Available online at www.agrifarming.org

DOI: http://dx.doi.org/10.18782/2582-7146.329

ISSN: 2582 – 7146

Current Research in Agriculture and Farming

Curr. Rese. Agri. Far. (2022) *3*(4), 25-33

Review Article

Peer-Reviewed, Refereed, Open Access Journal

Role of Drones and Remote Sensing in Agricultural Monitoring and Crop Management: A Review

Subhash Verma[1]*, Ramdeen Kumar[2]

[1]Ph.D scholar, Bihar Agricultural University, Sabour, Bhagalpur, Bihar

[2]Ph.D scholar, Institute of Agricultural Sciences, BHU, Varanasi, Uttar Pradesh

*Corresponding Author E-mail: subhashverma0052@gmail.com

Received: 17.06.2022 | Revised: 29.07.2022 | Accepted: 14.08.2022

ABSTRACT

The integration of drones and remote sensing technologies has transformed modern agricultural monitoring and crop management by enabling timely, accurate, and data-driven decision-making. This review highlights recent advancements in unmanned aerial vehicles (UAVs), multispectral and hyperspectral imaging, thermal sensors, and satellite-based remote sensing for assessing crop health, soil conditions, water stress, nutrient deficiencies, pest infestations, and disease outbreaks. These technologies support precision agriculture by improving resource-use efficiency, reducing production costs, and enhancing crop productivity. The review also discusses current challenges, including high implementation costs, data processing complexity, regulatory issues, and future prospects for sustainable and climate-smart farming.

Keywords: *Unmanned Aerial Vehicles; Remote Sensing; Precision Agriculture; Vegetation Indices; Crop Monitoring.*

INTRODUCTION

Agriculture is under unprecedented pressure to feed a global population projected to cross nine billion by 2050 while contending with climate change, shrinking arable land and limited freshwater resources (FAO, 2017). Conventional crop scouting is labour-intensive, subjective and cannot resolve within-field variability at agronomically meaningful scales. Remote sensing, defined as the acquisition of information about an object without physical contact, has therefore become central to modern agronomy. Where satellite-borne sensors such as Landsat-8 and Sentinel-2 provide synoptic, repetitive coverage, drones bridge the gap between satellite imagery and ground observation by offering ultra-high spatial resolution (often <5 cm), flexible revisit times and the ability to operate beneath cloud cover (Maes & Steppe, 2019). The convergence of miniaturised multispectral sensors, Global Navigation Satellite Systems (GNSS), structure – from - motion photogrammetry and machine-learning analytics has made UAVs an operational tool rather than a research curiosity.

Cite this article: Verma, S., & Kumar, R. (2022). Role of Drones and Remote Sensing in Agricultural Monitoring and Crop Management: A Review, *Curr. Rese. Agri. Far.* *3*(4), 25-33. doi: http://dx.doi.org/10.18782/2582-7146.329

Mitchell (2017) argued that drone-based monitoring is the most disruptive technology to enter agronomy since the green revolution. This review consolidates literature published up to 2022 on the components of drone-based remote sensing systems, the principal sensors and indices used, the major application areas in agricultural monitoring and crop management, and the constraints that still inhibit large-scale uptake. It draws on peer-reviewed publications, industry reports and FAO technical bulletins to provide a balanced, application-oriented synthesis.

Historically, agricultural remote sensing began with manned aircraft and Landsat-1 in 1972, evolving through the Advanced Very High Resolution Radiometer (AVHRR), SPOT, IKONOS and the contemporary Sentinel and Planet constellations. Until the early 2010s, however, sub-metre temporal flexibility was confined to expensive manned overflights. The rapid decline in inertial measurement unit, GNSS and camera prices after 2012, combined with open-source autopilots such as ArduPilot and PX4, enabled affordable civilian drones. By 2015 commercial agricultural UAV solutions had entered the market, and by 2020 they had become standard tools in many large vineyards, plantations and seed-production farms (Zhang & Kovacs, 2012; & Maes & Steppe, 2019). The present review therefore captures a decade of transformation and identifies the practices that have crystallised into operational standards.

