Issues in Information Systems
Volume 27, Issue 4, pp.695-707, 2026

DOI: https://doi.org/10.48009/4_iis_2026_159

Conceptualising a data-driven decision support system for commercial farmers in South Africa

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Abstract

Commercial farmers in South Africa lack a locally contextualised, data-driven decision support system that converts real-time agricultural data into straightforward, actionable daily recommendations that are tailored to their individual strategic and operational issues and decision-making requirements. The study conceptualises a data-driven decision support system to enable real-time and actionable recommendations to commercial farmers. The qualitative data were collected using the document analysis technique, from which 49 materials were gathered from various sources. The data were analysed by following the subjective technique. From the analysis factors, Data-driven enable decision, Real-time data, Local infrastructure, and Technology - Predictive analytics, were found to be the key to developing data-driven DSS for the South African farmers. The factors have implications for both the data analysts and farmers in developing and practising a data-driven decision support system for farming purposes.

Keywords: Analytics, Data-driven process, Decision support system, South African commercial farmers

Introduction

Agriculture is an essential sector in the economy of any country, including South Africa. This is because it is a primary source of food security. In South Africa, the sector contributes approximately 2.8% of GDP, and it is sustained by about 32,000 commercial farmers (Materechera & Scholes, 2022). This group of farmers produce about 80% of the country's total agricultural output across commodities such as grains, livestock, dairy and subtropical fruits (Materechera & Scholes, 2022).

The South African commercial farming operates at a scale that involves significant capital investment, formal market participation, and exposure to both local and international price volatility (Materechera & Scholes, 2022). Beyond its economic contribution, though, the sector plays a direct role in national food security at a time when climate change, rising input costs, and growing food demand are placing increasing strain on agricultural systems worldwide (Giller et al., 2021). This sector, therefore, necessitates more attention from both the farmers and other stakeholders, such as the government and researchers, to ensure continuous improvement. Improving the South African commercial farming sector requires an understanding of the variables that influence decision-making that affect farm produce.

What makes commercial farming so demanding includes variables such as soil conditions, rainfall patterns, and livestock health (Tuyishime & Adewusi, 2025). Additionally, input costs and commodity prices are all constantly shifting and deeply influence farming decision-making. In South Africa, these challenges are made even harder by load shedding, which regularly disrupts water irrigation systems and cold chain operations (Moeti et al., 2024). Load shedding is a term used to describe the rationalisation of the electricity

supply across the country (Mabunda et al., 2023). Other variables, which require well-informed decisions, include land management, labour, climate variability and market access (Giller et al., 2021). Enormous volumes and a variety of data are consistently generated from the various variables mentioned above. The challenge is that many farmers do not have the tools to make sense of the data quickly enough to act on it.

Data-driven decision-making is increasingly important and relevant in supporting farming activities in South Africa. The South African farming environment is unique based on some of the variables mentioned above. Thus, requiring a specific data-driven decision-making tool to support its farmers. Li et al. (2024) suggest that data-driven agriculture is about systematically collecting, integrating, and analysing farm-generated data to improve decision-making. Decision-making to support farmers is based on analysis and analytics of data, which include the use of machine learning.

Machine learning models have shown impressive results in this space, with crop yield prediction achieving R^2 values above 0.95 and livestock weight gain forecasting recording mean absolute errors as low as 2.21 kg (Marong et al., 2024). IoT-driven smart irrigation systems have demonstrated measurable improvements in water use efficiency in water-scarce farming environments (Bwambale et al., 2022). Precision farming platforms using data-driven recommendation engines have achieved fertiliser classification accuracy above 91%, demonstrating how precise these systems can be when soil data is properly integrated (Vijender Reddy et al., 2024). The evidence clearly shows that when farm data is properly analysed, it can fundamentally change the quality of decisions farmers make (Raji & Njoku, 2024). However, there seems to be no decision-making support tool that can be used to provide data-driven support for South African farmers.

Decision Support Systems (DSS) represent the most practical solution to this problem. A DSS integrates data, analytical models and domain knowledge into a single system designed to help users navigate complex decisions (Araujo et al., 2023). A cloud-based, IoT-integrated DSS combining machine learning and predictive analytics was demonstrated through the ID3SAS system to have achieved a 20.9% reduction in water use and a 26.4% increase in crop production compared to traditional farming methods (Arajuo et al., 2023). Javaid et al. (2022) further highlight how Agriculture 4.0 technologies, including DSS platforms, are enabling more efficient and evidence-based farming practices at scale. However, existing systems are still largely batch-based and are not built for the South African commercial farming environment. This research, therefore, seeks to address that gap by designing and developing a data-driven DSS prototype that delivers real-time, actionable recommendations to commercial farmers in South Africa.

