Large Language Model-Assisted Intelligent Advisory Systems for Sustainable Farm Management: A Conceptual Review

Asha Jain [1*], Sachin Gupta [2], Nikita Patel [3], Ankit Gupta [4], Simran Patel [5], Arjun Jain [6]

[1] Assistant Professor, Department of Food Technology, Punjab Agricultural University, Ludhiana, India
[2] Research Associate, Department of Food Technology, Punjab Agricultural University, Ludhiana, India
[3] Project Assistant, Department of Food Technology, Punjab Agricultural University, Ludhiana, India
[4-6] Professor, Department of Food Technology, Punjab Agricultural University, Ludhiana, India

*Corresponding author: **Asha Jain**

Received: 14 Dec 2025
Revised: 30 Dec 2025
Accepted: 19 Jan 2026
Published: 10 Feb 2026

E-ISSN: 2989-5359
DOI: https://doi.org/10.54660/ejsa.2026.6.1.37-45

ABSTRACT
Background: Traditional agricultural extension services, which rely predominantly on in-person agents and static informational materials, increasingly struggle to deliver timely, personalized guidance to a growing and diverse global farming population, particularly in remote and resource-constrained regions. The recent emergence of Large Language Models (LLMs) and generative artificial intelligence offers a potential pathway toward scalable, natural-language agricultural advisory services.
Objective: This review synthesizes current scientific and technical literature on LLM-assisted intelligent advisory systems for farm management, examining how these systems integrate multi-source agricultural data with natural language reasoning to support crop, irrigation, nutrient, and pest management decisions.
Framework: Drawing on peer-reviewed and archival literature published primarily between 2020 and 2026, this review conceptually describes the architecture of LLM-based advisory frameworks, encompassing agricultural knowledge integration, retrieval-augmented reasoning, context-aware recommendation generation, explainability mechanisms, and iterative refinement through user feedback.
Findings: The synthesized literature indicates that deployed and prototype LLM-assisted advisory platforms have been applied to crop selection, variety recommendation, irrigation scheduling, nutrient management, pest and disease diagnosis, and climate-adaptive farm planning, with several field-deployed systems reporting engagement across tens of thousands of farmers and hundreds of thousands of queries. Comparative and qualitative assessments in the literature consistently describe LLM-assisted systems as improving accessibility, personalization, multilingual reach, and scalability relative to conventional agent-based extension, while explainability, factual reliability, and reasoning depth remain comparatively less mature and are identified as active research priorities.
Significance: This review provides a structured, literature-grounded synthesis relevant to researchers, agricultural technology developers, extension agencies, and policymakers seeking to understand the current evidence base for LLM-assisted farm advisory systems.
Conclusion: LLM-assisted advisory systems represent a scientifically credible and rapidly evolving pathway toward scalable, personalized, and increasingly explainable agricultural decision support, though realizing their full potential will require continued progress in factual grounding, domain-specific reasoning, and equitable access for smallholder and low-connectivity farming communities.

Keywords: Generative artificial intelligence; conversational agricultural extension; retrieval-augmented reasoning; context-aware recommendation; digital farm advisory; agricultural knowledge integration; climate-adaptive decision support

1. Introduction
1.1. Digital Transformation of Agriculture
Agriculture continues to undergo substantial digital transformation, with sensor networks, remote sensing platforms, and mobile connectivity increasingly mediating how farmers access information and make production decisions. This transformation has generated growing volumes of agronomic, environmental, and operational data, creating both an opportunity and a challenge: translating this expanding data landscape into timely, comprehensible guidance for farmers of widely varying literacy, connectivity, and resource levels.

1.2. Evolution of Artificial Intelligence in Farming
Artificial intelligence applications in agriculture have progressed from narrow, task-specific models - such as image classifiers for disease detection or regression models for yield estimation - toward increasingly integrated systems capable of synthesizing multiple data modalities. Systematic reviews of AI in the agricultural sector document a broad expansion of machine learning and deep learning applications spanning crop monitoring, pest identification, and resource optimization, while noting that many of these systems remain narrowly scoped to single tasks rather than offering integrated, conversational decision support.

1.3. Emergence of Large Language Models

Large Language Models (LLMs) - generative AI systems trained on extensive text corpora and capable of producing coherent, context-sensitive natural language responses - have rapidly expanded into domain-specific applications across healthcare, finance, and, increasingly, agriculture. Agricultural-domain LLM systems and ecosystems have been proposed to integrate agronomic knowledge with conversational interfaces, aiming to bridge the gap between the technical complexity of precision agriculture data and the practical, natural-language information needs of farmers. Complementary reasoning-oriented benchmarks have highlighted that general-purpose LLMs, despite strong language fluency, often fall short in structured agronomic reasoning tasks, motivating growing interest in domain-adapted and retrieval-grounded architectures.

1.4. Intelligent Agricultural Advisory Systems

Intelligent advisory systems built on LLMs have moved from research prototypes toward field-deployed platforms. Conversational, generative-AI-powered agricultural chatbots have been deployed across multiple countries, reporting engagement with tens of thousands of smallholder farmers and hundreds of thousands of individual queries, and voice-based, retrieval-augmented advisory platforms have been developed for low-literacy and non-English-speaking farming populations. These systems commonly combine retrieval-augmented generation (RAG) - grounding LLM outputs in curated agricultural documents - with multilingual and, in several cases, multimodal (text, voice, image) interaction to improve accessibility.

1.5. Precision Agriculture and Smart Farming

LLM-assisted advisory systems are increasingly positioned as a natural-language interface layer atop precision agriculture infrastructure, translating sensor, remote sensing, and farm-management data into actionable, farmer-comprehensible recommendations. This integration reflects a broader convergence in the smart farming literature between data-intensive precision agriculture technologies and the conversational, knowledge-synthesis capabilities that generative AI systems provide.