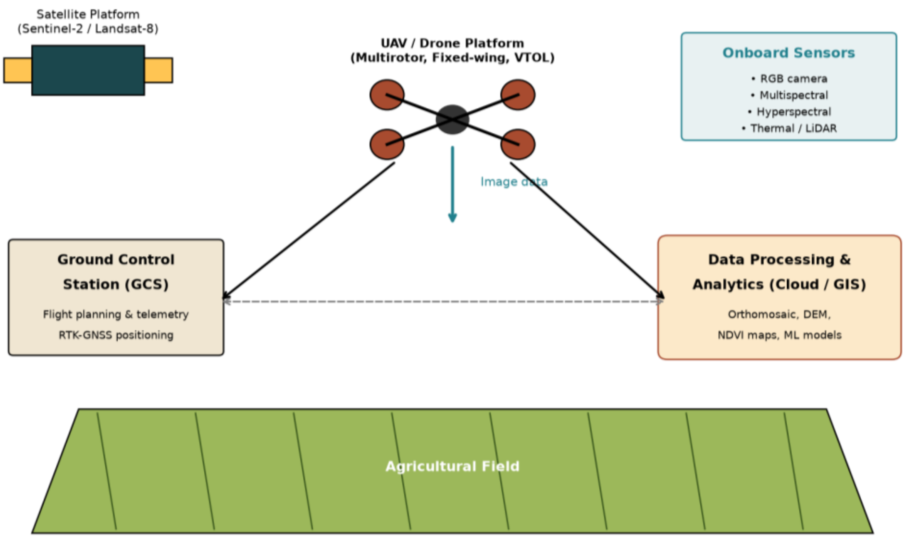

Figure1. Schematic of a UAV-based remote sensing system for agriculture showing the drone platform, onboard sensors, ground control station, satellite reference and cloud-based data processing pipeline

2. Drone Platforms and Onboard Sensors

2.1 UAV Platforms

Agricultural UAVs are broadly classified into multirotor (quadcopters, hexacopters), fixed-wing and hybrid Vertical Take-Off and Landing (VTOL) platforms. Multirotors offer hover capability and are suited to small fields and detailed inspection, while fixed-wing systems provide longer flight endurance (45–90 min) and are preferred for mapping large estates. VTOL platforms combine the launch flexibility of multirotors with the range of fixed wings (Tsouros, Bibi, & Sarigiannidis, 2019). Payload capacity in commercial agricultural drones ranged between 1 kg and 20 kg by 2022, with spraying drones such as the DJI Agras T30 carrying up to 30 L of liquid agrochemical.

2.2 Sensors

Sensor selection drives the agronomic information that can be extracted. RGB cameras are inexpensive and provide centimetre-level orthomosaics suitable for plant counting and canopy cover. Multispectral cameras such as the MicaSense RedEdge and Parrot Sequoia record discrete bands in the visible, red-edge and near-infrared (NIR) regions, enabling vegetation index computation. Hyperspectral imagers acquire hundreds of narrow contiguous bands and are valuable for nutrient and disease discrimination, although they remain expensive and data-intensive (Adão et al., 2017). Thermal infrared sensors quantify canopy temperature, which is closely linked to stomatal conductance and water stress, while LiDAR generates dense three-dimensional point clouds for plant height, canopy architecture and digital terrain modelling (Zhang & Kovacs, 2012). Auxiliary sensors such as Real-Time Kinematic (RTK) and Post-Processed Kinematic (PPK) GNSS receivers deliver positional accuracy of 1 to 3 cm, which is essential for precision spraying and for stitching imagery over multiple flights. Sensor calibration using reflectance panels and onboard incident-light sensors is mandatory whenever quantitative indices are to be compared across dates, locations or platforms.

