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Decision-Support Systems for Enhancing Yield Stability under Variable Climatic Conditions

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Article Information:
Received: 03 November 2025 | Revised: 05 December 2025 | Accepted: 04 January 2026 | Published: February 03, 2026

Cite this article:
Abhijit Debnath, Bashir A Alie, Mahua Banerjee and Chongtham Roben Singh. Decision-Support Systems for Enhancing Yield Stability under Variable Climatic Conditions. *Public Health Open Journal*. 11(1):80–88.
https://doi.org/10.17140/PHOJ.11.01.80

Abstract
Climate variability, characterized by droughts, heat waves, and irregular rainfall, has become a major constraint to agricultural productivity, causing yield fluctuations and threatening food security. In response, decision-support systems (DSS) have emerged as essential tools for climate-resilient agriculture by integrating climate data, soil properties, crop models, and management practices to provide timely, site-specific recommendations. DSS supports critical decisions such as sowing time, irrigation, nutrient management, and risk mitigation, thereby improving resource efficiency and reducing vulnerability to climatic uncertainties. The integration of advanced technologies like artificial intelligence, remote sensing, and IoT has further enhanced DSS through real-time monitoring and predictive analytics. By addressing multiple interacting climatic stresses and offering a holistic decision-making framework, DSS plays a vital role in improving crop resilience, yield stability, and sustainable agricultural systems under changing climatic conditions.

Keywords: *Decision-support systems; Climate variability; Yield stability; Crop modeling; Climate-smart agriculture; Precision agriculture; Artificial intelligence; Remote sensing; IoT.*

1. Introduction

Agriculture is highly dependent on climatic conditions and is therefore vulnerable to climate variability and long-term climate change [1, 2]. In recent decades, the increasing frequency of extreme weather events such as droughts, heat waves, and irregular rainfall has significantly affected crop productivity and yield stability [3, 4, 5]. These impacts have led to yield reductions in major staple crops like wheat, rice, and maize, posing serious threats to global food security [6, 7]. Yield stability—defined as consistent production under varying conditions—is essential for sustainable agriculture [8, 9]. However, climate variability, especially in rainfed systems, makes maintaining stable yields increasingly difficult [10, 11]. Combined stresses such as heat and drought further intensify yield losses by disrupting plant physiological processes [12, 13]. Traditional farming practices based on historical climate patterns are no longer sufficient to manage these uncertainties [16, 15]. This has led to the development of decision-support systems (DSS), which integrate climate data, crop models, soil information, and management practices to support informed decision-making [17, 18]. DSS helps optimize resource use, evaluate management strategies, and reduce risks associated with climate variability [20].

Advancements in technologies such as artificial intelligence, machine learning, remote sensing, and IoT have enhanced DSS capabilities by enabling real-time data analysis and improved predictions [24, 23]. Despite their potential, challenges related to data availability, model accuracy, and user accessibility remain [22]. This review aims to examine the role of DSS in improving yield stability under changing climatic conditions, highlighting key components, applications, and future research directions for climate-resilient agriculture.

2. Concept and Architecture of Decision-Support Systems

Decision-support systems (DSS) are interactive, computer-based tools designed to support complex decision-making processes by integrating large volumes of data, analytical models, and expert knowledge into a unified framework [23, 24]. In agriculture, DSS has evolved as a multidisciplinary approach that combines agronomy, meteorology, soil science, crop physiology, and information technology to provide site-specific and timely recommendations for improving crop productivity and yield stability under variable climatic conditions [17, 18, 20].

The concept of DSS in agriculture emerged from the need to manage uncertainty and variability in production systems. Early systems were primarily model-driven, focusing on crop simulation and yield prediction under different environmental scenarios [17, 19]. Over time, DSS has evolved to incorporate real-time data, machine learning algorithms, and remote sensing technologies, making it more dynamic and responsive to changing field conditions [24, 23].