1.6. Climate-Smart Agriculture

Climate-smart agriculture initiatives seek to enhance farmer resilience to increasingly variable weather and climate conditions through timely, locally relevant advisory information. Reviews of digital climate services in vulnerable farming regions emphasize the importance of location-specific, timely dissemination of seasonal forecasts and adaptive management guidance, a need that LLM-assisted systems - capable of synthesizing weather data with agronomic recommendations in conversational form - are increasingly positioned to address, provided that connectivity and infrastructure barriers can be overcome.

1.7. Knowledge-Based Decision Support

Historically, agricultural decision support systems have relied on structured rule bases, expert systems, or narrowly trained predictive models. LLM-assisted architectures extend this tradition by incorporating retrieval-augmented generation, allowing the system to ground its natural-language responses in curated, verifiable agricultural knowledge sources rather than relying solely on parametric knowledge learned during training, an approach reported to substantially reduce factual inconsistency relative to unconstrained generative responses.

1.8. Challenges of Traditional Extension Services

Traditional, agent-based extension services face well-documented constraints, including limited numbers of trained extension agents relative to farmer populations, difficulty scaling personalized guidance, and challenges reaching remote or low-connectivity communities. Systematic reviews of digital extension services identify a substantial body of both opportunities and persistent barriers - including infrastructure gaps, digital literacy constraints, and inadequate institutional coordination - that continue to limit the reach of both conventional and digitally mediated advisory services in many developing agricultural regions.

1.9. Global Research Status and Gaps

The literature on LLM applications in agriculture has expanded rapidly since 2023, spanning domain-specific model development, retrieval-augmented advisory platforms, and reasoning benchmarks that probe the limits of current models on agronomic tasks. Despite this growth, reviews consistently note gaps in explainability, factual reliability under domain-specific conditions, evaluation standardization, and equitable access for smallholder and low-literacy farming populations. Comparatively few studies have attempted to synthesize the architectural, application, and evaluation dimensions of LLM-assisted advisory systems within a single integrated decision-support framework oriented specifically toward sustainable farm management.

1.10. Objectives of This Review

This review addresses that synthesis gap. Specifically, it aims to: (i) conceptually describe the architectural components of LLM-assisted agricultural advisory frameworks, including knowledge integration, retrieval-augmented reasoning, and explainability mechanisms; (ii) synthesize literature-reported applications across major farm management decision domains; (iii) critically compare LLM-assisted advisory approaches with conventional extension and rule-based decision support systems along dimensions emphasized in the reviewed literature; and (iv) identify persistent challenges, ethical considerations, and future research directions for trustworthy, sustainable, LLM-assisted farm advisory systems.

2. Review Methodology

This review synthesizes peer-reviewed and archival preprint literature identified through structured searches of Scopus-indexed and open-access scholarly databases, including PubMed Central, ScienceDirect, Springer Nature Link, IEEE Xplore, MDPI, Nature Portfolio journals, and arXiv preprint repositories, using combinations of the keywords "large language models," "generative AI," "agriculture," "agricultural advisory," "decision support systems," "retrieval-augmented generation," "precision agriculture," "climate-smart agriculture," and "explainable AI." Publications were prioritized if they were peer-reviewed or hosted on established preprint archives, published in English, and addressed LLM-based or generative-AI-based systems applicable to agricultural advisory, extension, or decision-support contexts. Foundational review literature on agricultural big data, digital extension services, and federated or privacy-preserving learning was included where it underpins concepts discussed in the LLM-specific literature. Reviewed studies were synthesized narratively and organized thematically around system architecture, data integration, advisory applications, and comparative evaluation, consistent with established practice in interdisciplinary technology reviews. No primary experimental data were generated for this article, and no numerical performance results are reported as original findings; where the reviewed literature reports specific quantitative outcomes, these are attributed explicitly to their original source rather than presented as results of this review. Table 1 summarizes the review's search and synthesis framework, adapted to the LLM-assisted advisory domain.

Table 1: Literature review search and synthesis framework

Component	Description
Databases searched	PubMed Central, ScienceDirect, Springer Nature Link, IEEE Xplore, MDPI, arXiv, Google Scholar
Search period	2020-2026, with emphasis on 2023-2026 publications reflecting the rapid growth of agricultural LLM research
Core search terms	Large language models; generative AI; agricultural advisory; decision support; retrieval-augmented generation; precision agriculture; climate-smart agriculture; explainable AI
Inclusion criteria	Peer-reviewed or archival preprint status; English language; relevance to LLM- or generative-AI-based agricultural advisory or decision-support systems
Exclusion criteria	Studies lacking methodological detail on system architecture, data integration, or advisory application; non-English sources without translation
Synthesis approach	Thematic narrative synthesis organized around architecture, data integration, advisory applications, and comparative evaluation
Scope limitation	Conceptual and comparative synthesis; no primary experimental data, prompt scripts, API implementations, or deployment code is presented

3. LLM-Assisted Advisory Framework for Sustainable Farm Management

3.1. Agricultural Data Sources Integrated by Advisory Systems

The reviewed literature describes LLM-assisted advisory systems as drawing on a heterogeneous set of agricultural data sources. Soil characteristics and weather observations provide the biophysical context for recommendations; crop growth information and historical yield records support variety and management guidance; remote sensing datasets and IoT sensor observations contribute near-real-time field-condition monitoring; and farm management records together with pest and disease observation logs ground recommendations in each farm's specific operational history. Table 2 summarizes these data categories as conceptualized across the reviewed literature on LLM-based and related AI-assisted agricultural advisory systems.