Despite an understanding of the farming challenges, the gap remains, as commercial farmers in South Africa lack a locally contextualised, data-driven decision support system that converts real-time agricultural data into straightforward, actionable daily recommendations that are tailored to their individual operational issues and decision-making requirements. The study aims to conceptualise how a data-driven Decision Support System can be developed to enable real-time and actionable recommendations to commercial farmers

Literature Review

The literature focuses on the core aspects of the study. This includes data-driven agriculture, decision support systems, and commercial farming in South Africa.

Data-driven Agriculture and Analytics

Data-driven agriculture is the systematic gathering, integration, and analysis of farm-generated data to inform and improve farming decisions (Li et al., 2024). It covers the entire analytics spectrum, from

descriptive analytics that monitor current conditions to predictive analytics that forecast outcomes and prescriptive analytics that prescribe specific actions (Durai & Shamili, 2022). Machine learning algorithms examples include Random Forest, Decision Trees, and Support Vector Machines, which serve as the computational foundation for data-driven applications (Marong et al., 2024). Research has shown that agricultural output prediction accuracy exceeds R^2 = 0.95, and animal weight growth forecasting has a mean absolute error as low as 2.21kg (Raji & Njoku, 2024). This establishes data-driven agriculture as an effective enabler of evidence-based farm management on a commercial scale (Javaid et al., 2022).

Despite its potential, many gaps exist in how data-driven agriculture is developed and implemented in practice. One of the gaps is that most systems prioritise predictive outputs over prescriptive ones, stopping at forecasting rather than proposing action, leaving the entire interpretation responsibility on the farmer (Eze et al., 2025). Another gap is data quality issues, such as missing values, heterogeneous sources, and a lack of standardisation, which continue to hinder model dependability and transferability (Niloofar et al., 2021). Also, most data-driven solutions have been created and evaluated in controlled research environments rather than in actual commercial agricultural environments (Islam et al., 2024). The gap between laboratory performance and practical farm deployment remains one of the most pressing unresolved issues in the sector (Rozenstein et al., 2024).

In the South African context specifically, most commercial farmers are still not benefiting from data-driven approaches in practice, and the consequences of this are real. Moeti et al. (2024) found that IoT and data-driven technology adoption in South African agriculture is held back by knowledge gaps, cost barriers and a lack of supportive policy, meaning that even where infrastructure exists, it rarely translates into usable decision support. Farmers who continue to rely on intuition and experience rather than data tend to make decisions that often lead to resource waste and reduced yields (Rozenstein et al., 2024). Islam et al. (2024) further point out that Agriculture 4.0 adoption across emerging economies is constrained by poor infrastructure, low digital literacy, and an absence of locally contextualised tools, all of which apply directly to South Africa. The gap is not about data availability, but about the absence of tools that can convert that data into recommendations farmers can immediately act on. This makes a strong case for a decision support system that could help bridge the gap between what data-driven technology can do and what farmers experience in practice.

Decision Support Systems in Agriculture

A Decision Support System (DSS) is a computer-based system that helps users make complicated decisions by combining data, analytical models, and user expertise on a single interactive platform (Huo et al., 2024). DSSs have been developed in agriculture to help with decisions such as crop selection and irrigation scheduling, as well as livestock health monitoring and fertiliser application (Tuyishime & Adewusi, 2025). These systems range from simple rule-based tools that send threshold alarms to complex machine learning platforms that tailor recommendations based on past farm data (Marong et al., 2024). The evolution of agricultural DSSs has been strongly linked to advances in sensor technology, cloud computing, and mobile networking (Materechera & Scholes, 2022). This trend has gradually enabled more real-time and location-specific decision support in a variety of farming scenarios (Vijender Reddy et al., 2024).

Regardless of this progress, significant gaps remain in the design and implementation of agricultural DSSs. According to Li et al. (2024), the most significant gap in the sector is the ongoing move from dashboard-based data interpretation to automated, real-time prescriptive support. Existing systems are largely siloed, addressing a specific product or function rather than accommodating the complexities of mixed commercial farming operations (Black et al., 2023). They are also rarely co-designed with farmers, resulting in tools that are formed by developer assumptions rather than true operational demands, which directly contributes to low adoption rates (Javaid et al., 2022).