DSS operates by integrating multiple data streams, including weather forecasts, soil properties, crop characteristics, and management practices, to simulate crop growth processes and evaluate alternative management strategies [15, 16]. This integration allows users to assess potential outcomes under different scenarios and select optimal strategies to minimize risks and maximize productivity [10, 11].

2.1 Core Components of DSS

A typical agricultural DSS consists of four major components, each playing a critical role in the decision-making process:

2.1.1 Database Management System (DBMS)

The database management system forms the backbone of DSS, storing and managing large volumes of data related to climate, soil, crops, and management practices [17, 20]. These datasets include historical weather records, real-time meteorological data, soil characteristics, crop parameters, and input usage. The availability of accurate and high-quality data is essential for the reliability of DSS outputs [19, 22].

Recent advancements in big data analytics and cloud computing have significantly enhanced the capacity of DSS databases, enabling the integration of large-scale datasets from multiple sources, including satellite observations and sensor networks [25, 24].

2.1.2 Model Base System

The model base system is a central component of DSS, consisting of mathematical and simulation models that represent crop growth processes and environmental interactions [18, 17]. These models simulate physiological processes such as photosynthesis, transpiration, nutrient uptake, and biomass accumulation under varying environmental conditions [20, 31]. Crop simulation models such as DSSAT, APSIM, and WOFOST are widely used in DSS to predict crop performance under different climate scenarios [19, 18]. These models enable evaluation of management practices such as irrigation scheduling, fertilizer application, and planting dates [15].

In recent years, the integration of machine learning and artificial intelligence with traditional crop models has improved predictive accuracy and adaptability, allowing DSS to capture complex nonlinear relationships between climate variables and crop responses [23, 24].

2.1.3 Knowledge Base System

The knowledge base system incorporates expert knowledge, empirical relationships, and decision rules derived from agronomic research and field experience [24, 23]. This component enables DSS to provide practical recommendations based on established scientific principles and best management practices.

Knowledge-based DSS often uses rule-based systems and expert systems to translate complex scientific information into user-friendly recommendations [21]. For example, DSS can recommend optimal irrigation timing based on soil moisture thresholds or suggest pest management strategies based on weather conditions and crop stage [15].

2.1.4 User Interface

The user interface is the communication bridge between the DSS and its users, including farmers, researchers, and policymakers [23]. A well-designed interface ensures that complex data and model outputs are presented in a simple, understandable, and actionable format [24]. Modern DSS platforms increasingly utilize mobile applications, web-based dashboards, and decision dashboards to enhance accessibility and usability [25, 24]. These interfaces often include visualization tools such as graphs, maps, and alerts, which help users interpret data and make informed decisions quickly [26].

Table 1. Components of Decision-Support Systems and Their Functions

Component	Function	References
Database	Stores climate, soil, crop, and management data	[17]
Model base	Simulates crop growth and yield	[18]
Knowledge base	Provides expert rules and recommendations	[19]
User interface	Enables interaction and visualization	[21]

2.2 Types of Decision-Support Systems

DSS can be classified into different categories based on their structure and application:

2.2.1 Model-Driven DSS

Model-driven DSS relies on simulation models to analyze crop performance under different environmental and management scenarios [17, 18]. These systems are widely used for yield prediction, climate impact assessment, and resource optimization [20].

2.2.2 Data-Driven DSS

Data-driven DSS uses statistical techniques, machine learning, and artificial intelligence to analyze large datasets and identify patterns [23, 24]. These systems are particularly useful for real-time monitoring, stress detection, and predictive analytics.

2.2.3 Knowledge-Driven DSS

Knowledge-driven DSS is based on expert systems and rule-based approaches that incorporate domain knowledge into decision-making [24, 23]. These systems are commonly used in advisory services and extension systems.

2.2.4 Hybrid DSS

Hybrid DSS combines model-driven, data-driven, and knowledge-based approaches to provide more accurate and comprehensive decision support [21, 24]. This integrated approach is particularly effective in managing complex agricultural systems under climate variability.

