

## Review article

# A bibliographic study of integrating IoT and geospatial modelling for sustainable smart agriculture in developed countries: Focus on Australia

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## ABSTRACT

Integrating the Internet of Things (IoT) and geospatial modelling technologies is pivotal for advancing sustainable smart agriculture, particularly in resource-constrained environments like Australia. This systematic literature review examines the adoption and impact of these technologies in agriculture across Australia and select developed countries. Through an extensive analysis of 172 peer-reviewed articles published between 2013 and 2023, this study identifies key technological advancements such as unmanned aerial vehicles (UAVs), consumer-grade cameras (RGB cameras), and satellite platforms (Sentinel-2, LANDSAT-8) that have significantly influenced agricultural practices. The findings reveal Australia's progress in adopting these technologies but also highlight gaps compared to countries like Germany and the USA, especially in using UAVs, Synthetic Aperture Radar (SAR) and RGB cameras. The study underscores Australia's need to enhance its technological capabilities, particularly resource management, to foster more efficient and sustainable agricultural practices. This review provides valuable insights for policymakers, researchers, and technology providers, aiming to drive innovation and improve agricultural outcomes in the face of growing environmental challenges.

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## 1. Introduction

As the global population is projected to reach nearly 10 billion by the mid-21st century (De Marsily and Abarca-del Rio, 2016), feeding this ever-growing number of people is a critical challenge faced by many, especially the agricultural sector. This task is further complicated by climate change and the increasing scarcity of natural resources, heightening the need for innovative, sustainable, and efficient farming practices (Rickards, 2012). In response, sustainable smart agriculture has emerged as a forefront concept, advocating for advanced, eco-friendly farming methods.

Sustainable smart agriculture is critical to meeting the challenges of population growth and environmental pressures. This approach emphasises the use of advanced technologies to enhance the sustainability and productivity of farming operations. The Internet of Things (IoT) and geospatial modelling lead these innovations. IoT connects agricultural devices, allowing for real-time monitoring and precise control over farm operations, greatly improving resource management (Thilakarathne et al., 2021; Halder et al., 2025). Geospatial modelling optimises land use (Matthews et al., 1999) and improves crop yield predictions through detailed spatial analysis (Kingra et al., 2021). These technologies transform farming, aiming to assist farmers in increasing productivity while reducing their environmental impact.

The recent surge in research on IoT and geospatial modelling in agriculture has uncovered numerous opportunities and challenges, highlighting the need for comprehensive reviews to compile findings and identify gaps. While there is evidence of systematic literature reviews (SLRs) examining the incorporation of IoT and geospatial modelling in agricultural contexts, these themes are usually explored independently. Farooq et al. (2020) conducted an exhaustive analysis of IoT's role in agriculture, reviewing research articles from 2006 to 2019, and introduced an agricultural IoT framework elaborating on various IoT solutions to boost agricultural efficiency. Kim et al. (2020), in a separate review on agricultural automation via IoT, explored the potential to extend IoT applications within South Korea, providing detailed insights into IoT architectures and their diverse application areas in different agricultural operations. Xu et al. (2022) offered a systematic examination of agricultural IoT technologies, delineating a system architecture and exploring five key technological areas within the IoT agricultural sectors.

Additionally, there has been some evidence of reviews focusing on geospatial modelling within the agricultural sector. Obi Reddy et al. (2023) investigated the applications of big data and geospatial technologies in smart farming, addressing current challenges and future prospects in their book chapter. Mathenge et al. (2022) provided a systematic review of the application of Geographic Information Systems (GIS) in agriculture, highlighting the role of evidence-based decision-making in enhancing agricultural sustainability.

Prior reviews on digital agriculture have examined IoT deployments and, separately, remote sensing and geospatial modelling for precision agriculture and climate-smart practice. Yet most treat sensing and modelling as distinct literatures, adopt global or single-country scopes, and rarely deliver a crop-specific, cross-country synthesis for developed economies. This review addresses that gap by (i) jointly analysing IoT and geospatial modelling as components of integrated sensing–modelling–decision pipelines; (ii) structuring evidence by application domains—monitoring, estimation, and resource management; and (iii) providing a comparative lens on Australia against other developed producers. Technically, we add a synthesis of typical system architectures and deployment (Section 3.2.3), application-specific configurations (Section 3.2.4), and reported performance outcomes (Section 3.3), complementing the bibliometric mapping with technology-level insight. Conceptually, we frame these results within sustainability's environmental, economic and social dimensions to clarify how IoT–geospatial integration can optimise resource use, lower environmental burdens, support resilient productivity and inform risk management in grains and oilseeds (Symeonaki et al., 2019).

The cross-country comparison identifies Australia-specific gaps – notably lower representation of UAV-based RGB/multispectral and SAR deployments in resource-management tasks – despite Australia's exposure to water scarcity, climate variability and large-scale paddock operations. These gaps translate into actionable opportunities: (i) prioritise multi-year, multi-site on-farm trials that couple IoT sensing, geospatial modelling and variable-rate/automation in closed-loop workflows; (ii) harmonise reporting of technical and economic metrics to enable cross-study comparison and meta-analysis; and (iii) invest in connectivity, analytics capacity and co-design with growers and advisers so that technology pipelines mature into reliable, user-centred decision support for sustainable smart agriculture. IoT–geospatial pipelines are technically capable of advancing sustainability across environmental, economic and social pillars; the next step is scaling resource management oriented applications with rigorous, outcome-focused evaluation in Australian grain and oilseed systems.

The reviews mentioned above predominantly provide a global perspective, which can obscure specific regional nuances. Moreover, relatively few systematic literature reviews integrate IoT and geospatial modelling within a single study. This gap highlights the need for more comprehensive research that combines these technologies to better understand their synergistic potential in agriculture. Our review aims to fill this gap by focusing on Australia and selected Organisation for Economic Co-operation and Development (OECD) countries, using their similarities in technological and agricultural advancements to compare different approaches. This targeted approach clarifies how integrated technologies can be adapted and optimised for specific regional contexts.

This paper reviews the implementation of IoT and geospatial modelling in the Australian agricultural sector and compares it with practices in selected OECD countries. It is aimed to highlight the unique

challenges and successes in these regions by systematically examining how these technologies are integrated and analysing the differences. The goal is to showcase how variations in technology adoption impact farming efficiency and sustainability in developed countries, providing insights into how well-equipped agricultural systems are tackling similar challenges.

More specifically, contributions of this SLR include:

- We compared IoT and geospatial modelling technologies in agriculture across countries with similar technological and economic conditions, providing a fair and balanced comparison.
- We identified gaps in the use of IoT and geospatial modelling technologies in Australian agriculture compared to its peers.
- We integrated IoT and geospatial modelling into a single review, offering a comprehensive overview of technology use in agriculture, unlike previous reviews that focused on these topics separately.

The structure of this manuscript is as follows: in Section 2, we provide a detailed description of the research methodology applied in this study. In Section 3, we outlined the findings and discuss their implications. Finally, in Section 4, we conclude this study.

## 2. Research methodology

We have adopted a systematic literature review (SLR) as the methodology for this manuscript to investigate the adoption of IoT and geospatial technologies in Australia and selected OECD countries. We have followed the guidelines developed by Kitchenham and Charters (2007).

### 2.1. Research questions

Below, we outline several research questions that have motivated our systematic search. They are as follows:

1. **What are the key technological advancements in IoT and geospatial modelling that have influenced agricultural practices over the past decade in selected crop species in Australia and its developed peers?**

Identifying the key technological advancements in IoT and geospatial modelling over the past decade, specifically in selected crop species in Australia and its developed peers, is essential for understanding regional and crop-specific innovations. This information highlights the technologies that have significantly improved agricultural practices, enhancing efficiency, productivity, and sustainability. Additionally, it offers comparative insights into how different regions and crops have benefited from these advancements, guiding future research, policy-making, and technological development in agriculture.

2. **How does the use of IoT and geospatial modelling impact resource management and yield outcomes for selected crops in Australia and other developed countries?**

Investigating the impact of IoT and geospatial modelling on resource management and yield outcomes for selected crops in Australia and other developed countries is essential for evaluating the effectiveness of these technologies. This analysis will provide insights into how IoT and geospatial modelling enhance efficiency in resource usage, such as water and fertilisers, and improve crop yields. Understanding these impacts will help guide future agricultural practices, technology adoption, and policy decisions.

3. **How does Australia compare to other developed countries in adopting IoT and geospatial modelling technologies in agriculture?**

This research question compares Australia's adoption of IoT and geospatial modelling technologies in agriculture with other

**Table 1**

Average of 2010, 2015, and 2020 yields for selected agricultural crops (FAO-STAT (Unit: tonne per hectare)). Cotton is reported as seed cotton (unginned). Canola yield was not reported in the FAOSTAT data; therefore, we sourced this data from different sources labelled in the table footnote.

	Australia	Belgium	Canada	France	Germany	Spain	USA
Barley	1.97	8.54	3.51	6.24	6.64	3.19	3.93
Canola	1.44 <sup>a</sup>	3.99 <sup>c</sup>	0.87 <sup>d</sup>	3.25 <sup>c</sup>	3.79 <sup>c</sup>	2.42 <sup>c</sup>	1.99 <sup>b</sup>
Corn	6.98	10.09	9.86	8.38	9.11	11.43	10.30
Cotton	5.04	0.00	0.00	0.00	0.00	2.43	2.51
Sugarcane	82.95	0.00	0.00	0.00	0.00	42.78	78.82
Wheat	1.65	9.26	3.08	7.17	7.71	3.41	3.13

<sup>a</sup> ABARES.

<sup>b</sup> US Canola Association.

<sup>c</sup> Eurostat.

<sup>d</sup> Canola Council of Canada.

developed countries. This comparison will allow us to highlight other countries' best practices and innovative approaches, providing valuable insights for improving Australia's adoption of agricultural technology. The findings will support discussions on how Australia can enhance its use of IoT and geospatial modelling technologies, ultimately contributing to more efficient and sustainable agricultural practices.

### 2.2. Inclusion and exclusion criteria

In this SLR, our objective was to compare the adoption of IoT and geospatial modelling technologies in agriculture across Australia and other countries with similar technological and agricultural development levels. We initially considered OECD members as our primary focus group to achieve this. Given that corn, wheat, barley, canola, and sugarcane are among the top economic crops in Australia, our analysis further narrowed down to OECD countries that are also significant producers of most of these crops.

Utilising data from the Food and Agricultural Organisation (FAO) on the yields of these crops, we ranked OECD member countries based on the average yield for the years 2010, 2015, and 2020. This ranking enabled us to select seven countries that, along with Australia, demonstrate substantial agricultural productivity and technology use in farming (see Table 1). The countries selected for detailed comparison in this review are (i) Australia, (ii) Belgium, (iii) Canada, (iv) France, (v) Germany, (vi) Spain, and (vii) the United States.

Below, we outline the inclusion and exclusion criteria used in this analysis to determine the selection of literature for our review. These criteria were instrumental in ensuring that the studies included were relevant and provided a comprehensive understanding of how IoT and geospatial technologies are being adopted in the agricultural sectors of the selected countries.

#### 2.2.1. Inclusion criteria

1. **Geographic Focus:** Studies from Australia and developed countries like Canada, Belgium, France, Germany, Spain, and the USA.
2. **Subject Matter:** Research on adopting and implementing IoT and geospatial modelling in agriculture.
3. **Crops Covered:** Studies related to corn/maize, cotton, wheat, barley, canola, and sugarcane.
4. **Publication Date Range:** January 1, 2013, to December 18, 2023.
5. **Types of Publication:** Peer-reviewed journal articles and conference proceedings.
6. **Language:** English-language studies.