Existing agricultural DSS tools include the TAMSAT-ALERT system, which provides soil moisture forecasts to support decisions when planting crops in Africa (Black et al., 2023). As well as the ID3SAS system that combines IoT and machine learning to support irrigation and crop production decisions (Araujo et al., 2023). However, these systems share common limitations when considered in the South African commercial farming environment. Also, most of these systems are batch-based rather than continuous, and none of them accounts for conditions such as load shedding and local water scarcity that exist in the South African context (Giller et al., 2021; Moeti et al., 2024). From the 49 documents reviewed, no existing system was identified that provides real-time, prescriptive decision support tailored specifically to the operational context of South African commercial farming. This is a gap that this research directly seeks to address. However, to understand why this gap matters so much, it is important to first distinguish the South African farming environment from other contexts.

Commercial Farmers in South Africa

Commercial farmers are formally registered, market-oriented producers who manage substantial landholdings, hire workers, and trade in established commodity markets (Eze et al., 2025). In South Africa, over 32,000 commercial farmers provide roughly 80% of the country's total agricultural output in maize, beef cattle, dairy, and citrus (Materechera & Scholes, 2022). Many people run mixed crop and livestock businesses at the same time, which means their decisions must consider numerous commodity categories, each with its own set of data requirements and risk profile (Servia et al., 2022). This operational variability sets South African commercial farmers apart from the smallholder contexts that dominate agricultural DSS research in Sub-Saharan Africa (Giller et al., 2021). As a result, tools designed for smallholder operations are rarely convertible to commercial farming environments without major modification (Vijender Reddy et al., 2024).

Despite operating in data-rich contexts, commercial farmers continue to rely on intuition and experience rather than structured data analysis, largely because existing tools were not designed for their scale or context (Araujo et al., 2023). Their decision-making environment is unusual in that it includes input procurement, labour coordination, commodity pricing, and production planning while dealing with load shedding, water shortages, and climate variability (Moeti et al., 2024).

Research Methodology

The inductive approach was followed in this study primarily because it allows us to start with specific observations to build a new theory (Taherdoost, 2022). This was needed in conceptualising phenomena towards theory development, such as a data-driven DSS. The approach allows theories and patterns to emerge naturally from observed data, making it appropriate for the study. In this study, this reasoning guides the search for a possible solution through an evaluation of the existing framework in the literature towards the development of a data-driven decision support system. The qualitative research methods focus on understanding meanings, experiences, and contexts through non-numerical data (Wallwey & Kajfez, 2023). Also, the methods are considered most suitable for exploring complex phenomena that cannot easily be measured (Lim, 2025). This study seeks to gain an understanding of factors from the literature.

Based on the study's objective, which was to conceptualise a data-driven DSS for the South African farmers, qualitative data were collected using the document analysis technique. The technique was selected for two main reasons. Firstly, the document analysis technique allows the gathering of materials (literature) broadly. This means that it is not restrictive, as sofar, it is within the scope of the study. The second reason

is that it was going to be difficult to find farmers who have the experience of data-driven DSS, who could participate in the study.

Data Collection

Due to the rarity of similar studies on the continent, there were not too many materials to access. Thus, only a total of 49 documents were gathered and analysed. Table 1 presents a sample of the selected materials. The documents were purposively selected based on their relevance to the study's three focus areas: data-driven agriculture, decision support systems and farming. The following search terms were used across the databases: data-driven, commercial farming, decision support system, smart farming, smart agriculture, data analytics, prescriptive analytics, predictive analytics, data-driven prediction, precision agriculture and precision farming. Materials were included if they were published in academic journals and databases from 2020 onwards. Materials that were published before 2020 were excluded to ensure that the sources used in this study are both current and relevant. The credible academic databases from which the materials were sourced include EBSCO Host, IEEE, and AIS.

