



Leveraging Remote Sensing Technologies: A Review of Precision Cropping Challenges and Research Trend Analysis

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Received: 20 March 2025 / Accepted: 13 March 2026
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Abstract

Precision cropping is a driving force for modernising agriculture which uses technologies such as sensors, satellites, and drones to monitor crop health, soil, and environmental conditions by remote sensing. This provides real-time, high resolution data, facilitating improved processes. However, challenges associated with big data influx, integration, interpretation, and validation of data persistently complicate decision-making, necessitating the effective advanced tools and collaboration. This review explores the role of remote sensing technologies, tools, and data in addressing challenges of precision cropping. It focuses on three objectives: (1) examining the practical challenges faced by farmers, (2) assessing how remote sensing data can fix those challenges, and (3) analysing methods for integrating remote sensing data into operational tasks. Data was collected from Web of Science (WoS) database and analysed using VOSviewer (v. 1.6.20). After refining and screening 2,207 documents, 171 relevant articles were studied, with particular attention to precision cropping challenges, technologies, and integration. Key challenges identified include crop water stress, weed infestation, data redundancy, water management, and land usage ambiguity. Moreover, Unmanned Aerial Vehicles (UAVs) and satellites played a critical role in diagnosing soil needs, monitoring crop health, and predicting yields. We found that soil digital mapping, software, Artificial Intelligence (AI), and hybrid-based data featured among the integration methods for enhancing accuracy of crop management. Remote sensing, when integrated with other technologies, offers significant capacity to address precision cropping challenges. While barriers like maximisation complexity and sensor limitations exist, technological advancements and cost-reduction strategies are expected to improve sustainability and productivity in farming.

Keywords Challenges · Crop · Data · Management · Precision cropping · Remote sensing

Introduction

“Precision cropping is ‘a farm management system that uses information and technology to identify, analyse, and control the temporal and spatial variability within a field,’” according to Maurya et al. (2024). Precision cropping, also known as precision farming or precision agriculture, has significantly impacted modern agricultural practices. These practices aim to optimise crop production despite challenges posed by limited resources (Getahun et al., 2024; Zhang et al., 2024a, b). This is a strategy designed to reduced costs, improve efficiency, and enhance sustainability in crop production by aligning farming practices with the specific needs of each crop (Kumar et al., 2024). Remote sensing is essential for precision farming because it uses technologies such as radar, aerial photography, and satellite imagery (Sishodia et al., 2020) to provide real-time and high resolution data.

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Farmers use this data to understand their soil, crop health, and environment. They can get this information from tools like satellites, drones, and other aerial platforms which take pictures from the air (Fakhar & Khalid, 2023). This has made monitoring and managing agricultural systems more effective (Omia et al., 2023). However, challenges related to data integration, interpretation, and utilisation still exist (Maya & Bhargavi, 2020; Has et al., 2024).

It is clear that the application of remote sensing coupled with tools and big data in farming is growing in interest. This has led to an expanding body of research that is delving into their potential and shortcomings (Rejeb et al., 2022; Mgendi, 2024). For instance, numerous studies have focused on the specialised remote sensing aspects such as development of new sensors, platforms, and data processing approaches (Roitsch et al., 2019; Bill et al., 2022; Jafarbiglu & Pourreza, 2022; Mashala et al., 2023; Paheding et al., 2024). Secondly, the vast data amounts generated by the remote sensing technologies (Pantazi et al., 2020), namely UAVs, satellite imagery, and ground-based sensors contribute to the monitoring of farmers' fields with unprecedented detail and accuracy (Guebsi et al., 2024; Makam et al., 2024). Despite that, relatively less attention has been paid to the practical challenges faced by farmers when trying to boost their operations using these technologies, such as validation of maps (Abiri et al., 2023; Karunathilake et al., 2023; Fassnacht et al., 2024). Additionally, it is worth noting that as the data volume from remote sensing applications continues to grow, there is an increasing need for understanding how this data can be effectively used for tackling the real-world precision farming challenges (Weiss et al., 2020). On the other hand, the tools applied in remote sensing are more oriented to practicability in terms of expertise (Janga et al., 2023).

As previously mentioned, a new dimension to the role of remote sensing in precision farming has been provided by the emergence of big data (Huang et al., 2018; Radočaj et al., 2022). Such data exposes farmers and agricultural experts to vast volumes, velocity, and a variety of information by which they are able to harness insights for making informed decisions (Soussi et al., 2024). This means that remote sensing technologies can generate large amounts of data to be utilised for addressing a wide range of farming issues, including pest management, irrigation control, and crop yield prediction (Rajak et al., 2023; Wang et al., 2024). Integrating big data from different tools is clearly the better approach, as it effectively addresses the daily precision cropping challenges farmers face (Alahmad et al., 2023; Ramdani, 2023). The approach requires cross-disciplinary coordination in dealing with data overload and the need for advanced analytical tools for farmers to derive feasible and

functional insights from remote sensing (Li et al., 2016; Seif, 2022).

Despite the above observations and in line with the existing literature, there has not been clarity into how the technologies, tools, and data can be maximally harnessed to address the challenges of precision cropping. While many studies discuss separate components (Rejeb et al., 2022; Abiri et al., 2023; Alahmad et al., 2023; Fakhar & Khalid, 2023; Janga et al., 2023; Ramdani, 2023; Getahun et al., 2024; Zhang et al., 2024a, b; Kumar et al., 2024; Guebsi et al., 2024; Agrawal & Arafat, 2024) there is limited clarification of the frameworks or actionable strategies for their effective integration. Thus, this article serves to explore these possibilities. In light of this, the article is focusing on three objectives, namely: to scrutinise the practical challenges faced by farmers in trying to boost their operations using data from remote sensing technologies; to assess how data from remote sensing technologies can be utilised to address precision cropping challenges; and to analyse the methods of integrating remote sensing data and tools to counter challenges experienced in the daily operations of precision cropping. Paramount attention has been given to the objectives as key themes emerging from recent literature (Woz'niak & Ijaz, 2024).

This manuscript is organised into five main sections and several sub-sections. Section 1 introduces the concept of precision cropping and the role of remote sensing and big data. Section 2 outlines the materials and methods, including the search strategy, document selection criteria, and evaluation approach. Section 3 presents the results and discussion, structured into sub-sections covering publication characteristics, geographical distribution of studies, precision cropping challenges addressed by remote sensing, practical challenges faced by farmers, challenges in developing countries, utilisation of remote sensing data, sensor modalities, ground-based and GNSS-enabled sensing, data integration strategies, and optimal digital resource requirements for precision cropping. Section 4 discusses key gaps in the existing literature related to socio-economic, scalability, and ethical considerations of remote sensing in precision cropping. Section 5 concludes the study and outlines future research directions and practical recommendations for researchers and practitioners.

Materials and Methods

Searching Strategy

Data was collected through a comprehensive search of the WoS database whose choice was based on its large index size, wide scope, diverse content, and accessibility (Birkle

et al., 2020). Data collection took place over a week (01st to 07th January 2025) and focused on a ten-year range (2015–2024) to capture the latest advancements in the study topic. A combination of keywords was used, including “remote sensing,” “big data,” “precision,” “cropping,” and “precision cropping challenges.” The process involved several stages (Fig. 1): First, a general search arranged as ((“Remote sensing” OR “Satellite imaging” OR “Aerial sensing” OR “Environmental monitoring” OR “Geospatial data collection” OR “Spatial data acquisition”) AND “Precision” AND (“Cropping” OR “Agriculture”)) yielded 2,207 documents. Second, refining by document type (Article, Proceeding Paper, and Review Article) reduced this number to 2,171. Third, filtering by “English language” resulted in 2,150 documents. Finally, narrowing the search by including only those related to “challenges” led to 315 documents.

The WoS Core Collection was (<https://www.webofscience.com/wos/woscc/summary/63d20cbd-c6e9-4fac-82f3-e3e88ddee3b5-013ee6fd2b/relevance/1>).