### 2.2.2. Exclusion criteria

1. **Geographic Irrelevance:** Studies do not include the specified countries or have an unclear geographic focus.
2. **Beyond Scope:** Research unrelated to IoT or geospatial modelling in agriculture.
3. **Non-specified Crops:** Studies not addressing the selected crops.
4. **Publication Date:** Articles published outside the specified date range.
5. **Document Type:** Grey literature, opinion pieces, editorials, review articles, and non-peer-reviewed studies.
6. **Accessibility:** Studies behind paywalls that are not accessible by the authors.

### 2.3. Search strategy

A detailed search was conducted using the Web of Science, IEEE Xplore, and ACM Digital Library. We employed a comprehensive set of keywords and phrases like “IoT”, “geospatial modelling”, and “sustainable agriculture”, among others. Advanced search techniques, utilising Boolean operators AND, OR, and NOT, refined the search results. [Appendix A](#) details the specific search strategies for each database.

### 2.4. Study selection process

With the inclusion and exclusion criteria firmly established and a comprehensive search strategy in place as outlined in Sections 2.2 and 2.3, we embarked on selecting studies relevant to our review. The process of selecting studies was methodical and involved several stages:

1. **Searching Keywords:** We applied the search strategy defined in Section 2.3 across multiple databases, incorporating database-specific modifications to ensure comprehensive coverage.
2. **Title Screening:** We initially screened research articles based on their titles. This step involved eliminating articles that clearly did not meet the inclusion and exclusion criteria specified in Section 2.2.
3. **Abstract Screening:** Articles that passed the title screening were subjected to abstract screening. In this phase, we carefully read the abstracts to assess their relevance to the scope of this SLR. Given the focus of this manuscript, special attention was paid to ensuring that the articles pertained to the countries and crops mentioned in the inclusion criteria. Both title and abstract screening phases were often conducted concurrently to enhance efficiency.
4. **Eligibility Assessment:** Articles that appeared relevant from their abstracts underwent a full-text review to assess detailed relevance, especially in cases where the geographic focus or specific content was ambiguous in the abstract.
5. **Full-Text Analysis:** The final stage involved a thorough analysis of the full-text articles to ensure that each study comprehensively addressed the research questions of our review.

The study selection process and results are depicted in the PRISMA-2020 (Page et al., 2021) flow diagram shown in Fig. 1. Initially, we found 1668 research articles by keyword searching within the three databases, which, after removing any duplicates, became 1362 records. In the next phase, we went through the title and abstract screening process, during which research articles that met the exclusion criteria were rejected. However, since the title and abstract of an article did not always contain all the information necessary to judge whether the article in question meets any exclusion criteria, we retained articles that we were not sure about. This process resulted in 319 research articles for further processing. In the next phase, we rejected articles that were not accessible because they were behind a paywall ( $n = 31$ ), had been retracted since ( $n = 2$ ), or had not been available in full text ( $n = 2$ ). We determined an article is behind a paywall if none of the primary

educational institutions of this manuscript have an active subscription to the journal of the article in question. This phase resulted in 284 articles being included in our full-text analysis phase. In the full-text extraction phase, we further rejected 112 research articles based on the inclusion and exclusion criteria, which resulted in 172 research articles being included in our analysis of this review. A list of all of the articles we considered can be found in the supplementary materials.

### 2.5. Data extraction and synthesis

Data extraction was conducted on the studies identified through our selection process. We analysed the chosen articles to ascertain the specific Internet of Things (IoT) and geospatial modelling technologies utilised, their target application areas, and the motivations behind their use. Furthermore, we assessed the impacts of these technologies on resource management and crop productivity alongside the challenges and benefits reported by the authors, culminating in their key findings and conclusions. The template employed for data extraction is delineated in [Appendix B](#).

In addition, for each study we qualitatively coded whether the reported outcomes primarily contributed to environmental (e.g. reduced water or fertiliser use, reduced chemical load, lower emissions), economic (e.g. cost savings, improved input-use efficiency, yield stability) or social dimensions (e.g. labour savings, reduced production risk, improved knowledge and decision support for farmers) of sustainable agriculture. This allowed us to interpret patterns in IoT and geospatial technology adoption through an explicit sustainability lens.

After the data extraction stage, we proceeded to synthesise the data. Employing thematic analysis, we honed in on a comparative examination of how IoT and geospatial modelling technologies are adopted within Australian agriculture compared to their uptake in other selected developed nations.

### 2.6. Study limitations

While our study offers a detailed analysis of IoT and geospatial modelling in Australian agriculture compared to other developed countries, it has several limitations. We reviewed only peer-reviewed English-language articles, which enhanced the quality of our analysis but may have excluded important information found in grey literature or non-English sources. Our focus on specific countries (Australia, Canada, Belgium, France, Germany, Spain, and the USA) and selected crops (corn/maize, cotton, wheat, barley, canola, and sugarcane) means that relevant studies from other regions or involving other crops were not included. Additionally, our review covers literature published between January 1, 2013, and December 18, 2023, so recent developments or articles published outside this range may not be considered. Consequently, our findings and conclusions are based solely on the data we collected and analysed according to these criteria.

## 3. Results and discussion

In this section, we present our findings and discuss their implications. First, we discuss the overall trends and publication focus, both in terms of country focus and crop focus, of research publications in IoT and geospatial modelling in agriculture. The rest of the section is structured to answer the research questions mentioned in Section 2.1.

### 3.1. Publication focus and trend analysis

#### 3.1.1. Overall trend

The annual number of research publications on IoT and geospatial modelling in agriculture has shown a clear upward trajectory from 2013 to 2023, as shown in Fig. 2. The linear trend line, with an  $R^2$  value of 0.794, indicates a strong and consistent increase in publications over the decade, except for 2023, for which we did not have complete data

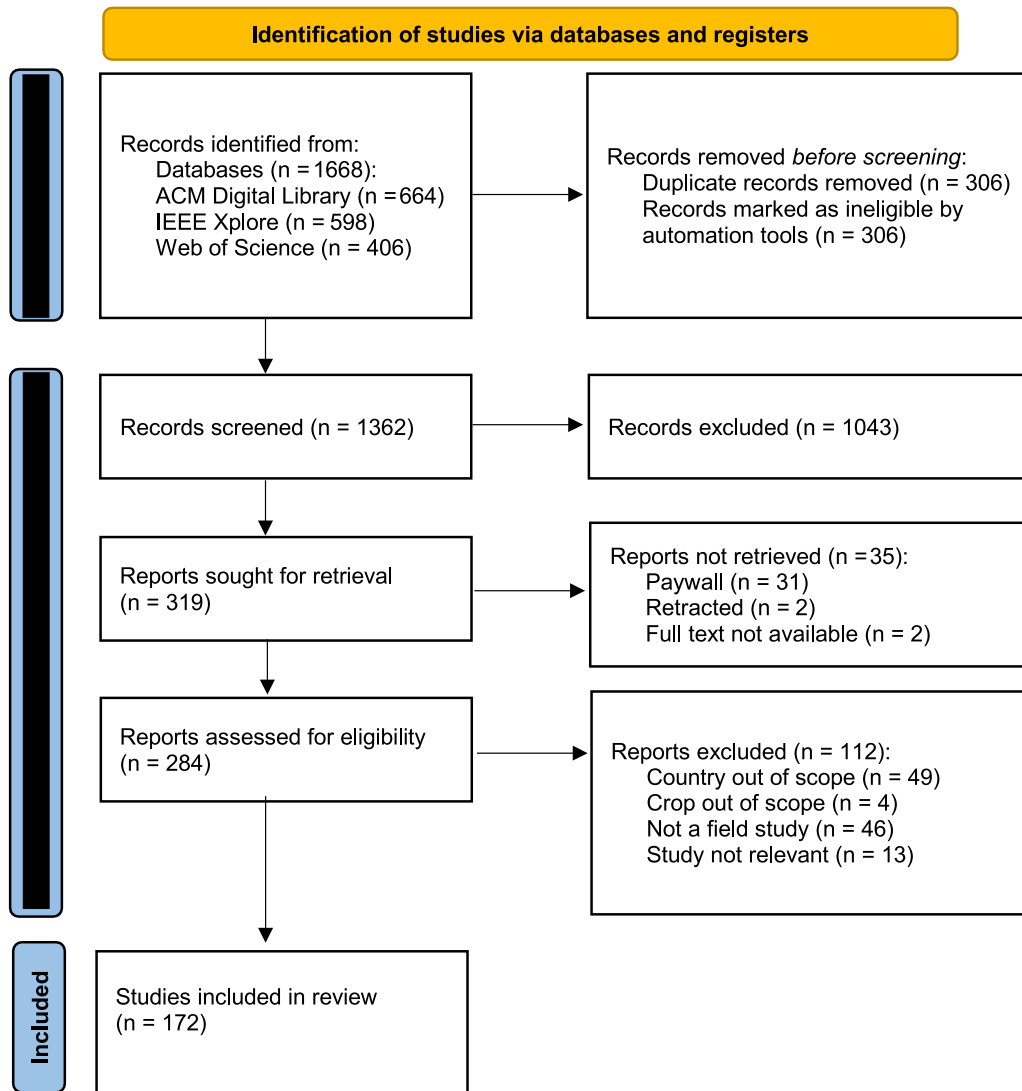


Fig. 1. PRISMA-2020 (Page et al., 2021) diagram of the study selection process.

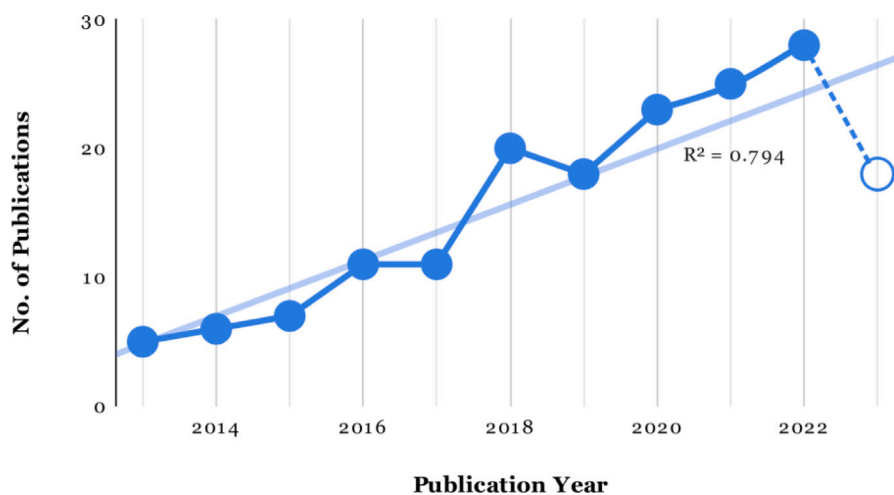


Fig. 2. Publication trend of the research articles between 2013 and 2023. The light blue line represents the linear trend of publications with an  $R^2$  value of 0.794. The hollow dot at the end of the line graph represents the data obtained for 2023, which, because of the search cut-off date, does not include the complete data.

