

Systematic Review

Precision Agriculture in Maize Production: A Systematic Review of Technologies, Applications, and Yield Optimisation

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Abstract

Precision agriculture (PA) has emerged as a data-driven approach for improving maize (*Zea mays* L.) production through the integration of remote sensing, Geographic Information Systems (GISs), Global Navigation Satellite Systems (GNSSs), the Internet of Things (IoT), and machine learning (ML). This systematic review evaluates the application of PA for yield optimisation and resource-use efficiency in maize production between 2020 and 2026. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, 464 records were identified from Scopus and Web of Science, of which 129 studies met the inclusion criteria. The reviewed literature comprised field experiments (28.6%), remote sensing and PA integration studies (25.5%), machine learning applications (19.4%), climate-informed PA strategies (23.4%), and soil degradation studies (3.1%). Remote sensing and integrated multi-technology systems were the most extensively investigated approaches, followed by ML-based models for yield prediction and crop monitoring. Overall, PA technologies enhanced maize productivity, nutrient-use efficiency, water-use efficiency, and yield prediction accuracy through site-specific management and data-driven decision support. Despite its considerable potential, the adoption of PA remains constrained by high implementation costs, technical complexity, and limited data availability. Collectively, these findings demonstrate that precision agriculture provides an effective framework for sustainable maize intensification by improving productivity, optimising resource-use efficiency, and strengthening resilience to climate variability.



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1. Introduction

Maize (*Zea mays* L.) is the third most-produced cereal crop worldwide, after wheat and rice, and serves as a primary source of food, feed, industrial raw materials, and biofuel for nearly one-third of the global population [1–3]. Rising population growth, urbanisation, and increasing demand for agricultural commodities are expected to increase global agricultural production by approximately 70% by 2050, with maize production projected to grow annually

by 2.2–2.4% to meet future food requirements [4,5]. However, global maize yield growth has slowed in recent decades owing to climate variability, soil degradation, water scarcity, pest and disease pressure, and the limitations of conventional crop management practices [1,6]. These challenges highlight the need for innovative, data-driven approaches that enhance productivity while promoting sustainable resource management [5,7].

Accurate monitoring of crop growth and yield is fundamental to improving maize productivity and ensuring global food security. Reliable assessment of crop development supports timely management decisions related to irrigation, fertiliser application, pest and disease control, and harvest planning [8–10]. Moreover, accurate yield estimation is essential for supply chain management, market forecasting, and agricultural policy development [9–12]. Nevertheless, conventional field-based monitoring methods are often labour-intensive, time-consuming, and incapable of capturing the spatial and temporal variability present within agricultural fields, thereby limiting effective decision-making under changing environmental conditions [7,8].

Precision agriculture (PA) has emerged as a promising strategy for overcoming these limitations by enabling site-specific crop management through the integration of digital technologies [13–15]. PA combines information technologies, global positioning systems (GPSs), geographic information systems (GISs), yield monitoring, and variable-rate technologies to optimise agricultural inputs while improving crop productivity and environmental sustainability [16–18]. By providing continuous information on crop and soil conditions, PA facilitates more efficient management of fertilisers, irrigation, pesticides, and other production resources, thereby improving farm profitability and reducing environmental impacts [19–22].

Recent technological advances have further expanded the capabilities of precision agriculture. Remote sensing, digital imaging, and unmanned aerial vehicles (UAVs) enable rapid, high-resolution monitoring of crop growth, plant health, and field variability across large production areas [23–26]. At the same time, machine learning (ML) and artificial intelligence (AI) techniques have substantially improved biomass estimation, yield prediction, crop classification, disease detection, and decision support systems through the analysis of large, multi-source agricultural datasets [5,27,28]. Similarly, Internet of Things (IoT) technologies facilitate the continuous monitoring of soil moisture, nutrient status, weather conditions, and crop performance, enabling real-time management decisions and improving resource-use efficiency [5,29].

The integration of these technologies has significantly advanced maize production systems by improving crop monitoring, yield forecasting, and input optimisation. Additionally, several studies have demonstrated that remote sensing, UAV-based imaging, machine learning algorithms, IoT-enabled sensing systems, and hybrid crop models can improve prediction accuracy and support evidence-based management decisions under diverse production environments [24–26,30–32]. The evidence from these studies remains fragmented because research tends to concentrate on individual technologies, specific management practices, or distinct production settings. Variations in sensing platforms, spatial and temporal resolutions, analytical methods, experimental designs, evaluation criteria, and agronomic indicators further hinder direct comparisons of technological performance across studies. Crucially, enhancements in prediction or monitoring accuracy do not always lead to tangible improvements in maize yield or resource-use efficiency. Consequently, a comprehensive assessment is necessary not only to identify the PA technologies applied in maize production but also to evaluate their effectiveness in enhancing agronomic productivity and optimising the use of agricultural resources.

While prior reviews have explored specific elements of precision agriculture, including remote sensing, UAVs, machine learning, and IoT applications, there is a scarcity of compre-

hensive syntheses regarding the application and efficacy of these technologies specifically in maize production systems [24–29]. Furthermore, existing literature has predominantly concentrated on individual technologies, methodological advancements, or general agricultural applications, rather than systematically assessing their collective impact on maize productivity and resource-use efficiency. Consequently, the available evidence remains fragmented, limiting comparisons among technologies and the development of generalisable recommendations across different agro-ecological conditions. To address this gap, this systematic review synthesises information on the application of precision agriculture technologies in maize production. Specifically, it aims to (1) characterise the major precision agriculture technologies applied in maize systems; (2) synthesise their applications in crop monitoring, input optimisation, and decision support processes; (3) assess their effects on maize productivity, resource-use efficiency, and key agronomic outcomes; and (4) identify current limitations, adoption barriers, and research gaps.

2. Materials and Methods

2.1. Literature Search Strategy

This systematic review was conducted in accordance with the PRISMA 2020 guidelines to ensure transparency and reproducibility [33]. Literature searches were performed in the Web of Science and Scopus databases to identify studies published from January 2020 to 15 April 2026 that were eligible for inclusion. An initial search was conducted on 10 February 2026 and updated on 15 April 2026 to include newly indexed publications.

Searches were conducted using the primary keywords ‘precision agriculture’, ‘smart farming’, ‘digital agriculture’, and ‘maize production’, which were combined using Boolean operators (AND/OR) to identify relevant studies related to precision agriculture and maize production. These terms formed the basis of the search strategy used in both databases.

All retrieved records were exported to Zotero (Corporation for Digital Scholarship, Vienna, Austria; <https://www.zotero.org/>) (accessed on 15 April 2026) for reference management and duplicate removal. The subsequent screening and study selection procedures followed the predefined eligibility criteria described in Section 2.2 and are summarised in the PRISMA 2020 flow diagram (Figure 1). The completed PRISMA 2020 checklist is provided in the Supplementary Materials. The review protocol was registered on the Open Science Framework (OSF) (<https://osf.io/9s23a>) (accessed on 1 June 2026), including the objectives, eligibility criteria, and analytical methods.

