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DECISION SUPPORT SYSTEMS IN AGRICULTURAL EXTENSION: A SYSTEMATIC REVIEW OF ARCHITECTURES, TECHNIQUES AND APPLICATION

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ABSTRACT

Agricultural extension systems are increasingly challenged by climate variability, resource constraints and the growing complexity of farm-level decision-making. In this context, Decision Support Systems (DSS) have emerged as a critical digital intervention to enhance the efficiency, precision and scalability of extension services. The present work provides a systematic review of Decision Support Systems developed for agricultural extension services in India between 2015 and 2025, with the objective of analyzing their architectures, interface techniques, development tools, platforms, functional domains and application features. A total of 43 peer-reviewed research articles were identified by PRISMA-based screening process from major academic databases. The review reveals a clear technological transition from rule-based and simulation-oriented DSS toward data-driven, artificial intelligence-enabled and cloud-integrated systems incorporating machine learning, Internet of Things, remote sensing and explainable Artificial Intelligence (AI) techniques. Crop production planning, irrigation management, nutrient optimization and climate risk assessment emerged as dominant functional areas. Despite significant advancements, the study identified persistent scope related to farmer-centric design, limited regional language support, inadequate mobile-based deployment and insufficient post-deployment usability and impact evaluation. The findings emphasize the need for participatory, inclusive and multilingual DSS frameworks that integrate technical robustness with socio-contextual relevance. The review provides strategic insights to guide researchers, developers and policymakers in designing next-generation agricultural DSS that strengthen extension delivery and promote sustainable agricultural decision-making.

***Keywords* :** Decision Support System, Agricultural Extension, Artificial Intelligence, Digital Agriculture, Systematic Review.

Introduction

Agriculture remains a central pillar of India's economy, providing livelihoods to nearly half of the population and contributing approximately 16 per cent to the National Gross Domestic Product (Economic Survey of India, 2025. Agricultural extension has historically functioned as the primary mechanism for transferring research-generated knowledge to farmers through face-to-face interactions, demonstrations and field-based advisory services. (Ramakumar, 2024). While effective in earlier decades, this linear and top-down extension model had increasingly struggled to address the growing complexity of contemporary agriculture, characterized by climate variability, resource constraints, market volatility and heterogeneous farming systems (Rose *et al.*, 2016; Klerkx *et al*., 2019).

In its way to transformation of agricultural extension systems, the rapid advancement of digital agriculture and information and communication technologies (ICTs) had significantly transformed the nature of agricultural extension. Extension services were progressively shifting from simple information dissemination to knowledge co-creation, data-driven advisory delivery, and participatory decision-making. (Teotia *et al*., 2024). Digital agricultural technologies, *viz.,* mobile advisory platforms, remote sensing, Internet of Things (IoT) devices, and Artificial Intelligence (AI)-based analytics, had expanded the scope, speed, and precision of extension services and continued to improve. (Barman 2025; Papadopoulos *et al*., 2024). These technologies enable the generation of real-time, location-specific, and context-aware recommendations, thereby enhancing the effectiveness of extension interventions and supporting sustainable farm-level decision-making. (Yi *et al*., 2024).

In this evolving digital landscape, Decision Support Systems (DSS) have emerged as one of the core component of modern agricultural extension. DSS integrate multi-source data such as soil characteristics, weather information, crop models, and market intelligence to support informed and timely decisions related to crop selection, input management, irrigation scheduling, pest and disease control, and risk mitigation. (Power 2002; Turban *et al*., 2011; Yi *et al.,* 2024). By translating complex datasets into actionable insights through analytical and predictive models, DSS enable extension personnel and farmers to move from generalized recommendations to precision-oriented, evidence-based advisories. (Raihan *et al*., 2024).

