Journal of Applied Data Sciences
Vol. 5, No. 4, December 2024, pp. 1614-1624

Transforming Agriculture: An Insight into Decision Support Systems in Precision Farming

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(Received: July 13, 2024; Revised: July 26, 2024; Accepted: August 14, 2024; Available online: October 15, 2024)

Abstract

Precision agriculture seamlessly incorporates advanced technologies and data analysis to improve farming efficiency and sustainability through immediate resource allocation. Therefore, this study aims to synthesize research findings related to agriculture, Decision Support Systems, and precision agriculture through a systematic literature review conducted in accordance with Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines. The search was performed on the Scopus database, specifically focusing on publications published in English between the years 2017 and 2023. Out of 126 periodicals, a rigorous process was used to determine which publications met the specific criteria for inclusion and exclusion. As a result, only 8 relevant studies were chosen. The review emphasizes the substantial capacity of Decision Support Systems in precision agriculture, demonstrating that DSS has the capability to enhance crop yields by 15% and decrease water consumption by 20%. Through the utilization of big data, machine learning, and advanced technologies, Decision Support Systems has the potential to transform the agricultural industry by enhancing productivity, optimizing resource allocation, and enabling early identification of pests and diseases. The utilization of real-time data from Decision Support Systems empowers farmers to make well-informed choices, effectively managing production while upholding environmental sustainability. This, in turn, plays a crucial role in ensuring the economic viability of farms and enhancing global food security. However, addressing challenges like data privacy concerns, enhancing user-friendly interfaces, establishing robust data administration infrastructure, and providing adequate training and support for end-users is imperative for the successful implementation of data-driven Decision Support Systems in precision agriculture.

Keywords: Process Innovation, Product Innovation, Agricultural Productivity, Agricultural Technology, Decision Support Systems, Food Security

1. Introduction

In modern agriculture, precision farming is a rapidly growing area of research, utilizing advanced technologies and data analytics to enhance efficiency and sustainability [1]. The aim is to allocate resources such as water, fertilizers, and pesticides with precision, based on real-time data, transforming how farmers make decisions. Tools like satellite imagery, sensors, drones, and machine learning enable smarter, more environmentally responsible farming practices. This innovative approach aligns with broader agricultural advancements, particularly through the integration of Decision Support Systems (DSS). DSS plays a crucial role in precision agriculture, serving as a key component across various agricultural sectors. These systems are designed to optimize economic returns, improve crop quality, and reduce environmental risks [2], [3], [4]. Similar to other information systems, the performance of agricultural DSS is vital in maintaining high standards in farming practices. Their capacity to manage complex data and provide actionable insights is instrumental in boosting the overall efficiency and sustainability of modern agriculture.

By employing DSS, farmers can reduce disease outbreaks, lower crop damage risk, and minimize the use of inorganic fertilizers and pesticides compared to traditional methods. DSS leverages data and advanced analytics, such as Artificial Intelligence (AI) and machine learning, to offer farmers actionable insights and recommendations [5], facilitating rapid

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DOI: https://doi.org/10.47738/jads.v5i4.274

decision-making in areas like planting, fertilizing, watering, and harvesting [6]. By precisely managing agricultural inputs, DSS significantly enhances productivity, enabling farmers to save time and money by targeting specific field areas with resources. This strategic resource allocation, coupled with timely interventions, leads to increased crop yields and quicker responses to disease outbreaks or pest infestations. Additionally, the use of DSS in precision agriculture reduces farming's environmental impact [7]. Targeted pesticide application reduces chemical runoff, while efficient irrigation systems conserve water, optimizing resource use and reducing costs. This combination of higher yields and lower input costs can significantly boost farmer revenue.

Innovative DSS also feature user-friendly interfaces and visual tools [8], making data collection and analysis more accessible for farmers. These systems are designed with simplicity in mind, ensuring that even those with limited technical knowledge can navigate them easily. Visual aids like graphs and charts further simplify complex data, empowering farmers to make informed decisions about resource management and productivity. This emphasis on usability makes advanced DSS a valuable tool for a wider range of users within the agricultural industry. This research seeks to address the following questions: "What are the technologies used in precision agriculture?" and "How can these technologies assist in precision agriculture?"