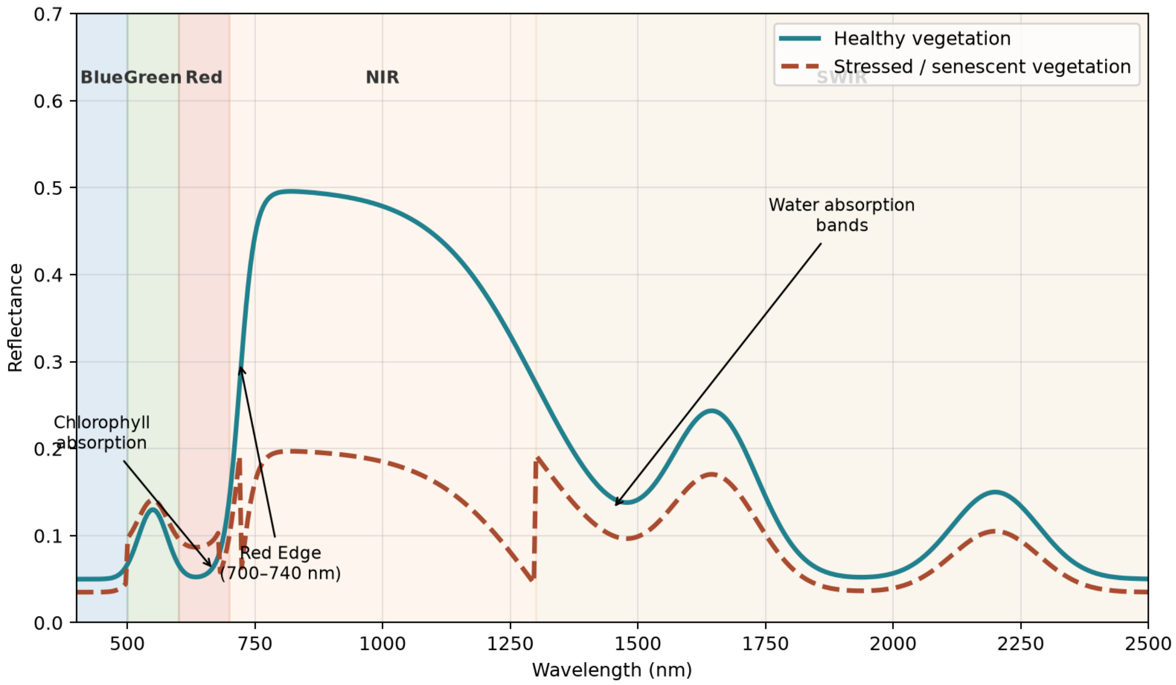

Figure2. Typical spectral reflectance curve of healthy versus stressed vegetation across the visible, near-infrared and short-wave infrared regions, highlighting the chlorophyll absorption trough, red-edge transition and water absorption bands exploited by agricultural sensors

3. Vegetation Indices and Image Analytics

Vegetation indices (VIs) reduce multi-band reflectance into single biophysical proxies. The Normalised Difference Vegetation Index (NDVI), formulated as (NIR − RED)/(NIR + RED), remains the most widely applied index since its introduction by Rouse, Haas, Schell, and Deering (1974). NDVI values typically range from −1 to +1, with healthy crops producing values between 0.6 and 0.9. To overcome saturation in dense canopies, the Enhanced Vegetation Index (EVI) and Soil-Adjusted Vegetation Index (SAVI) were proposed (Huete, 1988). The Green NDVI (GNDVI) is particularly sensitive to chlorophyll, whereas red-edge indices such as NDRE detect nitrogen stress earlier than NDVI (Gitelson, Kaufman, & Merzlyak, 1996).

Image analytics workflows convert raw frames into actionable maps. Structure-from-Motion (SfM) photogrammetry stitches overlapping frames into orthomosaics and digital surface models. Object-based image analysis (OBIA) and, more recently, deep convolutional neural networks have outperformed pixel-based classifiers for tasks such as weed segmentation and disease detection (Kamilaris & Prenafeta-Boldú, 2018). Cloud platforms such as Google Earth Engine, Pix4Dfields and DroneDeploy democratised access to these workflows by 2022, allowing growers to obtain processed prescription maps within hours of a flight. Open-source toolchains such as OpenDroneMap and the Python rasterio and scikit-image libraries have further reduced cost barriers for academic users and start-ups in emerging economies. The integration of edge computing on the UAV itself, where lightweight inference models run during flight, is shortening the latency between data capture and field response from days to minutes.