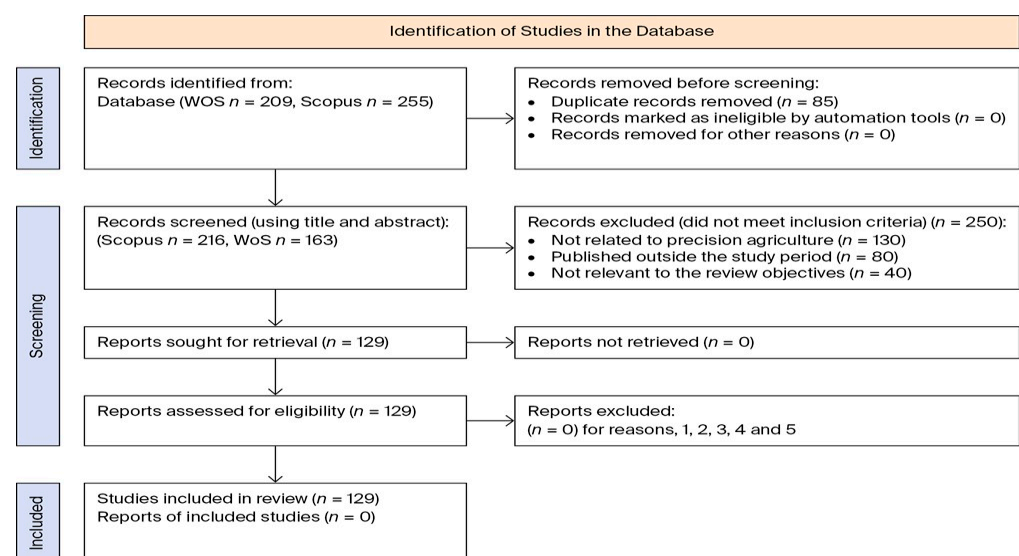


Figure 1. PRISMA flow diagram of the study selection process.

2.2. Eligibility Criteria and Study Selection

Studies were selected according to predefined inclusion and exclusion criteria following the PRISMA 2020 guidelines. Eligible studies met the following criteria: (i) were published as peer-reviewed journal articles; (ii) were written in English; (iii) were published between 2020 and 2026; and (iv) investigated the application of precision agriculture technologies, including digital agriculture, remote sensing, artificial intelligence, decision support systems, or related approaches relevant to maize production. Studies involving other cropping systems were included as supporting evidence when they evaluated precision agriculture technologies or methodologies applicable to maize production, such as crop monitoring, yield estimation, nutrient management, irrigation, or variable-rate application.

Studies were excluded if they (i) were unrelated to precision agriculture; (ii) were not published in English; (iii) were conference abstracts, editorials, book chapters, or publications without accessible full texts; (iv) were duplicate records; or (v) lacked sufficient methodological information relevant to the review objectives.

After duplicate removal, two reviewers (M.M.A.O. and R.K.) independently screened the titles and abstracts of 379 records based on the predefined eligibility criteria. Following screening, 87 records from Web of Science and 42 from Scopus were considered potentially eligible. These records were cross-checked by title, authors, and DOI, and no duplicates were identified; thus, 129 unique reports were assessed at the full-text stage. Each report was evaluated against all predefined inclusion and exclusion criteria. All 129 reports met the eligibility criteria and were included in the review; therefore, no reports were excluded at the full-text stage ($n = 0$). Disagreements were resolved through discussion and consensus. Inter-reviewer agreement was not formally measured. The complete selection process is presented in the PRISMA 2020 flow diagram (Figure 1), with a summary provided in Table 1.

Table 1. Overview of the literature search outcomes and study selection by database.

Database	Retrieved Records	Screened Records	Studies Included
WoS	209	163	87
Scopus	255	216	42

Source: Authors (2026).

2.3. Data Extraction Process

Data were extracted using a standardised form developed for this review. Extracted variables included publication year, country, study objectives, precision agriculture technologies, study design, methodological approach, agronomic indicators, and key outcomes related to maize productivity, resource-use efficiency, and sustainability. In response to the methodological requirements, the extraction was further expanded to capture experimental and sampling characteristics, including the number of fields or plots, biological replicates, sampled plants, repeated measurements, cultivar or hybrid, validation procedures, plant age, developmental stage, and sampled organ, where these characteristics were reported in the original studies. The distinction between true biological replication and multiple image-based observations, such as image tiles, pixels, or repeated flights, was also recorded where information was available. When the original study did not report a characteristic, it was recorded as “not reported” rather than inferred.

Descriptive analyses were conducted using Microsoft Excel 2016 (Microsoft Corporation, Redmond, WA, USA) to summarise publication trends, the geographical distribution, and the frequency of precision agriculture technologies. In contrast, linear trend analysis was performed to evaluate annual publication patterns, and the coefficient of determination ($R^2 = 0.7587$) was calculated to assess publication trends over the study period. The

extracted data were synthesised thematically to compare technologies, methodological approaches, and reported agronomic outcomes across the included studies.

2.4. Quality Assessment and Risk of Bias

The methodological quality of the included studies was assessed individually using a predefined qualitative framework informed by ROBIS principles. The first author (M.M.A.O.) assessed two domains: sampling clarity and analytical transparency. Sampling clarity covered the description of the study population or experimental material, sampling methods, study setting, and relevant sampling procedures. Analytical transparency focused on the clarity of methodological procedures, analytical methods, model development or validation, and outcome assessment. Each domain was rated as low, moderate, or high concern based on the completeness, clarity, and methodological adequacy of reported information. Two domains relevant to study interpretation were assessed, focusing on transparency of design, sampling or replication, outcome measurement, and validation. Low concern indicated clear, sufficient reporting with no major limitations; moderate concern reflected some limitations or incomplete reporting without major deficiencies; great concern denoted substantial deficiencies or insufficient information limiting confidence (Table 2).

Table 2. Detailed Methodological Quality Assessment of the 129 Studies Included in the Systematic Review.

Study	Methodological Approach/Design	Sampling Clarity	Analytical/ Transparency	Overall Methodological Concern
[20]	Field experiment	High	High	Low
[24]	Systematic literature review	High	High	Low
[5]	Literature review	Moderate	Moderate	Moderate
[7]	Sensor-driven decision model	Moderate	High	Low
[34]	Review of hyperspectral imaging technologies and agricultural applications	Moderate	High	Moderate
[35]	Observational + spatial modelling study	Moderate	High	Low

Source: Authors (2026).

