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Development of Reliable Decision Support for Precision Agricultural Farming

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Abstract

Decision Support Systems are becoming increasingly valuable for precision agriculture with direct applications in predicting crop productivity and disease outbreaks. This review article provides an introduction to decision support systems, along with use case examples of decision support tools being developed and marketed by various companies. We discuss the different types of decision support systems based on farm data, communication, knowledge, and predictions made by historical data, farmers or producers. Use case examples are presented by company products in the areas of managing the breadth and depth of resources, knowledge, and data within various types of sensing (soil sensing, remote sensing etc.) and farm management (nutrients, water etc.) while detecting and preventing disease outbreaks (integrated pest management and disease resistance) in crops and livestock. There is a significant increase in the levels of investment for agricultural decision support systems which suggests a growing level of farm-level acceptance of such technologies which deploy state-of-art data computation and data management tools. At the same time, there are several challenges and considerations in developing, testing, and implementing decision support systems that are also discussed here, including costs, data quality, data management, model development, reliability testing, reluctance of new technologies, and ethical considerations. We hope this article will provide a comprehensive summary of decision support tools in precision agriculture which will inspire future use cases that add value to our society.

Introduction

A Decision Support System is generally a software tool or software application (mobile app) designed to help individuals, farmers, producers or organizations in making informed decisions about their farm and farm practices [1-7]. It does this by collecting, processing, and analyzing data, and then providing actionable insights, recommendations, or forecasts. Such systems are widely used across various crop farms and livestock farms to support complex decision-making processes. It is a valuable tool for enhancing decision-making by providing data-driven insights and analysis. It can be tailored to meet the specific needs of different agricultural industries and decision-making contexts, helping users to navigate complex situations and make more informed choices [1-8].

Decision Support System Components

Three components of a decision support system are data collection/management, data modelling, and data visualization. A key component of a decision support system is the data management component that integrates data from various internal and external sources [5-12]. This can include on-farm databases, spreadsheets, data warehouses, and real-time data feeds. The system can also support data storage and retrieval where it manages the storage of data in a structured manner, making it easily retrievable for analysis.

Such decision support systems use various mathematical, statistical, and analytical models to process data [10-17]. These models can include predictive analytics, optimization algorithms, simulation models, and decision analysis techniques. This allows users to explore different scenarios and evaluate the potential outcomes of various decisions [15-21].

A decision support system can provide an interactive interface where the user interface allows users to interact with the system, input data, request information, and receive outputs in a user-friendly format. Graphs, charts, and dashboards can help in understanding and interpreting data and model outputs.

Types of Decision Support Systems

A data-driven decision support tool focuses on the collection, organization, and analysis of large volumes of data. They are appropriate for data mining, big data analysis, and business intelligence applications [17-25]. A model-driven decision support tool relies on mathematical and statistical models to analyze complex data and provide decision support. They are often used in optimization, simulation, and forecasting. A knowledge-driven decision support system uses artificial intelligence and expert systems to provide advice and recommendations based on a set of rules or knowledge base. These are used in application areas where expert judgment and specialized knowledge are critical. A communication-driven decision support system facilitates communication and collaboration among team members to support decision-making. These systems often include tools for online meetings, brainstorming, and consensus-building. A document-driven decision support system manages, retrieves, and manipulates unstructured information in a variety of formats, such as text documents, emails, and multimedia files [21-25].

Benefits of an On-Farm Decision Support System

It provides producers and farmers the improved decision quality by providing accurate and relevant information, a decision support system helps decision-makers evaluate options more effectively and choose the best course of action [24-30]. It provides efficiency and speed in agricultural activities by automating data analysis and model execution saves time, allowing for quicker responses to emerging issues and opportunities. Decision Support Systems enable farmers to leverage their data assets more fully, uncovering insights that may not be apparent through traditional analysis. By simulating different scenarios, decision-makers (such as farmers and producers) can anticipate potential outcomes and plan accordingly, thereby reducing risks and uncertainty. To improve consistency and objectivity, decision support systems generally use structured data and analytical models helps to reduce biases and inconsistencies in decision-making [24-30].

Use Case Examples in Agriculture

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Decision support tools in agriculture help farmers, agronomists, and agricultural managers make informed decisions by providing data-driven insights and recommendations [2-5]. These tools use various data sources and analytical models to assist with crop management, resource allocation, pest control, and more [1-12]. These decision support tools leverage advanced technologies such as IoT sensors, satellite imagery, machine learning, and predictive analytics to provide actionable insights. They help farmers optimize their operations, reduce input costs, improve yield and quality, and manage risks more effectively.

a) Crop Management Decision Support Tools

FieldView (by Climate Corporation) has developed a digital farming platform that provides real-time data on crop health, soil conditions, and weather patterns. It offers features like yield analysis, variable rate seeding, and field insights and helps optimize planting, monitor crop health, and improve yield predictions. Ag Leader Technology offers a suite of precision agriculture tools, including seed command, harvest monitoring, and nutrient management. Its tools enhances the planting accuracy, improves nutrient application, and provides detailed harvest data.

b) Irrigation Management Decision Support Tools

Within irrigation management, AquaSpy provides a soil moisture monitoring system that uses sensors to provide real-time data on soil moisture levels at various depths, and helps optimize irrigation scheduling, reduces water use, and prevents over-irrigation. Hortau provides an irrigation management system that uses sensors to monitor soil moisture, temperature, and other environmental factors. It provides real-time irrigation recommendations, helping to conserve water and improve crop health.