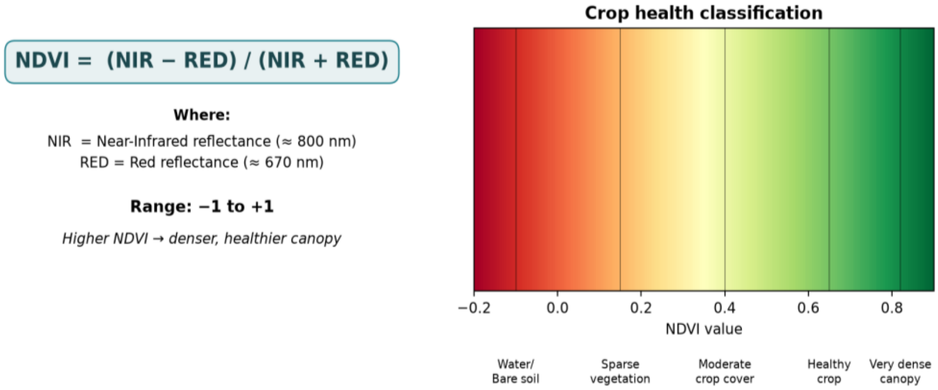

Figure3. NDVI formula, value range and corresponding crop health classification commonly used in operational drone-based monitoring

4. Applications in Agricultural Monitoring and Crop Management

4.1 Crop Health and Stress Detection

Multispectral and thermal imagery captured by drones can detect biotic and abiotic stress days or weeks before visible symptoms emerge. Zarco-Tejada et al. (2012) demonstrated that thermal-narrowband indices from a UAV detected Verticillium wilt in olive orchards with classification accuracies above 79 %. Similar studies on wheat, maize and rice have shown that red-edge indices identify nitrogen deficiency and fungal infections at sub-clinical stages, enabling targeted interventions and reducing prophylactic agrochemical use (Maes & Steppe, 2019). In cotton, drone-based NDVI maps have been used to delineate management zones for site-specific nitrogen top-dressing, raising nitrogen-use efficiency by 10–20 % without yield penalty. Comparable benefits have been reported in sugarcane, where red-edge indices flagged orange rust outbreaks approximately ten days before scouts could detect them visually, allowing fungicide application during the most sensitive infection window.

4.2 Biomass and Yield Estimation

UAV-derived canopy height models and vegetation indices have produced robust yield-prediction models for cereals, oilseeds and forages. Bendig et al. (2014) reported coefficients of determination above 0.80 between drone-based crop surface models and dry biomass in barley. Similar relationships have been established for sugarcane, cotton and potato. Such pre-harvest yield maps inform logistics, storage and procurement decisions and are increasingly integrated into crop insurance products. When fused with time-series satellite imagery and weather data, drone observations strengthen yield forecasting models used by government agencies, commodity traders and crop-insurance providers. In rice systems, UAV-based panicle counting using deep learning has achieved errors below 5 % compared with manual sampling, providing a scalable alternative to destructive sampling traditionally used for breeder trials and variety evaluation.

4.3 Water Stress and Irrigation Management

Thermal imagery exploits the canopy-air temperature difference to compute the Crop Water Stress Index (CWSI). UAV-mounted thermal cameras enable zone-specific irrigation scheduling, with water savings of 8–25 % reported in vineyards and orchards (Gago et al., 2015). Combined with soil moisture sensors, these maps drive variable-rate irrigation systems that align water application with actual plant demand. In semi-arid regions of India, pilot studies on wheat and mustard have shown that CWSI-guided irrigation can reduce water use by up to 20 % while maintaining or even improving grain yield. Such savings are particularly significant in groundwater-stressed states such as Rajasthan and Punjab, where over-extraction threatens long-term aquifer sustainability.

4.4 Weed, Pest and Disease Detection

High-resolution drone imagery, coupled with deep-learning object detection, supports site-specific weed control. Studies on maize and sunflower fields have achieved weed-mapping accuracies of 85–95 %, enabling herbicide reductions of 30–70 % through patch spraying (Lottes, Khanna, Pfeifer, Siegwart, & Stachniss, 2017). Insect infestations such as fall armyworm and locusts have also been monitored using drones, particularly in remote landscapes where ground access is difficult. During the 2019–2020 desert locust outbreak across East Africa and South Asia, drones were deployed to scout breeding grounds and deliver targeted biopesticides in inaccessible terrain. For disease management in plantation crops, hyperspectral UAV surveys have successfully discriminated huanglongbing in citrus, Panama wilt in banana and black sigatoka with accuracies that approach laboratory diagnostics, offering early-warning capability that protects entire production landscapes.

