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An Explainable AI-Driven Framework for Precision Agriculture: A Comprehensive Survey

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Abstract. This review focuses on crop recommendation systems and provides a thorough explanation of Explainable AI (XAI) in precision agriculture. The paper charts the development of predictive models that have been published in the literature, from straightforward, comprehensible algorithms to extremely accurate 'black box' ensemble and deep learning models, as well as their lack of transparency, which may erode farmers' confidence. In order to make these black box algorithms comprehensible and useful, the paper focuses on two XAI frameworks – LIME and SHAP – that are currently in use. The accuracy and explainability trade-off, problems with data heterogeneity, and the requirement for relevant user explanations are just a few of the significant gaps in the evidence base that are highlighted by the paper's synthesis of the research. The paper's concluding remarks provide a potential path toward integrated, reliable, and comprehensible AI systems that will enhance contemporary sustainable agriculture.

Key words: crop recommendation system, deep learning, explainable AI (XAI), LIME, machine learning, precision agriculture, SHAP, trustworthy AI.

INTRODUCTION

The global agricultural industry is at a critical point in the twenty-first century. Food production will have to be greatly rethought in light of the increasing pressures of climate change, a growing global population and sustainable use of natural resources (Hasan, 2024; Khaliq et al., 2025). As it attempts to find a balance amid these competing demands, Precision Agriculture (PA) has emerged as a significant paradigm shift that employs technology to facilitate a data-informed approach at the field level. The development of Precision Agriculture has progressed significantly over a period of time, since the 1970s, as a result of advancements in digital technology (e.g., cellular networks) and the introduction of new AI algorithms into agriculture itself.

A key driver of the paradigm shift is an increased reliance of Artificial Intelligence (AI), and more specifically, Machine Learning (ML), being the analytical 'engine' to the modern agricultural paradigm. In particular, the rise of AI-based crop recommendation systems is an exciting new development with the potential to increase agricultural productivity and profitability for farms as they will be able to recommend the most suitable crops for a particular piece of land, based on soil and climatic condition, alongside previous crop yield for that land (Doshi et al., 2018; Senapaty et al., 2024).

The development of these models in agriculture has followed a similar pattern, prioritizing prediction accuracy over other metrics like interpretability. The earliest studies leveraged relatively simple classification algorithms leveraging Decision Trees, Support Vector Machines, and Naïve Bayes, that provided some level of interpretability but were challenged by the non-linear complexity of agricultural datasets (Doshi et al., 2018; Bandara et al., 2020). The agricultural research community very quickly began to incrementally exceed predictive accuracy with ensemble algorithms such as Random Forests and Gradient Boosting, that combine multiple predictive models using deterministic or probabilistic aggregation strategies to improve predictive performance and robustness (Kulkarni et al., 2018; Shams et al., 2024). More recently, the agricultural research community has gravitated towards the application of deep learning methods or articulated techniques that use deep learning as a type of 'base algorithm framework exhibited optimal performance with complex multi-modal data, such as imagery data captured by satellite or sensor data collected in real time and is even raised the potential upper ceiling of predictive accuracy (Hasan, 2024; Malashin et al., 2024).

The ongoing push for precision, however, has resulted in an 'interpretability crisis'. As models have become more complex, the internal reasoning conducted by models has become less clear, making them into 'black boxes'. This lack of transparency introduces an enormous barrier to adoption, as farmers, quite reasonably, are likely not going to want to trust predictive recommendations and take action on them without knowledge of how the prediction occurred. To address this problem, the research field called Explainable AI (XAI) is being developed. For models in agriculture, fundamental XAI frameworks such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) are being repurposed in a post-hoc sense to provide crucial signals on how a prediction was made (Srikanth et al., 2023; Akkem et al., 2025; Yaganteeswarudu et al., 2025).

In conclusion, developing an integrated link between these two fields is more important for the future of AI in precision agriculture than pitting one against the other. We are about to embark on a research phase where engineered XAI techniques are gradually integrated from the ground up with high-performance predictive models. The goal is to build decision-support systems that are strong, reliable, transparent, and able to produce information that farmers or users can use (Turgut et al., 2024; Martin et al., 2024; Shastri et al., 2025). By doing this, the agricultural community will be able to build a foundation of mutual respect and trust for utilizing AI's power to create a resilient, strong, and sustainable food system in the future.