Table 2: Agricultural data sources conceptually integrated by LLM-assisted advisory systems

Data Category	Representative Variables	Advisory Relevance
Soil characteristics	Texture, pH, nutrient status, organic matter	Nutrient management, crop selection
Weather observations	Temperature, rainfall, humidity, forecast data	Irrigation scheduling, climate-adaptive planning
Crop growth information	Phenological stage, variety characteristics	Variety recommendation, sowing date optimization
Remote sensing datasets	Vegetation indices, canopy condition imagery	Pest/disease diagnosis, yield-related guidance
IoT sensor observations	Soil moisture, in-field microclimate readings	Real-time irrigation and monitoring advisories
Farm management records	Input timing, cultivar choice, prior interventions	Personalized, farm-specific recommendations
Historical yield data	Prior-season outcomes, input-output relationships	Contextualizing recommendations against past performance
Pest and disease records	Prior outbreak history, diagnostic reports	Pest and disease forecasting and diagnosis support

3.2. Large Language Model Advisory Architecture

Conceptually, an LLM-assisted advisory system integrates several interacting components. Agricultural knowledge integration curates extension manuals, agronomic research literature, and locally relevant crop calendars into a structured or semi-structured knowledge repository. Retrieval-augmented generation allows the system to identify and incorporate the most relevant curated content into its response for a given farmer query, grounding otherwise unconstrained generative output in verifiable sources and reducing the risk of agriculturally incorrect but plausible-sounding recommendations - a failure mode widely referred to in the literature as hallucination. Natural language interaction enables farmers to pose questions in conversational form, often in local languages and, in voice-enabled deployments, without requiring literacy. A context-aware recommendation engine synthesizes the retrieved knowledge with farm-specific data - soil, weather, management history - to generate personalized guidance, while an explainability component seeks to convey the rationale underlying each recommendation. Finally, user feedback incorporation and continuous refinement allow the system's knowledge base and response quality to improve iteratively based on farmer interactions and, where available, expert review. Figure 1 illustrates this conceptual workflow, and Figure 2 depicts a corresponding layered system architecture spanning data acquisition, knowledge integration, the LLM reasoning core, decision-support and explainability functions, and the farmer-facing interface.

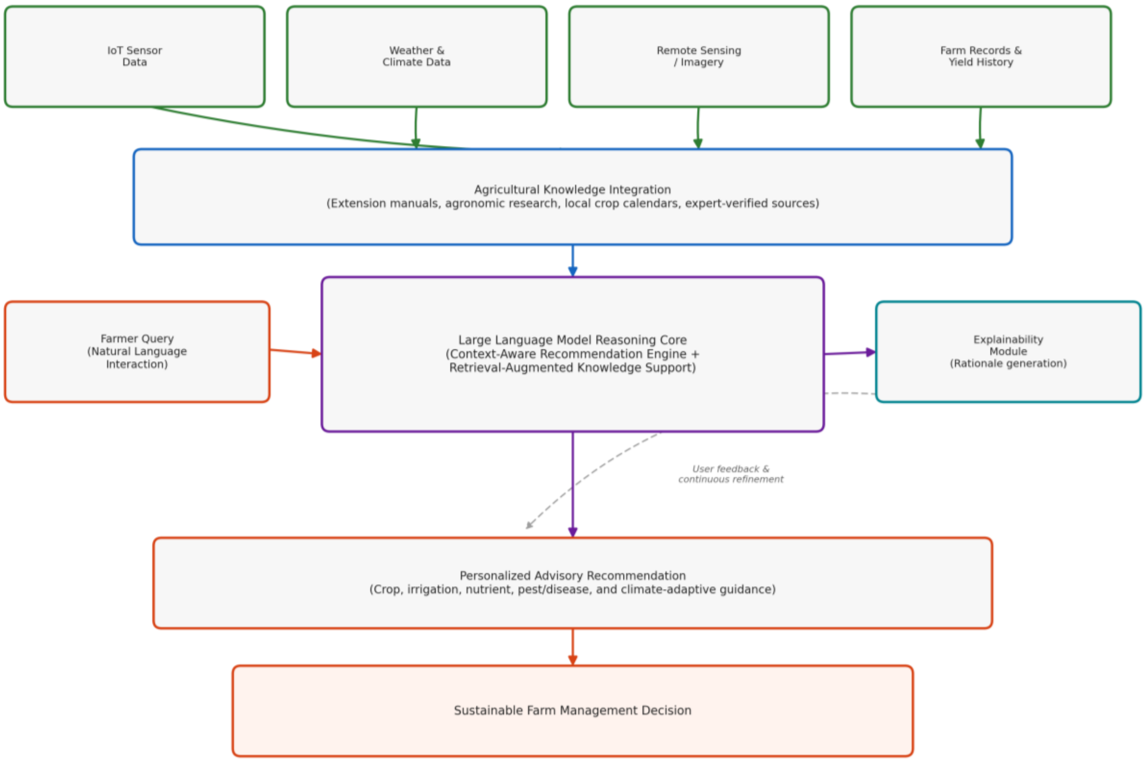

Fig 1: Conceptual workflow of an LLM-assisted intelligent advisory framework, illustrating agricultural data acquisition, knowledge integration, natural-language user interaction, context-aware reasoning, recommendation generation, explainability, and sustainable farm management decisions.