2.3 Evolution of DSS in Agriculture

The development of DSS in agriculture has progressed through several stages. Early DSS focused on standalone crop models and static datasets [17]. With advancements in computing technologies and data availability, DSS evolved to incorporate real-time data, spatial analysis, and interactive interfaces [21].

The recent integration of digital technologies such as artificial intelligence, IoT, and remote sensing has transformed DSS into dynamic and intelligent systems capable of real-time decision-making [23, 24]. These advancements have significantly improved the ability of DSS to address climate variability and enhance yield stability.

3. Role of Decision-Support Systems in Enhancing Yield Stability

Yield stability is a critical objective in modern agriculture, particularly under conditions of increasing climatic variability and uncertainty. Fluctuations in temperature, rainfall, and the occurrence of extreme events such as droughts and heat waves significantly influence crop growth and productivity [3, 4, 5]. Decision-support systems (DSS) play a pivotal role in stabilizing yields by enabling informed, data-driven decisions that optimize resource use and mitigate risks associated with climate variability [17, 15]. DSS enhances yield stability by integrating climate forecasts, crop models, soil data, and management practices into a unified framework. This integration allows farmers and stakeholders to evaluate different management options, anticipate potential risks, and implement adaptive strategies [16, 10]. The ability of DSS to simulate complex interactions between environmental factors and crop processes makes it a powerful tool for improving agricultural resilience [20, 11].

3.1 Climate-Based Decision Making

One of the primary functions of DSS is to incorporate climate information into agricultural decision-making. Seasonal climate forecasts and short-term weather predictions are used to guide key management practices such as sowing dates, crop selection, and irrigation scheduling [15, 16]. By analyzing historical and real-time climate data, DSS can identify optimal planting windows that minimize exposure to adverse weather conditions [10]. For example, adjusting sowing dates based on predicted rainfall patterns can help crops avoid drought stress during critical growth stages [11]. Similarly, DSS can recommend crop varieties suited to specific climatic conditions, thereby improving adaptability and yield stability [6, 7].

3.2 Crop Simulation and Yield Prediction

Crop simulation models are central to DSS and play a crucial role in predicting crop performance under varying environmental conditions [17, 18]. Models such as DSSAT, APSIM, and WOFOST simulate physiological processes including photosynthesis, respiration, transpiration, and nutrient uptake, allowing for detailed analysis of crop growth and yield formation [20, 19].

These models enable the evaluation of different management scenarios, such as varying irrigation levels, fertilizer applications, and planting dates, under different climate conditions [15]. By simulating potential outcomes, DSS helps farmers make informed decisions that enhance yield stability and reduce uncertainty [21].

Furthermore, recent advancements in machine learning have improved the predictive capabilities of DSS by enabling the analysis of large datasets and identification of complex patterns [23, 24].

3.3 Resource Optimization

Efficient use of resources such as water, nutrients, and energy is essential for sustainable agriculture and yield stability. DSS provides site-specific recommendations for resource management based on soil properties, crop requirements, and climatic conditions [32, 21].

For example, DSS can optimize irrigation scheduling by integrating soil moisture data and weather forecasts, thereby improving water-use efficiency and reducing the risk of drought stress [31]. Similarly, DSS can recommend appropriate fertilizer application rates and timing to enhance nutrient use efficiency and minimize environmental impacts [19, 20].

By optimizing input use, DSS not only improves productivity but also reduces production costs and environmental degradation [33, 34].

3.4 Risk Assessment and Management

Agricultural production is inherently risky due to uncertainties associated with climate variability, pest outbreaks, and market fluctuations [10, 11]. DSS plays a crucial role in assessing and managing these risks by analyzing historical data, real-time information, and predictive models.

DSS can identify potential risks such as drought, heat stress, and pest infestations, enabling farmers to implement preventive measures [15]. For instance, early warning systems integrated within DSS can alert farmers to impending drought conditions, allowing them to adjust irrigation practices or select drought-tolerant crops [16].