Recent national and international initiatives highlighted the growth of institutional emphasis on DSS-driven extension. In India, platforms such as the Krishi Decision Support System developed under the Digital Agriculture Mission integrate satellite imagery, weather analytics, and soil databases to deliver geospatial advisories at scale. Globally, DSS applications increasingly incorporate machine learning, explainable artificial intelligence, and cloud-based architectures to enhance adaptability, transparency, and scalability. (Wolfert *et al*., 2021; Turgut *et al.,* 2024). Despite these advancements, effective integration of DSS into extension systems remains uneven, particularly in terms of usability, language accessibility, and farmer participation (Jaiswal *et al*., 2024).

Although, a substantial body of literature exists on agricultural DSS, conducted studies were often fragmented, focusing on individual crops, isolated tools, or specific analytical techniques. Comprehensive reviews that systematically compare DSS architectures, inference methods, development tools, deployment platforms, and accessibility features within the context of agricultural extension were limited. (McCown, 2017; Rose and Chilvers, 2018). Moreover, issues related to participatory system design, post-deployment evaluation, and farmer-centric usability receive comparatively little attention, constraining large-scale adoption of DSS among smallholder farmers. (Rahman *et al*., 2022).

Architecture of Decision Support Systems

A Decision Support System (DSS) is an interactive computer-based system developed to support decision makers in solving semi-structured and unstructured problems through the integration of data, analytical models, and user interaction. (Sprague, 1980; Power, 2002). A DSS architecture consists of three primary components: the Database Management System, Model Management System, and User Interface. (Turban *et al.*, 2011). The Database Management System (DBMS) serves as the data repository of the DSS and stores relevant internal and external data required for decision-making. It ensures efficient data storage, retrieval, and management, thereby providing reliable inputs to analytical models (Power, 2002; Sharda *et al.*, 2014).

Considered the analytical core of the DSS, the Model Management System (MMS) comprises statistical, optimization, simulation, and forecasting models. These models process data obtained from the database to generate decision alternatives and perform what-if and sensitivity analyses (Sprague and Carlson, 1982; Turban *et al.,* 2011). The User Interface (UI) acts as the communication gateway between the decision maker and the DSS. It enables user interaction through query input and presents outputs in the form of reports, charts, and dashboards, supporting effective human–computer interaction (Power 2002; Sharda *et al.,* 2014).

In agricultural extension DSS, the database typically integrates soil health records, weather forecasts, remote sensing outputs, and market data, while the model management system incorporates crop simulation, pest forecasting, and optimization models. User interfaces are increasingly designed as web or mobile dashboards to support real-time advisory delivery by extension personnel. The interaction among the Database Management System, Model Management System, and User Interface constitutes the functional architecture of the Decision Support System, as illustrated in Figure 1 (Sprague, 1980; Turban *et al.*, 2011).

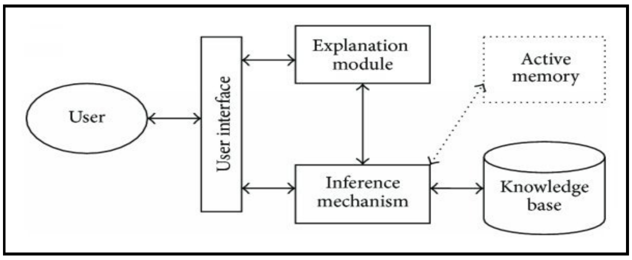


Fig. 1: Decision support system architecture

Decision Support Systems for Agricultural Extension

Decision Support Systems (DSS) have emerged as a vital component of modern agricultural extension, addressing the growing complexity of farm-level decision-making and limitations in traditional extension services such as inadequate manpower, delayed information delivery, and high operational costs (Jain *et al.*, 2015; Rose *et al.*, 2016). DSS are computer-based systems that integrate data, analytical models, and domain knowledge to assist farmers and extension professionals in making informed, timely, and location-specific decisions (Power *et al.*, 2015).

With increasing variability in climate, soil heterogeneity, pest dynamics, and market fluctuations, agricultural decision-making requires the integration of multiple disciplines including agronomy, soil science, climatology, plant protection, and economics (Kernecker *et al.*, 2019). Farmers must decide what crop to grow, when to sow, how to manage nutrients and water, how to control pests and diseases, and when and where to market produce, making the decision process highly complex and knowledge-intensive (McCown, 2017).