2. Literature Review

Precision farming employs advanced technologies such as computers, sensors, global positioning systems (GPS), and remote sensing devices to monitor environmental conditions and optimize crop development [9]. However, the development of DSS to facilitate precise decision-making remains a significant challenge [10]. The use of decision support and automation is critical to deriving value from precision farming, particularly in dairy systems [11]. Although there is a shortage of integrated DSS models specifically designed for health management on dairy farms, it is widely acknowledged that an effective DSS framework is crucial for the success of dairy farming [12], [13]. Moreover, the Decision Support System for Agricultural Technologies (DSSAT) provides essential support to farmers by enabling precise management of nutrients, water, energy, and pests [14].

The core components of precision agriculture include data and information, technology, and DSS [15]. Precision agriculture has advanced considerably, integrating DSS and machine-to-machine communications to improve farming methods [16]. However, the adoption and acceptance of current agricultural DSS remain limited due to their inability to incorporate the implicit knowledge and practical needs of farmers [17]. Furthermore, the successful implementation of precision irrigation requires a comprehensive DSS that can analyze and synthesize data across multiple levels [18]. DSS also play a critical role in agricultural management by increasing input profitability while ensuring the sustainable use of resources [19]. By utilizing data from satellite imagery, soil sampling, GPS field mapping, and other resources, these systems allow for customized agricultural practices that match the specific conditions of each plot of land.

Precision agriculture technologies aim to improve operational farming outcomes by leveraging the natural variability of soil properties, leading to greater profitability. Despite the progress in precision agriculture, the development of effective DSS for implementing precise decisions remains a major challenge. IoT-based farm management information systems facilitate the automation of data collection, processing, tracking, planning, decision-making, and management of farming activities. Ensuring the security and confidentiality of farmers' data is critical in precision agriculture, emphasizing the need for secure data handling and ethical considerations.

Nonetheless, the development of effective DSS for precision decision-making continues to be a major hurdle to widespread adoption [10]. Precision agriculture technologies have been shown to reduce greenhouse gas emissions, increase crop yields, and improve economic outcomes [20]. Research demonstrates that wireless sensor networks for site-specific irrigation can effectively address soil and other variations across agricultural fields, which is a key aspect of precision agriculture [21]. Moreover, precision agriculture represents a paradigm shift in conserving natural resources by making conservation decisions based on specific locations to maximize both conservation efforts and revenue. This results in agricultural ecosystems that are environmentally adaptive and multifunctional [22]. A study emphasizes that precision agriculture has the potential to meet the needs of Indian farmers while reducing their dependency on harmful inputs like inorganic fertilizers, pesticides, and manure. The study also explores several factors influencing the adoption of precision agriculture in the delta districts of Tamil Nadu, including demographic, agroecological, behavioral, institutional, informational, technological, and perceptual elements. It suggests that India should adopt precision farming techniques suited to its economic context rather than blindly following the advanced technologies used by more developed countries. The societal shifts occurring in India, such as increased production, urbanization, and rising energy demand, provide new opportunities for precision agriculture in the country.

Similarly, another study presents a research framework examining the factors that influence the adoption of Precision Agriculture Technologies (PATs) in Egypt. These factors are classified into five main domains: socio-demographic (e.g., age, education, experience), agro-ecological (e.g., farm size, land tenure, crops), financial (e.g., farm income, costs, perceived economic and environmental benefits), technological (e.g., use of digital devices, ease of technology use), and institutional (e.g., farm location, development pressures). The study highlights that perceived environmental benefits and development pressures are significant factors influencing farmers' decisions to adopt PATs.

However, precision agriculture faces numerous challenges across various domains, including technology, ecology, economy, and society. One major barrier to adoption is the limited acceptance of precision agriculture technologies [25]. The slow adoption and limited implementation of these technologies, particularly on non-mechanized farms, prevent the full realization of precision agriculture's potential. Water scarcity is another pressing issue in agriculture that will likely worsen in the coming years, making sustainable water management a critical requirement for precision agriculture [26].