Overall risk-of-bias was assigned qualitatively based on the combined domain ratings: low concern if both domains were low, moderate concern if one or both showed limitations without major deficiencies, and high concern if substantial deficiencies affected interpretation. No numerical weighting or item-level thresholds were applied; categories served as a structured qualitative appraisal rather than a validated numerical score. Percentages represent the descriptive distribution of studies across these categories.

This assessment identified methodological limitations to guide synthesis interpretation without excluding studies based on quality. ROBIS principles informed the process but were not used as a formal risk-of-bias tool across all designs. As the assessment relied on qualitative judgement of reported information and lacked independent duplication, classifications should be viewed as descriptive rather than precise risk-of-bias estimates. Full details are in Supplementary Table S1.

2.5. PRISMA 2020 Flow Diagram

The study's identification, screening, eligibility assessment, and inclusion process followed the PRISMA 2020 guidelines and is presented in Figure 1. Following the predefined eligibility criteria, 129 studies were included in the final qualitative synthesis.

2.6. Thematic Summary of Evidence

Table 3 summarises the thematic distribution of the 129 studies included in this review, highlighting the main research domains, methodological approaches, and agronomic, soil, and climatic indicators reported across the evidence base (Supplementary Tables S2 and S3). Field experiments were frequently integrated with remote sensing approaches [23,24], while

geographic information systems (GISs) were widely used for spatial analysis and precision management applications [30,33]. Climatic data were incorporated to support yield prediction and environmental variability assessment [36], and machine learning techniques were increasingly applied for crop monitoring and predictive modelling, particularly for yield estimation and classification tasks [7,36]. Additional studies combined multiple technologies, including decision support systems and geospatial tools, to improve resource-use efficiency and site-specific management in maize production [19,37].

Table 3. Multidimensional thematic categorisation of studies on precision agriculture technologies, applications, and yield optimisation in maize production.

Thematic Category	No. of Studies	Methodological Approach	Maize, Soil, and Climatic Indicators	Direction of Change (Key Findings)	Main Observations/Patterns	Representative References
Field-based agronomic and soil studies	37	Plot and on-farm field experiments, soil sampling, laboratory analysis, and long-term trials	Yield, biomass, SOC, N, P, K, pH, soil moisture, and plant nutrition indices	Yield: ↑; Nutrient-use efficiency: ↑; SOC: ↑/↓ (mixed); pH: →; soil fertility ↑/↓; weed detection accuracy ↑; Pesticides ↓; GHG ↓	Effects of variable-rate fertilisation, hybrid choice, and tillage on yield stability, soil fertility, and input efficiency	[8–10,38–45]
Remote sensing, PA, and mapping studies	33	Satellite/UAV imaging, proximal sensing, GIS analysis, and yield mapping	NDVI and related vegetation indices, canopy cover, spatial yield patterns, soil variability proxies, and rainfall/temperature overlays	Yield variability: ↑; in heterogeneity detection; mapping accuracy: ↑; pest detection accuracy: ↑; NUE: ↑; irrigation efficiency: ↑; bio-nano hybrid: →; Water Use Efficiency: →	Use of spatially explicit data to delineate management zones, monitor crop performance, and support site-specific input application	[7,23,34,36,45–51]
Machine learning and deep learning applications	25	Supervised ML, deep learning (CNNs, RNNs, and hybrid models), data fusion of field and remote sensing, and laboratory analysis	Yield prediction, soil moisture, SOM, nutrient status, stress indicators, and weather variables	Prediction accuracy: ↑; uncertainty: ↓; pest detection accuracy: ↑; nitrogen management efficiency: ↑; SOM: ↑	Data-driven models for yield forecasting, stress detection, and optimisation of site-specific management decisions	[19,27,28,52–57]
Soil degradation, erosion, and resilience	4	Field monitoring, erosion modelling, spatial analyses, and long-term observation	SOC redistribution, aggregate stability, erosion rates, runoff, rainfall intensity, and water use	SOC: ↑↓ zones; WUE: ↑; soil degradation risk ↓	Identification of degradation-prone areas; interactions between management, climate, and soil loss; and implications for PA-based conservation	[39,58–60]
Climate- and weather-informed PA management	30	Integration of meteorological data, crop models, remote sensing, and decision support tools	Rainfall, temperature, evapotranspiration, drought indices, yield, and water-use efficiency	WUE: ↑; climate risk exposure: →/↓ (context-dependent); pest detection accuracy ↑	Use of climate information with spatial data to schedule irrigation, adjust planting and fertilisation, and manage climate risks	[17–22,56,61–70]

Source: Authors (2026). **Note:** The thematic categories represent different analytical dimensions of the included evidence rather than mutually exclusive study-design categories. Individual studies could contribute to more than one category because precision agriculture technologies, methodological approaches, agronomic indicators, and management objectives are frequently combined within the same study. Therefore, the number of studies across categories is not expected to sum to the total number of included studies (129). The direction of change is denoted as follows: ↑ = increase/improvement; ↓ = decrease/reduction; → = no clear change; ↑/↓ = mixed or context-dependent findings.

3. Results

3.1. Overview and Characteristics of Included Studies

Following the PRISMA study selection process (Figure 1), 129 studies were included in the qualitative synthesis, comprising field experiments, observational studies, modelling studies, systematic reviews, and technology evaluation studies conducted across diverse agricultural systems.

The included studies evaluated the application of precision agriculture to improve crop management and agricultural productivity. The most frequently reported outcomes

included crop yield, nutrient-use efficiency, water-use efficiency, crop health, pest and disease management, resource-use efficiency, and environmental sustainability. Together, these studies provide the evidence base for the subsequent analyses of publication trends, precision agriculture technologies, agronomic impacts, and research gaps.

3.2. Temporal and Thematic Trends in Precision Agriculture Research

Figure 2 presents the annual publication counts indexed in the Web of Science (WoS) and Scopus databases from 2020 to 2025, revealing a marked upward trend indicative of intensifying scholarly engagement in the field. In WoS, publications rose from approximately 17 in 2020 to 66 in 2025, reflecting nearly a fourfold increase. Despite a transient decline in 2023 relative to 2022 (25 versus 30 publications), output rebounded sharply in the subsequent two years.