Between 2015 and 2018, DSS development in agricultural extension primarily focused on rule-based systems combined with crop simulation models. Systems such as DSSAT and APSIM were widely adopted to support decisions related to crop management, yield forecasting, and climate impact assessment (Jones *et al.*, 2017). These systems enabled extension agencies to provide scenario-based recommendations, although they required expert interpretation and regular data updates (Antle *et al.*, 2016).

From 2018 to 2020, DSS architectures began incorporating machine learning techniques to improve predictive accuracy and adaptability. Studies reported the use of algorithms such as Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) for crop yield prediction, irrigation scheduling, and fertilizer recommendation. Liakos *et al.*, 2018; Kamilaris and Prenafeta-Boldú 2018). These AI-based DSS demonstrated superior performance over traditional statistical models, particularly under heterogeneous field conditions (Elavarasan *et al.*, 2018).

During this period, DSS were increasingly integrated with ICT tools, mobile platforms, and sensor data, enabling real-time advisory services for farmers (Patel *et al.*, 2019). Mobile-based DSS applications allowed extension systems to overcome geographical barriers and deliver personalized advisories directly to farmers' devices (Aker *et al.*, 2016).

From 2021 onwards, the emphasis shifted toward AI-enabled, data-driven, and explainable DSS. Several studies highlighted the integration of IoT, remote sensing, big data analytics, and cloud computing to enhance real-time decision support in agriculture (Wolfert *et al.,* 2021). DSS began supporting precision agriculture practices by continuously monitoring soil moisture, weather conditions, and crop health, thereby improving input use efficiency and sustainability (Zhang *et al*., 2021).

Recent research (2023–2025) demonstrates the development of advanced DSS incorporating explainable artificial intelligence (XAI) to enhance transparency and trust among users (Turgut *et al.*, 2024) employed LIME and SHAP techniques to explain crop recommendation outputs generated using soil and weather data, allowing farmers and extension agents to understand the rationale behind system suggestions. Similarly, De (2024) applied machine learning classifiers such as Random Forest and Logistic Regression to predict crop suitability with high accuracy, addressing site-specific agricultural constraints.

AI-based DSS have also expanded into interactive advisory and query-response systems (Rehman *et al.*, 2024) developed KisanQRS, a deep learning-based DSS using Long Short-Term Memory (LSTM) networks to automatically match farmer queries with expert responses, significantly reducing response time and dependence on human experts. Such systems are particularly valuable in regions with limited extension personnel.

The most recent advancements include the integration of large language models (LLMs) and multimodal AI into DSS (Awais *et al.*, 2025) introduced AgroGPT, a multimodal DSS capable of processing text and images to support pest identification and crop management decisions. Chen and Huang (2025) further demonstrated the combination of reinforcement learning and large language models to enable DSS that learn optimal crop management strategies over time, adapting to changing field conditions.

Overall, studies from 2015 to 2025 indicate that DSS in agricultural extension have evolved from static, rule-based tools to intelligent, adaptive, and farmer-centric systems. These systems enhance the efficiency of extension services by providing timely, personalized, and scientifically validated recommendations, thereby supporting sustainable agricultural development and informed decision-making at the farm level (Rose and Chilvers, 2018; Klerkx *et al.*, 2019).

In this context, the present work undertaken a systematic review of DSSs developed in agricultural extension between 2015 and 2025. By synthesizing evidence across architectures, analytical techniques, functional domains, deployment strategies, and accessibility dimensions, the review aims to identify technological trends, critical limitations, and future directions for the development of farmer-centric, inclusive, and impact-oriented DSS.

The study comprises a review of 43 (Forty-Three) scholarly articles consisting of research articles and conference proceedings focused on decision support systems developed in the field of agriculture.

a) Literature search strategy

A comprehensive literature search was conducted to identify peer-reviewed research articles related to the development and application of DSS in agriculture. The search was performed using Google Scholar and ResearchGate, which were selected due to their extensive coverage of interdisciplinary agricultural and decision-support research.