Additionally, integrating DSS into Agriculture 4.0 presents challenges in organizing farming tasks, managing water resources, adapting to climate change, and reducing food waste [27]. Addressing these challenges is essential for the successful implementation of DSS in precision agriculture, as they stem from the complex environment in which data is collected on farms. Moreover, the conflicting economic outcomes between conservation efforts and crop production pose a significant challenge for precision agriculture [22]. Achieving a balance between conservation and profitability is crucial for the sustained success of precision agriculture. Beyond technological issues, social and ethical considerations are also important. Socio-ethical challenges of smart farming emphasize the need for a comprehensive approach to responsible research and innovation in precision agriculture [28].

3. Methodology

A literature review (LR) is a systematic process that involves identifying, evaluating, and interpreting a variety of research materials to address numerous research questions. The fundamental purpose of a literature review is to synthesize diverse research resources and briefly summarize research findings across various defined stages [29]. This study adheres to the guidelines set by Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). PRISMA encompasses various elements, including resources, inclusion and exclusion criteria, the systematic review process, data abstraction, and analysis. It serves as a collection of evidence-based criteria specifically crafted to aid authors in improving the reporting quality of their systematic reviews and meta-analyses. PRISMA ensures that reports of these investigations are thorough, comprehensive, and open to scrutiny, emphasizing a methodical and transparent approach.

Figure 1 illustrates the search query employed in this study, aimed at retrieving articles published between 2017 and 2023 that center around the intersection of agriculture, DSS, and precision agriculture. The query ensures the presence of these terms in the title, abstract, or keywords of the documents. It additionally refines the search criteria by limiting the results to articles written in English while excluding content from specific subject areas like psychology, veterinary science, nursing, arts, economics, pharmacy, and sociology. Further precision is achieved by specifying that the document type should be an article (DOCTYPE "ar") and that the source type should be a journal article (SRCTYPE "j"). This systematic approach enhances the relevance and specificity of the retrieved literature for the study's objectives.

ISSN 2723-6471

(TITLE-ABS-KEY ("agriculture") AND TITLE-ABS-KEY ("DSS") OR TITLE-ABS-KEY ("Decision Support System*") AND TITLE-ABS-KEY ("precision agriculture")) AND PUBYEAR > 2016 AND PUBYEAR < 2024 AND (LIMIT-TO (LANGUAGE , "English")) AND (EXCLUDE (SUBJAREA , "PSYC") OR EXCLUDE (SUBJAREA , "VETE") OR EXCLUDE (SUBJAREA , "NURS") OR EXCLUDE (SUBJAREA , "ARTS") OR EXCLUDE (SUBJAREA , "ECON") OR EXCLUDE (SUBJAREA , "PHAR") OR EXCLUDE (SUBJAREA , "SOCI")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (SRCTYPE , "j")).

Figure 1. Search Query

The Scopus search yielded 126 journals, with one record removed due to duplication. Inclusion and exclusion criteria were carefully devised to ensure the search results encompassed the latest research from the past 5 years and were pertinent to the study's subject. Ultimately, only 8 papers met these stringent criteria and were included in the review. As depicted in figure 1, the screening and eligibility assessment involved 125 records, and no adjustments were made to the search string within the Scopus database. This comprehensive and meticulous approach safeguards the reliability and integrity of the selected literature for the study. Figure 2 illustrates the methodology employed in this study, adhering to the PRISMA model. There were 3 stages involved which are identification, screening and included. In the identification stage, duplicates record was removed. Then, the records were screened and assessed for eligibility whereby 117 records excluded due to article are not based on empirical data or article are hard sciences or articles did not focus on precision agriculture or article does not focus on decision support system.