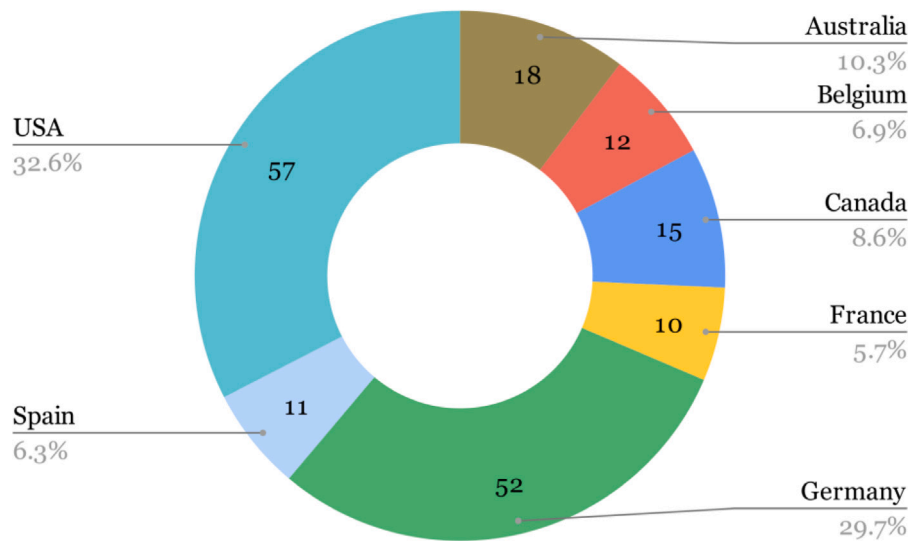


Fig. 3. Publication geographic focus analysis, which demonstrates the number of publications from each of the selected countries based on the research articles we reviewed between 2013 and 2023.

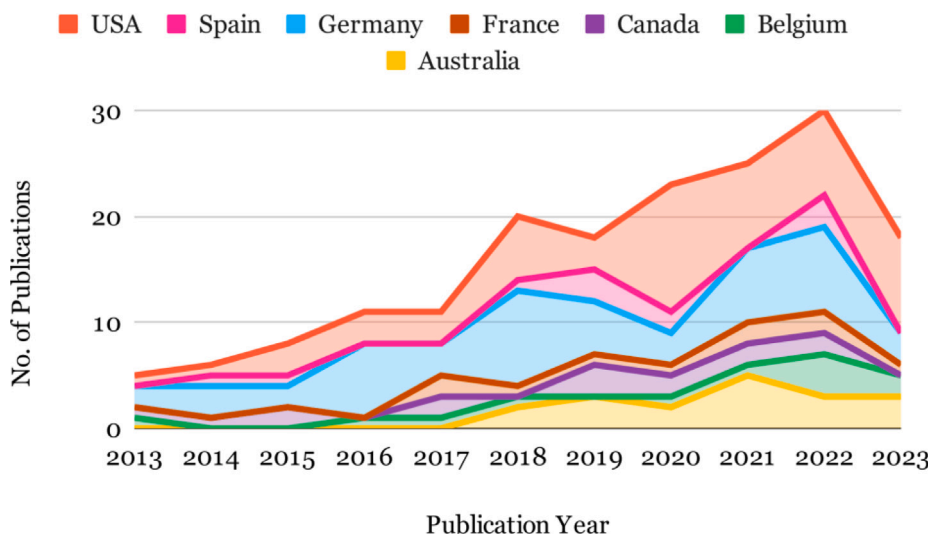


Fig. 4. Geographic trend of research publications considered in this SLR for each selected country.

because of the search cut-off date. Given the strong linear upward trend over the last decade, it is reasonable to expect a similar trend to continue in 2023. This growth suggests that the field is gaining significant traction and importance within the scientific community, especially in the context of Australia and selected OECD countries. It also indicates that these technologies are becoming increasingly vital in modern agricultural practices.

### 3.1.2. Geographic focus

Fig. 3 shows the geographic focus of the research articles reviewed. The USA leads the way with approximately 33% of all published studies (n = 57), while Germany closely follows with approximately 30% of all published studies (n = 52). Together, the USA and Germany published around two-thirds of all published articles we considered in this SLR. Australia and Canada published around 10% of the published studies each (n = 18 for Australia and n = 15 for Canada), while Belgium (n = 12), Spain (n = 11), and France (n = 10) made up the rest of the studies. This geographic distribution of IoT and geospatial modelling research in agriculture highlights the global nature of agricultural research and the varying focus areas driven by local governments in each country. The dominance of the USA and Germany in this field may indicate

strong institutional support and a well-established research infrastructure in these countries. Fig. 4 shows the trend of research publications, which also clearly demonstrates how the USA and Germany have been consistently trending positively in research publications in this field. It also demonstrates a strong positive trend in research publications in Australia over the second half of the decade.

### 3.1.3. Crop focus

Fig. 5 demonstrates the publications' focus in terms of crop species. Among the crop species we considered in this study, wheat (n = 80) and corn (n = 79) attracted most of the research publications. Barley (n = 15), cotton (n = 15), and canola (n = 14) attracted a similar number of publications, albeit a lower number compared to wheat and corn. Sugarcane attracted the least number of publications (n = 4). Fig. 6, on the other hand, shows the trend of research publications in each of the selected crops. We can clearly see that research publications on wheat and corn have shown a consistent positive upward trend. Other crops, such as canola, cotton, and barley, have attracted a small but steady interest in research publications over the last decade, while sugarcane did not show any noticeable pattern due to the low volume of total research attracted by it. Table 1 explains some of the phenomenon,

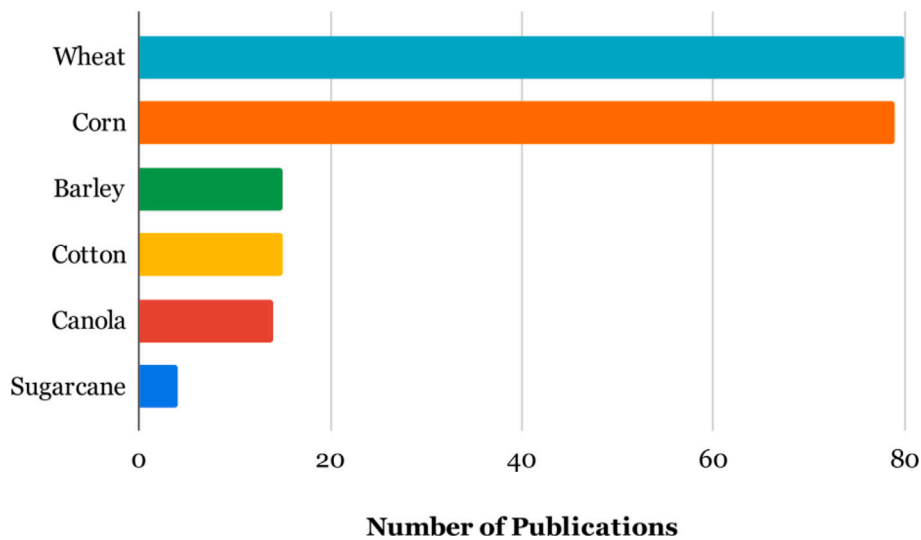


Fig. 5. Number of research articles published with a focus on each of the selected crop species based on the research articles we reviewed between 2013 and 2023.

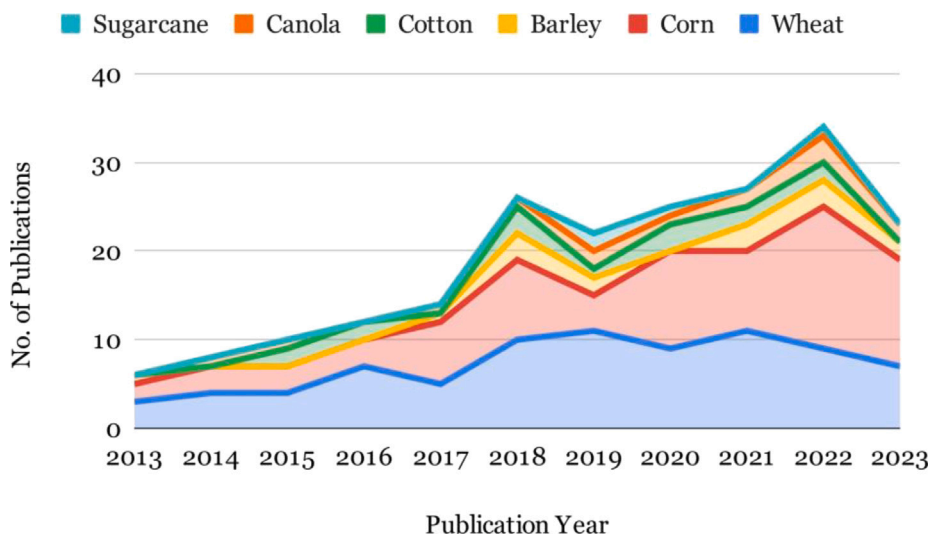


Fig. 6. Trend in research publication focused on each of the select agricultural crops based on the research articles we reviewed between 2013 and 2023.

which shows the average yield of selected crops in each country. Sugarcane was reported to be produced only in the USA, Australia, and Spain, which explains the low number of research articles focusing on sugarcane. However, although cotton was reported to be produced in the same countries as sugarcane, it attracted a considerably larger number of research publications than sugarcane. Also, while barley and canola were reported to be produced in all focus countries, compared to wheat and corn, significantly fewer research articles were published focusing on barley and canola compared to wheat and corn. These facts suggest that not all crop species have attracted equal attention from the research community in IoT and geospatial modelling. The research focus in each country changed due to different priorities and potential.

### 3.1.4. Publication channel

Most of the research articles on IoT and geospatial modelling in agriculture were published in academic journals (n = 142), with a smaller number appearing in conference proceedings (n = 30). We identified 46 unique academic journals that published 141 research articles, with most journals (n = 26) contributing only one article each. The average Journal Impact Factor (JIF) for these 46 journals is 4.96, ranging from 1.6 to 13.5, indicating a substantial variation

in the influence and reach of these publications. This highlights the prominence of certain journals in disseminating significant research findings in this field.

We have identified 13 unique conference venues, publishing 31 research articles. Similar to the journal articles, most conference venues (n = 11) published only one article each. Table 2 lists the publication channels that have published more than one research article in this review, showcasing the major outlets for research dissemination in this area.

The IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing stands out with 19 publications, followed closely by Remote Sensing and the IEEE International Geoscience and Remote Sensing Symposium (IGARS), each with 17 publications. These leading channels underscore their pivotal role in advancing the field by providing platforms for the dissemination of high-impact research. Other notable journals include Precision Agriculture, Sensors, and Computers and Electronics in Agriculture, contributing 11, 11, and 9 publications respectively, reflecting the specialised interest in applying technology to optimise farming practices.

It should be noted that since we sought research publications where the authors demonstrated the application of IoT and geospatial modelling in the field, some specialised journals or conferences might have

**Table 2**  
Major publication channels for IoT and geospatial modelling research articles (sorted according to number of publications).