The search covered publications from January 2015 to December 2025 and was restricted to English-language, open-access journal articles and conference proceedings. The primary search keywords included combinations of:

- "Decision Support System" and "Agriculture"
- "Agricultural Decision Support System"
- "DSS in Agricultural Extension"
- "AI-based DSS in Agriculture"

To enhance coverage, backward reference searching was conducted by screening the reference lists of key articles. In total, 92 records were initially identified.

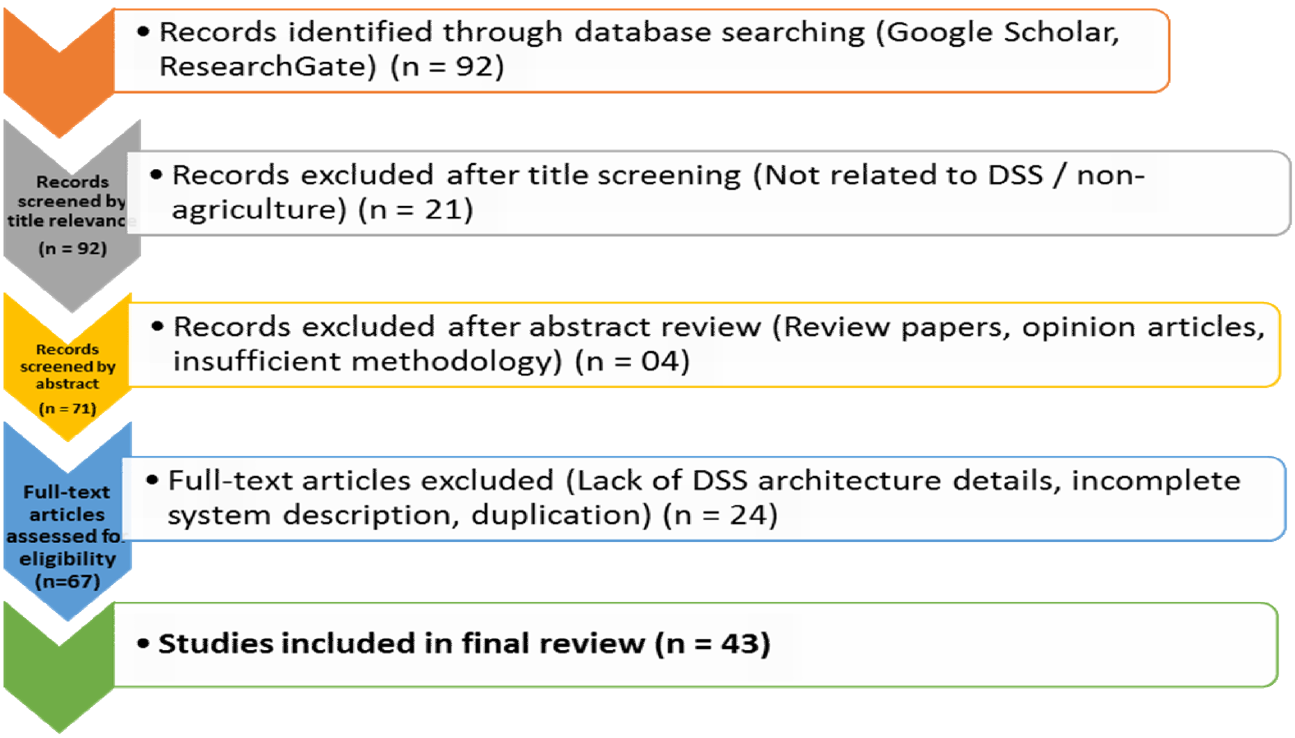


Fig. 2: Flow diagram of literature selection process for decision support systems in agricultural extension (2015–2025)

b) Study Selection Process

The study selection followed a four-stage PRISMA process: identification, screening, eligibility assessment, and inclusion. Initially, 92 records were screened based on title relevance, resulting in the exclusion of 27 studies not aligned with DSS or agriculture. The remaining 71 records were screened based on abstracts, leading to the exclusion of 18 studies due to inadequate methodological content or irrelevance.