c) Pest Management Decision Support Tools

Within pest and disease management, PestPredict developed a predictive modeling tool that forecasts pest and disease outbreaks based on weather data and historical trends. This allows for proactive management of pests and diseases, reducing crop loss and the need for chemical interventions. CropX has developed an agronomic farm management platform that includes tools for monitoring soil health, moisture, and pest pressure. This tool helps manage pest and disease risks and optimizes irrigation and nutrient application.

d) Nutrient Management Decision Support Tools

Within nutrient management, Agrian has developed a comprehensive agronomy software that provides tools for nutrient management, crop protection, and compliance tracking. This helps ensure balanced nutrient application, improve crop health, and comply with regulations. NutriSense has developed a nutrient management tool that provides recommendations for fertilizer application based on soil tests and crop needs. This enhances nutrient use efficiency and minimizes environmental impact.

e) Farm Management Decision Support Tools

Within farm management and planning tools, FarmLogs has developed a farm management software that tracks field activities, inputs, weather, and crop conditions. This simplifies record-keeping, improves planning, and supports decision-making with historical data analysis. AgriWebb has a digital farm management platform that offers tools for livestock and crop management, including grazing planning, feed management, and farm mapping. This provides a holistic view of farm operations, supports data-driven decisions, and enhances operational efficiency.

f) Remote Sensing Decision Support Tools

For remote sensing and satellite monitoring, Planet Labs provides high-resolution satellite imagery and analytics for monitoring crop health, assessing field variability, and tracking changes over time. This enables early detection of crop stress, improves field management, and supports precision agriculture. Sentera offers drones and sensors for capturing aerial imagery and data analytics, focusing on crop health, scouting, and yield estimation. This enhances scouting efficiency, provides detailed crop health insights, and aids in yield prediction.

g) Marketing and Financial Management Decision Support Tools

For market and financial decision-making, Granular has developed a farm management software that provides financial analysis, crop planning, and input tracking. This helps optimize input use, plan crop rotations, and analyze the financial performance of different crops. FARMserver is a precision farming tool that integrates agronomic data with financial records to provide insights into profitability and efficiency. This assists with budgeting, input cost analysis, and revenue forecasting.

Challenges and Considerations in Building Decision Support Tools

Implementing and maintaining a decision support system involves several challenges that can affect its effectiveness and adoption [3-7]. These challenges can be technical, organizational, or related to data management. Addressing these challenges requires careful planning, a clear understanding of the organization's needs, ongoing user engagement, and a commitment to maintaining and updating the system. Successful implementation also depends on providing adequate training and support to ensure that users can fully utilize the system capabilities [30-42].

The effectiveness of a decision support system depends on the quality, accuracy, and completeness of the on-farm data it collects and uses [40-49]. Poor or inaccurate data quality can lead to incorrect or misleading recommendations which will directly lower the reliability and adoption of such systems. Incomplete, outdated, or inconsistent data can lead to inaccurate analyses and unreliable recommendations. Integrating data from various sources, including structured and unstructured data, can be technically challenging and resource intensive. Ensuring that sensitive data is protected from unauthorized access and breaches is critical, especially in farm fields. Compatibility and integration with existing IT infrastructure on the farm can be challenging, requiring significant customization and technical expertise [40-49]. Regular maintenance, updates, and support are necessary to keep the system functioning correctly and to incorporate new data or changes in business needs.

The accuracy of the models and algorithms used in the decision support systems for agriculture is critical for reliable decision support for producers and farmers [35-47]. Inaccurate models can lead to poor decisions. Models can sometimes be too closely tailored to historical farm data, making them less effective in predicting future outcomes or generalizing across different scenarios. Farmers may find it challenging to interpret complex analytical outputs, leading to confusion or misuse of the information provided by the system. There is a risk that users may over-rely on the decision support system, potentially overlooking other important qualitative factors or expert judgment in decision-making.

To understand the value and information content of decision support tools, it is important to simplify the complexity and usability by designing a user-friendly interface that is accessible to users with varying levels of technical expertise can be challenging [40-49]. Creating an intuitive and user-friendly interface is crucial for ensuring that users can effectively interact with the system, especially for non-technical users. Complex decision support systems with advanced analytics and modeling capabilities may be difficult for users to understand and use, potentially limiting their effectiveness.

The development, testing, implementation, and support maintenance of this decision support system can be costly, requiring investment in software, hardware, and training [38-46]. The development and implementation of such systems can be expensive, involving costs for software, hardware, data acquisition, and training. There can be ongoing costs related to the maintenance, upgrades, and support require ongoing farm and human resources. In some industries, there are strict regulations governing data use, privacy, and decision-making processes, which the decision support system must comply with [3, 33]. Ensuring that the decision support system adheres to ethical standards, particularly in areas involving sensitive data or decisions impacting individuals' lives [30-37].

Successfully integrating a decision supports system into an organization requires changes in processes and culture, which can meet resistance from farmers and producers who are well-versed to existing technologies and reluctant to invest in new technologies without understanding and discussing the cost-benefit analysis [35-49]. Farm employees and farm managers may resist adopting a new system due to comfort with existing processes or skepticism about the decision support system's benefits. Adequate training is essential to ensure farm employees understand how to use the decision support system effectively and interpret its outputs correctly. It is important to ensure that the decision support system aligns with existing business processes and decision-making workflows can be challenging [1-10].

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