The present survey considers a number of significant contributions to the expanding body of literature regarding AI-enabled Agriculture. First, it describes the many different forms of predictive models/recommendations for crops currently in use and/or under development, including everything from simple, easily understood algorithms through highly complex, accurate ‘Black Box’ approaches. Second, it provides a review of several important pieces of technology related to Explainable AI (XAI), including LIME (Local Interpretable Model-agnostic Explanations), SHAP (SHapley Additive exPlanations), and Counterfactuals, and discusses possible ways to adapt these technologies for use in developing accountability and transparency for AI used in agriculture. In addition, the survey synthesizes the literature to identify and review several critical gaps and problems regarding how we define model performance and model interpretability. In the final chapter of the work, we will introduce a new theoretical framework and research opportunities based on XAI, including how both are related to the design of connected crops recommendation systems.

The remainder of this article is clearly arranged and sequential in order to show these contributions logically. The second section outlines the rigorous survey methodology utilized to curate the literature. The third part starts with a thorough introduction to crop recommendation systems, including their technology and historical background. The fourth section then describes XAI techniques and their applications in agriculture. A critical analysis of the highlighted research possibilities, obstacles, and gaps will be provided in the fifth part. The survey's final segment will conclude with a summary of the overall contributions and the necessity of creating reliable and understandable AI to support sustainable agriculture in the future.

SURVEY METHODOLOGY

In order to obtain a thorough and precise understanding of the present-day situation, a methodical search strategy was used. Several different literature search databases, including Scopus, IEEE Xplore, Web of Science, and Google Scholar, all returned the same results when queried with similar keywords. The key words were ‘precision agriculture’, ‘crop recommendations’, ‘explainable AI’, ‘machine learning’, and ‘SHAP/LIME’. The inclusion of studies in the sample involved only peer-reviewed articles or significant conference proceedings published mainly during the prior 8 years that were explicitly focused on either predictive modeling or explainability (interpretable) within an agricultural context. The process for selecting studies included initial review of titles and abstracts to eliminate papers that were not relevant to the study. After this initial process was completed, a more complete examination of the content of each selected article was performed to determine its scientific soundness as measured by the rigor of the original study, the degree of detail in the analysis and the degree to which it related to the core themes of the survey.

REVIEW OF CROP RECOMMENDATION SYSTEM

Crop recommendation systems have arisen within a clear trade-off between interpretability, forecast accuracy, and model complexity. Traditional machine learning models were used in the first generation of crop recommendation systems, which profited from these models' simplicity. Decision Trees (DT), K-Nearest Neighbors (KNN), and Naïve Bayes (NB) were appealing due to their ease of interpretation and ability to display the model's decision logic as straightforward flow-chart rules (Doshi et al., 2018; Bandara et al., 2020; Senapaty et al., 2024). However, the performance of these devices was compromised. First-generation crop recommendation models were unable to capture complex and non-linear relationships inherent in high-dimensional agricultural data, which therefore restricted the predictive power and accuracy of these first-generation models compared to models that utilized higher complexity (Kulkarni et al., 2018; Chitra et al., 2025).

To combat these limitations of accuracy, researchers have utilized more elaborate combination and advanced methods. Both Random Forests (RF) and Gradient Boosting (XGBoost), which are ensemble models with multiple base models of various forms created in succession that act as base models to stabilize predictions, quickly became the 'workhorses' of crop recommendation methods due to their consistent improvements in robustness and accuracy (Kulkarni et al., 2018; Shams et al., 2024; Chitra et al., 2025). Another recent group of model types that has yielded some promise are Deep Learning (DL) models or architectures, such as Convolutional Neural Networks (CNNs), that utilise very complicated models to draw information from complex data types such as satellite or drone imagery (Hasan, 2024; Malashin et al., 2024; Khaliq et al., 2025). These more advanced models reported improvements in predictive accuracy; however, due to the nature of the models and complexity of the underlying architecture of the model, they do provide challenges for explainability, and it can be very difficult to explain the model's recommendations.