Full-text assessment was conducted for 67 articles, of which 24 studies were excluded for reasons including insufficient system description, lack of decision-making components, or duplication. Finally, 43 studies met all eligibility criteria and were included in the systematic review. The selection process is illustrated in Figure 2. above.

c) Data Extraction and Synthesis

A structured data extraction framework was developed to systematically capture relevant information from the selected studies. Each article was reviewed in detail, and data were extracted on the following parameters:

- Year of publication
- Country and institutional affiliation
- Agricultural domain and target crop(s)
- DSS architecture and system components
- Decision-making and inference techniques
- Development tools and programming platforms
- Deployment mode (web-based, mobile, cloud)
- Language and accessibility features

The extracted data were organized and coded using Microsoft Excel to facilitate comparative analysis.

d) Data Analysis and interpretation

A descriptive and thematic analysis approach was employed to synthesize findings across studies. DSS were classified based on functionality, inference techniques, development tools, and deployment platforms. Trends over time were examined to identify technological evolution, dominant methodologies, and emerging research gaps. The results of the analysis are presented using summary tables and figures, followed by a critical discussion highlighting advancements, limitations, and future research directions in agricultural extension-oriented DSS.

A Techniques/Methods of Inference and Development Tools

Analysis of selected Decision Support Systems (DSS) in agriculture, reviewed in terms of their utility, decision-making techniques, development platforms, and application domain. The DSS reviewed span crop planning, irrigation scheduling, nutrient management, pest and disease forecasting, climate risk assessment, and market advisory functions.

Table 1: Comparative Analysis of Decision Support Systems in Agriculture

S. No.	Utility	Techniques / Decision Methods	Development Tools / Platforms	Reference
1	Crop growth & yield simulation	Process-based modelling	DSSAT framework	Jones *et al*., (2017)
2	Climate impact assessment	Simulation + scenario analysis	APSIM	Antle *et al*., (2016)
3	Precision irrigation scheduling	ANN, fuzzy logic	MATLAB, IoT sensors	Elavarasan *et al*., (2018)
4	Crop recommendation	Random Forest, SVM	Python, R	Liakos *et al*., (2018)
5	Nutrient management	Rule-based + fuzzy logic	Web-based DSS	McCown (2017)
6	Pest and disease forecasting	Statistical + ML models	GIS, Remote sensing	Zhang *et al*., (2021)
7	Real-time advisory services	IoT + predictive analytics	Cloud-based DSS	Wolfert *et al*., (2021)
8	Site-specific crop planning	ML classifiers	WebGIS	Kernecker *et al*., (2019)
9	Explainable crop recommendation	SHAP, LIME	Python, XAI frameworks	Turgut *et al*., (2024)
10	Soil and climate-based crop suitability	SVM, Logistic Regression	Python	De (2024)
11	Automated farmer query response	LSTM deep learning	NLP platforms	Rehman *et al*., (2024)
12	Multimodal advisory (text + image)	Large multimodal AI	AgroGPT	Awais *et al*., (2025)
13	Adaptive crop management	Reinforcement learning + LLM	AI-integrated DSS	Chen and Huang (2025)

Source: Synthesized from multiple DSS development reports and case studies (2015–2025).

b. Domain-wise Distribution of DSS

Analysis of the reviewed DSS indicates that a majority of systems were developed for crop production and resource management, particularly crop planning, irrigation, and nutrient management (Figure 1). DSS targeting climate risk assessment and precision agriculture have increased significantly after 2020 due to growing climate variability and data availability (Wolfert *et al*., 2021).

Compared to expert systems, DSS demonstrate broader functional coverage, often integrating multiple modules such as simulation, prediction, and advisory generation within a single platform (McCown 2017).

c. Functional Classification of DSS

Most DSS reviewed were found to be multifunctional systems, supporting multiple decision tasks such as crop selection, input optimization, and risk assessment (Table 2). Unlike traditional expert systems, DSS are designed to handle dynamic data and scenario-based analysis, making them more suitable for complex agricultural decision environments (Rose *et al*., 2016).