Journal/Conference name	Publication type	Number of publications
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	Journal	19
Remote Sensing	Journal	17
IEEE International Geoscience and Remote Sensing Symposium (IGARS)	Conference	17
Precision Agriculture	Journal	11
Sensors	Journal	11
Computers and Electronics in Agriculture	Journal	9
Agriculture-Basel	Journal	7
Agricultural Water Management	Journal	5
IEEE Transactions on Geoscience and Remote Sensing	Journal	5
Agronomy-Basel	Journal	4
Frontiers in Plant Science	Journal	4
Biosystems Engineering	Journal	3
Journal of Photogrammetry Remote Sensing and Geoinformation Science	Journal	3
Remote Sensing of Environment	Journal	3
International Journal of Applied Earth Observation and Geoinformation	Journal	3
International Journal of Remote Sensing	Journal	2
Agriculture and Forest Meteorology	Journal	2
Autonomous Air and Ground Sensing Systems for Agricultural Optimisation and Phenotyping	Conference	2
IEEE Geoscience and Remote Sensing Letters	Journal	2
Fields Crop Research	Journal	2
ISPRS Journal of Photogrammetry and Remote Sensing	Journal	2
Plant Methods	Journal	2

better aligned with our scope. Understanding these major publication channels not only helps researchers select the most appropriate venues for their work but also assists policymakers in accessing high-impact studies necessary for informed decision-making. The diversity of journals and conferences, ranging from specialised publications like Agricultural Water Management to interdisciplinary platforms such as the ISPRS Journal of Photogrammetry and Remote Sensing, reflects the dynamic and evolving nature of this research area. This broad spectrum of publication channels facilitates cross-disciplinary collaboration and drives advancements in agricultural technology by providing comprehensive insights and innovative solutions to agricultural challenges through the integration of IoT and geospatial modelling.

### 3.2. Key technological advancements

*RQ.1: What are the key technological advancements in IoT and geospatial modelling have influenced agricultural practices over the past decade in select crop species in Australia and its developed peers?*

This section discusses key technological advancements in IoT and geospatial modelling that have influenced agricultural practices over the past decade in select crop species in Australia and other developed countries. Fig. 7 presents a word cloud of the identified technologies used in IoT and geospatial modelling in agriculture, highlighting the prominence of imaging technologies (e.g., RGB cameras, SAR) and platforms enabling imaging (e.g., UAVs, satellites such as LANDSAT, RADARSAT, Sentinel). This indicates a significant shift towards high-throughput and high-resolution modelling of agricultural fields.

Fig. 8 outlines the trend of these technologies over the last decade, aligning with the overall publication trend shown in Fig. 2 and illustrating individual technology trends. Unmanned aerial vehicles (UAVs) and consumer-grade RGB cameras have consistently dominated and shown a positive usage trend. Synthetic aperture radars (SARs) have also demonstrated a continuous positive trend, underscoring their applicability in agriculture. Other technologies analysed, such as light detection and ranging (LiDAR) and satellite platforms like Sentinel-2 and LANDSAT-8, have shown steady positive trends over the past decade.

We categorised these technologies into four broad categories: (i) aerial and satellite platforms, (ii) sensors, (iii) imaging systems, and (iv) positioning and navigation systems. We discussed each of these categories below:

#### 3.2.1. Aerial and satellite platforms

Aerial and satellite platforms have continuously proved critical in the field of IoT and geospatial modelling in agriculture. These platforms provide high-resolution, large-scale, and continuous data that are essential for crop trait estimation (Thorsten et al., 2017; Allies et al., 2021; Rosso et al., 2022), crop monitoring (Allies et al., 2021; Jiao et al., 2022), and resource management (Fontanet et al., 2020; Fordyce et al., 2023). Technologies such as UAVs (n = 54), Sentinel satellite series (n = 20), LANDSAT satellite series (n = 15), MODIS Terra and Aqua (n = 5), RADARSAT (n = 4), RapidEye (n = 1), CubeSAT (n = 1), WorldView (n = 2), QuickBird (n = 1) etc. are some examples that added unique capabilities in geospatial modelling.

In particular, UAVs offer flexible, high-resolution and cost-effective imaging platforms, making them suitable for a variety of agricultural monitoring applications, such as crop health monitoring (Cai et al., 2019; Costa et al., 2020; Wiegman et al., 2022), yield estimation (Dilmurat et al., 2022; Maimaitijiang et al., 2023), and various crop trait estimation (Nelson et al., 2023; Nguyen et al., 2023). Therefore, it is unsurprising that UAVs are the most frequently mentioned platforms in our analysis, indicating their widespread adoption in agriculture. Similarly, satellite platforms such as LANDSAT-8 with its multispectral imaging capability, Sentinel-2 with its high spatial resolution and frequent revisit, Sentinel-1 with its synthetic aperture radar (SAR) imaging capabilities, MODIS Aqua and Terra with their daily global coverage has offered a host of unique opportunities for geospatial modelling of agriculture and consequently has seen a wide adoption within the research community (Al-Shammari et al., 2021; Skakun et al., 2021; Bazzi et al., 2022; Vallentin et al., 2022; Gobin et al., 2023).

The trend analysis (as shown in Fig. 8 for some technologies) reveals that UAVs have consistently grown in usage patterns, highlighting the reliance on UAVs for real-time, high-resolution data collection in agriculture. Sentinel and LANDSAT satellite series have demonstrated stable use over the years, reflecting their continued importance in providing multispectral and hyperspectral data for various agricultural applications. More recently, there has been an emerging trend of using aeroplane-based monitoring, which offers utility in monitoring large-scale applications (Shi et al., 2020; Belwalkar et al., 2021; Bouchat et al., 2022) where UAVs might not be a practical choice due to scale or regulatory constraints, while providing greater control and resolution compared to its satellite counterparts.

#### 3.2.2. Sensors and imaging systems

Sensors and imaging systems are fundamental components in IoT and geospatial modelling in agriculture. They provide precise, real-time, and high-resolution data that are crucial for assessing crop health (Valasek et al., 2016; Costa et al., 2020; Cummings et al., 2021; Schirmann et al., 2021), monitoring crop growth (Ashapure et al., 2019; Liu et al., 2022), soil property monitoring (Li et al., 2014; Valasek et al., 2016; Maia et al., 2022), and managing resources efficiently (Zermas et al., 2021; Rouze et al., 2021; Maia et al., 2022). Technologies such as RGB camera, synthetic aperture radar (SAR), light

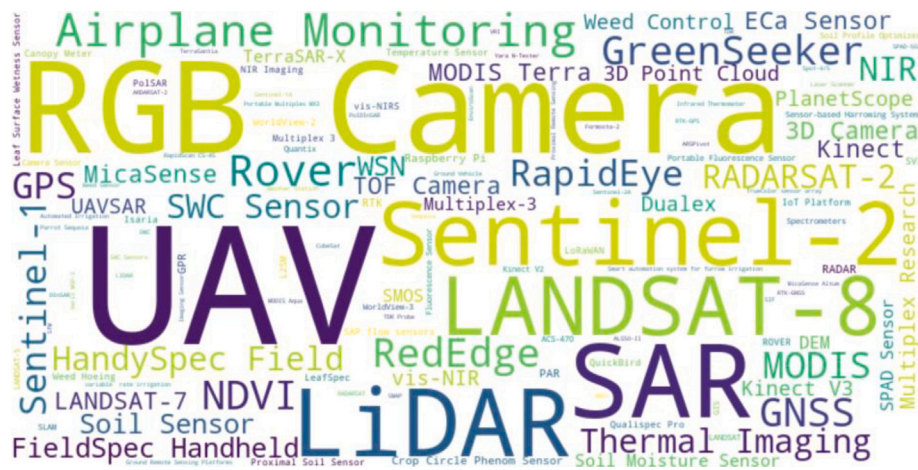


Fig. 7. Word cloud of the key technologies identified in the literature we reviewed. The font size of technologies represents the relative frequency of that specific technology.

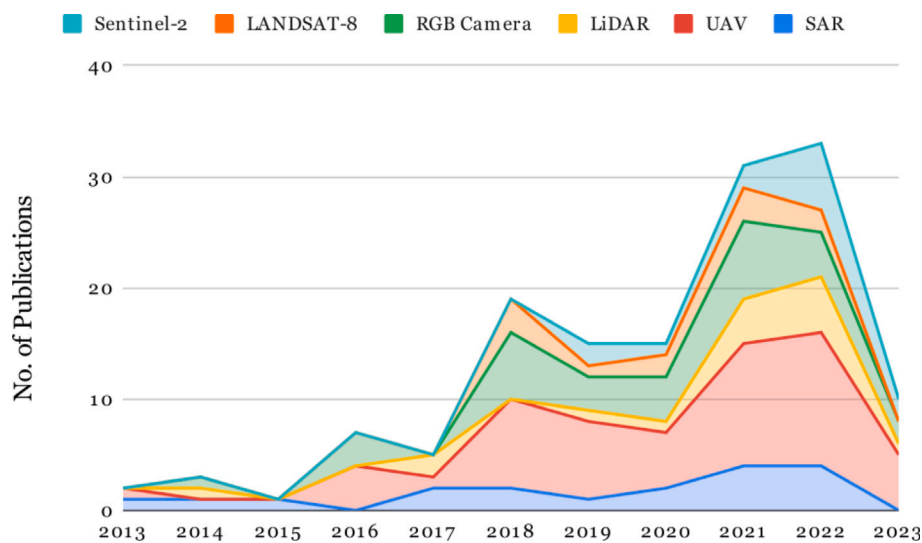


Fig. 8. Trend of select key technologies identified through this SLR where the number of publications utilising these technologies is reported for each year. The shaded area represents the respective proportion of that specific technology.

detection and ranging (LiDAR) (Banerjee et al., 2021; Colaço et al., 2021; Dilmurat et al., 2022), near-infrared (NIR) and online visible and near-infrared (vis-NIR) sensors (Baldocchi et al., 2020; Bebronne et al., 2020; Munnaf et al., 2022), thermal imaging sensors (Maestrini and Basso, 2018; Camino et al., 2019; Xu et al., 2021), various soil sensors such as soil water content (SWC) sensors (Li et al., 2014; Geesing et al., 2014; Foolad et al., 2017), soil moisture sensors (Fontanet et al., 2020; Maia et al., 2022), electrical conductivity sensors (Heil et al., 2018; Miao et al., 2018) etc. are identified in our literature review.

In particular, RGB cameras have been widely used for their cost-effectiveness compared to hyper- and multispectral counterparts, their simplicity, and their ability to provide clear, detailed images of crops and fields. RGB cameras have been fundamental for plant phenotyping (Jung et al., 2018; Costa et al., 2020; Zhang et al., 2020; Xu et al., 2021), weed control (Gao et al., 2018; Sapkota et al., 2020; Le et al., 2021), crop growth monitoring (Ashapure et al., 2019; Liu et al., 2022; Nelson et al., 2023), crop parameter estimation (Belton et al., 2019; Li et al., 2021; Wittstruck et al., 2022), and identifying visible signs of crop health issues (Costa et al., 2020; Schirrmann et al., 2021; Zermas et al., 2021).

Additionally, SAR sensors and their satellite and airborne platforms were among the most utilised sensor systems due to their ability to penetrate clouds and provide reliable data under all weather conditions,

day or night. Some of the agricultural applications include, but are not limited to, crop parameter estimation (Bouchat et al., 2022; Jiao et al., 2022), soil parameter estimation (Kim et al., 2018; Shi et al., 2020; Chen et al., 2020; Bouchat et al., 2021, 2022), crop biomass (Wiseman et al., 2014; Brancato and Hajnsek, 2017) and yield prediction (Ameline et al., 2018), and crop classification (Ma et al., 2013).