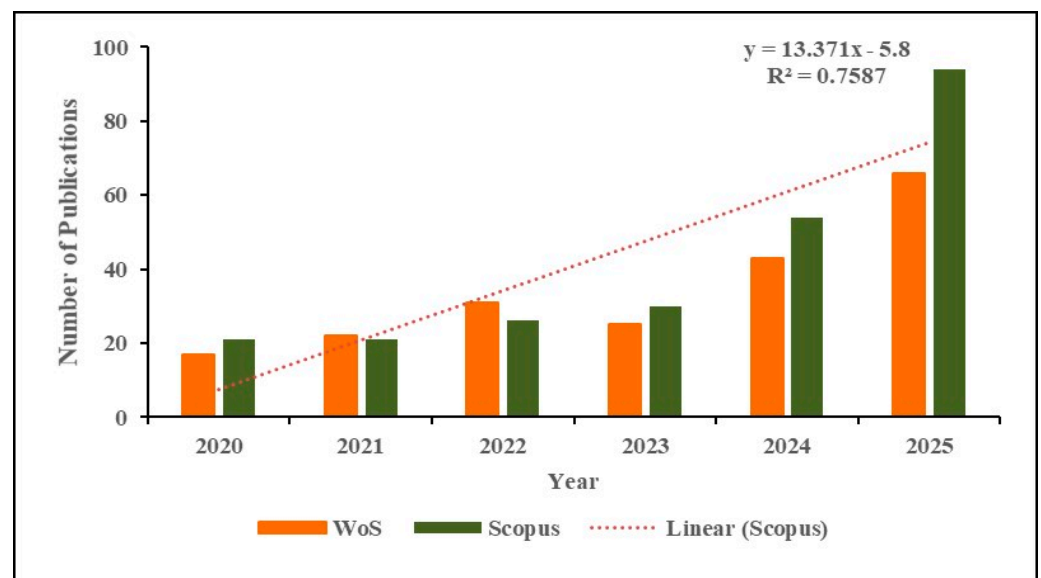


Figure 2. Trend of publications indexed in Scopus and WoS (2020–2025).

In Scopus, publications increased by approximately 348%, rising from 21 publications in 2020 to 94 publications in 2025. Similarly, publications indexed in WoS increased by about 276%, growing from 17 publications in 2020 to 64 publications during the same period. Although minor decreases occurred between 2020 and 2021 and again in 2022, a consistent upward trend was observed from 2023 onward, culminating in the highest publication volume in 2025.

Linear regression analysis of Scopus publications demonstrates a strong positive correlation between publication year and output ($R^2 = 0.7587$), indicating that approximately 75.9% of the variation in publication frequency is attributable to temporal progression. The overall increasing trends across both databases underscore expanding research activity and scientific interest, which were particularly pronounced during the final two years of the examined period (2024–2025).

Figure 3 presents the distribution of publications by country across the Scopus and Web of Science (WoS) databases. China emerges as the leading contributor, representing 33.4% of the total Scopus publications (91 documents) and 38.5% of WoS publications (79 documents), while India ranks second, accounting for 23.8% of Scopus publications (65 documents) and 18.04% of WoS publications (37 documents). The United States follows, contributing 17.6% and 17.5% in Scopus (48 documents) and WoS (36 documents), respectively. Collectively, these three countries constitute 74.8% and 74.04% of Scopus and WoS publications, respectively, underscoring their predominant role in the research domain.

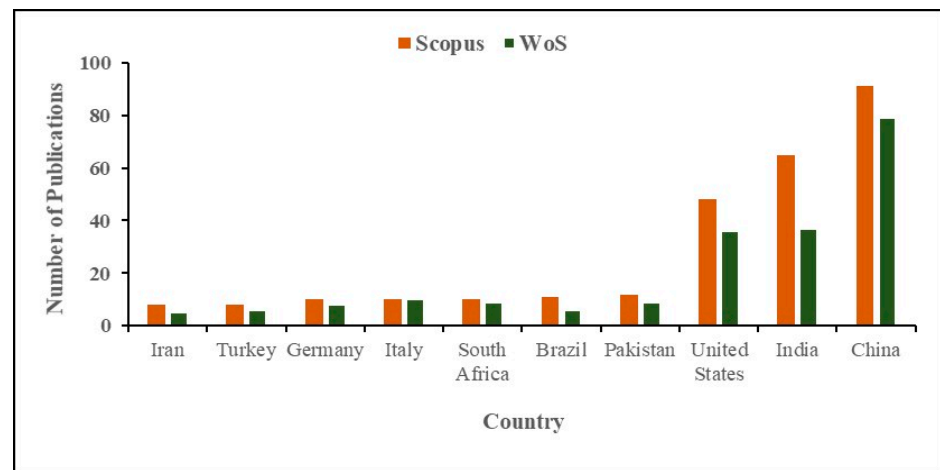


Figure 3. Geographical distribution of research publications by country. Data Source: Scopus and WoS (2020–2026).

Other countries contribute notably smaller shares: Pakistan accounts for 4.4% (12 documents) in Scopus and 4.4% (9 documents) in WoS, while Brazil contributes 4.02% and 2.9% in Scopus and WoS, respectively. Germany, Italy, and South Africa each account for 3.7% of Scopus publications (10 documents each), whereas in WoS, Italy, South Africa, and Germany account for 4.9% (10 documents), 4.3% (9 documents), and 3.9% (8 documents), respectively. The lowest publication proportions are observed for Iran and Turkey, each with 2.9% (eight documents) in Scopus; in WoS, they represent 2.5% (five documents) and 2.9% (six documents), respectively. Overall, Figure 2 highlights a pronounced concentration of research output within China, India, and the United States, with the remaining countries contributing minor proportions of the total publications.

Figure 4 illustrates the publication trends of the five leading journals identified by their total number of relevant publications during the 2020–2025 study period. Journals were ranked by publication count, with the top five selected for detailed analysis: Precision Agriculture and Computers and Electronics in Agriculture (each with 16 publications), Agronomy (15 publications), Agricultural Water Management (9 publications), and Field Crops Research (7 publications). The inclusion threshold was set at a minimum of seven relevant publications over the period.

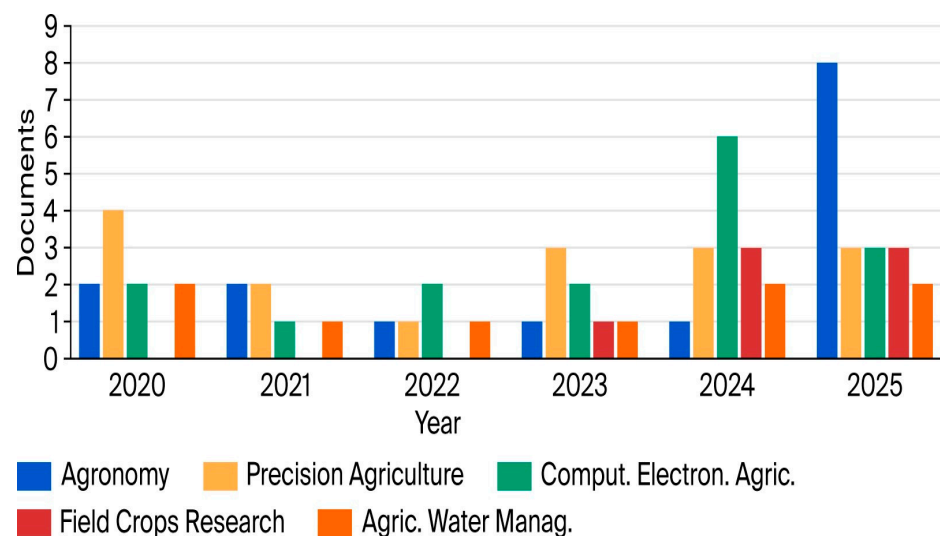


Figure 4. Annual distribution of the reviewed studies published in the five journals with the highest number of included articles. Source: Scopus (2020–2025).