3.5 Management of Abiotic Stress Interactions

Crops are often exposed to multiple abiotic stresses simultaneously, leading to complex interactions that significantly affect growth and yield. Studies have shown that combined stresses, such as heat and drought, have synergistic effects that exacerbate physiological damage and reduce productivity [12, 13, 14].

DSS provides a framework for managing these interactions by integrating multiple environmental variables and simulating their combined effects on crop performance [20, 31]. This enables the development of comprehensive management strategies that address multiple stress factors simultaneously, thereby enhancing yield stability.

3.6 Precision Agriculture and Site-Specific Management

The integration of DSS with precision agriculture technologies has further enhanced its role in improving yield stability. Precision agriculture involves the use of GPS, remote sensing, and IoT technologies to monitor field variability and implement site-specific management practices [21, 26]. DSS utilizes these technologies to provide location-specific recommendations, such as variable rate irrigation and fertilization, which improve resource-use efficiency and crop productivity [25, 24].

3.7 Enhancing Climate Resilience and Sustainability

DSS contributes significantly to climate-resilient agriculture by enabling adaptive management strategies that enhance the ability of cropping systems to withstand climatic variability [15, 1]. By optimizing resource use and reducing risks, DSS supports sustainable agricultural practices that minimize environmental impacts [33, 34].

Overall, decision-support systems play a multifaceted role in enhancing yield stability by integrating climate information, crop models, and management practices into a comprehensive decision-making framework. By enabling proactive and adaptive strategies, DSS helps mitigate the adverse effects of climatic variability and ensures sustainable agricultural productivity.

4. Integration of Emerging Technologies in Decision-Support Systems

The effectiveness and adaptability of decision-support systems (DSS) in modern agriculture have been significantly enhanced by the integration of emerging digital technologies. These technologies enable DSS to process large volumes of data, provide real-time insights, and improve the accuracy of predictions under variable climatic conditions [23, 24]. The convergence of remote sensing, artificial intelligence (AI), Internet of Things (IoT), and big data analytics has transformed DSS from static, model-based tools into dynamic, intelligent systems capable of supporting climate-resilient agriculture [21, 24].

These technological advancements allow DSS to better capture the complex interactions between climate, soil, and crop systems, which are critical for enhancing yield stability [26, 27]. Moreover, they facilitate site-specific management practices and enable farmers to respond promptly to changing environmental conditions [15, 31].

4.1 Remote Sensing and Geographic Information Systems (GIS)

Remote sensing and GIS technologies play a crucial role in improving the spatial and temporal accuracy of DSS. Satellite-based observations provide valuable information on crop health, vegetation indices, soil moisture, and land use patterns [26, 27]. These data are integrated into DSS to monitor crop conditions over large geographic areas and support decision-making at both field and regional scales [21]. Vegetation indices such as NDVI (Normalized Difference Vegetation Index) are widely used to assess crop vigor and detect stress conditions [28, 27]. Remote sensing also enables early detection of drought stress, nutrient deficiencies, and pest infestations, allowing timely intervention [26].

GIS further enhances DSS by providing spatial analysis tools that integrate multiple layers of information, including soil maps, climate data, and crop distribution [33, 21]. This spatial integration is essential for site-specific management and precision agriculture.

4.2 Artificial Intelligence and Machine Learning

Artificial intelligence (AI) and machine learning (ML) have revolutionized DSS by enabling advanced data analytics, pattern recognition, and predictive modeling [23, 24]. These technologies allow DSS to analyze complex and nonlinear relationships between environmental variables and crop responses, improving the accuracy of yield predictions [26, 28]. Machine learning algorithms such as neural networks, decision trees, and support vector machines are increasingly used in DSS for tasks such as yield forecasting, disease detection, and climate risk assessment [24]. AI-based DSS can also learn from historical data and continuously improve their performance over time, making them more adaptive to changing conditions [23]. Furthermore, AI integration enables automation of decision-making processes, reducing the need for manual intervention and enhancing efficiency [24].