We also identified some off-the-shelf devices that augmented agriculture's IoT and geospatial modelling capabilities. Examples include the GreenSeeker<sup>®</sup> handheld crop sensor (Roberts et al., 2013; Quebrado et al., 2015; Bushong et al., 2018), HandySpec Field<sup>®</sup> portable spectrometer system (Peteinatos et al., 2016; Zecha et al., 2018; Souza et al., 2021), FieldSpec HandHeld<sup>™</sup> spectroradiometer (Yu et al., 2013; Zecha et al., 2017), Multiplex<sup>®</sup> 3 hand-held multi-parameter optical sensor (Longchamps et al., 2022; Siqueira et al., 2022), SPAD-502<sup>®</sup> chlorophyll sensor (Bushong et al., 2018; Gabriel et al., 2019), DualEye<sup>®</sup> leaf clip chlorophyll sensor (Gabriel et al., 2019; Raya-Sereno et al., 2022), RapidScan CS-45<sup>®</sup> handheld crop sensor (Aranguren et al., 2020), and Kinect<sup>™</sup> (Hämmerle and Höfle, 2016; Vázquez-Arellano et al., 2018; Martinez-Guanter et al., 2019).

Over the years, we have seen consistent growth in the use of RGB cameras, SAR, and LiDAR sensors in agriculture. This trend indicates the growing importance of high-resolution, all-weather data for

detailed agricultural monitoring and analysis, enabling precise intervention and improved resource management. Different soil and thermal imaging sensors have maintained steady use, reflecting their critical role in precision agricultural practices over the years.

### 3.2.3. Positioning and navigation systems

Navigation and positioning systems are critical components in IoT and geospatial modelling. They provide precise location data essential for various agricultural applications, including machinery guidance and navigation (Emmi et al., 2014; Peshlov et al., 2017), yield mapping (Momin et al., 2019), and precision agriculture (Bates et al., 2022). In addition to utilising global positioning systems (GPS) and global navigation satellite systems (GNSS), several research articles have demonstrated the effectiveness of real-time kinematic (RTK) technology in obtaining highly precise location information (Emmi et al., 2014; Belton et al., 2019).

Over the years, we have observed a steady usage pattern of GPS and GNSS technologies, indicating their importance in agriculture. Additionally, there has been an increased use of RTK alongside GPS and GNSS systems, highlighting the potential for highly accurate positional information in modern agriculture.

### 3.2.4. Typical system architectures and deployment settings

Across the included studies, IoT and geospatial systems were implemented using a relatively small number of recurring architectural patterns. Most work combined one or more sensing platforms (satellites, uncrewed aerial vehicles, in-field sensor networks, ground-based vehicles or proximal devices) with a communications layer (local data loggers, short-range wireless, low-power wide-area networks or cellular networks) and either local or cloud-based analytics.

At the sensing layer, two broad groups dominated. The first comprised remote and proximal imaging systems, primarily RGB and multispectral cameras deployed on UAVs, tractors and fixed masts, complemented by a smaller number of thermal and hyperspectral systems. These solutions typically delivered centimetre-level ground sampling distances for UAV-based imaging and metre-scale resolutions for satellite products, with revisit intervals ranging from daily (fixed cameras) to weekly or fortnightly (UAV and constellations such as Sentinel or Landsat). The second group comprised in-field sensor networks, including soil-moisture probes, soil temperature sensors, microclimate stations and, less frequently, in situ nutrient sensors. Sensor spacing varied from dense grids in experimental plots to sparser deployments in commercial paddocks, with logging intervals commonly between 15 min and one hour.

The communications layer reflected both technological choices and infrastructure constraints. Short-range wireless protocols (Wi-Fi, Zig-Bee) and proprietary radio links were common in experimental settings, while LoRaWAN, Sigfox and cellular (3G/4G/5G) were increasingly used for commercial-scale deployments and long-range transmission to gateways or cloud servers. Edge computing capabilities were limited in most studies; data were typically logged locally and processed offline, although a subset of IoT deployments performed basic preprocessing or threshold-based alerting on microcontrollers or in-cab terminals.

Computation and storage were generally located either on-farm (e.g. in tractor-mounted terminals or local servers) or in cloud environments. Cloud-based pipelines were particularly prevalent in studies that integrated satellite data, external weather and soil maps, or that required computationally intensive machine learning models. Overall, the dominant architectural pattern was a sensing–communication–cloud analytics pipeline, with relatively little work on distributed or fully edge-based architectures.

### 3.2.5. Application-specific configurations of IoT and geospatial systems

The configuration of IoT and geospatial technologies varied systematically across the three application domains considered in this review—monitoring, estimation and resource management.

In *monitoring applications*, systems were typically configured to provide high spatial and/or temporal resolution information about crop or soil status without necessarily translating this information into explicit management recommendations. UAV-based imaging was the most common configuration for monitoring crop growth, canopy cover and disease symptoms, often using RGB or multispectral cameras operated at regular intervals during critical growth stages. Fixed cameras and time-lapse imaging were deployed to capture high-frequency canopy dynamics in experimental plots, whereas in-field sensor networks were primarily configured to monitor soil moisture, temperature and microclimate variables at one or more depths. These systems prioritised robustness, data continuity and coverage of representative field zones.

In *estimation applications*, the same sensing modalities were configured to support quantitative prediction of agronomic variables such as yield, biomass, leaf area index and crop nitrogen status. Here, remote sensing data were commonly combined with ancillary information (e.g. weather, soil maps, management records) to train empirical or machine learning models, or to drive crop growth models. Spatial and temporal resolutions were selected to balance prediction accuracy with cost and data availability. For example, UAV flights were often scheduled around key phenological stages known to be informative for end-of-season yield, while satellite-based approaches leveraged longer-term time series to capture inter-annual variability.

In *resource-management applications*, sensing and modelling components were explicitly configured to support decisions on irrigation, fertiliser application and other inputs. Typical configurations coupled soil-moisture sensor networks or satellite-/UAV-derived indices with decision-support rules, optimisation algorithms or variable-rate technology. For irrigation, systems used thresholds in soil water content, crop water stress indices or modelled evapotranspiration to trigger or schedule irrigation events. For fertiliser management, canopy and soil information derived from proximal or remote sensing was converted into prescription maps that controlled variable-rate application equipment. Compared with monitoring and estimation, these configurations placed more emphasis on integration with existing machinery, user interfaces and operational workflows.

Overall, across all domains, the reviewed literature illustrates a progression from relatively simple monitoring configurations towards more integrated systems in which sensing, modelling and actuation are tightly coupled. However, fully closed-loop systems that integrate IoT sensing, geospatial modelling and automated actuation remain comparatively rare, particularly at commercial farm scale.

## 3.3. Performance outcomes of IoT and geospatial applications

The reviewed studies reported a wide range of performance metrics, reflecting differences in objectives, scales and analytical approaches. Nevertheless, several patterns emerge regarding the effectiveness of IoT and geospatial systems for monitoring, estimation and resource management in major cereal and oilseed crops.

For *monitoring applications*, performance was most frequently reported in terms of agreement between remotely sensed or sensor-derived indices and ground-based measurements. UAV-based imaging combined with vegetation indices typically achieved moderate to strong relationships with canopy traits such as leaf area index, fractional cover and biomass, with reported coefficients of determination often in the range of approximately 0.6–0.9 and corresponding root mean squared errors that were acceptable for relative comparisons between treatments or management zones. Disease monitoring applications using multispectral or hyperspectral imaging coupled with classification algorithms frequently reported overall accuracies above 0.8, although performance could deteriorate under challenging illumination or background conditions. Sensor-network-based monitoring of soil and microclimate variables generally produced low absolute errors when sensors were carefully installed and calibrated, but long-term

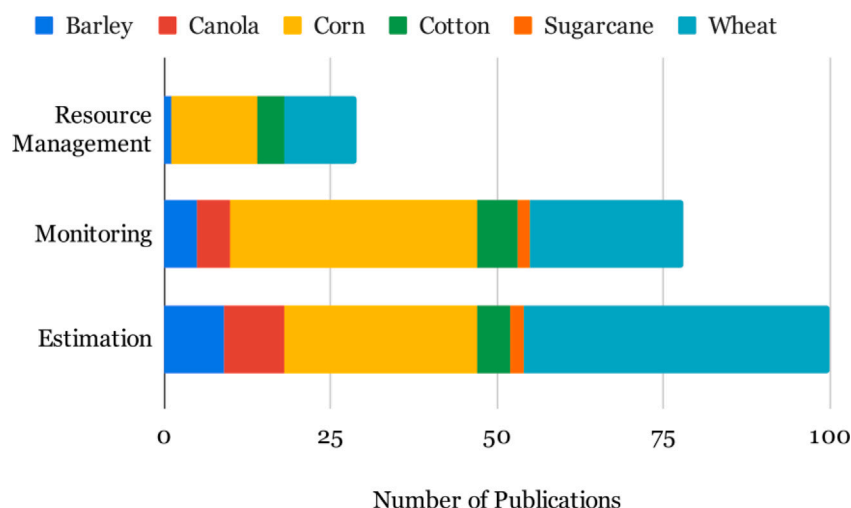


Fig. 9. The number of research articles in each major application domain, classified along with their focus crop species.

drift and maintenance issues were noted as practical challenges in some studies.

In *estimation applications*, performance was commonly expressed as the ability to predict end-of-season yield or biomass from in-season sensing data and models. Satellite-based approaches using multispectral imagery and empirical or machine learning models reported a wide range of performance, with coefficients of determination often between about 0.5 and 0.85 and yield prediction errors of approximately 0.5–1.5 t ha<sup>-1</sup> for wheat and maize under many conditions. UAV-based approaches, benefiting from higher spatial resolution and flexible sampling, sometimes achieved higher accuracy at the plot or small-field scale, but their performance was sensitive to flight timing, radiometric calibration and the representativeness of calibration data. Estimation of crop nitrogen status and uptake using proximal or remote sensing was likewise variable, with many studies reporting strong relationships in specific contexts, but fewer demonstrating robust generalisation across seasons, varieties and sites. For *resource-management applications*, performance outcomes were typically expressed in terms of water or nutrient savings, yield maintenance or gains, and improvements in resource-use efficiency or economic returns. Irrigation scheduling systems that combined soil-moisture sensors, weather data and geospatial information commonly reported water savings in the order of 10%–30% compared with conventional scheduling, while maintaining or modestly increasing yields and water use efficiency. Variable-rate fertiliser applications informed by sensing and modelling frequently demonstrated reductions in nitrogen application rates while maintaining yields, leading to improvements in nitrogen-use efficiency and, in some cases, gross margins. However, robust economic analyses were presented in only a subset of studies, and few studies evaluated long-term impacts across multiple seasons.

Taken together, these findings suggest that IoT and geospatial technologies are capable of delivering accurate monitoring information, reasonably reliable yield and status estimates in many contexts, and meaningful improvements in resource-use efficiency when carefully implemented. At the same time, the heterogeneity of reported metrics and the relative scarcity of large-scale, multi-season on-farm trials indicate that further work is needed to quantify performance under diverse conditions, to harmonise evaluation metrics and to strengthen the evidence base for economic and environmental benefits (see Tables 3 and 4).

### 3.4. IoT and geospatial monitoring application areas

RQ2: How have different countries used IoT and geospatial modelling to assist resource management and improve crop productivity?

Table 3

Classifying research articles we reviewed between 2013 and 2023 into monitoring, estimation, and resource management for each focus crop species.