The annual publication trends show notable variation among these journals. Agronomy exhibited the most significant growth, increasing from 2 publications in 2020 to 8 in 2025, a 300% rise. Computers and Electronics in Agriculture also showed substantial growth, rising from 2 publications in 2020 to 6 in 2024, followed by a decline to 3 publications in 2025. Precision Agriculture displayed a fluctuating pattern, decreasing from 4 publications in 2020 to 1 in 2022, then stabilising at 3 publications annually from 2023 to 2025.

Field Crops Research experienced a recent upward trend, with publications increasing from 1 in 2023 to 3 in both 2024 and 2025. Agricultural Water Management maintained relative stability, with annual publications mostly ranging between 1 and 2, except for 2 publications each in 2020 and 2021. Overall, these patterns suggest increasing research activity in certain major journals, particularly Agronomy and Computers and Electronics in Agriculture, while others show fluctuating or stable outputs.

3.3. Precision Agriculture Technologies Used in Maize Production

Table 4 summarises the occurrence of major precision agriculture (PA) technologies and applications across 129 studies (Supplementary Table S2). Classification was based on technology and application dimensions rather than mutually exclusive categories, as studies often combined multiple PA technologies and methods. For instance, a single study might simultaneously use UAV remote sensing, machine learning, GIS, and site-specific crop management. Thus, frequencies and percentages indicate the proportion of studies reporting each technology or application, not parts of a 100% total.

Table 4. Occurrence of precision agriculture technologies and applications reported across the included studies on maize production.

Category	Technology/Application	Studies Reporting Category (n)	Studies Reporting Category (%)
Sensing and Monitoring	Remote sensing (NDVI, UAV, and satellite imagery)	29	22.48
	Soil moisture/nutrient sensors (IoT-based systems)	14	10.85
Spatial Decision Tools	GIS-based field mapping	2	1.55
	GPS-guided management systems	1	0.78
Input Optimisation	Precision nutrient management	10	7.75
	Precision irrigation systems	7	5.43
	Precision pest and weed management	7	5.43
Analytics and Modelling	Machine learning/AI yield prediction	22	17.05
	Crop growth simulation models	8	6.20
Integrated Systems	Multi-technology precision farming systems	29	22.48
Total		129	100

Source: Authors (2026). **Note:** Percentages were calculated as the number of included studies reporting each technology/application divided by the total number of included studies ($n = 129$). Categories were not mutually exclusive; therefore, percentages are not expected to sum to 100%.

Remote sensing (NDVI, UAV, satellite imagery) and multi-technology integrated systems each appeared in 29 studies (22.48%). Machine learning and AI methods were reported in 22 studies (17.05%), reflecting their growing use in yield prediction, crop monitoring, and decision support [7,71]. Soil moisture and nutrient sensors appeared in 14 studies (10.85%), and precision nutrient management in 10 (7.75%) [72]. Crop growth simulation models were in 8 studies (6.20%), while precision irrigation and pest/weed management each featured in 7 studies (5.43%) [22,24,53,58,73]. GIS-based mapping and GPS-guided systems were less common, reported in 2 (1.55%) and 1 (0.78%) studies, respectively [15].

These results highlight remote sensing, integrated systems, and machine learning as the most frequently reported PA approaches, with other technologies applied more

selectively based on specific agronomic goals. Overall, there is a clear trend toward data-driven, integrated PA methods in maize production combining remote sensing, machine learning, sensing technologies, and spatial decision support. Frequencies reflect occurrence across studies rather than exclusive shares.

3.3.1. Geospatial and Remote Sensing Technologies

Spatial and topographic analyses are fundamental to precision agriculture (PA), enabling site-specific input applications such as irrigation and fertilisation through GPS-based monitoring of soil and crop variability [74]. While specialised IoT devices provide precise GPS positioning, smartphones offer practical, field-ready alternatives with sufficient computational capacity for complex GIS operations [36]. However, despite their importance, GPS-based management and field mapping systems are notably underrepresented, comprising only 0.78% of the literature.

Agro-meteorological data are predominantly collected via smartphone applications using Bluetooth or transmitted online for remote analysis and storage [75]. Therefore, integrating mobile platforms with sensor networks presents a cost-effective approach for real-time monitoring, enhancing PA system responsiveness.

Consistent with this review, GIS-based field mapping remains among the least studied spatial decision support technologies, accounting for only 1.55% of studies, despite its critical role in analysing spatial variability and enabling site-specific management to improve productivity and resource efficiency [75]. Advances in GISs, GNSSs, and remote sensing facilitate spatial data integration for crop monitoring, input management, and yield prediction [37,76–78]. Additionally, coupling GIS with remote sensing has improved biomass estimation and yield forecasting through spatially explicit analyses [79,80]. However, GIS is underutilised in crop disease management, with research favouring image-based detection over spatial decision support, underscoring the potential for enhanced disease surveillance and targeted interventions.

Remote sensing, especially satellite- and UAV-based platforms, dominates maize monitoring and yield estimation research, representing 22.48% of the studies. These platforms provide spatially explicit crop information via vegetation indices like NDVI and LAI, which are closely linked to growth and yield [53,81–83]. Satellites enable large-scale monitoring, while UAVs offer higher spatial resolution for field-level applications [5,34,53,84]. Multi-spectral and hyperspectral UAV imagery further refine growth and LAI estimation under variable conditions [34,47,53,84–86]. Additionally, integrating UAV data with crop models such as SAFY enhances yield predictions across moisture regimes [48,81]. UAV-based remote sensing is thus increasingly vital for precise maize management and site-specific decision-making [7,30,49].

3.3.2. Sensor-Based Technologies

Soil and crop sensing technologies, particularly IoT-based moisture and nutrient sensors, accounted for 10.85% of the included studies, highlighting their increasing role in precision maize management. Spatial variability in soil properties and climatic factors, including rainfall and temperature, strongly influences yield variability and requires site-specific interventions [12,29,87]. Wireless sensor networks enable real-time monitoring of soil moisture, temperature, and nutrient status, supporting precision irrigation and fertiliser management [36,88]. However, their field deployment may be constrained by sensor accuracy and calibration requirements, while variations in environmental conditions such as temperature, humidity, and soil properties can affect measurement reliability [36]. Advances in spectroscopy and deep learning have improved soil organic matter estimation, providing rapid and cost-effective alternatives to conventional analyses [39,49,72,89–91].

Furthermore, combining yield maps with targeted soil sampling improves the identification of within-field variability, optimises input application, and reduces environmental impacts compared with grid sampling approaches [20,54,92].