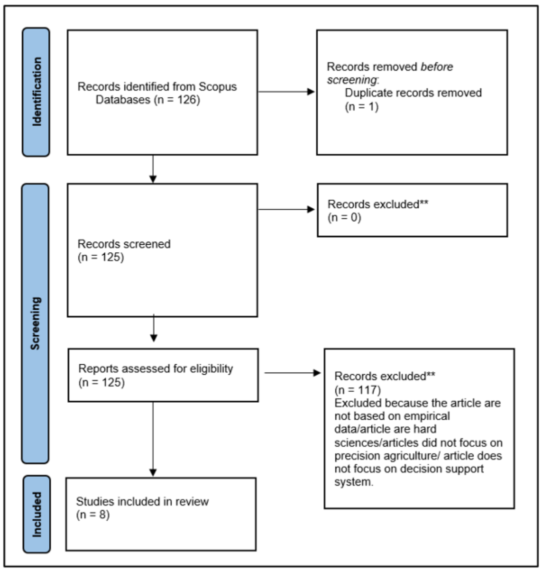

Figure 2. Flow Diagram of the Study [30]

4. Results and Discussion

Our comprehensive analysis of DSS in precision agriculture uncovered a broad range of applications and technologies aimed at improving agricultural decision-making processes.

4.1. Application of DSS in Precision Agriculture

Precision agriculture faces several challenges and opportunities in implementing DSS. The integration of the Internet of Things (IoT) in precision agriculture introduces architectural and technological innovations that can enhance decision-making processes [31]. Additionally, Unmanned Aerial Systems (UAS) for crop biomass monitoring offer new opportunities for data-driven decision support in precision agriculture [32]. However, fully realizing the potential of precision agriculture requires addressing challenges such as insufficient recognition of temporal variability, the lack of a comprehensive farm-wide approach, and the need for improved methods to assess crop quality [10]. Understanding how farmers perceive the benefits of precision agricultural technologies and their adoption levels is critical for the successful implementation of DSS [33], [34], [35]. Bridging the gap between conservation delivery and economic outcomes through precision agriculture is also vital to promoting sustainable farming practices [22]. Moreover, longitudinal aerial imaging can help detect and anticipate nutrient deficiencies, providing DSS with opportunities to enhance nutrient management in precision agriculture [36]. Exploring the future of precision agriculture in specific regions, such as Nepal, offers valuable insights into potential barriers and benefits for implementing DSS in diverse agricultural environments [37].

Within the evolving domain of agricultural DSS, researchers are addressing critical challenges such as disease prevention, irrigation management, and greenhouse operations. For example, figure 3 illustrates an IoT-based DSS developed to prevent potato late blight by analyzing real-time temperature and humidity data through the SIMCAST model. The system sends treatment warnings via SMS when certain risk thresholds are exceeded, but it faces limitations like high power consumption, lack of coverage for other diseases, and the need for more features like irrigation decisions in the infrastructure [38]. Advancements in IoT and image recognition have enabled the detection of diseases in various crops, including citrus, maize, cucumber, rice, and vine. However, this approach encounters challenges, such as the complexity of algorithmic analysis and the need for significant software development efforts.

Figure 4 highlights another study that emphasized the importance of DSS in diagnosing agricultural diseases through machine learning techniques. These systems analyze various data points, including plant images, environmental information, and growth data, to identify disease symptoms such as discoloration, spots, or unusual patterns on leaves or fruits [39]. This capability is crucial for preventing extensive crop losses and ensuring food security.

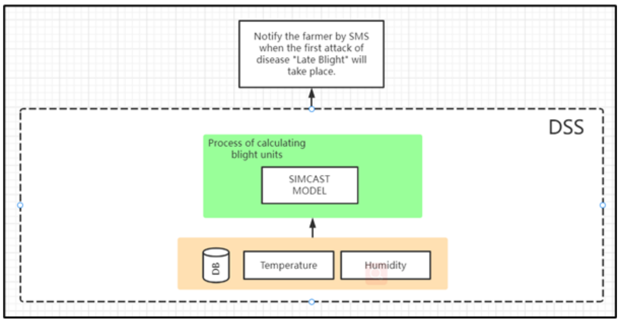

Figure 3. IoT-based DSS prevention of Diseases [38]