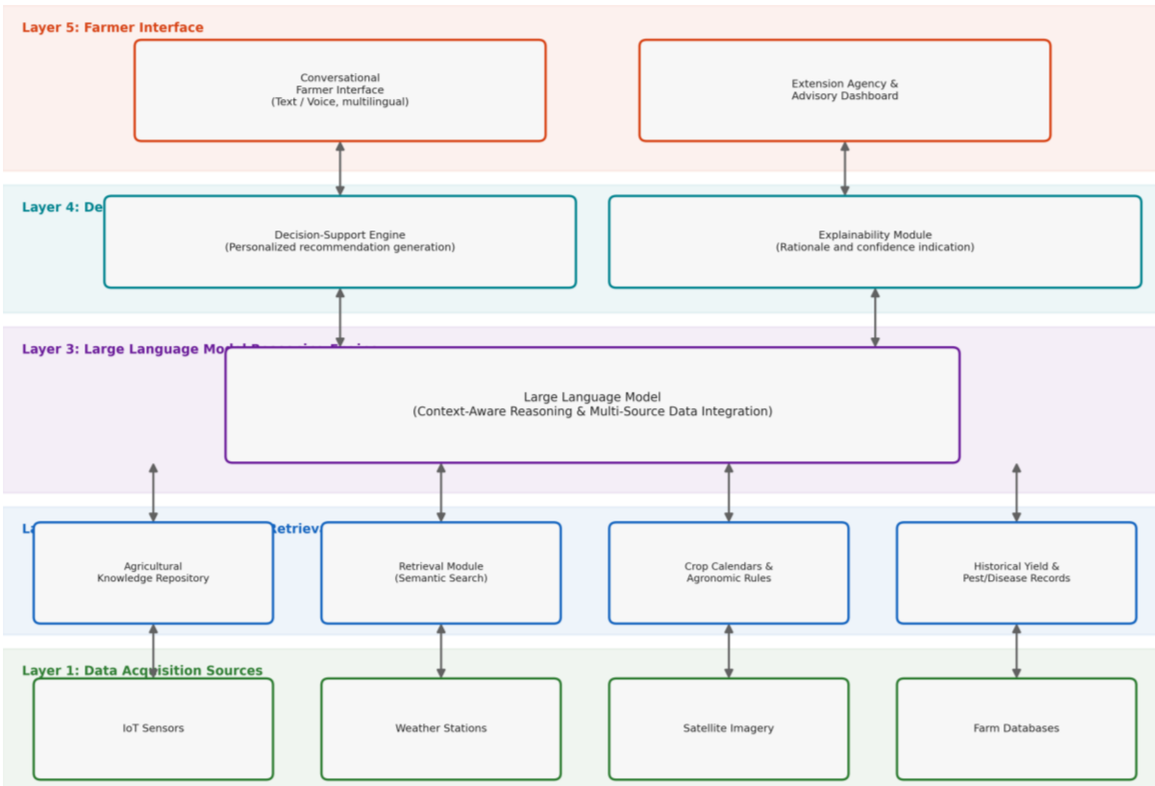

Fig 2: Layered system architecture showing the integration of IoT sensors, weather stations, satellite imagery, and farm databases with an agricultural knowledge repository, the Large Language Model reasoning core, the decision-support and explainability engine, and the farmer interface.

Table 3 summarizes the principal advisory modules described across the reviewed LLM-based agricultural systems, together with their typical inputs, knowledge sources, and intended farm management applications.

Table 3: Major advisory modules of LLM-based agricultural advisory systems

Advisory Module	Typical Inputs	Knowledge Source	Farm Management Application
Natural language query interface	Farmer's spoken or typed question	Conversational LLM front end	General farmer interaction, question answering
Retrieval-augmented knowledge module	Query embedding; document corpus	Extension manuals, agronomic literature, crop calendars	Grounding responses in verified agricultural knowledge
Context-aware recommendation engine	Farm-specific data (soil, weather, history)	Integrated multi-source farm datasets	Personalized crop, irrigation, and nutrient guidance
Pest/disease diagnosis module	Symptom descriptions; optionally images	Disease/pest reference databases	Diagnosis and treatment recommendation
Explainability module	Generated recommendation and supporting evidence	Retrieved source excerpts; model rationale	Transparency and farmer trust-building
Feedback and refinement module	Farmer ratings, corrections, follow-up queries	Interaction logs; expert review (where available)	Continuous improvement of recommendation quality

3.3. Explainability and Trustworthy Recommendation Generation

Explainability is increasingly treated as a core design requirement rather than an optional feature of agricultural LLM systems. Reviews of explainable AI in agriculture describe techniques ranging from source attribution - showing farmers which retrieved documents informed a given recommendation - to natural-language rationale generation that articulates why a particular practice is advised under the farmer's stated conditions. Retrieval-augmented systems evaluated for agricultural question answering have reported source attribution and semantic similarity scoring as practical mechanisms for assessing and communicating response reliability, complementing more general explainable-AI approaches developed for other agricultural AI tasks such as image-based disease detection.

4. Advisory Applications for Sustainable Farm Management

Across the reviewed literature, LLM-assisted advisory systems have been applied or proposed across a recurring set of farm management decision domains. Crop selection and variety recommendation applications synthesize soil, climate, and market information into guidance tailored to local growing conditions. Sowing date optimization and harvest scheduling applications combine weather forecasts with crop phenological knowledge. Irrigation scheduling and nutrient management applications integrate IoT sensor data and soil information with agronomic best practice. Pest and disease diagnosis applications, in several deployed systems, accept farmer-described symptoms or images and return diagnostic guidance grounded in curated reference material. Weather-based farm planning and climate-adaptive recommendations draw on the same digital-climate-service literature that has long emphasized the importance of timely, location-specific dissemination for smallholder resilience. Table 4 summarizes representative advisory applications together with illustrative literature sources.