3.3.3. Precision Crop Management Technologies

Variable-rate technology (VRT) remains underexplored in maize precision agriculture, with only 1.6% of studies assessing its application. It facilitates site-specific input delivery (water and fertilisers) to enhance resource efficiency and crop performance [41]. Additionally, variable-rate irrigation shows promise for improving water-use efficiency, but it is limited by challenges in creating accurate, dynamic management zones [93].

Precision land preparation and planting (7.0% of studies) focus on site-specific tillage, optimised seed placement, and variable planting density. Integrating GPS, remote sensing, UAVs, and sensor data refines seeding decisions based on soil variability and yield potential [55,94,95], while conservation tillage practices, such as no-till and residue retention, improve soil health, carbon sequestration, drought resilience, and productivity [58–60].

Precision nutrient management (7.75%) emphasises enhancing nitrogen-use efficiency through site-specific strategies. Sensor-based tools, including vis-NIR spectroscopy, chlorophyll meters, and Green Seeker systems, enable real-time nitrogen status assessment and variable-rate fertilisation [8,42,96,97], while decision support systems and remote sensing augment nutrient recommendations by integrating soil and crop spatial data [45,98]. Thus, emerging technologies combining sensors, GPS, and precision applicators further improve nutrient efficiency and sustainability [44,99].

Precision irrigation (5.43%) integrates soil moisture sensors, remote sensing, crop modelling, and automation to optimise water-use efficiency under limited water availability [5,100,101]. Real-time monitoring via sensors and wireless networks supports adaptive irrigation, reducing water loss [39,45,98]. Regional water-use efficiency assessments combine field data, models, and satellite metrics such as gross primary productivity and evapotranspiration [102,103]. Moreover, hybrid modelling and genetic improvements enhance drought tolerance and transpiration efficiency, contributing to yield stability [50,104,105].

Precision pest, disease, and weed management (5.43%) employs UAV-based targeted spraying to reduce chemical inputs and operational costs [61]. AI and machine learning, coupled with multispectral and hyperspectral imaging, improve pest and disease detection accuracy [56,106–108]. In contrast, remote sensing and computer vision facilitate precision weed management through targeted herbicide application, enhancing efficacy and reducing environmental impact [57,109–111].

3.3.4. Decision Support and Intelligent Systems

Crop simulation models based on the Decision Support System for Agro-technology Transfer (DSSAT) were identified in only two of the 129 studies (1.55%), indicating limited application in precision maize production (Supplementary Tables S2 and S3). Specifically, DSSAT is a process-based modelling framework used to simulate crop growth, yield variability, and management responses under different environmental conditions [22]. Recent developments integrating AI and real-time data have improved its predictive capability for crop growth and irrigation management [112].

Yield monitoring and harvest management were reported in 8.5% of studies, mainly involving GPS-enabled harvesting systems, yield mapping, and data-driven approaches for analysing spatial and temporal yield variability. Additionally, real-time yield monitoring supports post-harvest assessment and improves subsequent management decisions [111].

Integrated precision agriculture systems combine geospatial technologies, sensors, and crop models to enhance yield prediction and field variability assessment [55,74,92]. Mecha-

nistic models, including APSIM and WOFOST, simulate crop growth using physiological indicators such as the leaf area index (LAI) [35,73,113–115]. Additionally, recent approaches incorporating machine learning, optimisation algorithms, and multi-source data platforms have further improved prediction accuracy [116,117]. Crop forecasting systems integrating models with climate information provide additional support for data-driven yield estimation and management decisions [22].

3.4. Applications and Methodological Approaches in Precision Maize Agriculture

The reviewed literature demonstrates the methodological diversity of precision agriculture research (Table 5; Supplementary Materials Table S3). Field experiments and review articles each accounted for 24.0% of the included studies, reflecting both practical technology evaluation and the growing maturity of the field [16]. In contrast, studies using UAVs, remote sensing, machine learning, deep learning, and spatial modelling represented 20.9%, highlighting the increasing adoption of artificial intelligence and geospatial technologies [38]. The remaining 31.0% comprised simulation, decision support, bibliometric, and model-based studies that support the development of precision agriculture applications [16]. Overall, these findings indicate a shift towards multidisciplinary, data-driven approaches for crop monitoring and site-specific management [16,38].

Table 5. Precision agriculture technologies and applications in maize production.

Purpose	Precision Agriculture Technology	Application	References
Crop growth monitoring	Remote sensing	Monitoring maize growth and managing the quantity and quality of maize production	[13]
	LAI		
	NDVI		
Crop water management	UAV	Calculating plant height values	[14]
	GIS	Soil moisture sensor	[15]
	DPP	Pest control (post-tasseling stages)	[16]
Plant protection and disease control	UAVs	Weed control	[17]
	Remote sensing	Monitoring crop diseases and insect pests	[18]
	ANN	Identifying weeds in corn fields	[19]
Crop nutrient management (precision nutrient)	Green seeker	Comparison against blanket fertiliser application	[20]
	LAI	Site-specific nutrient management	
	NDVI	Variable-rate N application	[21]
Yield prediction monitoring	DSSAT	Crop models to understand the causes of spatial yield variability	[22,23]
	CRAFT	Yield forecasting and its ability and applicability	
	Crop-BiSeNet V2	Crop row detection	[24]

Source: Authors (2026).

Reviewed studies show a shift from individual precision agriculture technologies to integrated systems combining sensing, spatial analysis, computational modelling, and AI. For instance, UAV-based RGB imagery, plant-height data, and machine learning predict maize growth and yield [14]. GIS combined with soil data aids soil fertility assessment and crop recommendations [15]. Image-based data with machine and deep learning detect pests, diseases, weeds, and crop rows [18,21,74]. Crop modelling integrates spatial soil, weather, crop, and management data with DSSAT, CRAFT, and statistical models for spatial maize yield forecasting [22]. These examples highlight integrated frameworks that merge sensing and spatial data with analytical and modelling tools for crop monitoring, prediction, and site-specific management.

3.5. Agronomic and Environmental Impacts

3.5.1. Integrated Evidence of Yield Optimisation Through Precision Agriculture in Maize

Studies were classified as having a low, moderate, or high risk of bias, with 70.7%, 26.2%, and 3.1% assigned to each category, respectively (Supplementary Table S1). These assessments were used to inform interpretation of the evidence rather than to quantitatively weight individual studies. Precision agriculture technologies were frequently reported in association with improved maize productivity through enhanced input management, crop monitoring, and site-specific decision-making [23,118]. Remote and proximal sensing, GIS applications, variable-rate technologies, and predictive models were used to support yield assessment, resource-use management, and spatially targeted interventions across diverse agro-ecological conditions. Sensor-based studies identified within-field variability in soil properties, moisture availability, and crop performance, providing information for targeted management interventions [4,16,25,94]. Remote sensing platforms were frequently applied to crop monitoring and stress detection [5,7,46], while machine learning approaches were used for biomass and yield prediction through integration of multi-source data [27,28,52,71]. However, reported benefits varied among studies according to environmental conditions, technology type, management practices, and study design. In addition, adoption of remote sensing and machine learning approaches was reported to be constrained by costs, data complexity, infrastructure requirements, technical capacity, and accessibility [24].