Document Selection, Organisation, and Evaluation Criteria

Selection Criteria

In total, 315 documents were downloaded and manually screened by reviewing their titles, abstracts, and content. Document selection was based on relevance to the focus and criteria of study. Guided by Frampton et al. (2017), document inclusion focused on remote sensing technologies, tools, and data, precision cropping challenges, and adoption issues. On the other hand, exclusion was applied to

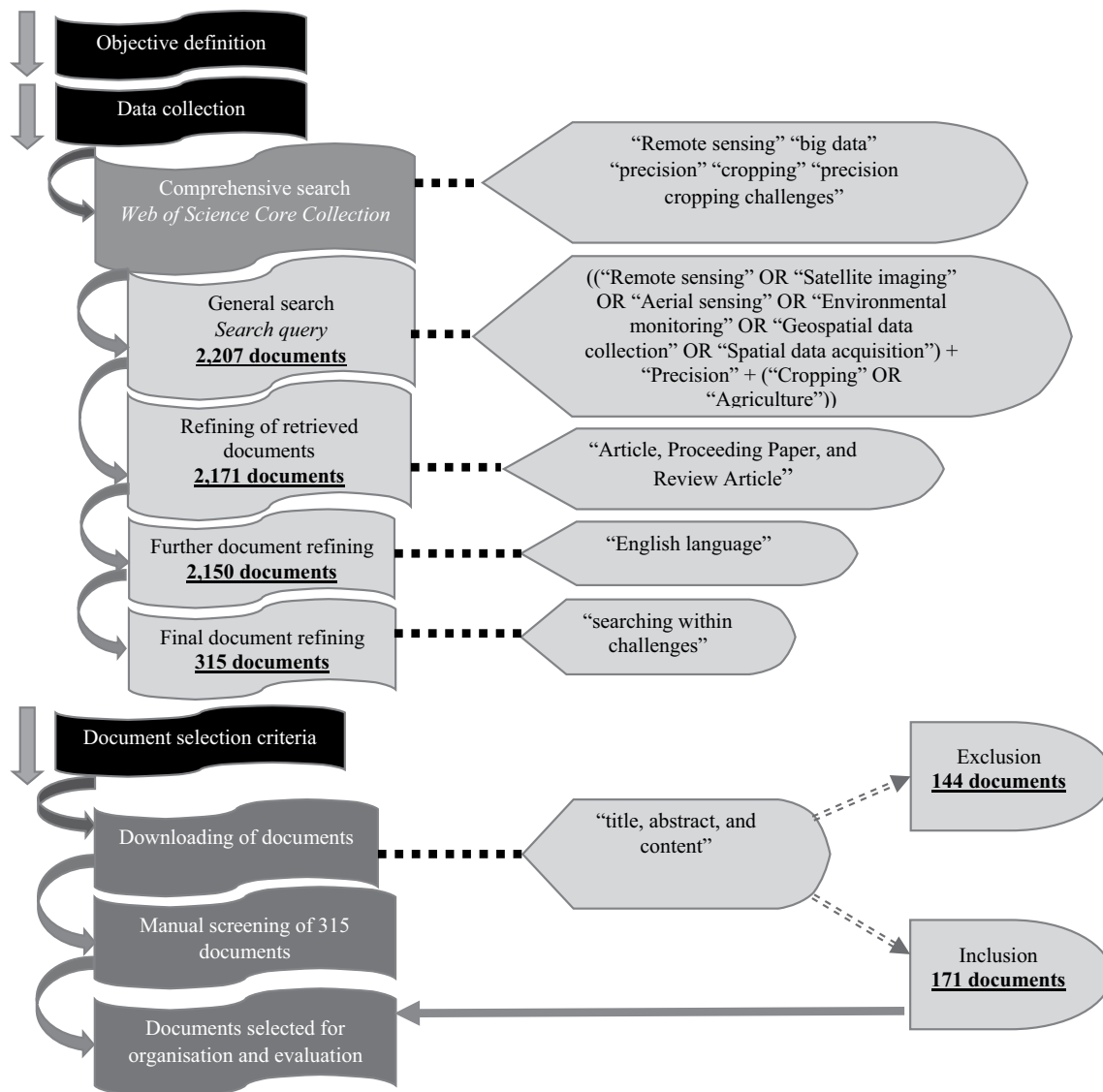


Fig. 1 Process flow of the data collection, document selection criteria, and document organisation and evaluation

documents unrelated to precision cropping or those focusing on other farming sectors or those carrying a comparison of remote sensing devices. After excluding 144 irrelevant documents, 171 documents were maintained for further analysis.

Organisation and Evaluation

The screened data was exported to Microsoft Excel for organisation, analysis, and processing, as recommended by Broman and Woo (2018). Documents were then sorted and structured for future reference. Keywords were analysed and visualised using VOSviewer (v. 1.6.20) (CWTS, Netherlands). Data formatting was done by publication type, author(s), article type, and source title. In addition, documents were categorised into themes, including practical challenges in precision cropping, utilisation of remote sensing technologies data, and integration methods. Furthermore, beyond the application-based thematic analysis, the reviewed literature was also classified according to the remote sensing sensor modalities and ground-based sensing approaches employed in precision agriculture.

Geographical Classification of Publications

In addition to thematic and bibliometric analyses, the geographical distribution of the reviewed publications was examined. Each document was assigned a country based on the primary study location reported or, where unavailable, the corresponding author's affiliation. The distribution of publications across continents and countries was then tabulated to identify regional research trends in remote sensing applications for precision cropping. This approach allows for assessing the global representation of research and highlighting underrepresented regions in the literature.

Results and Discussion

Clarification of Publication Type, Author(s), Article Title, and Source Title

Publication Type

Conferences were 10, Journals 157, and ScienceDirect 4 (Fig. 2). The 10 documents from the search were from academic conference presentations. This number was relatively low, and it could be attributed to the search query being focused on more established, peer-reviewed, and finalised research other than early-stage findings. The large number (157) of journal articles is typical of platforms where most scholarly research was published after rigorous scrutiny from peer reviewers. Only 4 publications which were returned by ScienceDirect could be due to minimal match of the search query with the database's content. Secondly, articles found in ScienceDirect could have been included in the journals.

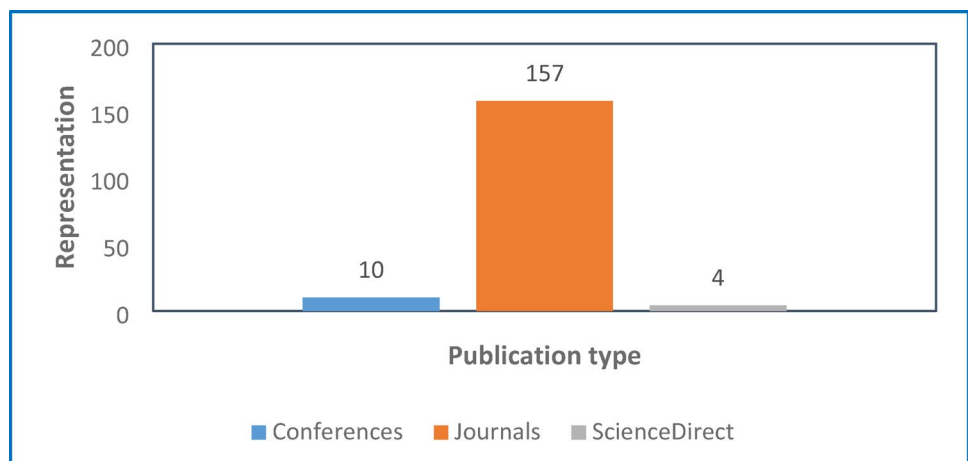
Author(s)

There were frequent co-authorships for two sets of authors (Anderson & McElrone). Their work displayed a remarkable connection of 35 interactions with other authors' publications as shown in Fig. 3. This means their work was highly connected to other publications on precision cropping, and it could be explained by the researchers' shared research interests and shared research institutions, laboratories, or academic networks.

Article and Source Titles

All articles by their titles were found linked to respective sources. The search results highlight the multidisciplinary nature of precision cropping research, with significant contributions from remote sensing, data science, smart

Fig. 2 Representation of the selected documents by publication type



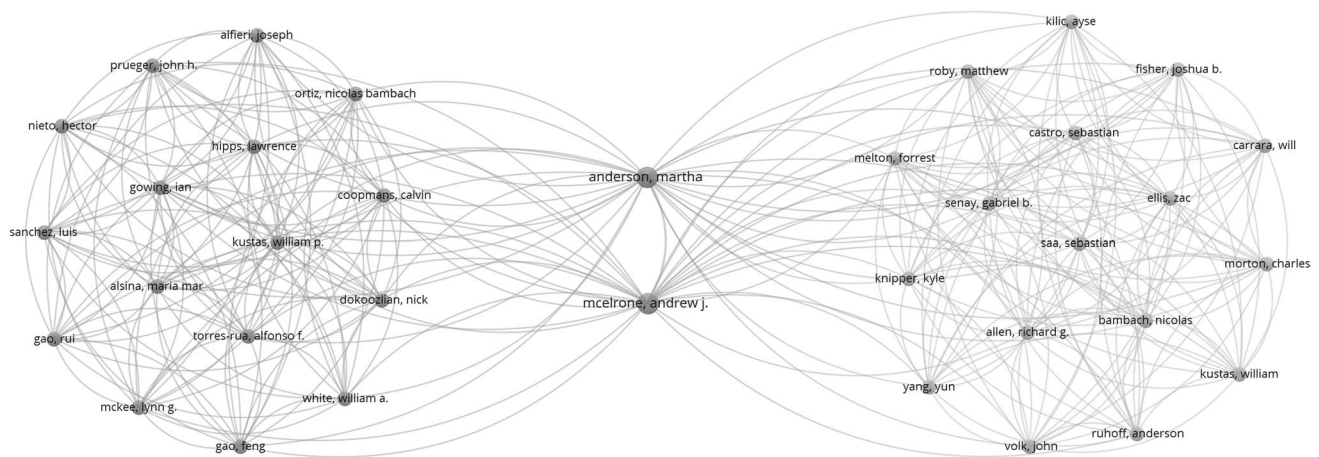


Fig. 3 Co-authorship-author interactions in remote sensing technologies with precision cropping

agriculture, and environmental sciences. Notably, the journal *Remote Sensing* produced the highest number of publications (28), indicating its central role in the field. Other prominent sources included *Agronomy-Basel* (12 publications), *Computers and Electronics in Agriculture* (11), and *IEEE Publications* (11), reflecting the increasing focus on technological integration in agriculture. These findings emphasise the growing interest in utilising advanced technologies, such as remote sensing and data-driven methods, to address challenges in precision cropping. The diversity of journals and disciplines involved highlights the broad and evolving nature of research in smart agriculture and its potential to enhance farming practices.