4.3 Internet of Things (IoT) and Sensor-Based Systems

The Internet of Things (IoT) has significantly enhanced the real-time capabilities of DSS by enabling continuous monitoring of field conditions through sensor networks [24, 30]. IoT devices collect data on soil moisture, temperature, humidity, and crop growth parameters, which are transmitted to DSS platforms for analysis [29, 30].

This real-time data integration allows DSS to provide dynamic recommendations for irrigation, fertilization, and pest management, thereby improving resource-use efficiency and crop productivity [31, 21]. For example, soil moisture sensors can trigger automated irrigation systems, ensuring optimal water use and reducing drought stress [32].

IoT-based DSS also supports precision agriculture by enabling site-specific management practices tailored to field variability [30].

4.4 Big Data and Cloud Computing

The increasing availability of large datasets from various sources, including satellites, sensors, and weather stations, has led to the emergence of big data in agriculture [23, 24]. DSS leverages big data analytics to process and analyze these datasets, providing insights into climate patterns, crop performance, and management practices [29]. Cloud computing facilitates the storage, processing, and sharing of large datasets, enabling DSS to operate efficiently and provide real-time services [30, 24]. Cloud-based DSS platforms allow users to access information and recommendations from anywhere, enhancing accessibility and scalability [23].

4.5 Integration of Technologies for Smart Agriculture

The integration of remote sensing, AI, IoT, and big data into DSS has led to the development of smart agriculture systems that are capable of real-time monitoring, predictive analytics, and automated decision-making [21, 24]. These integrated systems enable a holistic approach to agricultural management by combining multiple data sources and analytical tools.

Such integrated DSS platforms are particularly effective in managing climate variability, as they can simultaneously analyze multiple stress factors and provide comprehensive management strategies. Similar to the complex interactions observed under combined abiotic stresses, which significantly affect crop growth and yield formation, integrated DSS systems are designed to address multiple challenges in a coordinated manner [12, 14].

4.6 Challenges and Limitations

Despite the significant advantages of integrating emerging technologies into DSS, several challenges remain. These include high implementation costs, lack of technical expertise, data privacy concerns, and limited accessibility in developing regions [23, 24]. Additionally, the accuracy of DSS predictions depends on the quality and availability of data, which can be a limiting factor in many agricultural systems [21].

Overall, the integration of emerging technologies has significantly enhanced the functionality and effectiveness of decision-support systems in agriculture. By enabling real-time monitoring, predictive analytics, and site-specific management, these technologies contribute to improved yield stability and resilience under variable climatic conditions.

This real-time data integration allows DSS to provide dynamic recommendations for irrigation, fertilization, and pest management, thereby improving resource-use efficiency and crop productivity [31, 22]. For example, soil moisture sensors can trigger automated irrigation systems, ensuring optimal water use and reducing drought stress [32].

IoT-based DSS also supports precision agriculture by enabling site-specific management practices tailored to field variability [35].

5. DSS Framework for Climate-Smart Agriculture

Decision-support systems (DSS) serve as a foundational component of climate-smart agriculture by integrating climate data, crop models, soil information, and management practices into a unified framework [15, 21]. Climate-smart agriculture aims to enhance productivity, increase resilience, and reduce greenhouse gas emissions, and DSS plays a central role in achieving these objectives [34, 1].

The DSS framework typically involves three major stages: data acquisition, data processing, and decision generation. Data acquisition includes the collection of climate data, soil characteristics, crop parameters, and management practices [17, 20]. These inputs are processed through simulation models and analytical tools to evaluate different management scenarios [18, 19]. Finally, DSS generates recommendations that support optimal decision-making under variable climatic conditions [15].