4.5 Soil and Field Mapping

Drone-based digital elevation models, combined with multispectral indices, characterise within-field variability in soil organic matter, salinity and drainage. These products are foundational for management-zone delineation and variable-rate seeding, fertilisation and liming. LiDAR drones extend this capability into forestry, agroforestry and rice paddy levee mapping with vertical accuracies below 10 cm (Zhang & Kovacs, 2012). Multitemporal drone surveys also enable monitoring of soil erosion, gully formation and the impact of conservation practices such as contour bunding and cover cropping. In arid and semi-arid zones, including parts of Rajasthan and Gujarat, drone-based salinity mapping has supported targeted gypsum application and the design of leaching schedules tailored to local conditions.

4.6 Precision Spraying and Seeding

Beyond sensing, drones now act as autonomous applicators. Spraying drones can treat 8–12 ha per hour with 30–50 % less pesticide volume than conventional boom sprayers, due to lower drift and prescription-map-driven flow control. By 2022, China had registered more than 100,000 agricultural spraying drones, while India had begun pilot deployments under the Sub-Mission on Agricultural Mechanization (FAO, 2018). Drones have also been used to broadcast cover-crop seed, deliver biological control agents such as Trichogramma egg cards over sugarcane and maize, and overseed pastures with legumes. These autonomous applications are especially relevant for terraced terrain, swampy rice fields and steep orchards where conventional ground machinery cannot operate safely or efficiently.

4.7 Livestock and Aquaculture Monitoring

Drones with RGB and thermal payloads count livestock, detect lameness, monitor grazing intensity and locate strays. In aquaculture, drones map algal blooms, inspect cages and assess pond effluent. These applications extend remote sensing beyond crops to the broader agricultural enterprise. In silvopastoral and rangeland systems, thermal UAV surveys at dawn have been used to estimate herd thermal comfort and detect early signs of disease, while LiDAR data quantify forage biomass available for grazing. For sericulture and apiculture, drones have shown promise in monitoring mulberry plantation health and the floral resources available to pollinators, linking spatial information to value-chain outcomes.

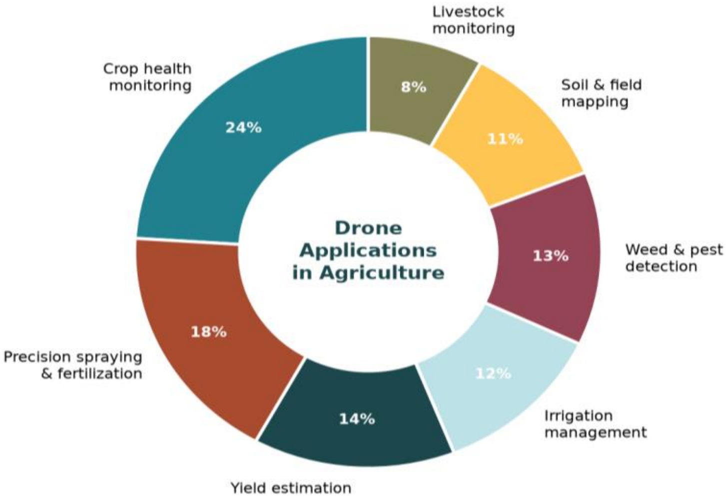

Figure4. Indicative distribution of major application areas of UAVs in agriculture

5. Market Growth and Adoption Trends

The global agricultural drone market expanded rapidly between 2015 and 2022. According to industry analyses from MarketsandMarkets and PwC, the market grew from roughly USD 0.7 billion in 2015 to about USD 4.8 billion in 2022 (Mitchell, 2017). Growth has been fastest in Asia-Pacific, led by China, Japan and India, driven by labour shortages, government subsidies and the dominance of smallholder rice and horticulture systems. North America has focused on large-acreage row crops and viticulture, while Europe has emphasised vineyards, orchards and regulatory innovation through the European Union Aviation Safety Agency (EASA). In India, the liberalised Drone Rules, 2021, along with the Production-Linked Incentive scheme for drone manufacturing, catalysed a wave of domestic start-ups offering agricultural drone services on a per-acre fee model. The introduction of Standard Operating Procedures for drone-based pesticide application by the Central Insecticides Board, and the Kisan Drone programme of the Ministry of Agriculture and Farmers Welfare, signalled a policy shift from experimentation to mainstreaming of UAV technology in Indian agriculture.