Geographical Distribution of Reviewed Studies

Analysis of the 171 reviewed publications revealed a marked regional concentration of research efforts (Table 1; Fig. 4). Asia accounted for the majority of publications (102), led by China (66) and India (17), followed by Malaysia (10). Europe contributed 30 studies, with Spain (8) and Italy (5) as the most active countries. North America accounted for 8 publications, primarily from the United States of America (USA) (6). South America had 17 publications, predominantly from Brazil (14), while Africa contributed 8 studies, mainly from Morocco (3) and South Africa (2). Only one study originated from a transcontinental country (Russia), and five studies were classified as other because they did not specify a country (Table 1).

This distribution highlights both regional research strengths and underrepresented areas, particularly in Africa and certain European and Asian countries. These results further indicate that precision cropping research leveraging remote sensing is heavily concentrated in Asia and Europe, particularly in countries with more advanced agricultural technology infrastructure. The underrepresentation

of Africa and certain other regions may reflect both technological access limitations and fewer research initiatives in these areas. This geographical insight complements the thematic analysis, highlighting where challenges in precision cropping are being actively studied and where research gaps remain.

Precision Cropping Challenges Addressed by Remote Sensing

Results showed 6 major categories of precision cropping challenges on which attention was drawn to 24 evaluated documents presented in Table 2. These challenges broadly fall under biotic and abiotic stress domains, alongside land use and field variability considerations. The first and most frequently reported challenge relates to crop water stress and biotic pressures from pests and diseases, which together constitute major abiotic and biotic stressors affecting crop productivity (Katsigiannis et al., 2016; Cubero et al., 2020; Segarra et al., 2020; Lammoglia et al., 2024; Fuentes-Penailillo et al., 2024; Delavarpour et al., 2021; Abdullah et al., 2023; Vinayaka & Prasad, 2024). These stresses directly reduce photosynthetic efficiency, plant vigour, and yields, while increasing input costs for irrigation and chemical control (Richard et al., 2022). Remote sensing facilitates early detection of stress symptoms through vegetation indices, thermal imagery, and canopy reflectance, enabling timely and spatially targeted interventions (Zhang et al., 2023). A second major category concerns water management in relation to drought and flooding, representing critical abiotic stresses under increasing climatic variability. Studies highlight the role of remote sensing in monitoring soil moisture dynamics, rainfall patterns, evaporation, and crop water requirements (Knipper et al., 2024; Bonfante et al., 2019; Ennatiqi et al., 2024; Anand et al., 2021, 2024; Fuentes-Penailillo et al., 2024; Vinayaka & Prasad, 2024; Zeyliger

Table 1 Geographical distribution of reviewed publications on remote sensing applications in precision cropping (2015–2024)

Continent/Region	Country	Number of papers	Percentage (%) of total papers
Africa	Morocco	03	4.7%
	South Africa	02	
	Cote d'Ivoire	01	
	Rwanda	01	
	Tanzania	01	
Asia	China	66	59.7%
	India	17	
	Malaysia	10	
	South Korea	02	
	Bangladesh	01	
	Indonesia	01	
	Iran	01	
	Japan	01	
	Pakistan	01	
	Sri Lanka	01	
	Vietnam	01	
Europe	Spain	08	17.5%
	Italy	05	
	Netherlands	03	
	Greece	02	
	Croatia	02	
	Germany	02	
	Portugal	02	
	Belgium	01	
	Finland	01	
	France	01	
	Hungary	01	
	Romania	01	
North America	Switzerland	01	4.7%
	USA	06	
South America	Canada	02	9.9%
	Brazil	14	
	Argentina	01	
	Chile	01	
Transcontinental	Colombia	01	0.6%
	Russia	01	
Other / Unspecified	-	05	2.9%
Total	-	171	100%

et al., 2024). These applications support precision irrigation scheduling and risk mitigation against crop failure caused by water scarcity or excess. Importantly, soil macro- and micro-nutrient stresses and deficiencies emerge as a distinct precision cropping challenge addressed by remote sensing. Nutrient imbalances, including nitrogen, phosphorus, potassium, and micro-nutrients such as iron and zinc, are recognised abiotic stresses that strongly influence crop growth and yield. Several studies demonstrate how multispectral and hyperspectral data can detect nutrient stress through changes in chlorophyll content, leaf pigment concentration, and canopy spectral response, enabling site-specific nutrient management and fertiliser optimisation (Dong et al., 2024; Mendez & Dasig, 2020; Zhang et al., 2024a, b;

Kuldeep et al., 2024). Another category involves variable crop field conditions, including spatial heterogeneity in soil texture, structure, organic matter, and nutrient availability. Remote sensing provides high-resolution spatial data to map within-field variability, allowing for precision irrigation and fertilisation strategies tailored to site-specific soil properties (Dong et al., 2024; Mendez & Dasig, 2020; Zhang et al., 2024a, b; Kuldeep et al., 2024). This capability reduces resource wastage while improving crop uniformity. Ambiguous land usage is also addressed through the use of up-to-date satellite and UAV imagery, which enables accurate delineation of land boundaries, identifying of underutilised or misclassified agricultural areas, and improved land management planning (Viskovic et al., 2019; Sacomani et al., 2024). Lastly, weed infestation, a biotic stress competing with crops for water and nutrients, is detected at early growth stages using remote sensing techniques. Mapping weed distribution allows for site-specific herbicide application, reducing chemical use and environmental impact, particularly in annual crops such as soybean (Roslim et al., 2021; Anand et al., 2021). Overall, these findings demonstrate that remote sensing plays a critical role in addressing a wide spectrum of biotic and abiotic precision cropping challenges, from nutrient and water stress to pests, weeds, and land management, thereby supporting sustainable and resource-efficient agricultural practices.

At 33.3%, crop water stress together with biotic stresses from pests and diseases represent the most frequently reported challenges directly affecting crop health and yield. Remote sensing supports early detection of these stresses, enabling the identification of affected areas and optimisation of inputs such as irrigation and pesticides (Zhang et al., 2023). Ambiguous land usage and weed infestation, each documented by 8.3%, are less prevalent but remain significant challenges; remote sensing facilitates accurate land boundary delineation and identification of underutilised or misclassified agricultural areas (Gafurov, 2023), as well as early weed detection that reduces reliance on broad-spectrum herbicides, particularly in annual crops such as soybean (Roslim et al., 2021).

Water management challenges associated with drought and flooding, accounting for 33.3% of the reviewed studies, highlight the role of remote sensing in supporting informed irrigation decisions under variable climate conditions, thereby reducing the risk of crop loss due to water stress or excess moisture (Anand et al., 2024). Furthermore, 16.7% of the documents address soil macro- and micro-nutrient stresses, demonstrating how spectral and canopy-based indicators can reveal nutrient deficiencies and support site-specific fertiliser management. A similar proportion (16.7%) focuses on variable crop field conditions, where high-resolution remote sensing data enable the identification of

Fig. 4 Geographical distribution and relative contribution of publications on remote sensing in precision cropping (2015–2024). The pie chart shows the proportional contribution of papers from each region, highlighting the predominance of research from Asia (59.7%), followed by Europe (17.5%) and South America (9.9%), with smaller contributions from Africa (4.7%), North America (4.7%), Transcontinental (0.6%), and other or unspecified regions (2.9%)