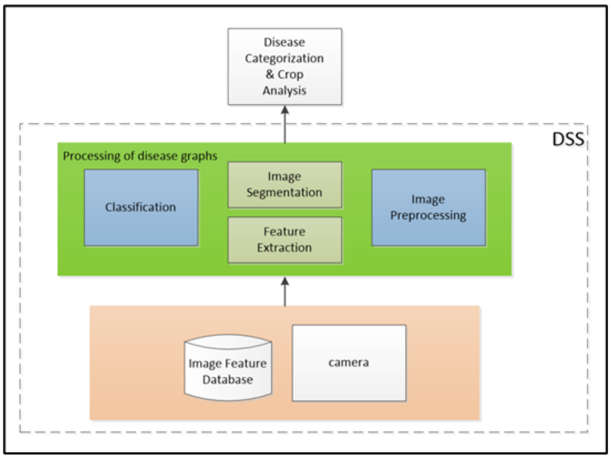

Figure 4. DSS for Plant Identification and Disease Identification Management [39]

In the field of water management, a DSS for irrigation management, illustrated in figure 5, was developed to predict weather conditions and provide ongoing monitoring based on sensor data [40]. While this system improves irrigation practices, it has drawbacks such as the need for manual interventions and the absence of machine learning modules to optimize decision-making processes. The importance of integrating AI technologies in agricultural DSS is a recurring theme in several studies [50], [51], [52], highlighting the need for further research in this area.

A real-time greenhouse monitoring system, shown in figure 6, was developed to enhance the efficiency of greenhouse operations by incorporating variables like temperature, humidity, and CO2 levels [42]. This marks significant progress in precision agriculture, although challenges such as soil degradation and high initial costs remain. Early identification of pest outbreaks and timely treatment applications, supported by DSS, also play a vital role in disease and pest management [43].

ISSN 2723-6471

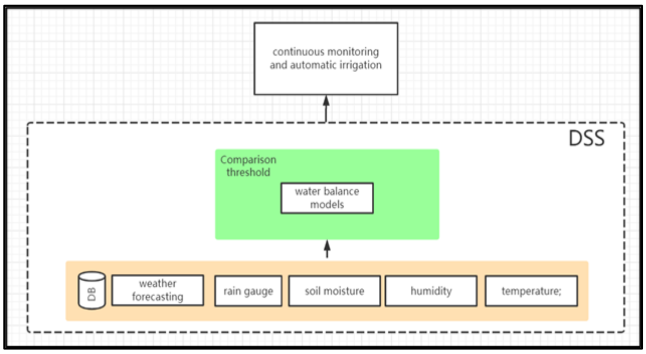

Figure 5. DSS for irrigation management [40]

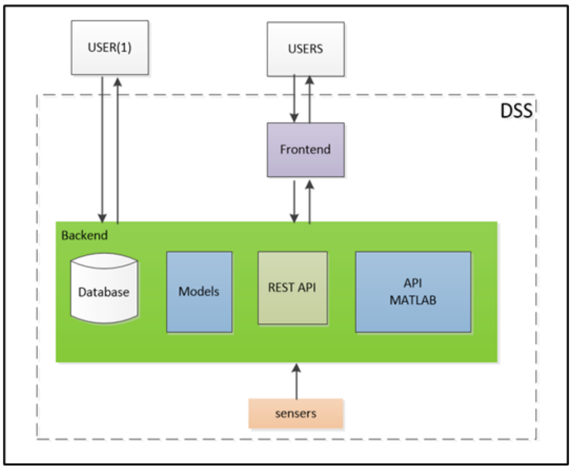

Figure 6. IoT Applications of Greenhouse and Plant Growth Data [42]

Other research, illustrated in figure 7, focused on developing a greenhouse DSS that integrates IoT and machine learning to enable real-time monitoring and rapid decision-making for predicting and managing pest and disease outbreaks effectively [45].