Application domain	Barley	Canola	Corn	Cotton	Sugarcane	Wheat
Monitoring	5	5	37	6	2	23
Estimation	9	9	29	5	2	46
Resource management	1	0	13	4	0	11

To answer how IoT and geospatial modelling impact resource management and crop productivity, we classified each of the research articles into three broad application domain categories, namely: (i) Monitoring, (ii) Estimation, and (iii) Resource Management. We categorised publications into the monitoring category if the major focus of the research was to monitor changes in one or more particular phenomena related to crop production over time, such as crop biomass monitoring (Wiseman et al., 2014), soil property monitoring (Li et al., 2014), monitoring crop growth stages (Ashapure et al., 2019), monitoring crop parameters such as leaf area index (LAI) (Bauer et al., 2019), nitrogen (Gabriel et al., 2019), and normalised difference vegetation index (NDVI) (Prey et al., 2018), and monitoring crop stress (Cai et al., 2019). On the other hand, we categorised research articles into estimation category if the main focus of that publication was to assess, predict, estimate, or classify crop conditions such as early detection of disease (Yu et al., 2013), soil (Chakrabarti et al., 2015) and crop (Vázquez-Arellano et al., 2018) property estimation, high throughput phenotyping (Jung et al., 2018), crop biomass estimation (Schirrmann et al., 2016), and yield prediction (Heil et al., 2018). Finally, we categorised publications into the resource management category if the primary focus of that study was to manage the resources related to crop production, such as nitrogen management (Bushong et al., 2018), weed control (Emmi et al., 2014), water supply and irrigation management (Andrade et al., 2020), and management zone delineation (Miao et al., 2018). Because of the interconnected nature of these three application areas, some of the research publications focused on more than one application area. However, to keep the analysis simple, we categorised publications into one of the categories based on that publication's major focus.

Fig. 9 represents the total number of research publications focused in each application domain along with specific crop species for that research. We can clearly see that estimation is the major application domain for IoT and geospatial modelling in agriculture (n = 76), followed by monitoring (n = 69) and resource management (n = 27). Trend analysis shown in Fig. 10 demonstrates that both monitoring and estimation application domains saw a consistent positive trend,

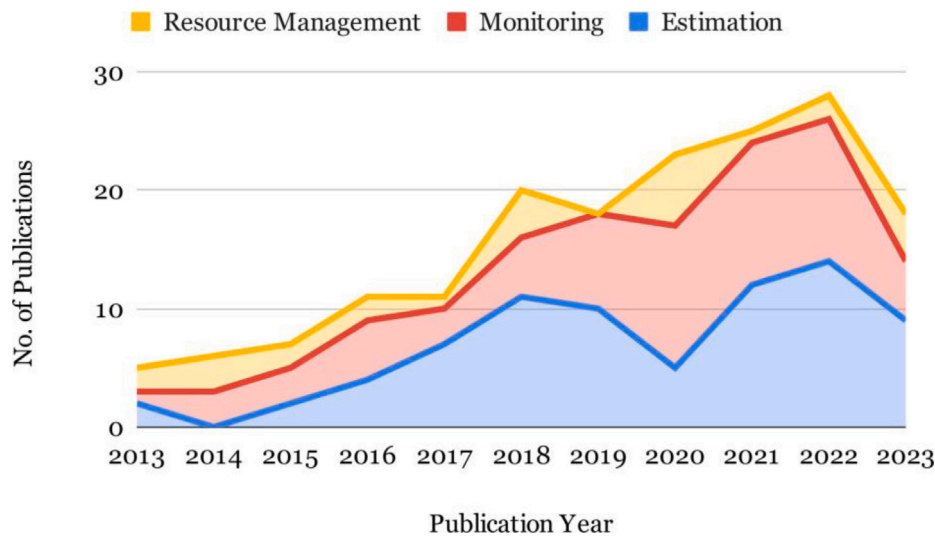


Fig. 10. Trend of publications by application domain.

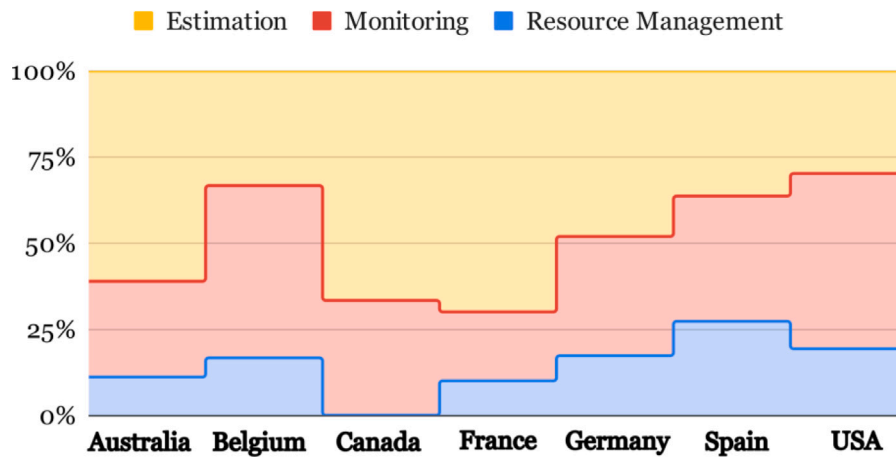


Fig. 11. Proportion of domain specific research in each focus countries.

Table 4

Classifying research articles we reviewed between 2013 and 2023 into monitoring, estimation, and resource management for each focus country.

Application domain	Australia	Belgium	Canada	France	Germany	Spain	USA
Monitoring	5	6	5	2	18	4	29
Estimation	11	4	10	7	25	4	17
Resource management	2	2	0	1	9	3	11

while resource management saw a steady and consistent use over time. Also shown in Fig. 9 is the breakdown of research publication in each of the application domains based on the focus crop species. This suggests that while wheat, barley and canola have research publications similar to the overall research trend (in the order of estimation followed by monitoring and resource management), corn and cotton still have monitoring as the major application area followed by estimation and resource management. Considering the overall trend, this suggests the research direction in corn and cotton might change in the near future from monitoring to estimation, which is a major shift in research direction, especially for corn. Also, yield data (Table 1) suggest that Belgium, Canada, France, Germany, and Spain do not produce cotton and sugarcane; therefore, a low number of research articles for these two crops is justified.

Fig. 11 represents the proportion of research focus of each country over the last decades. Researchers in Australia published most of their research articles focusing on estimation (n = 11), followed by

monitoring (n = 5), and resource management (n = 2). As shown in Fig. 12, most of Australia’s research focus in the estimation area was concentrated on wheat. However, we did not find any research articles from Australia focusing on corn in any of the application areas, which is surprising considering the fact that corn attracted research focus from all of the other focus countries in most of these application areas. Researchers from Belgium published most of their research focused on monitoring (n = 6), followed by estimation (n = 4) and resource management (n = 2). From Fig. 12, we can see that Belgium mostly published in corn and wheat, conforming to the overall publication trend. However, Belgium’s focus on monitoring is the highest among the focus countries (60%). Researchers from Canada published two-third of their research in estimation (n = 10) while publishing nothing in the resource management area. Canola, corn, and wheat attracted the most research focus in this country. France published 70% of their research articles focusing on estimation, which is the most for any focus country. On the other hand, France did not publish anything focusing

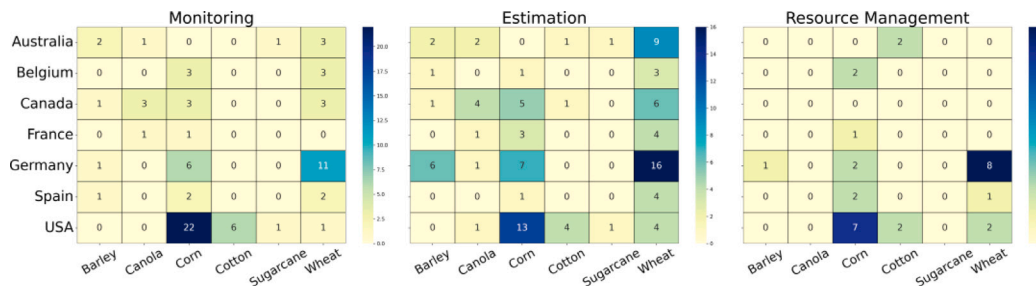


Fig. 12. Application area specific breakdown of research publications for each focus crop species and focus countries.

on barley, cotton, and sugarcane. Germany on the other has shown a strong publication track in each of the monitoring areas while focusing mostly on estimation (n = 25), which is the most in terms of number of research publications among the focus countries. Researchers from Germany published most of their research focusing on wheat (n = 35), which is also the most common among the focus countries. Researchers from Spain have distributed their research focus evenly among the three application areas (4:4:3 as in estimation : monitoring : resource management). Spain published mostly focusing on corn and wheat. While the USA showed a strong research publication track in corn, cotton, and wheat, the majority of the research focus was on corn (n = 42). Also, the USA’s research focus was mostly in the monitoring area, with 29 research publications in this area, which is also the most among the focus countries.

However, it is very difficult to demonstrate a clear connection between the use of IoT and geospatial modelling in agriculture and their impact on resource management and crop productivity, largely due to the study’s limitations. According to the research methodology of this SLR, we did not focus on the grey literature and non-English literature. While we have not found any such SLR that focuses on an extensive review of all possible literature sources, it would be interesting to explore whether such a connection could be made with the addition of grey literature and non-English literature. Additionally, soil fertility has a significant impact on yield, which is not entirely dependent on published literature in this domain. This discussion aside, we found numerous evidence of IoT and geospatial modelling helping in better resource management and crop productivity. For instance, Link et al. (2013) demonstrated the effectiveness of an aerial sensor platform in helping with resource management decisions, Li et al. (2014) demonstrated the use of a wireless sensor network (WSN) in monitoring real-time soil properties, enabling enhanced real-time soil management, Peteinatos et al. (2016) used optical sensors to identify various stress factors in wheat, which in turn could potentially improve yield by addressing specific stress factors effectively, among many other research specifically addressing issues related to resource management and crop productivity. Given the numerous research articles demonstrating a positive impact on resource management and crop productivity, it is safe to assume that IoT and geospatial modelling contribute to improved resource management and crop productivity.

### 3.5. Sustainability implications

Taken together, the reviewed applications demonstrate that IoT and geospatial technologies already contribute to sustainability in several ways, although often implicitly. From an environmental perspective, many resource-management and monitoring studies report more precise water, nitrogen and agrochemical use, or improved detection of stress and disease, which can reduce inputs, minimise off-site impacts and support adaptation to climate variability. From an economic perspective, estimation-focused studies that improve yield forecasting, biomass assessment or risk prediction enable better input planning and potentially more stable farm incomes, even though few papers

Table 5

Key technology usage of Australia, Germany, and the USA in each application area.

Technology	Estimation (%)	Monitoring (%)	Resource management (%)
Sentinel-2	16.67	0.00	0.00
LANDSAT-8	12.50	4.00	0.00
RGB Camera	16.67	28.00	37.50
LIDAR	16.67	14.00	0.00
UAV	31.25	50.00	50.00
SAR	6.25	4.00	12.50

explicitly quantify profitability. From a social perspective, some studies highlight benefits such as reduced manual scouting, easier access to field information and better-informed decision-making, suggesting potential improvements in labour efficiency, occupational safety and knowledge sharing in rural communities. These observations align with broader analyses of climate-smart agriculture and geospatial technology that position digital tools as enablers of both food security and progress towards the SDGs (Symeonaki et al., 2019; Pandey and Pandey, 2023).

### 3.6. How Australia compares

RQ.3. How does Australia compare to other developed countries in adopting IoT and geospatial modelling technologies in agriculture?