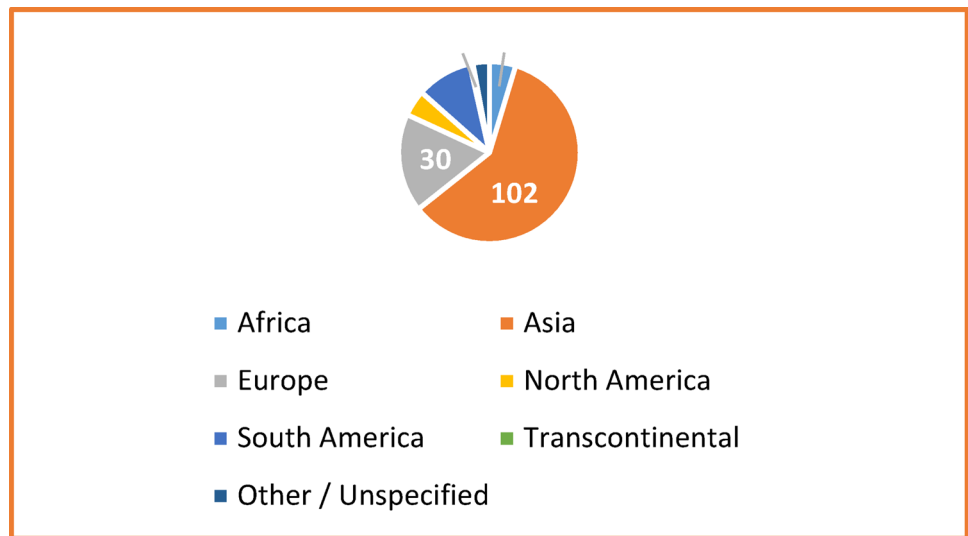


Table 2 Precision cropping challenges addressed by remote sensing, and authors and number of documents

Category of challenges	Author(s)	Number of document counts/24	Percentage (%)
Crop water stress and biotic stresses (pests and diseases)	Katsigiannis et al., 2016; Cubero et al., 2020; Segarra et al., 2020; Delavarpour et al., 2021; Abdullah et al., 2023; Fuentes-Penailillo et al., 2024; Lammoglia et al., 2024; Vinayaka & Prasad, 2024	08	33.3
Water management (drought and flooding effects – abiotic stress)	Bonfante et al., 2019; Anand et al., 2021; Anand et al., 2024; Ennatiqi et al., 2024; Fuentes-Penailillo et al., 2024; Knipper et al., 2024; Vinayaka & Prasad, 2024; Zeyliger et al., 2024	08	33.3
Soil macro- and micro-nutrient stress/deficiencies (abiotic stress)	Dong et al., 2024; Mendez & Dasig, 2020; Zhang et al., 2024a, b; Kuldeep et al., 2024	04	16.7
Variable crop field conditions (soil variability and structure)	Mendez & Dasig, 2020; Dong et al., 2024; Kuldeep et al., 2024; Zhang et al., 2024a, b	04	16.7
Ambiguous land usage	Viskovic et al., 2019; Sacomani et al., 2024	02	8.3
Weed infestation (biotic stress)	Anand et al., 2021; Roslim et al., 2021	02	8.3

Percentages may exceed 100% due to overlap across challenge categories

spatial soil variability to support precision irrigation (Xiao et al., 2024).

Practical Challenges Faced by Farmers Using Data from Remote Sensing Technologies

In this study, a total of 9 major practical challenges, referring to technology, was recorded from 141 publication counts (Table 3). These were: complexity in maximising the multi-temporal characteristics of cropped land (27 publication counts), difficulties in generalising models to new and unseen data (21), limited automation in implementation of remote sensing technologies (20), high cost (18), low spatial-temporal resolution (17), variations in spectral and spatial scales (17), noise and ambiguity in spatial segmentation (10), sensor limitations and time constraints (7), and strict regulations (4). This result is shown in Fig. 5.

The key challenges faced by farmers in utilising remote sensing data for precision cropping are underscored in this study, and they are; complexities in maximising multi-temporal characteristics, difficulties in generalising models to new and unseen data, and limited automation in implementation. An example is the variability from remote sensor data obtained from studying the host-pathogen interactions (Oerke, 2020; Peng et al., 2024; Xu et al., 2024) in some crops. This is coupled with a lack of operational knowledge on crop nutrient estimation by reflectance sensors (Silva et al., 2023). Relatedly, the specific technologies of UAVs and sensors demand maximum or more human involvement (Rejeb et al., 2022).

High cost, low resolution, and variations in spectral and spatial scales further complicate effective use. However, high cost was contested by Dong et al. (2024), Rokhafrouz et al. (2021), Jing et al. (2024), Zhang et al. (2024a, b), and Li et al. (2024). They reported that remote sensing

Table 3 Authors and publication counts against the practical challenges of remote sensing technologies data

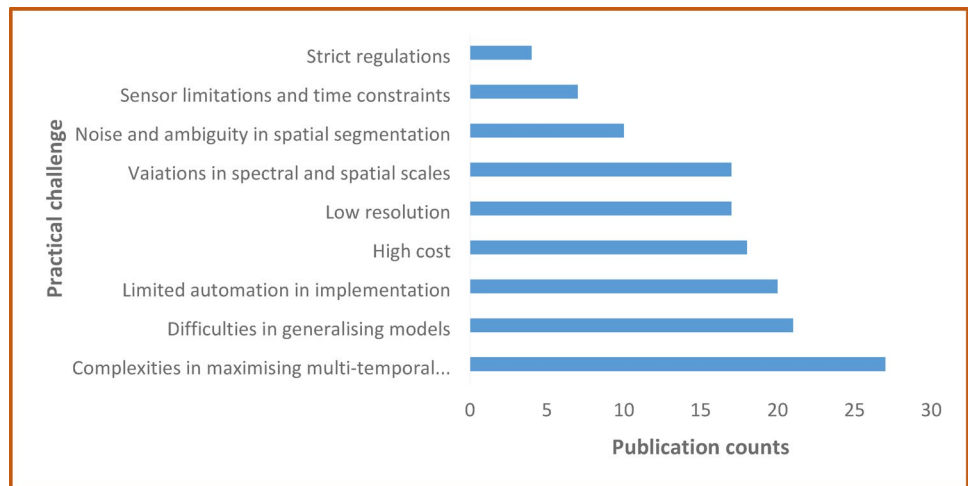
Practical challenge	Author and publication date recorded	Publication counts
Complexity in maximising multi-temporal characteristics of cropped land.	Beneduzzi et al., 2017; Moriarty et al., 2018; Yang, 2018; Viskovic et al., 2019; Tsouros et al., 2019; Oerke, 2020; Randhawa et al., 2020; Delavarpour et al., 2021; Roslim et al., 2021; Arjoune et al., 2022; Karapetsas et al., 2022; Radocaj et al., 2022; Vayssade et al., 2022; Dutta et al., 2023; Molina-Rotger et al., 2023; Shi et al., 2023; Alexopoulos et al., 2023; Vidican et al., 2023; Agrawal & Arafat, 2024; Anderegg et al., 2024; Bendini et al., 2024; Afsar et al., 2024; Aliloo et al., 2024; Hu et al., 2024; Peng et al., 2024; Wang et al., 2024; Xu et al., 2024	27 documents
Difficulties in generalising models to new and unseen data	Milas et al., 2018; Tripodi et al., 2018; Randhawa et al., 2020; Delavarpour et al., 2021; Arjoune et al., 2022; Karapetsas et al., 2022; Vayssade et al., 2022; Molina-Rotger et al., 2023; Piccoli et al., 2023; Shi et al., 2023; Vidican et al., 2023; Aliloo et al., 2024; Anderegg et al., 2024; Konara et al., 2024; Qiu et al., 2024; Tan et al., 2024; Vélez et al., 2023; Vinayaka & Prasad, 2024; Wang et al., 2024; Yuan et al., 2024; Zhu et al., 2024	21 documents
Limited automation in implementation of remote sensing technologies	Katsigiannis et al., 2016; Zude-Sasse et al., 2016; Tsouros et al., 2019; Viskovic et al., 2019; Randhawa et al., 2020; van der Merwe et al., 2020; Arias et al., 2021; Delavarpour et al., 2021; Radocaj et al., 2022; Alexopoulos et al., 2023; Rivera et al., 2023; Shi et al., 2023; Afsar et al., 2024; Agrawal & Arafat, 2024; Andrés-Anaya et al., 2024; Bendini et al., 2024; Konara et al., 2024; Luo et al., 2024; Vélez et al., 2023; Wang et al., 2024	20 documents
High cost	Manfreda et al., 2018; Moriarty et al., 2018; Bonfante et al., 2019; Tsouros et al., 2019; Jewan et al., 2021; Jurado et al., 2022; Karapetsas et al., 2022; Li et al., 2022; Radocaj et al., 2022; Alexopoulos et al., 2023; Agrawal & Arafat, 2024; Aliloo et al., 2024; Konara et al., 2024; McCauley et al., 2024; Peng et al., 2024; Vélez et al., 2023; Vinayaka & Prasad, 2024; Xiao et al., 2024	18 documents
Low spatial-temporal resolution	Beneduzzi et al., 2017; Yang, 2018; Mendez & Dasig, 2020; Delavarpour et al., 2021; Shafi et al., 2022; Alexopoulos et al., 2023; Agrawal & Arafat, 2024; Andrés-Anaya et al., 2024; Bendini et al., 2024; Farbo et al., 2024; Killeen et al., 2024; Konara et al., 2024; Lee et al., 2024; Nogueira et al., 2024; Peng et al., 2024; Qiu et al., 2024; Tan et al., 2024	17 documents
Variations in spectral and spatial scales	Yang et al., 2017; Milas et al., 2018; Yang, 2018; Mukherjee et al., 2019; Tsouros et al., 2019; Niu et al., 2020; Delavarpour et al., 2021; Serrano et al., 2021; Li et al., 2022; Guo et al., 2023; Aliloo et al., 2024; Jiang et al., 2024; Konara et al., 2024; Luong et al., 2024; Mehedi et al., 2024; Wu et al., 2024; Xiao et al., 2024	17 documents
Noise and ambiguity in spatial segmentation	Mukherjee et al., 2019; Karapetsas et al., 2022; Shi et al., 2023; Afsar et al., 2024; Agrawal & Arafat, 2024; Luong et al., 2024; Peng et al., 2024; Thakkar & Vanzara, 2024; Vélez et al., 2023; Wang et al., 2024;	10 documents
Sensor limitations and time constraints	Qiao et al., 2022; Aliloo et al., 2024; Dakshinamurthy et al., 2024; Konara et al., 2024; Vélez et al., 2023; Vinayaka & Prasad, 2024; Wu et al., 2024	7 documents
Strict regulations	Tsouros et al., 2019; Delavarpour et al., 2021; Agrawal & Arafat, 2024; Aliloo et al., 2024	4 documents