This integrated framework enables farmers to adapt to climate variability by selecting appropriate crop varieties, optimizing planting dates, and managing resources efficiently [16, 10]. DSS also facilitates scenario analysis, allowing users to assess the impact of different climate conditions and management strategies on crop productivity [11]. The DSS framework integrates multiple data sources such as weather forecasts, soil information, crop simulation outputs, and management practices to generate actionable recommendations, thereby enhancing decision-making efficiency and supporting adaptive management under uncertain climatic conditions [15, 21].

Furthermore, DSS enables dynamic feedback mechanisms, where real-time data from sensors and remote sensing platforms are continuously incorporated into the system to update recommendations [24, 26]. This real-time adaptability is critical for responding to sudden climatic changes and minimizing risks associated with extreme weather events [11].

The framework also supports multi-scale decision-making, ranging from field-level management to regional and national agricultural planning [21, 24]. By integrating spatial and temporal data, DSS facilitates site-specific recommendations that improve resource-use efficiency and crop productivity [26, 27]. In addition, DSS contributes to sustainable agricultural practices by promoting efficient use of inputs such as water, fertilizers, and energy, thereby reducing environmental

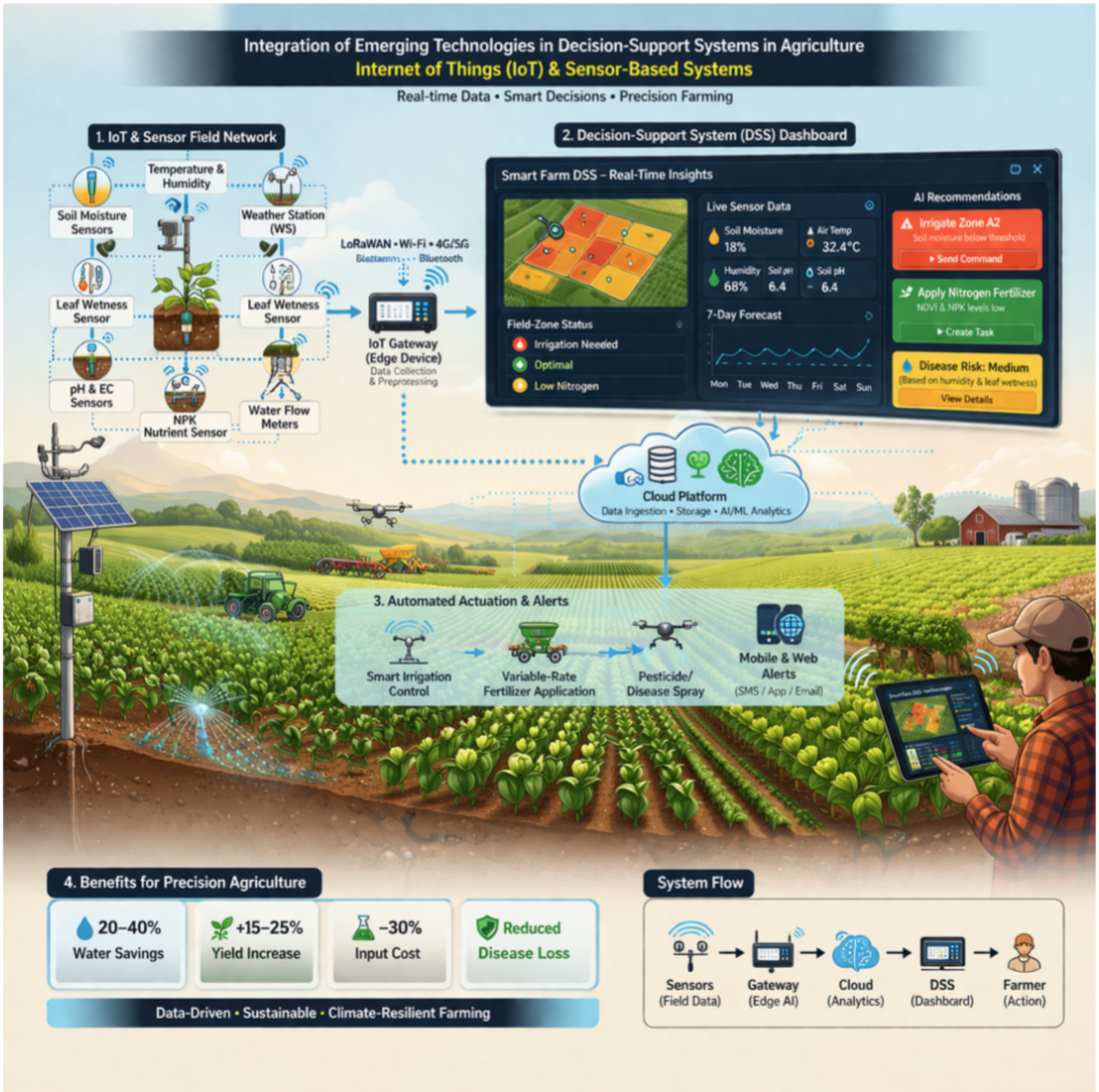

Figure 1: Integration of Emerging Technologies in Decision-Support Systems in Agriculture: Internet of Things (IoT) and Sensor-Based Systems

impacts [33, 34]. The integration of DSS with climate-smart agriculture strategies ensures that productivity gains are achieved without compromising environmental sustainability.

6. Discussion

The increasing complexity of agricultural systems under variable climatic conditions necessitates the adoption of integrated and adaptive management approaches. Decision-support systems (DSS) have emerged as a transformative tool in this context, enabling data-driven decision-making by integrating climate information, crop models, soil characteristics, and management practices [24, 23]. The ability of DSS to process large datasets and simulate multiple scenarios allows for a comprehensive understanding of climate–crop interactions, which is essential for enhancing yield stability [17, 20].

One of the key strengths of DSS lies in its capacity to address the inherent uncertainty associated with climate variability. By incorporating seasonal climate forecasts and real-time weather data, DSS enables proactive decision-making that reduces risks and improves resilience [15, 16]. This is particularly important in regions where agricultural productivity is highly dependent on rainfall and temperature patterns [10, 11].

Another important aspect is the integration of multiple stress factors within DSS frameworks. Crops are frequently exposed to combinations of abiotic stresses, such as heat and drought, which interact in complex