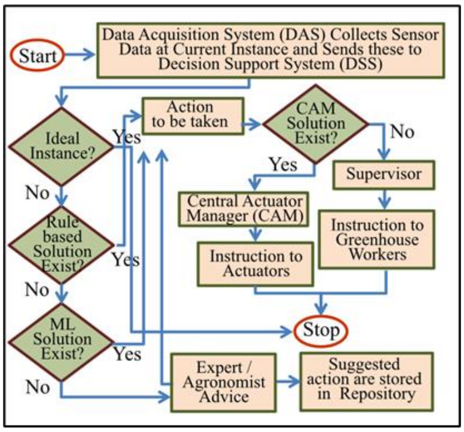

Figure 7. Greenhouse DSS based on IoT and machine learning [45]

DSS are also being utilized in optical and photonic technologies for evaluating crop health, as seen in figure 8, through advanced sensors and multispectral imaging, although the lack of hyperspectral imaging and machine learning modules limits their full potential [46]. Another system, shown in figure 9, utilizes LoRaWAN technology to enhance crop productivity through automated monitoring of environmental data. Like other systems, it faces similar constraints related to the integration of multispectral imaging and advanced AI tools [47].

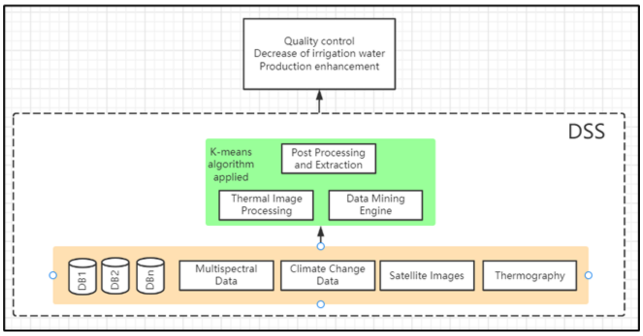

Figure 8. Optical and photonic technologies based DSS for health care [46]

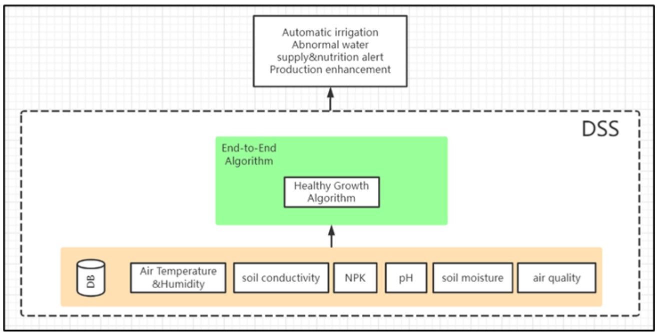

Figure 9. DSS based on LoRaWAN for crop yield management [47]

4.2. Key Findings and Challenges

The studies reviewed emphasize the transformative potential of DSS in precision agriculture, particularly in disease management, irrigation efficiency, and overall crop management. Despite the advancements, significant limitations remain. Many systems still require manual intervention, lack scalability, and face barriers to integrating advanced machine learning and AI techniques. These constraints highlight the need for continued research and development to enhance the effectiveness and usability of DSS in agriculture.

Furthermore, DSS face data privacy challenges and cybersecurity risks. Unauthorized access to sensitive data, such as crop yields and soil conditions, can result from poor security protocols or cyberattacks. Data misuse, unauthorized sharing, or lack of consent also threaten farmer trust and financial security. To address these issues, strong access controls, multi-factor authentication, and regular security audits should be implemented. Data anonymization can help protect sensitive information, and limiting data collection to only what is necessary for DSS functionality can reduce privacy risks. Addressing these vulnerabilities will improve trust in precision agriculture technologies while ensuring data security and integrity.

In summary, the development of DSS for precision agriculture continues to evolve, but overcoming current challenges is essential for fully harnessing the potential of these technologies. Tackling issues such as data privacy, manual dependency, scalability, and the integration of advanced AI techniques will be crucial for the broader adoption and success of DSS in achieving sustainable and efficient farming practices.

5. Conclusion and Future Works

The use of data-driven DSS in precision agriculture presents significant potential to promote environmentally sustainable farming practices. By leveraging large-scale data analysis, AI, and innovative technologies such as optical and photonic systems, DSS can transform agricultural operations, leading to enhanced efficiency, optimized resource allocation, improved crop yields, early detection of pests and diseases, and many other benefits. Moreover, DSS provide farmers with up-to-date, actionable information, enabling them to make well-informed decisions that balance productivity with environmental sustainability. This contributes not only to the economic viability of farms but also to global food security and environmental conservation.