3.5.2. Key Agronomic Outcomes of Precision Agriculture Adoption in Maize Cultivation

Technological or algorithmic performance was clearly distinguished from agronomic and management outcomes. Improvements in prediction, classification, or detection accuracy reflect enhanced analytical or sensing system performance but do not directly indicate increases in maize yield, reduced input use, profitability, or environmental benefits. Thus, improvements in model accuracy were treated as evidence of technological performance, while agronomic or resource-use benefits were based only on studies evaluating corresponding management or production outcomes. This distinction was maintained throughout to avoid inferring agronomic benefits from algorithmic gains alone.

The synthesis of 129 studies (Table 6; Supplementary Table S3) identified three evidence domains: technological performance, management and resource-use outcomes, and agronomic outcomes. Technological outcomes included prediction, classification, and accuracy in pest or stress detection. Management and resource-use outcomes covered nutrient-use efficiency (NUE), water-use efficiency (WUE), input optimisation, and precision application. Agronomic outcomes included maize yield and related performance. Some studies reported yield increases following precision management [119], alongside improvements in NUE and WUE linked to site-specific nutrient management, sensor monitoring, and precision irrigation [100,103,120]. Conversely, remote sensing, machine learning, and automated monitoring mainly improved technological performance, especially in pest detection and crop monitoring accuracy [53,61,80], without direct evidence of yield or resource-use gains unless explicitly evaluated.

These results reflect reported trends rather than pooled effect sizes. The studies varied widely in design, sample size, technology, outcome definitions, validation, and uncertainty reporting. Therefore, findings were synthesised descriptively, and improvement frequencies should not imply uniform treatment effects. Contrasting responses were considered mixed or context-dependent, particularly for soil fertility outcomes influenced by soil, climate, and management factors [63,121]. Overall, precision agriculture offers clear technological benefits in sensing and analysis, with some studies showing agronomic and resource-use advantages, though their extent and consistency depend on context.

Table 6. Overall trends in key agronomic, soil, and precision agriculture indicators reported across the reviewed studies ($n = 129$).

Indicator	Overall Trend
Yield	Mostly positive
Prediction accuracy	Positive
Nutrient-use efficiency (NUE)	Positive
Water-use efficiency	Positive
Pest detection accuracy	Positive
Soil fertility	Mixed

Source: Authors (2026).

4. Discussion

This systematic review highlights the rapid expansion of precision agriculture (PA) research in maize cultivation. To provide broader methodological and technological context, selected studies from other cropping systems were also considered when their PA technologies or approaches addressed functions relevant to maize production [51,62–64,119,121–130].

4.1. Evolution and Technological Integration

Publications from 2023 to 2025 show growing integration of crop science, sensing technologies, spatial analysis, and computational methods [29,88]. Precision agriculture research is shifting from individual technologies to integrated systems combining GPS/GNSS, GIS, UAV and satellite remote sensing, proximal sensors, and predictive or decision support models [36,76,77,87]. UAV multispectral imaging and vegetation indices like NDVI are widely used to assess crop condition, canopy development, and biomass variation [6,86]. AI and machine learning increasingly support prediction, classification, and detection tasks such as yield forecasting, nutrient assessment, and stress monitoring [18,21,31,41,52,71].

However, improved technological or analytical performance does not guarantee agronomic benefits. Better yield prediction accuracy shows enhanced prediction, but not increased maize yield, and improved pest or stress detection reflects monitoring capability unless followed by management actions with evaluated agronomic impact. The value of integrated systems depends on the full pathway from sensing and modelling to diagnosis, management, and measurable agronomic or resource-use outcomes.

Precision management in open-field maize differs from technology-enabled environmental control in protected horticultural systems. In open-field maize, remote sensing, UAVs, soil and weather sensors, variable-rate application, and crop models are used to characterise spatial and temporal variability and support adaptive management under conditions where rainfall, temperature, and other atmospheric factors cannot be directly controlled [22,74,81,112,123]. Their role is mainly diagnostic and adaptive, supporting more targeted irrigation, fertilisation, crop monitoring, and risk forecasting [62–64,98,100,104]. In protected horticulture, the greater capacity to regulate environmental and crop inputs allows sensing and decision support technologies to be more closely integrated with management interventions. Although the general principles of sensing, crop-state assessment, modelling, and feedback-based decision support are transferable, implementation requires system-specific calibration, infrastructure, and control capacity. Technologies such as spatial soil assessment, UAV and satellite monitoring, and variable-rate application are particularly relevant to open-field maize because they address field-scale heterogeneity and environmental uncertainty, whereas highly automated environmental-control approaches require infrastructure not generally available in open-field production. This distinction is important for commercial implementation and climate-change adaptation because open-field maize relies on improved monitoring, prediction, and adaptive management of environmental

variability, whereas protected systems can combine monitoring with direct modification of the crop environment.

Variable-rate technologies and crop simulation models are less represented than sensing and machine learning [22,112], indicating that future work should focus more on converting data and predictions into actionable prescriptions and assessing their agronomic, economic, or environmental benefits.

4.2. Agronomic and Environmental Implications

Precision agriculture can improve maize management by revealing spatial and temporal variability and enabling more targeted input use. However, the size and direction of these benefits depend on the technology, management practice, environmental conditions, and whether sensing or modelling outputs are actually translated into field action. Variable-rate nutrient management can improve nitrogen-use efficiency by matching supply to crop and soil needs [41,99], while precision irrigation can improve water-use efficiency by adjusting application to crop demand and field variability [62–64,88].

The underlying physiological pathway is better synchronisation of nutrient and water supply with crop demand. Improved nitrogen management can enhance uptake and canopy development, while better water management helps maintain crop water status during sensitive stages and reduce stress. These effects can support photosynthesis, biomass accumulation, reproductive development, and grain filling, potentially benefiting yield when other limiting factors are controlled. However, such physiological mechanisms must be directly measured, not inferred from sensing or model accuracy alone.

Some studies also report environmental benefits, including reduced nutrient losses, improved soil conservation, and lower greenhouse gas emissions [65,66,131]. However, these outcomes are not universal and depend on the practices, conditions, and technologies used. Remote sensing and crop models can support climate-resilient management by improving assessment of variability [39,67–69,113], but better monitoring or modelling capability alone does not indicate environmental improvement. Preserving soil biological integrity and avoiding unintended environmental effects remain important alongside input optimisation [70].