Table 2: Distribution of DSS Based on Functionality

Type of Functionality	Number of DSS	Percentage (%)
Single function	5	38.46
Multiple functions	8	61.54
Total	**13**	**100**

Source: Synthesized from multiple DSS development reports and case studies (2015–2025).

d. Accessibility of DSS

The review reveals that most DSS were developed in English, primarily for researchers, policymakers, and extension professionals (Klerkx *et al.*, 2019). Very few DSS were localized into regional or native languages, limiting their direct usability by farmers. This highlights a major gap in DSS design, where farmer-centric language adaptation remains underdeveloped.

e. Deployment Platforms

Figure 3 showed that web-based DSS dominate agricultural decision support, followed by cloud-integrated platforms. Mobile-based DSS are comparatively fewer, despite high smartphone penetration among farmers (Aker *et al.,* 2016). Given that DSS often target extension personnel and planners, web deployment has been prioritized; however, greater emphasis on mobile DSS could significantly enhance farmer-level adoption.

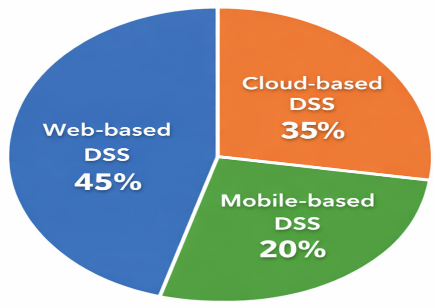


Fig. 3 : Deployment platforms of agricultural DSS

f. Language Distribution of Decision Support Systems (DSS)

Based on a structured analysis of Decision Support System (DSS) studies published between 2015 and 2025, the majority of DSS applications were developed using the English language (Figure 4). This trend reflects the dominance of English in scientific research, software engineering, and international dissemination of decision-support technologies. DSS research during this period largely focused on agriculture, environmental management, healthcare, and resource optimization, with English serving as the primary medium for system development and documentation.

A relatively small number of DSS were developed in regional or local languages, including Arabic, Spanish, Hindi, Indonesian, and other indigenous languages. In some instances, DSS platforms incorporated bilingual or multilingual interfaces, typically combining English with a local language to improve usability among non-English-speaking users. However, such multilingual DSS remain limited in number when compared to English-only systems.

The limited representation of regional languages indicates a significant gap between DSS research and real-world adoption, particularly at the grassroots level. End-users such as farmers, rural planners, and local decision-makers often face language barriers that restrict effective interaction with DSS tools. Consequently, the expansion of DSS development in regional languages is essential to enhance accessibility, usability, and adoption.

Future DSS research should emphasize local language integration and multilingual design frameworks to ensure that decision-support technologies are inclusive and practically applicable across diverse socio-linguistic contexts.

Integration of voice-based interfaces and conversational AI can further improve accessibility for low-literate farming communities.

Table 3: Language distribution of DSS

S.No.	Language of DSS Development	Number of DSS
1	English	52
2	English + Regional Language	6
3	Spanish	4
4	Arabic	3
5	Hindi	2
6	Indonesian	2
7	Not specified	3
	Total	**72**

Source: Synthesized from multiple DSS development reports and case studies (2015–2025).