Despite these benefits, the effective integration of data-driven DSS in precision agriculture encounters various challenges. These include concerns over data privacy and security, the need for more user-friendly interfaces, the development of strong data management infrastructures, and the provision of sufficient training and support for end-users. Addressing these challenges is essential to unlocking the full potential of DSS in agriculture, fostering a more sustainable and secure future for food production.

Several studies have underscored that the adoption and successful use of DSS depend heavily on farmers’ perceptions and ease of interaction with these systems. For instance, research on precision agriculture technologies in the United States revealed that farmers who recognized greater benefits from these technologies were more likely to adopt them. However, many also reported difficulties in using complex systems, emphasizing the need for intuitive interfaces and effective training. Similarly, research on autosteer technology adoption among cotton producers highlighted the significance of ease of use, while studies in South Dakota showed that larger farms were more likely to adopt precision technologies, but concerns about long-term reliability and data privacy remained prevalent across all farm sizes.

These findings highlight that the successful implementation of DSS in agriculture requires more than just technological advancements. It also demands a user-centered design approach, considering farmers' experiences, providing comprehensive education, and fostering trust. Future developments in DSS should prioritize incorporating feedback from farmers, ensuring that the systems are designed to meet real-world needs and constraints. This includes creating intuitive interfaces, providing tailored training for varying levels of technological proficiency, and offering continuous support to help farmers maximize the benefits of these technologies.

From an economic perspective, several studies have demonstrated the financial benefits of using DSS in precision agriculture. For example, the implementation of GPS mapping in crop production has led to cost reductions, while other studies have shown that precision agriculture technologies yield a significant return on investment (ROI) across

 ISSN 2723-6471

different crops and geographies. In irrigation management, DSS-directed precision irrigation has resulted in substantial water savings without compromising crop yields, further supporting the economic and environmental value of these systems. Nevertheless, the economic advantages of DSS can vary depending on factors such as farm size, crop type, and regional conditions, emphasizing the need for customized solutions and detailed cost-benefit analysis when implementing DSS.

Looking ahead, future research should focus on advancing AI and machine learning algorithms tailored to agriculture. This includes refining predictive models for crop yields, disease outbreaks, and resource optimization, as well as exploring deep learning methods to improve the precision of disease detection through image analysis. Additionally, there is a need to investigate the integration of data from diverse sources, such as satellite imagery, IoT sensors, and drones, into unified and compatible systems. Standardizing data formats and protocols across agricultural DSS would significantly improve their functionality and foster broader adoption.

Future work should also prioritize improving the user interface and experience of DSS to make them more accessible to farmers with varying levels of technological proficiency. Research into effective training methods and strategies for promoting adoption is essential to achieving widespread use. Additionally, developing DSS that can adapt to regional farming practices, crops, and climates will be critical to their success. Customization of these systems to local conditions will improve accuracy and outcomes.

As DSS adoption grows, addressing ongoing concerns about data privacy and security will become increasingly important. Research into secure data handling practices—such as encryption, anonymization, and robust access controls—will help protect sensitive information and build trust in these systems. Finally, future efforts must focus on creating DSS that deliver long-term economic and environmental benefits, supporting the transition to sustainable and resilient agricultural practices.

6. Declarations

6.1. Author Contributions

Conceptualization: D.Y., L.J., G.H., Z.X., Y.L., S.S.M., W.H.W.I., dan W.W.; Methodology: S.S.M.; Software: D.Y.; Validation: D.Y., S.S.M., dan W.W.; Formal Analysis: D.Y., S.S.M., dan W.W.; Investigation: D.Y.; Resources: S.S.M.; Data Curation: S.S.M.; Writing Original Draft Preparation: D.Y., S.S.M., dan W.W.; Writing Review and Editing: S.S.M., D.Y., dan W.W.; Visualization: D.Y.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

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

ISSN 2723-6471

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