Table 4: Advisory applications of LLM-assisted systems for sustainable farm management, with representative literature sources

Advisory Application	Conceptual Approach Reported in Literature	Representative Sources
Crop selection / variety recommendation	Context-aware synthesis of soil, climate, and market data via conversational query	(Singh *et al*., 2024) [1] (Patne *et al*., 2025) [10]
Sowing date optimization	Integration of weather forecasts with crop phenological knowledge	(Zaremehrjerdi *et al*., 2025) [3] (Marinoudi *et al*., 2024) [8]
Irrigation scheduling	IoT/soil-moisture data combined with agronomic retrieval-augmented guidance	(Samuel *et al*., 2025) [9] (Wolfert *et al*., 2017) [19]
Nutrient management	Soil property data synthesized with fertilizer-practice knowledge sources	(Yang *et al*., 2024) [4] (Devi *et al*., 2025) [14]
Pest and disease diagnosis	Symptom/image description matched against curated diagnostic references	(Ameen *et al*., 2025) [2] (Elbasi *et al*., 2023) [11]
Weather-based / climate-adaptive planning	Forecast integration with locally relevant adaptive practice guidance	(Katiyatiya *et al*., 2026) [17] (Tzachor *et al*., 2023) [12]
Sustainable resource management	Multi-domain synthesis supporting resource-efficient, climate-resilient decisions	(Shahriar *et al*., 2025) [13] (Klerkx *et al*., 2026) [15]

3.4. Agricultural Knowledge Graphs and Multimodal Integration

A complementary strand of the reviewed literature explores structuring agricultural knowledge as graphs - explicitly encoding relationships among crops, practices, pests, and environmental conditions - to improve the precision with which retrieval-augmented systems answer farming-related questions. Knowledge-graph-informed retrieval has been described as particularly useful for compositional queries that require reasoning across multiple linked agronomic facts, complementing the more general document-level retrieval used in many deployed advisory chatbots. Multimodal integration, incorporating images (for example, of diseased leaves) alongside text and voice queries, has similarly been highlighted as an important direction, with vision-language models increasingly evaluated for tasks such as crop and weed classification and fruit-quality assessment; several reviewed advisory prototypes describe combining such visual analysis with LLM-based natural-language explanation to make diagnostic outputs more accessible to farmers without technical training.

3.5. Comparative Synthesis: LLM-Assisted versus Conventional Advisory Approaches

Figure 3 presents a qualitative, literature-grounded comparison of LLM-assisted advisory systems against conventional, agent-based extension approaches across several dimensions repeatedly emphasized in the reviewed literature: response accessibility, personalization, scalability, multilingual and low-literacy support, explainability, and continuous knowledge updating. This comparison synthesizes directional trends described across multiple reviewed studies rather than reporting measured experimental outcomes from a single controlled study, and should be interpreted as an interpretive synthesis.

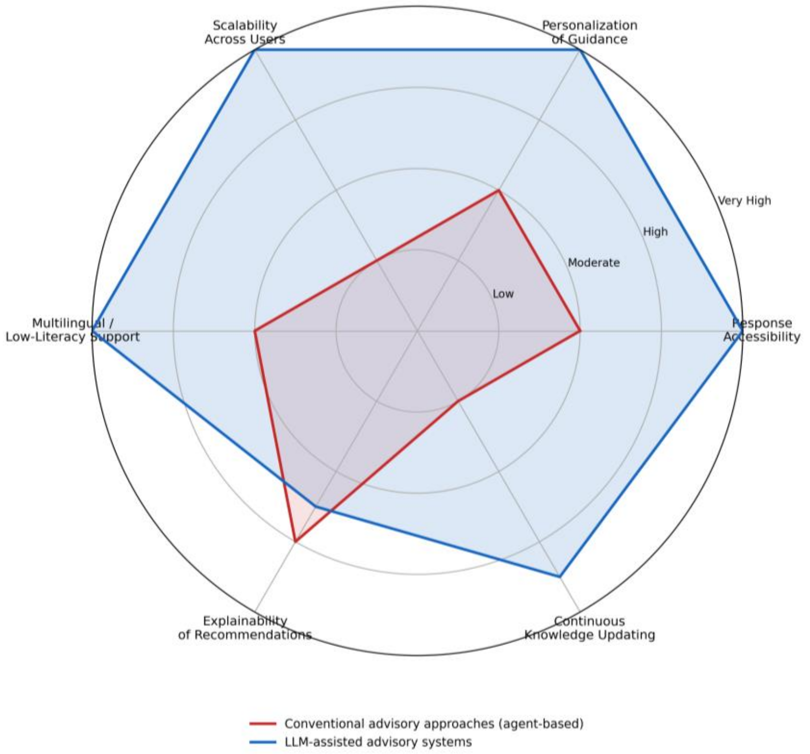

Fig 3: Conceptual comparison of LLM-assisted advisory systems and conventional agent-based extension approaches, synthesizing qualitative directional trends reported across the reviewed literature. Axis positions represent literature-reported relative tendencies rather than measured experimental scores from a single study.

The reviewed literature consistently describes LLM-assisted systems as offering substantially improved accessibility and scalability relative to conventional, agent-dependent extension services, particularly where voice-based or multilingual interfaces are deployed for low-literacy populations. Field-deployed conversational advisory platforms report engagement figures - such as tens of thousands of farmers and hundreds of thousands of queries across multiple countries - that would be difficult to achieve through in-person agent-based extension alone, underscoring the scalability advantage frequently cited in this literature. Personalization is similarly reported as a strength, since LLM-assisted systems can, in principle, tailor responses to farm-specific data in ways that generic printed or broadcast advisory content cannot. However, the reviewed literature is equally consistent in identifying limitations: general-purpose LLMs evaluated on agronomic reasoning benchmarks have been reported to achieve modest accuracy on complex, context-specific questions, and reviewed retrieval-augmented systems evaluated for soil-science queries have reported accuracy in the range of roughly two-thirds correct responses, with performance declining further for compound or highly contextual questions. Explainability, while improving through retrieval-based source attribution, is generally reported as less mature than the explainability achieved in narrower, single-task agricultural AI systems such as image-based diagnostic tools. Table 5 provides illustrative examples of the type of recommendation generated for common farm management scenarios, synthesized from patterns described across the reviewed literature rather than reproduced verbatim from any single deployed system.