technologies are of low cost compared to traditional moisture detection methods in cropland area delineation, field sampling for nutrients, and detection of crop features such as capitula in sunflower. Further contest came from Su et al. (2023) and Mukherjee et al. (2019) on a particular application of small multi-rotor UAVs. Relatedly, Arjoune et al. (2022) defended the cost-effectiveness of using these technologies in detecting soybean cyst nematode. According to Delavarpour et al. (2021), the capability of precision cropping tools lowers operational costs. Besides, the low resolution was attributed to the vulnerability of technologies to weather and environmental influences. In contrast, Jing et

al. (2024) argue that these technologies offer high resolution especially in the identification of certain crop features as in the case of sunflower. Equally, variations exist in the application of UAVs especially in determining the Leaf Area Index (LAI). These were explained by sensor capabilities, flight parameters, and environmental conditions.

Furthermore, noise and ambiguity in spatial segmentation, along with sensor limitations and time constraints, and strict regulations added to the practical barriers. This ambiguity was mainly associated with field areas of wheat and other grain, fruit, and vegetable crops (Karapetsas et al., 2022; Afsar et al., 2024; Thakkar & Vanzara, 2024). The

Fig. 5 Proportion of practical challenges in the use of data from remote sensing technologies



challenge of sensor limitations was linked to insertion difficulties on hard soil particularly in measuring soil moisture (Chavanne & Frangi, 2024). The regulations in place were cited to limit the flight of UAVs to certain altitudes in some regions (Tsouros et al., 2019; Delavarpour et al., 2021; Agrawal & Arafat, 2024; Aliloo et al., 2024). Addressing these challenges through improved technology, better model adaptability, and cost-effective solutions is essential for enhancing the effectiveness of precision cropping.

Challenges of Precision Cropping in Developing Countries

In addition to the technical challenges outlined, precision cropping in developing countries faces significant socio-economic and structural constraints. Farms in these regions are often small, fragmented, and irregularly shaped, which limits the applicability of UAVs, GNSS-guided machinery, and large-scale remote sensing interventions (Sharma & Shivandu, 2024). Limited access to advanced technologies, insufficient technical training, and low digital literacy further hinder the adoption of precision agriculture tools (Inoue, 2020; Padhiary et al., 2024). Economic bottlenecks, including the high upfront costs of sensors, drones, and associated software exacerbate these challenges, making investment in precision cropping less feasible for smallholder farmers (Fuentes-Penailillo et al., 2024). Consequently, while remote sensing technologies have demonstrated high potential in improving crop management, water use efficiency, and yield optimisation (Ashraf et al., 2023), their real-world impact in developing regions is constrained by fragmented landholdings, low technology penetration, and financial limitations (Almohsen, 2024). Tailored strategies such as low-cost sensor networks, shared equipment models, and farmer training programmes, are critical to bridge these gaps and enable broader adoption of precision agriculture practices.

Utilisation of Data from Remote Sensing Technologies

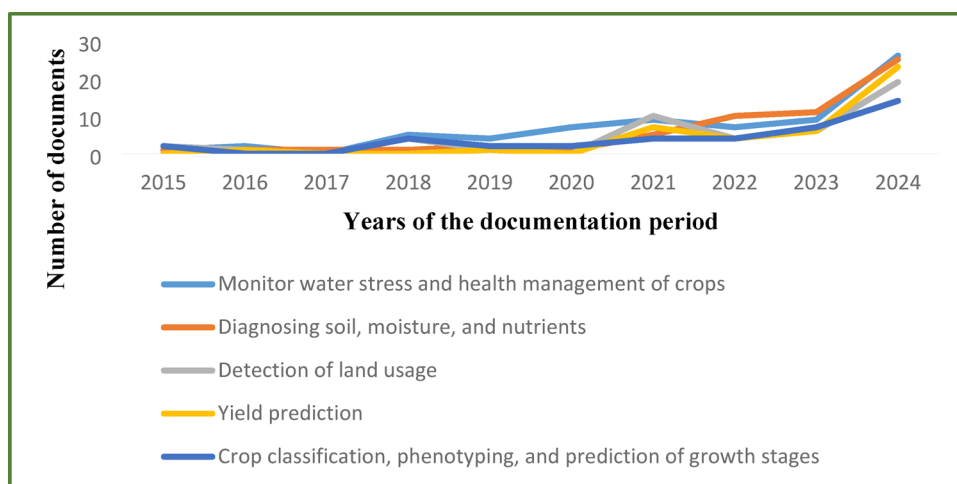
Real-time monitoring of crop health (Liu et al., 2024), soil conditions, and environmental factors (Radočaj et al., 2022) were documented as the defining linchpins for remote sensing data that precision farmers would utilise to optimise inputs, improve yields, and reduce environmental impact on crops (Sishodia et al., 2020; Alahmad et al., 2023). Specifically, literature pointed out five major areas where data provided by remote sensing technologies was supportive of precision cropping, and each year produced a recorded number of documents against a utilisation area (slot) as indicated by Table 4. Consequently, Fig. 6 depicts the respective trend of the documented data areas towards the year 2024.

In the first place, most literature (70 documents) reported that data from remote sensing technologies is used to monitor water stress and health management of crops in precision cropping. Katsigiannis et al. (2016) demonstrated the use of a multi-sensor imaging system to manage the water within an orchard of pomegranates. Similarly, Bonfante et al. (2019) recorded the importance of this data in monitoring the status of soil water in a maize case study in southern Italy. Health management was specific on pest, disease, and weed detection and control, as highlighted by Yang et al. (2017), Kerkech et al. (2020), and Ang and Seng (2021).

Secondly, the data is utilised for diagnosing soil, moisture, and nutrients required for various types of crop plants, specifically cereals and legumes, as revealed by 58 documents. Nduku et al. (2023) described the way fertiliser inputs can be better managed by using remote sensing technologies to identify soil properties suitably attached to crops as the case was in the growing of winter wheat. Likewise, in their study, Baradaran and Tavazoei (2024) provide sensors as an approach for determining the water consumption amount by plants. Relatedly, in monitoring the status of

Table 4 Major areas of literature for remote sensing technologies data 2015–2024

Literature area	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Number of documents
Monitor water stress and health management of crops	1	2	0	5	4	7	9	7	9	26	70
Diagnosing soil, moisture, and nutrients	1	1	1	1	2	1	5	10	11	25	58
Detection of land usage	2	1	0	4	1	0	10	4	6	19	47
Yield prediction	0	1	0	0	1	0	7	4	6	23	42
Crop classification, phenotyping, and prediction of growth stages	2	0	0	4	2	2	4	4	7	14	39
Total	6	5	1	14	10	10	35	29	39	107	256

Fig. 6 Major areas with documents supportive of remote sensing technologies data for the period, 2015–2024

nutrients for crops, Misbah et al. (2022) noted the value of employing hyperspectral imaging technology on nutrients, nitrogen, phosphorus, and potassium. For this reason, data from remote sensing was insightful in scientific management of the three parameters, soil, moisture, and nutrient content for crops (Kubiak et al., 2024).

In the same context, as recorded by 47 documents, the data facilitates the detection of land usage (Chen & Zhang, 2023). Information gathering about size, quality, and appearance is reported to have been performed mostly on grain, vegetable, and fruit crops (Omia et al., 2023). Remote sensing images such as Landsat-8 are used to classify land use and land cover, as stated by Carrillo et al. (2022) and Wang et al. (2024), though the latter disclose that there is a difficulty in effectively identifying small land plots using those techniques. Moreover, Abrahams et al. (2023) mentioned the incapability of capturing land fragmentation in the mapping of land for the neglected and underutilised crop species. In different regions of China, as conducted by Zhu et al. (2024), the data was utilised in delineating the boundaries of land associated with degradation by engaging the colour space augmentation (CSA) approach.