To answer how Australia compares in adopting IoT and geospatial modelling in agriculture, we will first focus on specific technologies commonly used in IoT and geospatial modelling in agriculture, and then examine specific application areas to identify any gaps in technology adoption. Based on our analysis of key technologies in Section 3.2, we identified six key technologies that have been utilised in more than 10 research articles. Additionally, based on the publication focus analysis for both crop and geographic focus, we selected two crops (wheat and canola) and two countries (the USA and Germany) to compare with Australia. Crop focus analysis revealed that sugarcane and cotton are not the primary crops of most of the countries we considered. Canola and barley, although produced in all of the countries, attracted a very low number of research articles, making any meaningful comparison difficult. On the other hand, while Canada’s research output was comparable to that of Australia’s, given Canada’s limited focus in the resource management application area, we decided to exclude it from this analysis. Additionally, Belgium, France, and Spain have a very low number of research articles published, making it difficult to conduct a meaningful comparison (see Fig. 14).

Fig. 13 demonstrates the overall usage of six key technologies in Australia, Germany, and the USA. While Australia lags behind Germany and the USA in all six key technologies, the disparity is most pronounced in SAR and RGB camera usage, as well as in UAV technology. From Table 5, we can see that RGB cameras and UAVs have been very impactful in the monitoring application area. At the same time, UAVs have been instrumental in the field of estimation applications.

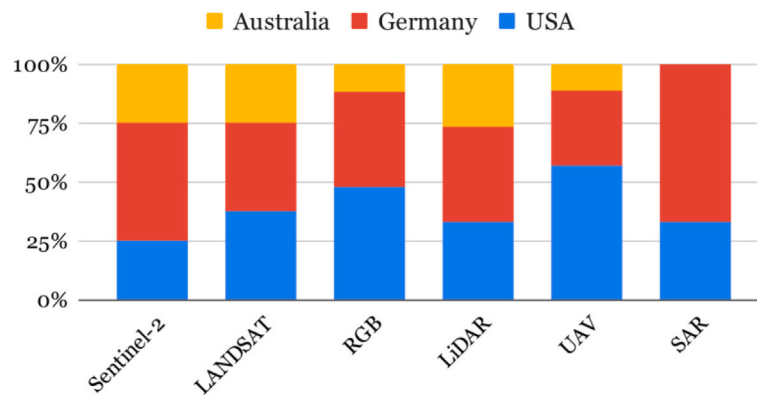


Fig. 13. Proportion of key technology usage in Australia, Germany, and the USA calculated for each technologies.

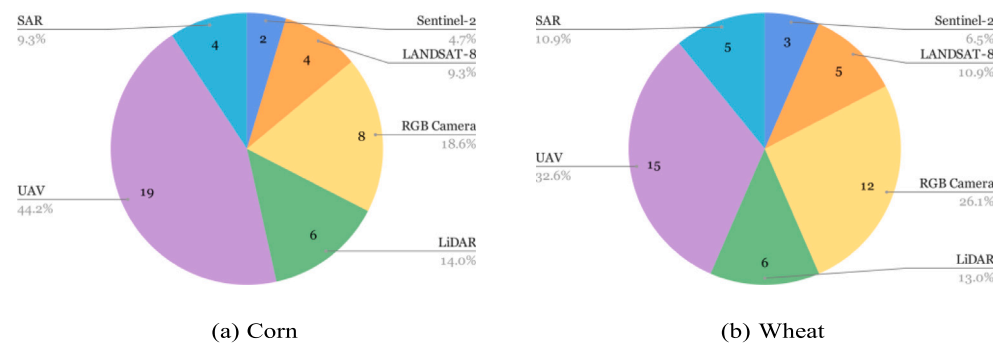


Fig. 14. Key technology usage of Australia, Germany, and the USA in select crops; (a) corn, (b) wheat.

Additionally, resource management application areas have been using these three technologies exclusively. Therefore, given that Australia’s research focus at the moment is primarily on estimation application areas, Australia must explore the application of RGB cameras and UAV technology to achieve a more balanced research focus. Additionally, given that Australia has the lowest proportion of research focus in the resource management area among these three countries, and since Australia is one of the most resource-constrained environments for agriculture (Lamb et al., 2021), it is vital that Australia looks into increasing research in the resource management area, and thus looks into the use of these three key technologies.

### 3.7. Challenges and opportunities for Australia in adopting IoT and geospatial modelling

The comparative analysis across countries highlights several features that are particularly salient for the Australian context. These relate both to the adoption patterns observed in the reviewed literature and to structural characteristics of Australian grain and oilseed production systems.

On the challenge side, the review indicates that Australian studies have made less frequent use of certain technologies—especially UAV-based RGB and multispectral imaging, as well as synthetic aperture radar—than studies in countries such as the United States and Germany, particularly in resource management applications. This suggests a potential lag not only in the level of adoption but also in the uptake of technologies that, elsewhere, have been closely associated with advancements in variable-rate fertiliser application, irrigation optimisation and site-specific management. The very large paddock sizes and low population density in many Australian grain-growing regions also create challenges for dense sensor deployments, reliable low-cost connectivity and frequent high-resolution data acquisition, especially

where cellular coverage is limited and the cost of repeated UAV flights is prohibitive.

Australia’s climate introduces additional constraints. High inter-annual variability in rainfall and temperature, frequent droughts and episodic extreme events complicate the calibration and transferability of sensing-based models developed in more stable environments. Models trained on a small number of seasons or sites may struggle to capture the full range of conditions experienced in Australian systems, reducing their reliability for decision support. Furthermore, several studies note constraints related to digital skills, data literacy and integration of heterogeneous data sources into farm management software, which can limit the practical uptake of sophisticated IoT-geospatial solutions even when the underlying technologies are technically available.

At the same time, the review points to important opportunities for Australia. The combination of large, relatively homogeneous paddocks and well-developed agricultural research and extension infrastructures positions Australia as a natural testbed for scalable IoT and geospatial solutions that can be deployed and evaluated at commercial farm scale. The strong emphasis on water-efficient and climate-resilient production, driven by both economic and environmental imperatives, aligns closely with the domains in which sensing and modelling have shown the greatest promise in other countries—namely irrigation scheduling, soil-water monitoring and nutrient management.

Australia also stands to benefit from open-access satellite data and national geospatial initiatives that reduce the marginal cost of spatial information. Integrating these resources with targeted on-farm sensing and robust modelling could enable cost-effective decision-support systems tailored to Australian conditions. Finally, there is a clear opportunity for coordinated investment in resource-management-oriented applications, where the review suggests that Australian studies are under-represented relative to peers. Prioritising multi-year, multi-site trials that integrate IoT sensing, geospatial modelling and variable-rate

technologies, and that explicitly quantify economic and environmental outcomes, would help close the evidence gap and accelerate adoption.

In summary, while Australia faces distinctive challenges in implementing IoT and geospatial modelling at scale—related to geography, climate, connectivity and skills—it also has the potential to become a leading example of sustainable smart agriculture in water-limited, extensive cropping systems. Realising this potential will require targeted research, infrastructure and extension efforts that build on the technological foundations identified in this review and translate them into robust, user-centred solutions for Australian grain and oilseed growers.

#### 4. Conclusion

This systematic review examined how IoT and geospatial modelling technologies have been applied in agriculture across Australia and selected developed countries, with a focus on key crop species and three main application domains: monitoring, estimation, and resource management. Over the period 2013–2023, the evidence shows a steady growth in research activity, confirming the strategic role of UAVs, RGB cameras, SAR, satellite platforms, and in-situ sensors for generating high-resolution information on crop status, soil conditions, and production risks.

The analysis reveals clear geographic and thematic imbalances. The USA and Germany dominate the literature, while Australia and other countries contribute a smaller but growing body of work. Wheat and corn are the most intensively studied crops, whereas barley, canola, cotton, and especially sugarcane are comparatively neglected. Technologically, most studies focus on monitoring and estimation tasks such as biomass, yield, and disease assessment. Far fewer explicitly “close the loop” by using IoT and geospatial outputs to optimise concrete management actions, for example variable-rate irrigation, fertiliser application, or targeted pest and weed control. This indicates a persistent gap between the capacity to measure and predict, and the routine use of this information to drive decision-making at farm level.

For Australia, the review highlights both progress and missed opportunities. Australian researchers increasingly employ IoT and geospatial tools, particularly in wheat systems, yet Australia still trails the USA and Germany in the intensity of UAV and SAR use and shows the weakest emphasis on resource-management-oriented applications. In a climate- and water-constrained context, this under-utilisation is significant: there is considerable scope for Australian agriculture to leverage IoT and geospatial analytics to improve water, nutrient, and risk management, and to support more climate-resilient production systems. The findings therefore have implications for policymakers, funding bodies, and industry partners, who may wish to prioritise research and innovation that directly links sensing and modelling outputs to practical on-farm decisions and scalable advisory tools.

Interpreting these findings through a sustainability lens, the integration of IoT and geospatial modelling has clear implications for the environmental, economic and social dimensions of agricultural systems. Environmentally, higher-resolution sensing and modelling enable more efficient use of water, fertilisers and agrochemicals, with potential reductions in emissions, runoff and land degradation, and improved resilience to climate variability. Economically, improved monitoring and prediction of crop and soil conditions can support better input allocation and risk management, helping farmers stabilise yields and reduce waste. Socially, digitally enabled decision-support tools may reduce labour and time burdens, enhance safety by limiting exposure to hazardous conditions, and improve access to timely agronomic advice, particularly in remote or resource-constrained regions. These roles are consistent with broader evidence that positions IoT- and geospatial-driven agriculture as a key pathway to food security and the achievement of multiple SDGs.

The review has limitations that also help to frame the findings. It focuses on peer-reviewed, English-language publications, a defined set

of developed countries, and a specific group of crops. Relevant practice-based knowledge in grey literature, non-English publications, and other regions is not fully captured. In addition, relatively few studies integrate techno-economic, social, and environmental evaluation with biophysical and geospatial performance, limiting our understanding of the broader sustainability impacts and adoption barriers associated with these technologies.

On the basis of the evidence synthesised here, several key directions for future research can be identified:

1. Broaden crop and regional coverage by extending IoT and geospatial studies to under-represented crops (barley, canola, cotton, sugarcane) and diverse Australian production environments, including marginal and water-limited areas.
2. Shift from estimation to decision support by designing, trialling, and rigorously evaluating IoT- and geospatial-enabled resource management strategies (e.g. variable-rate water, nitrogen, and chemical use) under real farm conditions.
3. Develop integrated, interoperable platforms that fuse satellite, UAV, proximal, and in-situ data into farmer-friendly decision-support systems and advisory services, reducing the technical burden on end-users.
4. Embed techno-economic and sustainability assessment by coupling geospatial analytics with cost-benefit analysis, labour and skills requirements, and environmental indicators such as emissions, soil health, and biodiversity.
5. Conduct comparative international studies to explore how policy settings, infrastructure, and institutional arrangements shape adoption pathways, and to identify transferable lessons that can accelerate uptake in Australia.

Advancing these research directions would help move IoT and geospatial technologies beyond isolated pilots towards mature, evidence-based tools that support sustainable smart agriculture, enabling farmers and decision-makers in Australia and other developed countries to respond more effectively to intertwined challenges of productivity, climate risk, and environmental stewardship.

#### CRediT authorship contribution statement

**Quazi Mamun:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Asaduz Zaman:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Ryan H.L. Ip:** Writing – review & editing, Supervision, Methodology, Conceptualization. **K.M. Shamsul Haque:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Conceptualization.

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#### Declaration of competing interest

The authors declare that they have no known competing interests that could have appeared to influence the work reported in this paper.

#### Appendix A. Search strategy and keywords

See [Table A.6](#).