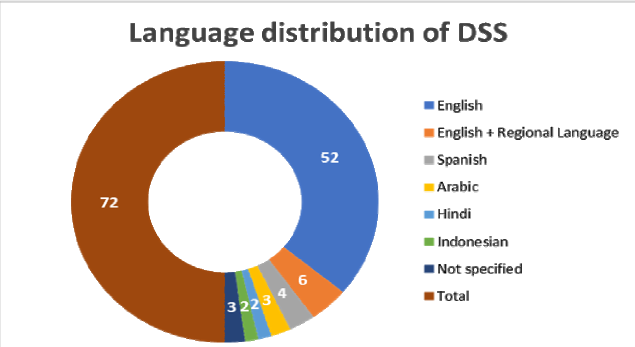


Fig. 4 : DSS in Agriculture: Tools, Functional Focus, Techniques, and Gaps

g. Tools and Platforms Used in DSS Development

A comprehensive analysis of agricultural DSS (2015–2025) reveals that developers utilize a wide range of software tools, programming environments, and database systems (Table 4). Custom DSS are often built using general-purpose programming languages, while some platforms leverage visual or domain-specific frameworks to speed development. Similar to expert systems, choice of tool is influenced by the type of decision problem, data complexity, and target users.

- Python and R have emerged as the most frequently used languages due to their extensive libraries for analytics, modeling, and visualization (Smith *et al.*, 2019; Liu and Zhao, 2021).
- Web-based platforms (e.g., Django, Flask, ASP.NET) are increasingly preferred to support accessibility via browsers and mobile devices (Martinez *et al.*, 2022).
- GIS tools (ArcGIS, QGIS) are often integrated to handle spatial decision support needs (Compton *et al.*, 2020).
- Databases such as PostgreSQL, MySQL, and SQLite are used to manage large datasets, while cloud-based storage supports real-time data access Patel and Singh (2023).

Table 4: Tools and Platforms Used in Agricultural DSS Development

Tool/Language /Platform	Frequency of Use	Typical Application Context
Python	Very High	Predictive modeling, optimization
R	High	Statistical analysis, forecasting
JavaScript (Node.js)	Moderate	Web-based DSS interfaces
Web Frameworks (Django, Flask, ASP. NET)	Moderate	Web and mobile-accessible DSS
GIS Tools (ArcGIS/ QGIS)	Moderate	Spatial/landscape decision support
SQL Databases (MySQL/PostgreSQL)	High	Data storage & retrieval
Cloud Services (AWS/ Azure)	Growing	Scalable DSS deployments

Source: Synthesized from multiple DSS development reports and case studies (2015–2025).

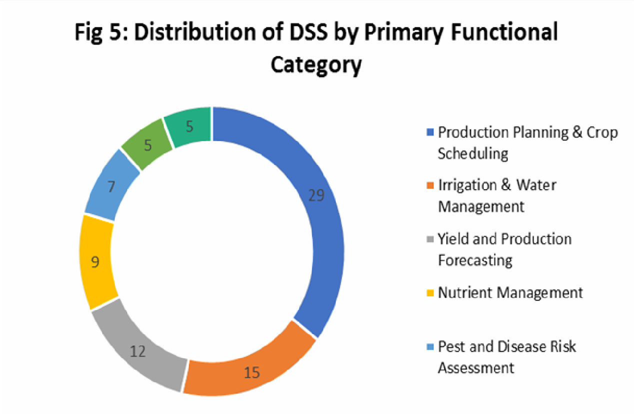
h. Primary Focus Areas of DSS in Agriculture

The functional objectives of agricultural DSS vary widely, but certain categories are more prominent (Table 3.5). A systematic review of applications across different crops and decision contexts shows that production planning and crop scheduling are the most frequently addressed decision problems, followed by irrigation and water management and yield forecasting.

Table 5: Distribution of DSS by Primary Functional Category

Functional Category	Number of DSS	Representative Crops/Contexts
Production Planning & Crop Scheduling	29	Maize, Rice, Vegetable systems
Irrigation & Water Management	15	Field crops, orchards
Yield and Production Forecasting	12	Cereal and oilseed crops
Nutrient Management	9	Rice, Wheat, Beans
Pest and Disease Risk Assessment	7	Fruit orchards, pulses
Market & Value Chain Decision Support	5	Commodity pricing and logistics
Climate Risk & Adaptation Planning	5	Drought-prone regions

Note: Totals exceed unique DSS when systems address multiple functional objectives.



