2016; Madec et al., 2017)

4. Flight, Calibration, and Processing Workflow

Best practice emphasizes **mission planning** (GSD targets; ≥70–80% overlap/sidelap), **radiometric discipline** (reflectance panels; downwelling light sensors), and **precise georeferencing** (RTK/PPK) (Aasen et al., 2015; Daponte et al., 2019). Processing typically follows: image QA → orthomosaic/DSM/CHM → reflectance conversion → index computation → analytics (Kamilaris & Prenafeta-Boldú, 2018; Torres-Sánchez et al., 2015). Consistency across dates requires attention to **illumination/BRDF** and phenological stage (Brook et al., 2019)

5. Analytics: Machine Learning, Deep Learning, and Edge AI

Classical ML (RF, SVM) leveraging indices/textures has been eclipsed by **CNN/Transformer** models for object- and pixel-level tasks in disease and weed mapping (Kamilaris & Prenafeta-Boldú, 2018; Ashurov et al., 2024; Radočaj et al., 2025). **Multimodal fusion** (RGB+multispectral+thermal) improves discrimination between nutrient, water, and pathogen stresses (Deery et al., 2016). Emerging trends include **self-supervised pretraining**, **few-shot transfer** to new crops, **explainability**, and **on-board inference** (Elfouly et al., 2025; Upadhyay et al., 2025).

6. Agronomic Applications

6.1 Nutrient and Vigor Monitoring

Red-edge/NIR features correlate with chlorophyll and **nitrogen status**, enabling top-dressing and zone management (Hunt et al., 2013; Li et al., 2018). UAV-guided variable-rate management has improved efficiency and reduced input waste in field trials (Roth et al., 2021).

6.2 Water Stress & Irrigation

Thermal imaging with **CWSI** supports timing and zoning of irrigation; fusion with multispectral data separates heat and nutrient stress (Jackson et al., 1981; Berni et al., 2009; Deery et al., 2016; Ndlovu et al., 2024).

6.3 Pest and Disease Detection

Deep models detect and grade infections (e.g., late blight, rust) before canopy-wide symptoms, enabling targeted responses (Mohanty et al., 2016; Polder et al., 2019; Ashurov et al., 2024; Radočaj et al., 2025).

6.4 Weed Mapping & Targeted Control

High-resolution RGB/MS supports inter-row weed detection and **site-specific** control, reducing herbicide loads and drift (Peña et al., 2015; Louargant et al., 2018; Lottes et al., 2017).

6.5 Stand Counts, Emergence, Lodging, Yield

Object detection and CHMs quantify stand density, identify gaps and **lodging**, and improve **yield forecasts** when tracked through phenology (Madec et al., 2017; Gao et al., 2020; Wallace et al., 2016).

6.6 Operations, Policy, and Capacity

Scaling requires pilot licensing, airspace zoning, and SOPs for mapping and spraying. Streamlined frameworks (e.g., national drone rules) and training programs are enabling wider, safer use (Government of India, 2021; Patras Law Chambers, 2025)

7. Economics, ROI, and Environmental Impact

UAV monitoring reduces scouting time and **targets inputs**, contributing to **lower chemical and water use** while safeguarding yield. Documented benefits include improved irrigation efficiency and reduced operator exposure when spraying is done with strict SOPs (Miller et al., 2020). Programmatic deployments report water savings and yield gains when UAV intelligence informs decisions at scale.

8. Limitations and Open Challenges

Key constraints include **battery endurance and wind**, **radiometric comparability** across dates, **mosaicking artifacts**, and **domain shift** that degrades model performance on new farms/seasons (Aasen et al., 2015; Brook et al., 2019). Building **diverse, labeled datasets**, adopting **best-practice calibration**, and using **domain adaptation** are central to robust deployment. Regulatory compliance is mandatory, particularly for sprayer UAVs (Government of India, 2021).

9. Future Directions

1. **Multimodal fusion** of MS+thermal+LiDAR with IoT soil/leaf sensors for diagnosis-grade mapping.
2. **3D/BRDF-aware** and **time-aware** retrievals that stabilize reflectance and phenology effects.
3. **Edge autonomy** and **swarms** for rapid coverage and real-time advisories.
4. **Foundation models** pre-trained on large agro-image corpora for few-shot adaptation and explainable outputs.
5. **Standards and benchmarks** (radiometry, formats, open datasets) to ensure comparability across crops and regions.

10. Conclusion

UAVs now deliver **actionable, quantitative crop intelligence** across nutrients, water, pests, weeds, and structural risks. With sound **radiometric practice**, **good ground truth**, and **modern DL pipelines**, farms can shift from reactive to **proactive, precise** management. Policy support and training ecosystems are accelerating mainstream adoption. The next leap—sensor fusion, 3D/time-aware retrievals, and edge/foundation AI—will turn drone imagery into **fast, field-side decisions** that raise productivity while lowering environmental footprints.

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