**Table A.6**  
Search strategy and keywords used to find relevant publications.

Database	Keywords
IEEE Xplore	(IoT* OR Internet of Things OR Sensors) AND (Sustainable Agriculture OR Smart Agriculture OR IoT* in agriculture OR Precision Agriculture OR AgTech OR Precision Farming OR Smart Farming OR Climate smart agriculture OR digital agriculture OR Connected Farms OR Agricultural Sensors Network) AND (Geospatial modelling OR GIS OR geographic* information system* OR WebGIS OR spatial modelling OR spatial analysis ) AND (Australia OR USA OR Canada OR Germany OR Netherlands OR Belgium OR France OR Spain) AND (Wheat OR Barley OR Cotton OR Canola OR Sugarcane OR Sugar cane OR Maize OR Corn)
ACM Digital Library	AllField: (IoT* OR Internet of things OR Sensor*) AND AllField: (Sustainable Agriculture OR Smart Agriculture OR IoT* in agriculture OR Precision Agriculture OR AgTech OR Precision Farming OR Smart Farming OR Climate smart agriculture OR digital agriculture OR Connected Farms OR Agricultural Sensors Network) AND AllField: (geospatial modelling OR GIS OR geographic* information system* OR WebGIS OR spatial modelling OR spatial analysis) AND AllField: (Wheat OR Barley or Cotton OR Canola OR Sugarcane OR Sugar cane OR Corn OR Maize) AND AllField: (Australia OR USA OR Canada OR Germany OR Belgium OR France OR Spain) AND AllField: (NOT medic* AND NOT langu* AND NOT lingu* AND NOT edu* AND NOT game*)
Web of Science	(TS = (IoT* OR "Internet of things" OR Sensors OR WSN)) AND (TS = (Smart Agriculture OR IoT in Agriculture OR Precision Agriculture OR Digital Agriculture OR AgTech OR Precision Farming OR Smart Farming OR Climate smart agriculture OR Connected Farms OR Agricultural Sensor Network)) AND (TS = (Wheat OR Barley OR Cotton OR Canola OR Sugarcane OR Sugar Cane OR Maize OR Corn)) AND (CU = (Australia OR USA OR Canada OR Germany OR Spain OR Belgium OR France))

**Appendix B. Information extraction template**

From each articles, we tried to extract information based on the following information extraction template-

1. Document Identification
  - (a) Author(s)
  - (b) Title
  - (c) Journal/Conference Name
  - (d) Publication Year
  - (e) Crop Species Mentioned
  - (f) Study Location
2. IoT and Technology Adoption Assessment
  - (a) Primary IoT Technology Used
  - (b) Types of IoT Sensors and Technologies Used
  - (c) Any Specific Algorithms used
3. Agricultural Application
  - (a) Applications in Agriculture
  - (b) Purpose of Technology Usage
  - (c) Impact on Resource Management
  - (d) Impact on Crop Productivity
  - (e) Benefits Noted
  - (f) Challenges Faced
4. Additional Insights
  - (a) Statistical Data (if any)
  - (b) Case Studies or Examples
5. Synthesis and Conclusions
  - (a) Main Findings
  - (b) Author's Conclusions
6. Short Summary

**Appendix C. Yearly trend of technologies**

See [Table C.1](#).

**Table C.1**

Tech	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
3D camera	0	0	0	1	0	0	1	1	0	0	0
3D point cloud	0	0	0	0	0	0	1	0	0	0	1
ACS-470	0	0	0	0	0	0	0	0	1	0	0
Airplane monitoring	0	0	1	0	2	0	1	1	2	1	0
ALS50-II	0	0	0	0	1	0	0	0	0	0	0
ARDARSAT-2	0	0	0	0	0	0	0	1	0	0	0
ARSPivot	0	0	0	0	0	0	0	1	0	0	0
Canopy metre	0	0	1	0	0	0	0	0	0	0	0
Crop circle phenom sensor	0	0	0	0	0	0	0	0	2	0	0
CubeSat	0	0	0	0	0	0	1	0	0	0	0
DEM	0	0	0	0	0	0	0	0	1	1	0
DInSAR	0	0	0	0	1	0	0	0	0	0	0
DMC	0	0	0	0	0	0	0	0	0	0	1
Dualex	0	0	0	0	0	0	1	0	0	1	0
Eca sensor	0	1	0	0	0	2	0	0	0	0	0
EnviroScan	0	1	0	0	0	0	0	0	0	0	0
FieldSpec handheld	1	0	0	0	1	2	0	0	0	0	0
Formosta-2	0	0	0	0	1	0	0	0	0	0	0
GIS	0	0	1	0	0	0	0	0	0	0	0
GNSS	0	0	0	0	0	0	0	1	5	0	0
GPR	0	0	0	1	0	0	0	0	1	0	0
GPS	0	0	0	0	1	0	1	0	0	3	0
GreenSeeker	1	0	1	0	0	2	0	0	1	1	0
Ground vehicle	0	1	0	0	1	0	2	1	3	1	0
HandySpec field	0	0	0	1	1	1	0	0	1	0	0
Infrared thermometer	0	0	0	0	0	0	0	0	0	0	1

(continued on next page)

Table C.1 (continued).

Tech	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Isaria	0	0	0	1	0	0	0	0	0	0	0
Kinect	0	0	0	1	0	2	0	0	0	0	0
Kinect V2	0	0	0	0	0	1	0	0	0	0	0
Kinect V3	0	0	0	0	0	1	1	0	0	0	0
L2SM	0	0	0	0	1	0	0	0	0	0	0
LANDSAT	0	0	0	0	1	0	0	0	0	0	0
LANDSAT-5	0	0	0	0	0	0	0	0	0	1	0
LANDSAT-7	0	0	0	0	0	1	0	1	0	1	0
LANDSAT-8	0	0	0	0	0	3	1	2	3	2	0
Laser scanner	0	0	0	0	0	0	0	0	1	0	0
Leaf surface wetness sensor	0	0	0	0	0	0	0	0	1	0	0
LeafSpec	0	0	0	0	0	0	0	1	0	0	0
LiDAR	0	1	0	0	2	0	1	1	4	5	1
LIDAR	0	0	0	0	0	0	0	0	1	0	0
LoRaWAN	0	0	0	0	0	0	0	0	0	1	0
MicaSense	0	0	0	0	0	0	1	0	2	0	0
MicaSense altum	0	0	0	0	0	0	0	0	0	1	0
MMS1	1	0	0	0	0	0	0	0	0	0	0
MODIS	1	0	0	1	1	0	2	0	0	0	0
Multiplex 3	1	0	0	1	1	0	0	1	0	2	0
NDVI	0	0	2	0	0	1	0	2	0	1	0
NIR	0	0	0	0	0	0	0	2	1	1	0
NIR imaging	0	0	0	1	0	0	0	0	0	0	0
PAR	0	0	0	1	0	0	0	0	1	0	0
Parrot sequoia	0	0	0	0	0	0	1	0	0	0	0
PlanetScope	0	0	0	0	0	0	0	0	0	2	0
PolDInSAR	0	0	0	0	1	0	0	0	0	0	0
PolSAR	0	0	0	0	0	0	1	0	0	0	0
Proximal soil sensor	0	0	0	1	0	0	0	0	0	0	0
Qualispec Pro	1	0	0	0	0	0	0	0	0	0	0
Quantix	0	0	0	0	0	0	0	0	1	0	0
QuickBird	0	0	0	0	0	0	1	0	0	0	0
RADARSAT	0	0	0	0	1	0	0	0	0	0	0
RADARSAT-2	1	1	0	0	1	0	0	1	0	0	0
RapidEye	0	0	1	0	0	1	1	0	0	2	0
RapidScan CS-45	0	0	0	0	0	0	0	1	0	0	0
Raspberry Pi	0	0	0	0	0	0	1	0	1	0	0
RGB camera	0	1	0	3	0	6	3	4	7	4	2
RTK	0	1	0	0	0	0	1	0	0	0	0
RTK-GNSS	0	0	0	0	0	0	1	0	0	0	0
RTK-GPS	0	1	0	0	0	0	0	0	0	0	0
SAP flow sensors	0	0	0	0	0	0	0	0	0	0	1
SAR	1	1	1	0	2	2	1	2	4	4	0
Sentinel-1	0	0	0	0	0	0	0	0	2	2	1
Sentinel-1A	0	0	0	0	0	1	0	0	0	0	0
Sentinel-2	0	0	0	0	0	0	2	1	2	6	2
Sentinel-2A	0	0	0	0	0	1	0	0	0	0	0
Sequoia	0	0	0	0	0	1	0	0	0	0	0
SfM	0	0	0	0	0	0	0	0	1	0	0
SIF	0	0	0	0	0	0	0	1	0	0	0
SLAM	0	0	0	0	0	0	1	0	0	0	0
SMAP	0	0	1	0	0	0	0	0	0	0	0
Smart automation system for furrow irrigation	0	0	0	0	0	1	0	0	0	0	0
SMOS	0	0	1	0	1	0	0	0	0	0	0
Soil moisture sensor	0	0	0	0	0	0	0	1	0	1	0
Soil profile optimiser	0	0	0	0	0	0	0	0	0	0	1
Soil sensor	0	1	0	0	0	0	0	0	0	0	3
SPAD sensor	0	0	0	0	0	1	1	0	0	0	0
SPAD-502	0	0	0	0	0	0	1	0	0	0	0
Spectrometers	1	0	0	0	0	0	0	0	0	0	0
Spot-4/5	0	0	0	0	1	0	0	0	0	0	0
SVI	0	0	0	0	0	0	1	0	0	0	0
SWC sensor	0	1	0	0	0	1	0	1	0	0	0
SWC sensor,	0	0	0	0	1	0	0	0	0	0	0
SWC sensors	0	1	0	0	0	0	0	0	0	0	0
TDR	0	0	0	0	0	0	0	0	0	0	1
TDR probe	0	0	0	1	0	0	0	0	0	0	0
Temperature sensor	0	0	0	0	0	0	0	0	0	1	0
TerraSantia	0	0	0	0	0	0	0	1	0	0	0
TerraSAR-X	0	0	0	0	2	0	0	0	0	0	0
Thermal imaging	0	0	0	0	0	1	1	1	1	0	0
TOF camera	0	0	0	1	0	2	0	0	0	0	0
TrueColor sensor array	0	0	0	0	0	0	0	0	0	1	0
UAV	1	0	0	4	1	8	7	5	11	12	5
UAVSAR	0	0	0	0	0	1	1	0	0	0	0

(continued on next page)

Table C.1 (continued).

Tech	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
variable rate irrigation	0	0	0	0	0	0	0	0	0	0	1
Veris MSP-3	0	0	0	0	0	0	0	0	0	0	1
vis-NIR	0	0	0	0	0	0	0	0	0	2	0
vis-NIRS	0	0	0	0	0	0	0	0	0	0	1
VRI	0	0	0	0	0	0	0	1	0	0	0
Weed control	0	0	0	0	0	0	0	1	0	1	0
Weed Hoeing	0	0	0	0	0	0	0	0	0	0	1
Weed sensor	0	1	0	0	0	0	0	0	0	0	0
WorldView-2	0	0	0	0	0	0	1	0	0	0	0
WorldView-3	0	0	0	0	0	0	0	0	1	0	0
WSN	0	1	0	1	0	0	1	1	0	0	0
Yara N-Tester	0	0	0	0	0	0	0	1	0	0	0

## Appendix D. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.compag.2025.111289>.

## Data availability

Data will be made available on request.

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