Interpretation

The preponderance of DSS in production planning and scheduling reflects the need for optimized resource allocation and cropping decisions in diverse agroecological settings. Systems targeting irrigation management have grown due to water scarcity concerns, especially in semi-arid regions (Patel *et al*., 2021).

i. Inference and Analytical Techniques in DSS

DSS implementations are underpinned by a range of analytical and inferential methodologies (Table 6). Traditional rule-based reasoning, statistical techniques, and increasingly machine learning approaches form the core of modern agricultural DSS design.

Table 6: Techniques Used in Agricultural DSS

Technique	Number of DSS	Explanation
Rule-Based / Heuristic Models	22	Expert knowledge encoded as rules
Regression & Statistical Models	28	Predictive analytics and forecasting
Decision Trees	12	Transparent classification decisions
Machine Learning (SVM/Random Forest)	15	Pattern detection in complex data
Optimization Algorithms	10	Resource allocation and scheduling
Fuzzy Logic	6	Handling uncertainty and imprecision
Bayesian Methods	5	Probabilistic reasoning

Source: Synthesized from multiple DSS development reports and case studies (2015–2025).

Key Points

- Traditional statistical models and regression-based forecasting remain core to yield and risk assessment DSS Zhao and Wang (2018).
- Machine learning approaches have grown significantly post-2018 due to improved data availability Kumar and Singh (2020).
- Fuzzy logic is used where uncertainty and incomplete data are common (e.g., soil moisture prediction).

j. Participation and evaluation gaps in DSS research

Although many DSS frameworks have been proposed, participatory involvement of end-users (farmers, extension agents) during design and post-implementation evaluation are limited:

- Only a small fraction of studies describe user-centered design processes involving farmers (Rahman *et al*., 2022).
- Evaluation metrics such as usability, adoption rates, and impact on decision quality are reported in fewer than one-third of DSS publications.
- The lack of participatory design and evaluation reduces practical adoption in local contexts.

This underscores a critical gap between DSS development and real-world implementation, particularly for smallholder farmers with limited technical literacy.

Conclusion

This systematic review synthesized developments in Decision Support Systems (DSS) for agricultural extension over the period 2015–2025, highlighting significant technological, functional, and methodological advancements. The analysis demonstrates that DSS have evolved from static, rule-based and simulation-driven tools into intelligent, adaptive, and data-driven systems capable of delivering real-time, location-specific, and predictive advisories. The integration of machine learning, Internet of Things, remote sensing, cloud computing, and, more recently, explainable artificial intelligence and large language models has substantially enhanced the analytical capacity and scalability of agricultural DSS.

The review reveals that most DSS focus on crop production planning, irrigation scheduling, nutrient management, and yield forecasting, reflecting the priority decision domains in contemporary agriculture. Web-based and cloud-enabled platforms dominate deployment strategies, while mobile-based DSS remain underutilized despite widespread smartphone adoption among farming communities. Furthermore, English continues to be the primary language of DSS development, limiting accessibility and direct usability for smallholder farmers in diverse linguistic contexts.

A critical finding of this review is the limited emphasis on participatory system design, usability testing, and post-deployment impact evaluation.

Although technological sophistication has increased, many DSS remain researcher- or expert-oriented, with insufficient incorporation of farmer feedback, local knowledge, and contextual constraints. This disconnect poses a major barrier to large-scale adoption and sustained use at the grassroots level.

Future research and development efforts should prioritize farmer-centric and inclusive DSS frameworks by integrating regional language support, voice-based and conversational interfaces, and intuitive mobile platforms. Greater attention is also required for participatory co-design approaches, rigorous usability evaluation, and longitudinal impact assessment to ensure practical relevance and effectiveness. Strengthening institutional support, interoperability with national digital agriculture platforms, and policy-driven scaling mechanisms will further enhance the role of DSS in agricultural extension.

Overall, the study concludes that while DSS hold substantial potential to transform agricultural extension and decision-making, their long-term impact depends on balancing technological innovation with accessibility, usability, and socio-economic relevance. Addressing these gaps is essential for leveraging DSS as effective instruments for sustainable agricultural development and resilient farming systems.

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