Another consideration is yield prediction through the use of remote sensing technologies data, documented by 42 documents. It was applied in California in the USA on cultivated sugar beet in a study conducted by Hu et al. (2024). Zhang et al. (2023) also reported the use of such

data in predicting the yield of tobacco through a hyperspectral approach. The same approach was applied to palm oil, as described by Rashid et al. (2021). The use of spectral images, vegetation indices (VIs), and machine learning algorithms (MLA) was crucial in all instances.

Finally, 39 documents captured the use of this data in crop classification, phenotyping, and prediction of growth stages. The notable aspects focused on were crop type and crop vitality, describing crops that fit in a particular area basing on their biological characteristics, and assessing the well-being of mainly horticultural and cereal crops (Zhang et al., 2019) such as sugar beet, parsley, spinach, winter, and corn (Song et al., 2023). Although it was reported to be affected by precipitation, management among other factors, these aspects were instrumental in guiding the rotation of crops, according to Barriere et al. (2024).

In addition to application-based utilisation, the reviewed literature was further analysed based on the type of remote sensing sensors employed, as different sensor modalities provide distinct information relevant to precision cropping. The major sensor categories identified include optical multispectral, thermal, hyperspectral, microwave (Synthetic Aperture Radar – SAR, and radiometry techniques), and fluorescence-based sensors (Table 5).

Optical multispectral sensors were the most widely used, supporting applications such as crop health monitoring, land use and land cover classification, crop classification,

Table 5 Partitioning of reviewed literature based on remote sensing sensor types used in precision agriculture (2015–2024)

Remote sensing sensor type	Typical applications in precision cropping	Representative studies	Number of documents
Optical (multispectral)	Crop health monitoring, land use detection, crop classification, yield prediction	Zhang et al., 2019; Carrillo et al., 2022; Wang et al., 2024	112
Thermal	Water stress detection, irrigation scheduling, evapotranspiration estimation	Katsigiannis et al., 2016; Bonfante et al., 2019; Baradaran & Tavazoei, 2024	61
Hyperspectral	Nutrient stress diagnosis, disease detection, crop phenotyping, yield prediction	Rashid et al., 2021; Misbah et al., 2022; Zhang et al., 2023	54
Microwave (SAR and radiometry)	Soil moisture monitoring, flood assessment, land degradation mapping	Chen & Zhang, 2023; Zhu et al., 2024	39
Fluorescence	Photosynthetic activity monitoring, early stress detection	Liu et al., 2024	18

Totals exceed the number of reviewed documents as several studies employed multiple sensor types

and yield estimation (Zhang et al., 2019; Carrillo et al., 2022; Wang et al., 2024). These sensors are favoured for their broad spatial coverage and long-term data availability, although their performance is limited under cloud-covered conditions (Ouattara et al., 2020). Thermal sensors were predominantly utilised for water stress detection and irrigation management, owing to their ability to capture canopy temperature variations linked to plant transpiration and evapotranspiration (Katsigiannis et al., 2016; Bonfante et al., 2019; Baradaran & Tavazoei, 2024). Hyperspectral sensors were primarily associated with nutrient stress diagnosis, disease detection, and detailed crop phenotyping, as their high spectral resolution enables discrimination of subtle biochemical and physiological changes in crops, particularly for nitrogen, phosphorus, and potassium monitoring (Rashid et al., 2021; Misbah et al., 2022; Zhang et al., 2023). Microwave sensors, including SAR and radiometry, were employed mainly for soil moisture estimation, flood assessment, and land degradation mapping, benefitting from their cloud-penetrating capability and sensitivity to surface roughness and moisture content (Chen & Zhang, 2023; Zhu et al., 2024). Fluorescent-based sensing, although less frequently represented, was applied in advanced studies targeting photosynthetic activity and early stress detection,

offering direct insight into plant physiological functioning under biotic and abiotic stress conditions (Liu et al., 2024).

Ground-Based and Global Navigation Satellite System (GNSS)-Enabled Remote Sensing for Precision Agriculture

While satellite- and UAV-based remote sensing dominate recent precision agriculture research, several studies also highlight the importance of ground-based and positioning-enabled remote sensing technologies, particularly for field-scale soil mapping and site-specific management (Guebsi et al., 2024). These approaches complement image-based remote sensing by providing high-resolution subsurface and positional information that is critical for precision cropping decisions.

Ground Penetrating Radar (GPR) has been applied in precision agriculture to characterise subsurface soil properties, including soil layering, compaction zones, root depth, and drainage patterns (Zajícová & Chuman, 2019). Such information supports improved soil management, irrigation planning, and root-zone assessment, particularly in heterogeneous fields where surface imagery alone is insufficient (Pathirana et al., 2023). GPR-based measurements are especially valuable for detecting hardpans and assessing soil structure variability at the field level (Lombardi et al., 2022). GNSS-enabled remote sensing, including both aerospace-based satellite positioning and field-based GNSS receivers mounted on agricultural machinery, plays a foundational role in precision agriculture (Radočaj et al., 2023). GNSS technologies enable accurate geo-referencing of remote sensing data, yield mapping, variable rate application (VRA), and automated guidance systems (Vélez et al., 2024). These positioning capabilities allow spatially explicit integration of sensor-derived data with field operations, ensuring that management decisions are applied precisely at the required locations. In addition, large-scale (field-level) soil mapping has been widely supported through proximal sensing technologies combined with GNSS, such as electromagnetic induction, electrical resistivity, and GPR (De Benedetto et al., 2019). These methods facilitate detailed mapping of soil texture, moisture distribution, salinity, and compaction within individual fields, enabling site-specific soil and nutrient management (Babaeian et al., 2019). Such approaches are particularly relevant for precision cropping systems where within-field variability strongly influences crop performance and input efficiency (Rodrigues Jr et al., 2015).

Overall, the integration of ground-based sensing, GNSS-enabled positioning, and field-scale soil mapping (Table 6) enhances the effectiveness of precision agriculture by

Table 6 Ground-based and GNSS-enabled remote sensing technologies used in precision agriculture

Technology	Scale of application	Key uses in precision agriculture	Contribution to precision cropping
Ground Penetrating Radar (GPR)	Field/Sub-field	Soil stratification, compaction detection, root-zone analysis	Improves soil management, drainage planning, and root development assessment
GNSS (aero-space and field-based)	Field/Machinery level	Geo-referencing, yield mapping, variable rate application, auto-guidance	Enables spatially precise input application and data integration
Proximal soil sensing (resistivity)	Field scale	Soil texture, moisture, salinity mapping	Supports site-specific irrigation and nutrient management
GNSS-integrated soil mapping	Field scale	High-resolution soil variability mapping	Enhances precision decision-making at within-field level

bridging the gap between remote observations and on-ground management actions.

Integrating Remote Sensing Data to Counter Daily Precision Cropping Challenges

The challenges faced by precision crop farmers ranging from crop water stress to weed infestation rely significantly on accurate data derived from remote sensing, that facilitates decision-making and efficient resource management, as recorded by Sharma and Shivandu (2024). This record is complemented by Inoue (2020) and Padhiary et al. (2024) who disclose that remote sensing data, together with tools, such as sensors and drones require an incorporation into precision cropping practices for resource optimisation, improved crop yield, and ultimate sustainability (Fig. 7). Therefore, the instances in this study where data was integrated to provide actionable approaches of addressing common challenges in precision cropping are presented below.

Hyperspectral remote sensing, as recommended by Zhang et al. (2023) in their review on tobacco quality, yield, and stress detection, is an economical option. However, its effectiveness needed support from both reflectance and agronomic parameter data whereby UAVs were utilised as tools for capturing visible light images. Although considered slow by Zhang et al. (2023), agronomic parameter data can be obtained from Leaf Area Index (LAI) device, Soil