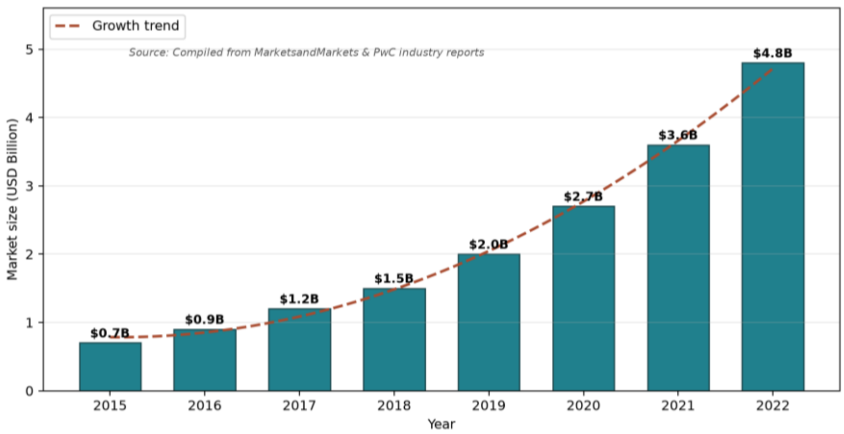

Figure5. Estimated growth of the global agricultural drone market from 2015 to 2022. Values are indicative figures compiled from MarketsandMarkets and PwC industry reports

6. Operational Workflow

A standard drone-based crop monitoring workflow comprises six sequential stages (Figure 6). Mission planning defines the flight path, altitude and overlap based on agronomic objectives. The UAV then captures geo-referenced imagery, followed by pre-processing for radiometric and geometric correction. Orthomosaic generation and vegetation-index computation produce field-level rasters that are analysed using rule-based or machine-learning models. The output is a prescription map that drives precise field actions such as fertigation, spot spraying or selective harvesting (Tsouros et al., 2019).

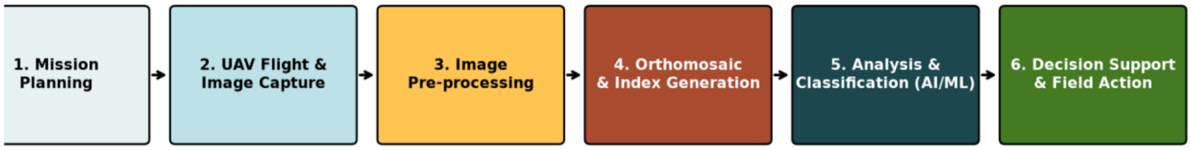

Figure6. Six-stage operational workflow of drone-based crop monitoring from mission planning to decision support

7. Challenges and Limitations

Despite rapid progress, several constraints persist. Battery endurance limits multirotor flight to 20–40 min, restricting coverage. Regulatory frameworks vary widely; many countries still impose strict line-of-sight, altitude and beyond-visual-line-of-sight (BVLOS) restrictions that hamper commercial scaling. Data volumes generated by hyperspectral and LiDAR sensors challenge storage and analytics infrastructures, particularly in low-bandwidth rural areas. The cost of high-end sensors and analytics services remains prohibitive for small and marginal farmers, who form the majority in South and Southeast Asia. Finally, the shortage of trained pilots and agronomists capable of translating drone outputs into agronomic decisions remains a critical bottleneck (Kamilaris & Prenafeta-Boldú, 2018). Weather sensitivity further reduces operational windows: high wind speeds, precipitation and low solar angles compromise data quality. Privacy, insurance and air-traffic management for unmanned operations also raise unresolved policy questions that influence farmer confidence and investor appetite.

8. Future Perspectives

Emerging trends up to 2022 indicate convergence of drones with the Internet of Things, 5G connectivity, swarm robotics and edge artificial intelligence. Multi-UAV swarms coordinated through cloud platforms can cover thousands of hectares simultaneously and exchange real-time information with ground robots and irrigation systems. Integration with satellite constellations such as Sentinel-2, Planet and CubeSats yields multi-scale data fusion, where drones validate satellite products and downscale them to plant level. Coupling these data streams with crop-simulation models will enable digital twins of farms that anticipate stress events and recommend pre-emptive action.