Table 1: Data Collection Using the Document Analysis Technique

Focus Area	Sample of materials
Data-driven	Durai, S.K.S. & Shamili, M.D. (2022). Smart farming using Machine Learning and Deep Learning techniques. Decision Analytics Journal, 3, 100041.
	Marong, M., Husin, N. A., Zolkepli, M. and Affendey, L. S. (2024). Data-driven rice yield predictions and prescriptive analytics for sustainable agriculture in Malaysia, *International Journal of Advanced Computer Science and Applications*, 15(3), 385–395.
	Servia, H., Pareeth, S., Michailovsky, C. I., de Fraiture, C. and Karimi, P. (2022). 'Operational framework to predict field level crop biomass using remote sensing and data-driven models', International Journal of Applied Earth Observations and Geoinformation, 108, 102725.
	Tuyishime, K. and Adewusi, M. A. (2025). 'Data-driven prediction of cattle weight gain for evaluating key growth factors with machine learning approaches', Discover Computing, 28(1), 275.
Decision support	Araujo, S. O., Peres, R. S., Filipe, L., Manta-Costa, A., Lidon, F., Ramalho, J. C. and Barata, J. (2023). 'Intelligent Data-Driven Decision Support for Agricultural Systems-ID3SAS', IEEE Access, 11, pp. 115206–115222.
	Black, E., Asfaw, D. T., Sananka, A., Aston, S., Boult, V. L. and Maidment, R. I. (2023). 'Application of TAMSAT-ALERT soil moisture forecasts for planting date decision support in Africa', Frontiers in Climate, 4, 993511.
	Niloofar, P., Francis, D. P., Lazarova-Molnar, S., Vulpe, A., Vochin, M.-C., Suciu, G., Balanescu, M., Anestis, V. and Bartzanas, T. (2021). 'Data-driven decision support in livestock farming for improved animal health, welfare, and greenhouse gas emissions: overview and challenges', Computers and Electronics in Agriculture, 190, 106406.
	Raji, I. and Njoku, T. K. (2024). 'Data-driven decision making in agriculture: enhancing productivity and sustainability through predictive analytics', International Journal of Research Publication and Reviews, 5(9), pp. 2708–2719.
Farming	Javaid, M., Haleem, A., Singh, R.P. & Suman, R. (2022). 'Enhancing smart farming through the applications of Agriculture 4.0 technologies', International Journal of Intelligent Networks, 3(4).
	Materechera, F. and Scholes, M. C. (2022). 'Understanding the drivers of production in South African farming systems: a case study of the Vhembe District, Limpopo, South Africa', Frontiers in Sustainable Food Systems, 6, 722344.
	Moeti, M. N., Mokwena, S. N. and Selape, M. (2024). 'Factors influencing the adoption of Internet of Things in the agricultural sector in Limpopo province', South African Journal of Information Management, 26(1), a1669.
	Vijender Reddy, G. V., Reddy, M. V. K., Spandana, K., Subbarayudu, Y., Albawi, A., Chandrashekar, R., Singla, A. and Praveen. (2024). 'Precision farming practices with data-driven analysis and machine learning-based crop and fertiliser recommendation system', E3S Web of Conferences, 507, 01078.

Data Analysis

The analysis of the data followed the subjective approach from the interpretive paradigm perspective. This was primarily because the approach allows us to associate meanings with the material properties of the phenomenon being studied. Subjective technique analysis of data is increasingly more rigorous (Jordan, Troth & Yan, 2025; Harrison et al., 2020). This adds to the substantive point of quality. Jarrahi, Ma and Goray (2023) thus suggest that the subjective technique helps to gain situational understandings and changes in one's knowledge. The gaps identified through the literature were analysed purposes to directly shaping the design and development of a data-driven DSS for South African farmers.

Conceptualising a Data-Driven DSS for Commercial Farmers

The conceptualised DSS would integrate real-time agricultural data from publicly available APIs and online databases. These include weather and forecast data from the South African Weather Service (SAWS), the Copernicus Climate Data Store, as well as satellite-based vegetation and crop monitoring data from Google Earth Engine. The system would then collect data from these sources in real-time, process it using predictive analytics to generate predictions, and then convert them into actionable information that the farmers can immediately act on. This information would support decisions such as irrigation scheduling and help tackle conditions unique to South Africa, for instance, water scarcity and load shedding. Therefore, rather than exposing farmers to data that is complex, the system would present clear and actionable guidance that farmers can act on, without the heavy burden of interpretation. The development of such a system, however, requires an understanding of critical factors that must be in place for it to function effectively.

From the analysis, four factors were found to be key to the development of a data-driven decision support system for farmers. The factors include data-driven, real-time data, local infrastructure, and technological solutions such as predictive analytics. As shown in Figure 1, the factors must be influenced by other dynamical factors, which include context, content, relevance, and support system.