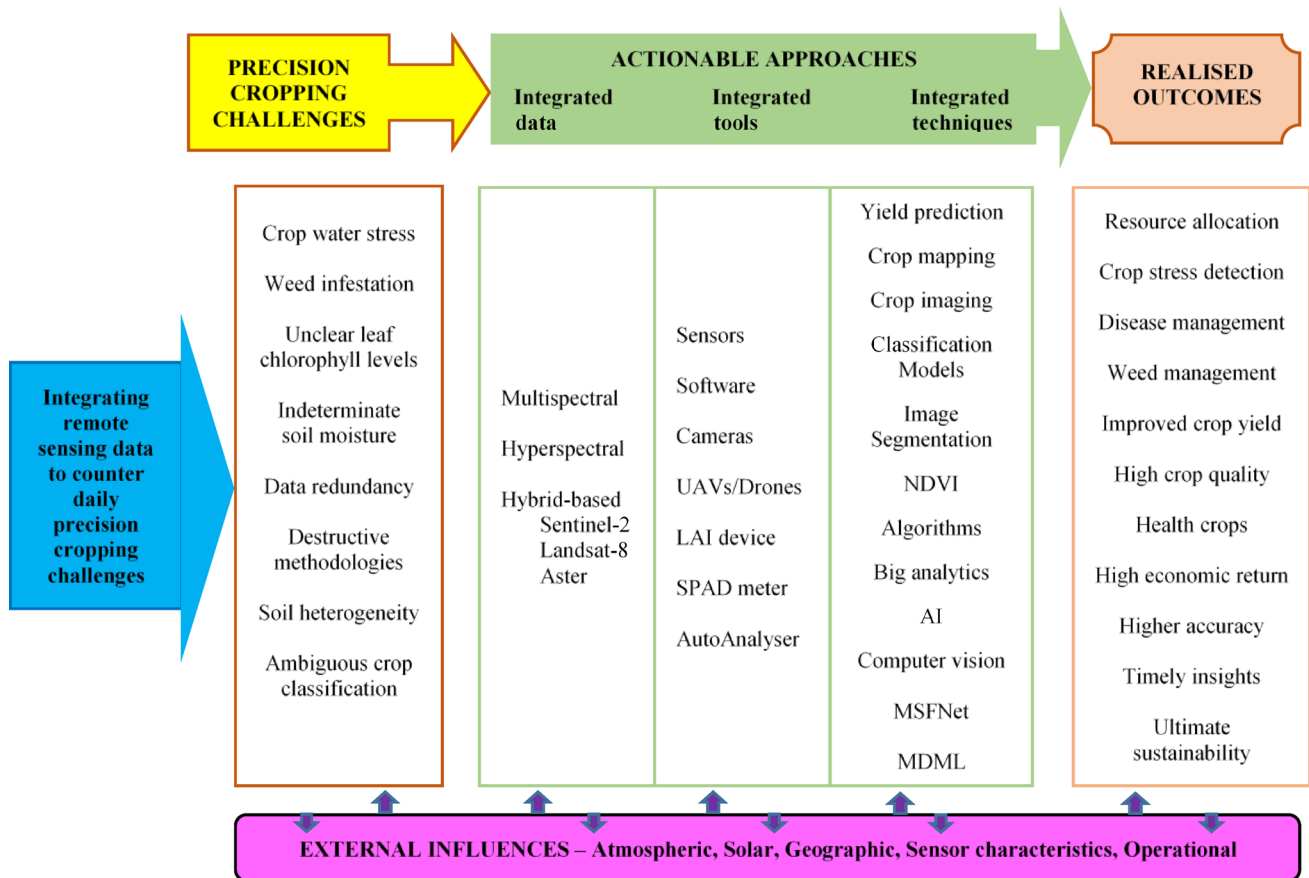


Fig. 7 Logic model of challenges, actionable approaches, and realised outcomes

Plant Analysis Development (SPAD) meter, and AutoAnalyser. Supported by Makam et al. (2024), a combination of the data could allow for detailed monitoring of crop land areas. Specifically, the sensors or cameras fixed on UAVs specifically capture near-infrared (NIR) images, and provide valuable insights into crop health (Zhang et al., 2024a, b). In instances, such as mapping and imaging, UAVs were reported to serve as platforms for gathering thermal spectral images (Mukherjee et al., 2019; Roslim et al., 2021; Nduku et al., 2023; Li et al., 2024; Qiu et al., 2024). This implies evidence of integrating tools and their methodologies, featuring as a precursor to high economic return of precision cropping. Similarly, this approach was used in China's Heilongjiang Province as a complement of disease and weed management under crop classification models (Zheng et al., 2024). Researchers pointed out some outcomes on this integration as; higher accuracy (Anam et al., 2024; Chen et al., 2024; Jewan et al., 2021), reduced operational cost (Guebsi et al., 2024) on agrochemical use, especially herbicides, and improved crop health through active field protection (Barbosa et al., 2022), through putting together images and multispectral data obtained from UAVs (Vélez et al., 2023).

Hybrid-based data from different sources such as Sentinel-2 Satellite is used for delineating land management zones as documented in a study conducted in Wielkopolskie Voivodeship, Poland (Rokhafrouz et al., 2021). This integrated data eased fertilisation recommendation for precision cropping. In a study conducted in Italy's Piemonte Region, future estimates of the Normalised Difference Vegetation Index (NDVI) on corn using this approach proved accurate (Farbo et al., 2024). Relatedly, results from a study on modelling the status of water on vineyard showed successful planning and management of irrigation for the crop (Giannico et al., 2024). In addition, object detection algorithms offer a simplified approach for detecting and monitoring leaf chlorophyll levels, soil moisture, crop stress, and features of specific plants (Afsar et al., 2024). To illustrate this argument, the You Only Look Once (YOLO) technology was applied in Shandong Province of China to monitor maturation processes of sunflower capitula. According to Jing et al. (2024), the results indicated an innovative and effective means of precision cropping where multiple tasks could be integrated into one network. In other cases, integration of data was performed by soil digital mapping to provide accurate representations of soil characteristics such as soil moisture, texture and pH across a landscape are drawn (Jewan et al., 2021).

On a similar note, there are cases where data is captured across a very wide range of wavelengths in the electromagnetic spectrum (Li et al., 2024). However, there are incidents of interference by irrelevant signals with actual data being collected, resulting in data redundancy, according to

Tao et al. (2022). In such circumstances, it is possible to predict leaf chlorophyll in crop plants using a non-destructive way (Huang et al., 2024). For example, multi-processing techniques and algorithms such as Fast Fourier Transform were applied in Anhui Province of China to counter background noise and duplication of data in predicting winter wheat SPAD (Nian et al., 2024). In a similar instance, Baressel et al. (2017) earlier recommended the use of a digital consumer camera for detecting the chlorophyll content of field wheat leaves after conducting three comparable experiments in Dürnast's Munich Technical University research station of Germany. The results in those related experiments showed high quality images as part of the focus for precision cropping.

Equally important, the variation in soil properties, structure, and composition that characterises crop areas (Yang et al., 2022), as it occurs at different spatial scales, is a critical determinant of crop growth, as indicated by Piotrowska-Długosz et al. (2016) and Tesfahunegn and Gebru (2020). Addressing soil heterogeneity for cropland requires an integration of remote sensing data for improved precision cropping, as described by Wang et al. (2024). Specifically, the process of setting soil management zones in São Paulo State of southeastern Brazil required a blend of Landsat-8, Aster, and Sentinel-2 images from proximal soil sensing and remote sensing (Rodrigues et al., 2023). According to Rodrigues et al. (2023), this study provided a careful understanding of specific soil conditions, including fertiliser requirements, within the zone of study. Similarly, soil analysis combined with yield prediction and mapping of spatial variability from the field trial of Bambara groundnuts conducted in Semeniyih, Malaysia indicated an increased performance and stability of models based on multi-temporal data over single-stage data, as compiled by Jewan et al. (2021). Fuentes-Penailillo et al. (2024) also reported increased capabilities and crop growth tracking through the use of integrated tools, big analytics, and Artificial Intelligence (AI). According to Fuentes-Penailillo et al. (2024), the innovation highlighted critical factors like soil moisture, pH, and nutrients.

Another challenge is crop classification which can easily be handled by image segmentation. As revealed by Hu et al. (2024), a Multi-Scale Fusion Network (MSFNet) together with Model Diagnostic Meta Learning (MDML) approaches were employed to address an imbalance of land cover types. This revelation agrees with that of Yu et al. (2024) where algorithms such as clustering were used for improved accuracy of image segmentation and better error identification. On the same note, it was easier to analyse and interpret the data provided from the images of individual sugarcane fields using an image segmentation study in China's Fusui County. Evidence from Yuan et al. (2024) confirms the use

of multiple approaches to providing high-resolution image data for sugarcane crop field. Furthermore, it required utilisation of two methods, Random Forest and Machine algorithms, for classifying, monitoring and managing the fruit fly pest on olive crops in Spain's Balearic Islands Research Institute. As recorded by Molina-Rotger et al. (2023), there was an increased classification accuracy despite the use of a small training dataset in the experiment. Therefore, besides offering significantly accurate and timely insights, these approaches optimised precision cropping practices, reduced resource wastage, and boosted crop yields (Kumar et al., 2024).

Finally, precision cropping demands capturing of images using advanced imaging technologies, informative features, and computational techniques. Some of imaging technologies are machine learning (ML) involving AI and computer vision (Ghazal et al., 2024); the informative features include spatial resolution, spectral resolution, and data fusion (Yu et al., 2024); and the computational techniques can be NDVI of spectral analysis, where a band ratio guides the determination of plant cover health (Lu et al., 2020). This study observed feature mining applied in integration with ML algorithms in applying hyperspectral images. According to Ma et al. (2022), the nitrogen status in wheat crop plants was reported using such combined techniques and an accurate assessment of grain parameters, specifically protein content. Similarly, a network of devices, sensors, and software was applied by Imade et al. (2024) under the Internet of Things (IoT) and remote sensing technologies. Data accuracy and efficient resource allocation on crops were the results from this innovation. Lastly, through an analysis of bibliography on the yield estimation of tree crops, Trentin et al. (2024) recommended integrating different data sources. Their declaration was aligned with higher accuracy levels of up to 99% which were provided by techniques involving ML. The overall implication is that precision cropping practices can be optimised with efficient integration of remote sensing and ML to solve the existing challenges, as earlier stated by Wang et al. (2024).