Table 5: Illustrative examples of LLM-assisted advisory recommendations across farm management scenarios, synthesized from patterns described in the reviewed literature

Farming Scenario	Advisory Domain	Illustrative Nature of Generated Guidance
Smallholder cereal farm, semi-arid region, onset of dry spell	Irrigation scheduling	Guidance referencing local soil-moisture status and short-term forecast to suggest adjusted irrigation timing
Vegetable farm reporting leaf discoloration	Pest and disease diagnosis	Symptom-based diagnostic suggestion grounded in retrieved reference material, with a recommendation to confirm with local extension services
Mixed cropping system planning next season	Crop selection / variety recommendation	Comparative discussion of locally suitable varieties referencing soil and historical yield data
Farm preparing for anticipated erratic monsoon onset	Climate-adaptive farm planning	Synthesis of seasonal forecast information with locally relevant adaptive practice suggestions
Row-crop farm approaching topdressing window	Nutrient management	Nutrient-timing guidance referencing soil nutrient status and crop growth stage
Farm nearing harvest under uncertain weather	Harvest scheduling	Weather-informed discussion of harvest timing trade-offs

6. Evaluation Dimensions Reported in the Literature

Rather than presenting original performance measurements, this review synthesizes the evaluation dimensions that the literature on LLM-assisted agricultural advisory systems has employed, together with the general nature of reported outcomes. Recommendation accuracy and standard classification-style metrics (precision, recall, F1-score) have been applied primarily in retrieval-augmented question-answering evaluations, where exact-match, F1, BLEU, and ROUGE scores, together with embedding-based semantic similarity measures, have been used to assess response quality against reference answers. Response quality and user satisfaction have been assessed in several deployed systems through farmer surveys, engagement statistics, and qualitative feedback rather than solely through automated metrics. Decision consistency and computational efficiency - including retrieval time, generation time, and total response latency - have been reported as practical deployment considerations, particularly for voice-based and low-bandwidth contexts. Table 6 synthesizes representative reviewed studies, summarizing the AI approach, agricultural application, data sources, and general nature of reported findings, without reproducing precise numerical results from the original sources as though they were generated by this review.

Table 6: Comparative summary of representative reviewed studies on AI-based and LLM-based agricultural advisory systems

Study (First Author, Year)	AI Approach	Agricultural Application	Explainability Emphasis	Nature of Reported Findings
(Singh *et al*., 2024) [1]	Generative AI chatbot (RAG-based)	Multi-crop conversational advisory	Source-grounded responses	Large-scale multi-country farmer engagement reported
(Ameen *et al*., 2025) [2]	Voice-based RAG advisory system	Crop management, disease control (Bengali)	Retrieval-grounded responses	Composite quality score improvement over prior benchmark reported
(Zaremehrjerdi *et al*., 2025) [3]	Large reasoning models vs. conventional LLMs	Expert-curated agronomic reasoning benchmark	Reasoning trace generation	Reasoning models reported to outperform conventional LLMs on benchmark accuracy
(Patne *et al*., 2025) [10]	Multimodal LLM-RAG survey/framework	Multi-domain advisory, crop disease detection	Multimodal source integration	Literature synthesis indicating productivity and decision-making improvements
(Elbasi *et al*., 2023) [11]	Systematic review of AI in agriculture	Cross-domain agricultural AI	Not application-specific	Broad expansion of AI applications documented, with adoption barriers noted
(Tzachor *et al*., 2023) [12]	LLMs for agricultural extension services	Extension knowledge dissemination	Discussion of reliability considerations	Conceptual and applied potential for extension-service augmentation discussed

6.1. Statistical and Comparative Evaluation Approaches in the Literature

Beyond natural language generation metrics, several reviewed studies employ conventional statistical techniques to characterize advisory system performance and underlying agricultural data relationships. Analysis of variance has been used in comparative evaluations to assess whether differences in response quality across multiple candidate LLMs are statistically distinguishable rather than attributable to sampling variation. Correlation analysis has been applied to examine relationships between retrieved-context relevance and downstream answer quality, with reviewed retrieval-augmented systems reporting a positive association between the semantic similarity of retrieved content and the perceived accuracy of generated responses. Principal component analysis and regression-based approaches appear more frequently in the underlying precision-agriculture and remote-sensing literature that LLM-assisted systems draw upon, rather than in the LLM evaluation literature itself, reflecting a broader pattern in which advisory-system evaluation and agronomic data analysis remain somewhat separate methodological traditions that future integrative research could usefully bridge.

7. Discussion

7.1. The Role of Large Language Models in Agriculture

The reviewed literature positions LLMs as a coordinating, natural-language interface capable of synthesizing outputs from more narrowly specialized agricultural AI models and data sources into coherent, farmer-comprehensible guidance. This coordinating role has been described as extending beyond simple question answering toward orchestration of multiple underlying AI capabilities - vision, retrieval, structured data analysis - within a single conversational system, a pattern consistent with broader trends in general-purpose LLM agent architectures being adapted to the agricultural domain.

7.2. Intelligent Advisory Systems and Digital Agricultural Extension

Field-deployed conversational advisory platforms demonstrate that LLM-assisted systems can meaningfully extend the reach of agricultural extension, particularly in regions where trained extension agents are scarce relative to farmer populations. At the same time, digital extension literature cautions that technology deployment alone does not resolve underlying barriers - including connectivity, affordability, and digital literacy - that have long constrained the reach of both conventional and digitally mediated advisory services, particularly across sub-Saharan Africa and other resource-constrained regions.