4.3. Challenges, Research Gaps, and Future Directions

Reviewed studies reveal a shift from standalone precision agriculture technologies to integrated systems combining sensing, spatial analysis, computational modelling, and AI. UAV-based RGB imagery, plant-height data, and machine learning predict maize growth and yield [14]. GIS paired with soil data supports soil fertility assessment and crop recommendations [15]. Image data with machine and deep learning detect pests, diseases, weeds, and crop rows [18–20,24]. Crop modelling integrates spatial soil, weather, crop, and management data with DSSAT, CRAFT, and statistical models for spatial maize yield forecasting [22,132]. These examples highlight frameworks merging sensing and spatial data with analytical and modelling tools for crop monitoring, prediction, and site-specific management.

Adoption barriers include high costs, limited infrastructure, and inadequate technical capacity, especially for smallholders [74]. Limited GPS/GIS use relates to hardware/software costs, required expertise, and preference for UAV-based imaging [34,36,37,53,75–78,81–85]. Remote sensing and modelling face data quality issues like cloud cover, atmospheric interference, sensor variability, and missing data [81,133–135].

Variable-rate technologies and DSSAT-based models face distinct challenges. Variable-rate systems require accurate spatial data, prescription maps, compatible machinery, positioning, and calibration; adoption depends on economic benefits outweighing added costs [21,42,99]. DSSAT approaches are limited by reliable soil, weather, crop, and management data and model parameterisation, calibration, and validation [22,112]. Thus,

variable-rate systems confront infrastructure, integration, and economic barriers; DSSAT systems face data and modelling constraints.

Future research should therefore tailor solutions according to the specific requirements of each PA technology. Variable-rate systems need improved integration of sensing, geospatial data, prescription generation, positioning, and compatible machinery, while DSSAT-based approaches require standardised datasets, local parameterisation and calibration, and stronger integration with remote sensing and field observations. More broadly, integrated PA frameworks should be evaluated not only for technological and agronomic performance but also for interoperability, connectivity, maintenance requirements, data governance, labour and training needs, and economic feasibility. Long-term and multi-location trials should combine agronomic, environmental, and economic assessments and should report ROI, operational costs, and adoption-related factors. Validation across developmental stages, cultivars or hybrids, and contrasting environments is also needed to establish the robustness, transferability, and scalability of PA technologies for maize production.

4.4. Review Limitations

Study heterogeneity in objectives, methods, technologies, and metrics constrained direct comparisons and meta-analysis, and geographic concentration limits global generalizability. Additionally, restricting the search to English-language, Scopus- and Web of Science-indexed articles (2020–2026) may have excluded relevant data. Thus, broader geographic inclusion and standardised methodologies are essential for robust future evaluations of PA.

A further limitation was the inconsistent reporting of experimental and sampling characteristics among the included studies. Details such as the number of fields and plots, biological replicates, sampled plants, repeated measurements, cultivar or hybrid, and validation procedures were frequently unavailable or reported heterogeneously, limiting systematic assessment of sampling adequacy and reproducibility across studies.

The interpretation of relationships between precision agriculture measurements and crop responses was also constrained by inconsistent reporting of plant age, developmental stage, and sampled organ among the included studies. These factors may influence spectral, physiological, biomass, and yield relationships and should therefore be considered in future studies and systematic reviews. For imaging and machine learning studies, the available literature did not consistently distinguish biological replication from image tiles, pixels, repeated flights, augmented images, or multiple observations originating from the same experimental unit. Consequently, large image datasets should not be interpreted as evidence of equivalent biological replication, and the independence of observations could not be systematically assessed across all studies.

5. Conclusions

This systematic review synthesised evidence from 129 studies published between 2020 and 2026 to evaluate the application of precision agriculture technologies in maize production. The findings demonstrate a rapid increase in research activity and the growing integration of remote sensing, UAVs, sensors, machine learning, artificial intelligence, GISs, and decision support systems to support site-specific maize management.

The reviewed evidence indicates that these technologies improve crop monitoring, input optimisation, and yield prediction, thereby contributing to higher maize productivity, improved nutrient-use efficiency, enhanced water-use efficiency, and more effective detection of biotic and abiotic stresses. Remote sensing integrated with machine learning emerged as the most frequently applied approach, highlighting the shift towards data-driven precision agriculture.

Despite these advances, the review identified important challenges, including the limited adoption of technologies such as variable-rate technology and crop simulation models, high implementation costs, technical complexity, and insufficient evidence on long-term performance, economic feasibility, and adoption in smallholder farming systems.

Overall, precision agriculture has considerable potential to improve the productivity and sustainability of maize production. Future research should prioritise integrated decision support frameworks, long-term field validation, standardised evaluation methods, and wider adoption across diverse agro-ecological and farming systems.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/agronomy16171681/s1>, Table S1: Detailed Methodological Quality Assessment of the 129 Studies Included in the Systematic Review; Table S2: Summary of findings of included studies on precision agriculture: technologies, applications, and yield optimisation (2020–2026); Table S3: Summary of assessment studies and findings supporting precision agriculture: technologies, applications, and yield optimisation; PRISMA 2020 Checklist.

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Abbreviations

The following abbreviations are used in this manuscript:

IT	Information Technology
PA	Precision Agriculture
IoT	Internet of Things
GPS	Global Positioning System
GIS	Geographical Information System
ICTs	Information and Communication Technologies
UAVs	Unmanned Aerial Vehicles
ML	Machine Learning
AI	Artificial Intelligence
LAI	Leaf Area Index
NDVI	Normalised Difference Vegetation Index
DPP	Drone Plant Protection
GS	Green Seeker
DSSAT	Decision Support Systems for Agro-technology
CRAFT	Regional Agricultural Forecasting Toolbox

GNSS	Global Navigation Satellite System
CNN	Convolutional Neural Network
SSCM	Site-specific Crop Management
VRA	Variable-Rate Application
SOM	Soil Organic Matter
VRT	Variable-Rate Technology
VRI	Variable-Rate Irrigation
EVI	Enhanced Vegetation Index
NDRE	Normalised Difference Red Edge Index
LSTMs	Long Short-Term Memory
PRB	Practices Like Permanent Raised Beds
SOC	Soil Organic Carbon
CPT	Climate Predictability Tool
SSS	Site-Specific Seeding
SFI	Soil Fertility Indexing
SSNM	Site-Specific Nutrient Management
NUE	Nutrient Use Efficiency
NE	Nutrient Expert
WUE	Water-Use Efficiency
GPP	Gross Primary Productivity
ET	Evapotranspiration
ULV	Ultra-Low-Volume
SVMs	Support Vector Machines
RFs	Random Forests
GHG	Greenhouse Gas
CO ₂	Carbon dioxide
N ₂ O	Nitrous oxide
CMIP6	Coupled Model Intercomparison Project Phase 6

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