Optimal Remote Sensing and Digital Resource Requirements for Overcoming Precision Cropping Challenges

Addressing the diverse biotic, abiotic, technological, and socio-economic challenges of precision cropping requires an integrated and multi-layered sensing ecosystem. An optimal precision farming framework would combine space-borne, aerial, proximal, and IoT-based resources to deliver timely, accurate, and actionable information across spatial and temporal scales (Table 7). Such integration is particularly critical in contexts characterised by fragmented cropland,

Table 7 Optimal space, aerial, proximal, and IoT resource requirements for overcoming precision cropping challenges

Resource layer	Optimal requirements	Key challenges addressed
Space-borne (Satellite)	High spatial and temporal resolution; multispectral, hyperspectral, and SAR sensors; open-access data	Crop water stress, land use ambiguity, drought and flooding, large-area monitoring
Aerial (UAVs)	Low-cost UAV platforms; multispectral, thermal, and hyperspectral cameras; autonomous flight and shared services	Fragmented cropland, pest/disease detection, weed infestation, crop health monitoring
Proximal/ground-based	Soil moisture, nutrient, pH, salinity sensors; GPR and resistivity tools; GNSS-enabled machinery	Soil variability, nutrient stress, site-specific irrigation and fertilisation
IoT and digital integration	Real-time sensor connectivity; cloud computing; AI and machine learning analytics; mobile decision-support systems	Data integration, automation, model scalability, farmer adoption

climatic variability, and limited operational capacity (Fuentes-Penailillo et al., 2024; Padhiary et al., 2024). Together, the following optimally configured resources enable a holistic precision cropping system that improves crop productivity, resource-use efficiency, and resilience, while addressing both technical and socio-economic constraints.

At the space-borne level, high spatial- and temporal-resolution satellite imagery is essential for large-area monitoring of crop health, water stress, and land use dynamics, and climate-driven risks (Table 7). Multispectral and hyperspectral sensors enable vegetation health and nutrient stress detection, while SAR provides all-weather capability for soil moisture estimation and flood monitoring, particularly under cloud-covered conditions (Bonfante et al., 2019; Chen & Zhang, 2023; Zhu et al., 2024). Open-access satellite platforms are especially important for improving accessibility and cost-effectiveness in developing regions.

At the aerial level, UAV-based remote sensing offers ultra-high spatial resolution suitable for smallholder and fragmented fields. Multispectral, thermal, and hyperspectral UAV sensors support early detection of pests, diseases, weeds, and water stress, as well as detailed crop phenotyping. Autonomous flight planning, on-board processing, and shared UAV service models represent optimal requirements

to reduce labour demand and operational costs (Roslim et al., 2021; Vélez et al., 2023).

Proximal and ground-based sensing resources provide critical in situ measurements that complement image-based observations. Soil moisture, nutrient, salinity, and pH sensors, combined with geophysical tools such as electrical resistivity and GPR, enable detailed characterisation of within-field soil variability. GNSS-enabled positioning supports accurate geo-referencing, yield mapping, and variable rate application, ensuring that management interventions are spatially precise (De Benedetto et al., 2019; Radočaj et al., 2023).

Finally, IoT infrastructure and digital integration platforms form the backbone of an effective precision cropping system. IoT-enabled sensor networks facilitate real-time data acquisition and transmission, while cloud-based analytics and artificial intelligence support data fusion, model generalisation, and decision support. Farmer-oriented interfaces, such as mobile applications and dashboards, are critical for translating complex data into practical recommendations, thereby enhancing technology adoption and usability (Imade et al., 2024; Fuentes-Penailillo et al., 2024).

Gaps to be Addressed in the Role of Technologies, Tools, and Data from Remote Sensing

Whereas the authors conducted an exhaustive review from a broad range of articles, several gaps need further attention. In particular, literature did not adequately describe the socio-economic barriers to adopting remote sensing technologies, data and tools. Secondly, literature did not delve deeper into the scalability of remote sensing technologies for different farm sizes, unintended consequences of degradation on the environment, and/or geographical regions. Furthermore, the ethical and regulatory implications, with regard to data overload, privacy, security, and ownership was not sufficiently discussed.

Conclusion

This review critically examined how remote sensing technologies are leveraged to address precision cropping challenges, with specific emphasis on practical constraints faced by farmers, the utilisation of remote sensing data, and the integration of sensing tools and analytical methods. Based on a systematic analysis of 171 peer-reviewed studies published between 2015 and 2024, the findings reveal that remote sensing has become a cornerstone of precision cropping, offering effective solutions to both biotic and abiotic

stresses, including water stress, pests, diseases, nutrient deficiencies, land use ambiguity, and spatial field variability.

The review demonstrates that data derived from multi-spectral, hyperspectral, thermal, microwave, and fluorescence sensors are widely utilised for real-time crop health monitoring, soil and nutrient diagnosis, land use planning, yield prediction, and crop classification. When effectively applied, these data enable farmers to optimise irrigation, fertiliser application, and pest management, thereby improving productivity and resource-use efficiency. However, the analysis also highlights persistent practical challenges that hinder adoption, notably data complexity, limited automation, difficulties in model generalisation, sensor limitations, regulatory constraints, and cost barriers. These challenges are particularly pronounced in developing countries, where fragmented landholdings, limited technical capacity, and financial constraints restrict the effective deployment of precision technologies.

Importantly, the review shows that integrating remote sensing data with complementary tools and methods, such as UAV platforms, ground-based sensing, GNSS positioning, machine learning, and IoT-enabled systems, significantly enhances the ability to counter day-to-day precision cropping challenges. Data fusion and hybrid modelling approaches consistently improve accuracy, reduce operational costs, and support site-specific decision-making.

Overall, the study underscores that while remote sensing technologies hold substantial promise for advancing precision cropping, their full potential can only be realised through integrated, scalable, and farmer-oriented solutions. Addressing technical, socio-economic, and regulatory gaps will be critical for ensuring sustainable and inclusive adoption of precision cropping practices worldwide.

Potential Areas for Future Exploration of Precision Cropping Technologies

Several areas can be explored to further advance the understanding and practical application of remote sensing technologies to overcome precision cropping challenges. There is a need for developing low-cost remote sensing technologies or more affordable access to data aligned with small-holder farmers especially in developing regions of the world. Further, it is important to examine the long-term impact of remote sensing technologies and tools on soil health and biodiversity. Lastly, it is crucial to investigate the impact of varied environmental conditions and landscapes, such as dust and vineyards respectively, on remote sensing data quality and developing methods to mitigate such effects.

Recommendations for Navigating the Results of the Study

Academicians, researchers, and practitioners seeking to navigate the results of the study on leveraging remote sensing technologies, tools and data to overcome precision cropping challenges can be guided by the following principles and recommendations.

A thorough grasp of the strengths and limitations of these technologies, including a focus on the practical capabilities of remote sensing tools, for framing future research questions and contributing to technological advancements. Next is collaboration with experts from different fields, such as engineering, and professionals beyond the farming community, such as technology providers. To address this further, research should be conducted about the cost-benefit analysis and evaluating the financial feasibility of using remote sensing technologies, tools, and data for overcoming precision cropping challenges. Finally, academicians and practitioners would engage in continuous learning and training to stay updated with emerging technologies and build skilled workforce, understanding, and use of these technologies, tools and data.

Acknowledgements The authors are grateful for the data provided by Web of Science database upon which the basis of this writing was made. Additional acknowledgement goes to TKP2021-NKTA-32 *Víz- zel kapcsolatos kutatások* Fund and the János Bolyai Research Scholarship of the Hungarian Academy of Sciences for availing financial assistance to the University of Debrecen for research purposes. Lastly, the authors wish to acknowledge the academic support and encouragement rendered by the administration and staff of the University Institute of Land Use, Engineering and Precision Farming technology.

Author Contributions Conceptualisation, R.K., E.A.H.M., and M.M.A.O.; methodology, R.K., B.S. and P.R.; original draft preparation, R.K. and M.M.A.O.; writing review and editing, R.K., E.A.H.M., B.S., and A.T.; supervision and quality control, A.T. and P.R.

Funding Open access funding provided by University of Debrecen. Project no. TKP2021-NKTA-32 *Víz- zel kapcsolatos kutatások* has been implemented in the University of Debrecen Institute of Land Use, Engineering and Precision Farming Technology with the support provided by the Ministry of Culture and Innovation of Hungary from the National Research, Development and Innovation Fund, financed under the TKP2021-NKTA funding scheme. This paper was also supported by the János Bolyai Research Scholarship of the Hungarian Academy of Sciences (BO/00068/23/4).

Declarations

Conflict of interest The authors declare no conflict of interest.

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