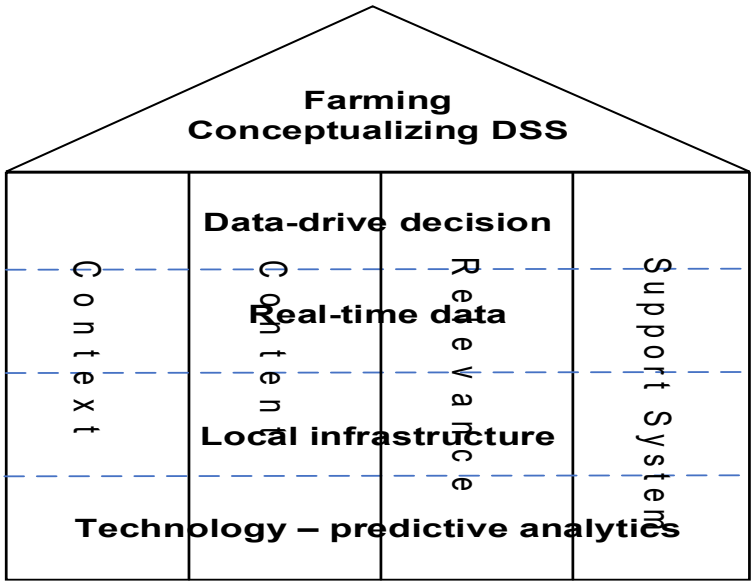


Figure 1. Conceptual DSS for Farming

Data-driven Enable Decision
Data-driven decision support systems for agriculture are well documented in the literature (Raji & Njoku, 2024). However, the gap between what these systems can do and what they deliver in practice remains wide. Most existing systems were designed either for smallholder or international contexts that look very different from South African commercial farming (Mhlanga & Ndhlovu, 2023). Consequently, the systems can predict outcomes but fail to provide real-time recommendations tailored to the South African commercial farming environment (Huo et al., 2024).

Farmer trust in data-driven platforms also remains low due to unresolved concerns around data ownership, privacy, and the perceived lack of demonstrated value from adopting these systems (Rozenstein et al., 2024). In the context of this DSS, data-driven decision-making means that the farmers' decisions must be informed by real-time data, rather than intuition or experience alone. This ensures that decisions regarding farming activities, such as when to irrigate, when to apply fertiliser and how to respond to weather changes, are grounded in current, accurate information. This is increasingly important due to the rapid and sudden changes in the weather.

Real-time Data
Based on the 49 documents reviewed, no existing system was identified that provides real-time, prescriptive decision support tailored specifically to the challenges of South African commercial farming. For the conceptualised DSS, real-time data refers to continuously updated inputs from sources such as the South African Weather Service (SAWS) and Google Earth Engine. The data is then processed and translated into clear, actionable information for the farmer to enable informed decision-making. With commercial farms increasingly moving toward precision agriculture technology, the window to develop a locally contextualised DSS is essential and urgent (Javaid et al., 2022).

Local Infrastructure
Decision support systems are significant for commercial farmers in South Africa because they help address the specific challenges faced within the agricultural sector. Load shedding, water scarcity and climate variability all play a role in daily farming decisions, yet these farmers lack a system that accounts for all these factors identified in their context (Moeti et al., 2024). A local DSS that processes real-time data and converts it into actionable daily recommendations would directly address this gap. Therefore, reducing reliance on intuition and improving the quality of their decisions made under pressure (Araujo et al., 2023).

South Africa's economy and food security depend heavily on agriculture, yet commercial farmers continue to face challenges in making timely, evidence-based decisions in an environment influenced by fluctuating market conditions and rising operational complexity (Moeti et al., 2024). Although decision support systems for agriculture have been developed, challenges persist. This can be attributed to the fact that the solutions are primarily not contextual and do not adequately address the specific challenges encountered by commercial farmers in South Africa. The challenges include load shedding on farm operations and local water scarcity (Huo et al., 2024). These challenges shape what local infrastructure means for this DSS. In the South African context, this refers to the country's power supply managed by Eskom, network connectivity in certain farming provinces like Limpopo, and the water supply infrastructure. These parts of the infrastructure that the DSS must account for to operate reliably within the South African commercial farming environment.