7.3. Explainable AI for Farm Management

Explainability remains a comparatively underdeveloped dimension of LLM-assisted agricultural advisory systems relative to narrower, single-task agricultural AI applications such as image-based disease classifiers, where visual explanation techniques are comparatively mature. Retrieval-augmented architectures partially address this gap by allowing source attribution, but the reviewed literature suggests that fully articulating the reasoning chain behind a complex, multi-factor agronomic recommendation remains more challenging than explaining a single-label classification decision.

7.4. Comparison with Previous AI-Based Advisory Studies

Comparative reading of the reviewed literature suggests a progression from early, narrowly scoped agricultural chatbots using deterministic dialogue flows and limited language support toward more flexible, generative, retrieval-grounded systems capable of multilingual and, in some cases, multimodal interaction. This progression mirrors developments in the broader LLM literature, where retrieval augmentation and reasoning-oriented training have been introduced specifically to address the factual reliability limitations of earlier generative systems.

7.5. Practical Applications and Implementation Potential

Practical implementation examples described in the literature span multiple countries and languages, from multi-country, multi-crop conversational platforms to language-specific voice advisory systems designed for low-literacy rural populations. These implementations suggest that LLM-assisted advisory systems are transitioning from research prototypes toward operational deployment, though the reviewed studies also emphasize that sustained impact depends on ongoing knowledge-base maintenance, local contextual adaptation, and integration with existing extension infrastructure rather than technology deployment in isolation.

7.6. Limitations

As a literature-based conceptual review, this article does not present new empirical results, and its synthesis is shaped by the scope and quality of the underlying reviewed studies, several of which report findings from pilot or limited-scale deployments rather than large, randomized comparative trials. The qualitative comparison in Figure 3 reflects an interpretive synthesis of directional trends reported across multiple studies rather than a single controlled experimental comparison, and should be read accordingly. Because the LLM-and-agriculture literature is expanding rapidly, this review reflects the published evidence available at the time of writing.

7.7. Ethical Considerations

The reviewed literature raises several recurring ethical considerations relevant to LLM-assisted agricultural advisory systems. Data governance and privacy concerns arise where farm-specific data informs personalized recommendations, echoing broader agricultural data-ownership debates. Algorithmic bias and equitable access are highlighted as concerns where system training data or deployment infrastructure may inadequately represent smallholder, women, or marginalized farming populations. Over-reliance on AI-generated guidance, particularly where factual reliability is imperfect, has also been identified as a risk requiring continued human expert oversight and clear communication of system confidence and limitations to end users.

7.8. Future Research Opportunities

Future research directions consistently identified across the reviewed literature include the development of domain-adapted reasoning models specifically trained or fine-tuned for agronomic decision-making; standardized, agriculture-specific benchmarks for evaluating recommendation accuracy and reasoning quality; deeper integration of multimodal inputs (text, voice, image, sensor data) within a unified advisory framework; and continued attention to equitable deployment strategies that extend LLM-assisted advisory benefits to smallholder, low-connectivity, and low-literacy farming communities rather than concentrating benefits among better-resourced producers.

7.9. Toward Standardized Benchmarking

A recurring methodological theme across the reviewed literature is the absence of a widely adopted, agriculture-specific benchmark suite comparable to those established in other LLM application domains such as medicine or law. Expert-curated agronomic reasoning benchmarks represent an early step in this direction, revealing that even strong proprietary models achieve only moderate accuracy on open-ended agricultural science questions, particularly those requiring multi-step, context-specific reasoning rather than simple factual recall. The reviewed literature suggests that standardized benchmarking - encompassing not only factual accuracy but also explainability quality, response consistency across repeated queries, and performance across diverse linguistic and regional contexts - would meaningfully strengthen the evidence base for comparing competing advisory architectures and tracking progress over time.

8. Toward an Integrated Decision Support Framework

Synthesizing the architectural, application, and evaluation themes discussed above, Figure 4 presents an integrated conceptual framework in which a farmer's natural-language query, combined with multi-source agricultural data, is processed by an LLM-assisted decision-support core to generate personalized recommendations spanning crop planning, irrigation management, nutrient management, pest and disease control, harvest planning, and climate-resilient farm management.

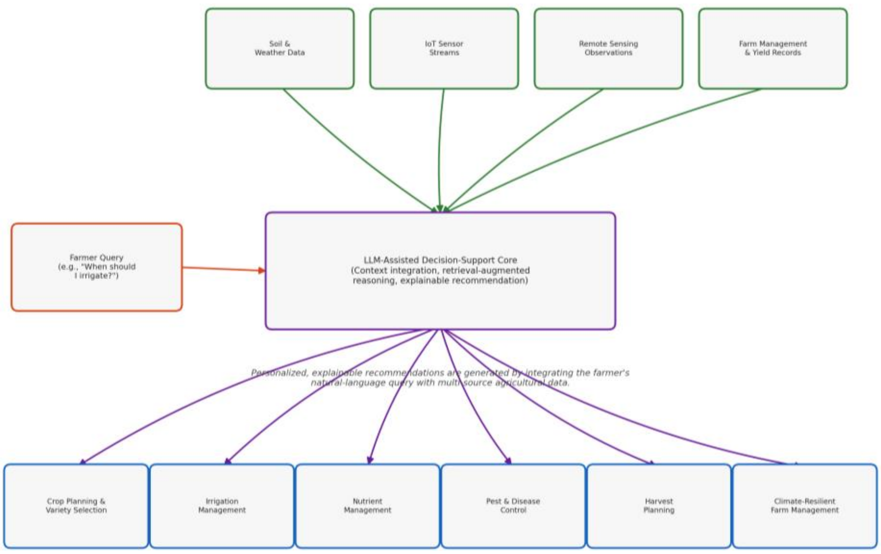

Fig 4: Integrated conceptual decision-support framework illustrating how a farmer's natural-language query, combined with integrated agricultural datasets, is processed through an LLM-assisted decision-support core to generate personalized recommendations across crop planning, irrigation, nutrient management, pest and disease control, harvest planning, and climate-resilient farm management.