For developing economies, drone-as-a-service business models, custom-hiring centres and government subsidy schemes such as the Indian Drone Rules 2021 and the Kisan Drone initiative are expected to democratise access. Capacity building, harmonised standards and open data ecosystems will determine how quickly the technology delivers on its promise of climate-smart, resource-efficient agriculture. Research priorities going forward include the development of lightweight hyperspectral sensors, swarm coordination algorithms, robust cross-platform calibration protocols, and farmer-centric decision-support interfaces in local languages. Equally important will be inter-disciplinary training programmes that combine agronomy, data science and aviation, so that the human capital required to operate this ecosystem matches the pace of technological progress.

CONCLUSION

Drones and remote sensing have evolved from experimental tools into core enablers of precision agriculture. By providing centimetre-scale, on-demand information on crop status, water, soil and inputs, they support timely and targeted management decisions that improve productivity, profitability and environmental performance. The literature up to 2022 demonstrates clear benefits across crop health monitoring, yield estimation, irrigation scheduling, weed and pest management, and precision application of agrochemicals. To unlock the full potential of these technologies, future efforts must address regulatory harmonisation, affordability, data interoperability and farmer capacity. With sustained investment and inclusive policies, drone-based remote sensing is poised to become an indispensable pillar of climate-smart and digitally enabled agriculture in the coming decade.

Acknowledgements:
The authors are grateful to all co-authors for their continuous support and collaboration in manuscript preparation.

Funding:
No external funding was obtained.

Conflict of Interest:
The authors declare no conflicts of interest.

Author Contributions:
All authors contributed to drafting, reviewing, editing, and final approval of the manuscript.

REFERENCES

Adão, T., Hruška, J., Pádua, L., Bessa, J., Peres, E., Morais, R., & Sousa, J. J. (2017). Hyperspectral imaging: A review on UAV-based sensors, data processing and applications for agriculture and forestry. *Remote Sensing, 9*(11), 1110.

Bendig, J., Bolten, A., Bennertz, S., Broscheit, J., Eichfuss, S., & Bareth, G. (2014). Estimating biomass of barley using crop surface models (CSMs) derived from UAV-based RGB imaging. *Remote Sensing, 6*(11), 10395–10412.

FAO (2017). The future of food and agriculture: Trends and challenges. *Rome: Food and Agriculture Organization of the United Nations*.

FAO (2018). E-agriculture in action: Drones for agriculture. Bangkok: *Food and Agriculture Organization of the United Nations and International Telecommunication Union*.

Gago, J., Douthe, C., Coopman, R. E., Gallego, P. P., Ribas-Carbo, M., Flexas, J., & Medrano, H. (2015). UAVs challenge to assess water stress for sustainable agriculture. *Agricultural Water Management*, *153*, 9–19.

Gitelson, A. A., Kaufman, Y. J., & Merzlyak, M. N. (1996). Use of a green channel in remote sensing of global vegetation from EOS-MODIS. *Remote Sensing of Environment, 58*(3), 289–298.

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, *25*(3), 295–309.

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture, 147*, 70–90.

Lottes, P., Khanna, R., Pfeifer, J., Siegwart, R., & Stachniss, C. (2017). UAV-based crop and weed classification for smart farming. In Proceedings of the IEEE International Conference on Robotics and Automation (ICRA) (pp. 3024–3031). Singapore: IEEE.

Maes, W. H., & Steppe, K. (2019). Perspectives for remote sensing with unmanned aerial vehicles in precision agriculture. *Trends in Plant Science, 24*(2), 152–164.

Mitchell, J. (2017). Clarity from above: Commercial applications of drone technology. London: PwC Drone Powered Solutions.

Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. In Third ERTS Symposium, *NASA SP-351* (Vol. 1, pp. 309–317). Washington, DC: NASA.

Tsouros, D. C., Bibi, S., & Sarigiannidis, P. G. (2019). A review on UAV-based applications for precision agriculture. *Information*, *10*(11), 349.

Zarco-Tejada, P. J., González-Dugo, V., & Berni, J. A. J. (2012). Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera. *Remote Sensing of Environment*, *117*, 322–337.

Zhang, C., & Kovacs, J. M. (2012). The application of small unmanned aerial systems for precision agriculture: *A review*. *Precision Agriculture*, *13*(6), 693–712.