Technology - Predictive Analytics
A recurring problem in agricultural technology is that existing decision support tools are rarely designed with the operational realities of their intended users in mind. In developing countries, most existing agricultural decision support tools address a narrow set of functions and are rarely evaluated for practical

adoption in real farming environments (Huo et al., 2024). Additionally, most platforms simply display raw data on dashboards without informing farmers what to do with the actual data, meaning that farmers carry the full burden of the interpretation on their shoulders (Vijender Reddy et al., 2024).

Furthermore, models that incorporate predictive analytics do exist, but they are mostly batch-based rather than continuous, and lack the real-time integration required to convert farm data into timely recommendations for South African commercial farmers (Giller et al., 2021). Thus, these farmers lack a locally contextualised system capable of providing real-time, integrated, and actionable decision support tailored to their operational needs (Tuyishime & Adewusi, 2025). Predictive analytics, in this case, is used to analyse real-time data to understand why and how agricultural conditions change. This includes how weather patterns influence crop performance. Consequently, it shifts farming decisions away from assumption and presumption, towards decisions that are based on data-driven analysis.

Implications for Farmers and Research

The findings from the research have implications for both farmers and researchers. The implications include commercialisation, infrastructure enablement, and meteorologists, as tabulated in Table 2 below.

Table 2: Implication for farmers and research

Factors	Farmer	Research
Commercial Farmers	The farmers will need to enhance their digital literacy to gain a better understanding of how to use the decision support system. This is to increase their chances of gaining benefits from the DSS. Therefore, enhancing technological knowledge and training should be considered part of implementing the DSS, not an afterthought (Adereti et al., 2024).	In the South African context, there is a need to continue investigating how digital literacy initiatives can be developed and tailored specifically for commercial farmers to ensure that they're equipped to engage with data-driven tools (Nxumalo & Chauke, 2025).
Infrastructure	Existing infrastructure may need to be upgraded to support the agricultural data demands of the DSS. This matters because the implementation of data-driven agricultural tools has been shown to depend on supporting infrastructure (Xu et al., 2024). Thus, if the current infrastructure is unable to support it, the system's usefulness will be limited.	From a research perspective, there is a need to continue investigation that draws and aligns emerging infrastructure with farming activities in both the developed and developing world.
Meteorologists	The DSS cannot generate accurate, real-time recommendations on its own. It will require a connection to other systems, especially weather and meteorological data sources, to stay up to date. The connection enables the feeding of weather data from these sources into the system, in a format that the DSS can use (O'Grady et al., 2020).	There is a need to further investigate and establish the synergy between the farming community and meteorologists to enable continuous access to real-time data (Makokha et al., 2025).

Limitations

Despite the comprehension of the study, there are limitations. We identify three limitations: empirical evidence, system development, and a DSS framework.

Empirical evidence
This study used document analysis to collect the data. While this method is suitable for a study of this nature, it has a limitation. It does not include any empirical evidence gathered directly from the people involved in the agricultural sector. Thus, the views and experiences of the actual farmers, infrastructure owners and meteorologists aren't reflected in the study. Future research should therefore include the participation of stakeholders to help provide insights based on real experiences.

System development
This study conceptualises a data-driven DSS for commercial farmers in South Africa but doesn't go further to develop the actual working system. Future research should focus on moving from the conceptualisation to the development of the system.

Development of a DSS framework
Beyond developing the system, future research should work towards developing a DSS framework that is specific to the South African commercial farming context. Developing such a framework would make the proposed DSS scalable and easier for future researchers and developers to build on (Onwujekwe & Weistroffer, 2025).

Conclusion

The significance of a data-driven DSS goes beyond individual farm productivity. It could be used by locales that share infrastructure. Commercial farmers in South Africa produce approximately 80% of the country's total agricultural output, making it critical to enhance their farming activities through this type of solution. This means that improving their ability to make decisions can directly affect the economy and national food security. Thus, developing a data-driven DSS that is suited to the South African farming environment could play a significant role in helping these commercial farmers make better decisions and improve agricultural sustainability in the long term. The significance of the problem makes this study a huge contribution from both theoretical and practical standpoints because it provides direction for a strategic and operational solution.

If these gaps remain unaddressed, commercial farmers will continue to make decisions based on experience and intuition, resulting in resource inefficiencies, reduced crop yields, weakened competitiveness in both local and global markets, and broader implications for South Africa's food security and agricultural economy.

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