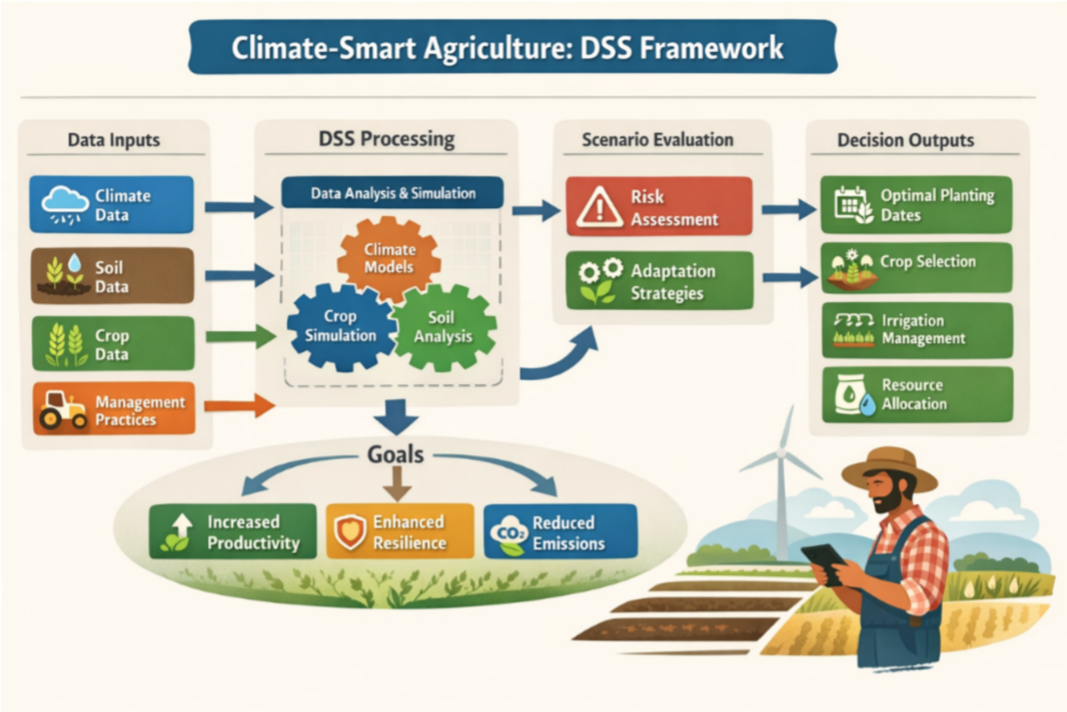

Figure 2. Conceptual Framework of Decision-Support Systems (DSS) for Climate-Smart Agriculture Integrating Climate, Soil, Crop Models, and Management Strategies to Enhance Productivity, Resilience, and Sustainability.

ways to influence physiological and biochemical processes. Studies have demonstrated that such combined stresses lead to synergistic effects, resulting in greater yield reductions than individual stresses alone [12, 13, 14]. DSS provides a holistic platform to analyze these interactions and develop integrated management strategies that address multiple stress factors simultaneously [31, 20].

The integration of emerging technologies such as artificial intelligence, remote sensing, and IoT has further enhanced the capabilities of DSS. These technologies enable real-time monitoring, predictive analytics, and automated decision-making, thereby improving the accuracy and efficiency of DSS [23, 24]. For instance, AI-based DSS can identify patterns in large datasets and provide accurate yield predictions, while IoT sensors enable continuous monitoring of field conditions [24, 30].

Despite these advancements, several challenges limit the widespread adoption of DSS. These include issues related to data availability and quality, model uncertainty, high implementation costs, and lack of technical expertise among farmers [21, 24]. Additionally, DSS must be tailored to local conditions and farming practices to ensure relevance and usability [15]. Bridging the gap between scientific research and practical application remains a key challenge in DSS development. Furthermore, socio-economic factors such as access to technology, education, and institutional support play a crucial role in determining the effectiveness of DSS [10, 1]. Capacity building, extension services, and policy support are essential to promote the adoption of DSS and maximize its benefits.

Overall, DSS represents a powerful tool for managing agricultural systems under climate variability. However, its success depends on continuous improvement in data integration, model accuracy, user accessibility, and stakeholder engagement.

7. Conclusion

Decision-support systems (DSS) have become an essential component of modern agriculture, offering significant potential to enhance yield stability under variable climatic conditions. By integrating climate data, crop simulation models, soil information, and management practices, DSS provides a comprehensive framework for informed decision-making [17, 18]. DSS enables farmers to optimize resource use, reduce risks associated with climate variability, and improve productivity through site-specific and timely recommendations [15, 21]. The integration of advanced technologies such as artificial intelligence, remote sensing, and

IoT has further strengthened DSS capabilities, enabling real-time monitoring and predictive analytics [23, 24]. The ability of DSS to address multiple and interacting climatic stresses is particularly important in the context of climate change. As demonstrated by studies on combined stress conditions, the interaction of multiple stresses can significantly affect crop growth and yield formation [12, 14]. DSS provides an integrated approach to managing these complexities, thereby enhancing resilience and sustainability in agricultural systems.

Despite its potential, challenges related to data availability, model accuracy, cost, and user adoption need to be addressed to fully realize the benefits of DSS. Future research should focus on improving data integration, developing user-friendly interfaces, and enhancing the adaptability of DSS to diverse agro-ecological conditions [24, 21].

In conclusion, decision-support systems represent a critical tool for achieving climate-resilient agriculture. Their continued development and adoption will play a vital role in ensuring sustainable agricultural production, improving yield stability, and addressing the challenges posed by climate variability.

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