9. Conclusion

This review has synthesized the existing scientific literature, technology on Large Language Model (LLM) based intelligent advisory systems in the area of sustainable crop farming practices. The evidence gives credence to the effectiveness and rapid evolution of LLM-based technologies (infrastructure that taking into account agricultural knowledge repositories, retrieval-augmented reasoning, context-aware recommendations, and explainability that provides unique highly relevant and timely opportunities for modern agriculture). From crop choice and irrigation scheduling to nutrients management and pest/disease detection to climate-based planning the various LLM applications confirms the diversity of its usage in the farming sector in the existing literature. It is possible to state that initiatives implemented in the field point to the possibility of extending the presence of agricultural extension beyond real limitations of agent-based charters. Using adapted reasoning, standardized evaluation metrics, and multimodal integration signifies the leading trends. For agricultural extension stakeholders and technology developers, it suggests the significance of grounding the LLM outcomes in validated local knowledge and using supervision by human experts in implementation instead of considering LLM as a substitute already capable of providing agricultural advice. For policymakers, it provides an insight regarding the necessity of developing the governance framework related to data secrecy, algorithmic discrimination, and fair usage, which are becoming the necessity for the further development of digital agriculture. If the LLM technologies are developed further and their reliability, explainability, and fairness issues remain addressed, LLM-assisted advisory systems can be widely utilized in sustainable farm management.

References

1. Singh N, Wang'ombe J, Okanga N, Zelenska T, Repishti J, Jayasankar GK, *et al*. Farmer.Chat: scaling AI-powered agricultural services for smallholder farmers. arXiv:2409.08916. c2024.
2. Ameen MR, Islam A, Aktar F, Rafat MS. KrishokBondhu: a retrieval-augmented voice-based agricultural advisory call center for Bengali farmers. arXiv:2510.18355. c2025.
3. Zaremehrjerdi H, Ganguly S, Rairdin A, Tranel E, Feuer B, Di Salvo JI, *et al*. Towards large reasoning models for agriculture. arXiv:2505.19259. c2025.
4. Yang S, Liu Z, Mayer W. ShizishanGPT: an agricultural large language model integrating tools and resources. arXiv:2409.13537. c2024.
5. Zhou Q, Li F, Wang J, Sun T. AgriGPT: a large language model ecosystem for agriculture. arXiv:2508.08632. c2025.
6. Liu Q, Zhang H, Wu Y. Harnessing large vision and language models in agriculture: a review. Frontiers in Plant Science. 2025;16:1579355.
7. Ryan M. The social and ethical impacts of artificial intelligence in agriculture: mapping the agricultural AI literature. AI & Society. 2023;38(6):2473-2485.
8. Marinoudi V, Benos L, Villa CC, Kateris D, Berruto R, Pearson S, *et al*. Large language models impact on agricultural workforce dynamics: opportunity or risk? Smart Agricultural Technology. 2024;9:100677.
9. Samuel DJ, Skarga-Bandurova I, Sikolia D, Awais M. AgroLLM: connecting farmers and agricultural practices through large language models for enhanced knowledge transfer and practical application. arXiv:2503.04788. 2025.
10. Patne A, Ranjane S, Walke O, Owhal R. AgriSaathi: a comprehensive survey on large language models and multimodal AI for agricultural advisory systems. International Journal of Multidisciplinary Research. 2025;7(6):1-15.
11. Elbasi E, Zaki N, Topcu AE, Abdelbaki W, Zreikat AI, Cina E, *et al*. Artificial intelligence technology in the agricultural sector: a systematic literature review. IEEE Access. 2023;11:171-202.
12. Tzachor A, Devare M, Richards C, Pypers P, Ghosh A, Koo J, *et al*. Large language models and agricultural extension services. Nature Food. 2023;4(11):941-948.
13. Shahriar S, Corradini MG, Sharif S, Moussa M, Dara R. The role of generative artificial intelligence in digital agri-food. Journal of Agriculture and Food Research. 2025;20:101787.
14. Devi DGP, Balachandra M, Kamath R. Explainable AI in agriculture: review of applications, methodologies, and future directions. Machine Learning: Science and Technology. 2025;6(1):012001-012025.
15. Klerkx L, Rose D, Fielke S. Scale, trust, and the digital divide: a systematic review of AI and ML for agricultural applications. Frontiers in Artificial Intelligence. 2026;9:1-22.
16. Anonymous. The opportunities and barriers in developing interactive digital extension services for smallholder farmers as a pathway to sustainable agriculture: a systematic review. Sustainability. 2025;17(7):3007.
17. Katiyatiya CLF, *et al*. A review of climate-smart agricultural extension services as a catalyst for sustainable farming in South Africa. Africa's Public Service Delivery and Performance Review. 2026;14(1):1-15.
18. Kairouz P, McMahan HB, Avent B, Bellet A, Bennis M, Bhagoji AN, *et al*. Advances and open problems in federated learning. Foundations and Trends® in Machine Learning. 2021;14(1-2):1-210.
19. Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big data in smart farming: a review. Agricultural Systems. 2017;153:69-80.