New models and assorted data sources are moving advanced systems from improved individual crop recommendations to fully connected smart agriculture systems. The new goal is not simply to recommend an optimum crop, but a whole way in which to manage crops. For example, systems based on AI may now aggregate soil analysis and variable irrigation and fertiliser recommendations to create their own system to maximise efficiency of use (Khaliq et al., 2025). IoT devices passively tracking and monitoring farms to provide real-time updates and support adaptive decision making, coupled with historical year data with yield and market trends to support long-term strategic agricultural planning (Martin et al., 2024; Baishya & Dutta, 2025; Baraian et al., 2025). This is the multidimensional development pipeline and will be next generation, where AI technology is not only recommended optimum information, but operates with some central intelligence and a holistic approach to farm operations.

Dataset Considerations and Feature Engineering

Table 1 displays the criteria of crop recommendation studies that employs the well-known Crop Recommendation Dataset as the starting dataset, which consists of important features such as soil nutrients (N, P, K), climate, and soil pH to develop models for recommending crops (Kulkarni et al., 2018; Kumar & Kumar, 2024; Senapaty et al., 2024). However, the area is rapidly moving beyond the traditional Crop Recommendation Dataset, in order to create more robust and complete agricultural intelligence systems. To create automated disease detection systems, for example, researchers have started experimenting with datasets that increase model capabilities, such as image datasets of plant diseases (Madharam et al., 2024; Sharma et al., 2024; Dhage et al., 2025;). When utilizing a Crop Yield Prediction Dataset, which integrates a more deliberate collection of features, such as historical yields, weather patterns, and remote sensing products to capture NDVI, there is a notable shift in agricultural intelligence from crop recommendation to forecasting and optimization (Hasan, 2024;

Malashin et al., 2024; Jagan Mohan et al., 2025). The most advanced technologies already show a clear path toward more complex and comprehensive applied systems with multidimensional, data-dense precision agriculture by using Early Crop Classification Datasets, which incorporate time-series satellite image datasets that monitor and classify crops early in the growing season (Chan et al., 2023).

Table 1. Datasets and feature types in crop recommendation

Sr. No.	Name of dataset	Features	Useful for	Used in references
1	Recommendation Crop Dataset	Soil Nutrients: Nitrogen (N), Phosphorus (P), Potassium (K); Climatic Conditions: Temperature, Humidity, Rainfall; Soil Property: pH	Identifying the optimal crop based on specific soil and environmental parameters.	Doshi et al., 2018; Kulkarni et al., 2018; Bandara et al., 2020; S & Parvathi, 2021; Musanase et al., 2023; Cartolano et al., 2024; Dey et al., 2024; Kumar & Kumar, 2024; Madharam et al., 2024; Martin et al., 2024; Senapaty et al., 2024; Shams et al., 2024; Sharma et al., 2024; Turgut et al., 2024; Akkem et al., 2025; Baishya & Dutta, 2025; Baraian et al., 2025; Chitra et al., 2025; Khaliq et al., 2025; Shastri et al., 2025; Yaganteeswarudu et al., 2025
2	Plant Disease Datasets	Images of plant leaves and stems in healthy and diseased conditions	Automated plant disease detection and classification from images	Madharam et al., 2024; Sharma et al., 2024; Dhage et al., 2025
3	Crop Yield Prediction Datasets	Past crop yield records, climatic trends, soil classification data, fertilizer application records, and remote sensing indicators (e.g., NDVI)	Forecasting agricultural output and optimising farm management for better productivity	Srikanth et al., 2023; Hasan, 2024; Malashin et al., 2024; Venugopal et al., 2024; Jagan Mohan et al., 2025
4	Early Crop Classification Datasets	Time-series satellite imagery from sources like Sentinel or Landsat	Classifying different crop types from satellite data early in the growing season for monitoring and planning	Chan et al., 2023

A review of AI approaches in crop recommendation

Table 2 provides a review of a selection of research papers that have incorporated the use of Artificial Intelligence (AI) in agriculture and in the area of crop recommendations. The studies reviewed in this article utilize various algorithms such as Random Forest Classifier (RFC) and Stochastic Gradient Descent Classifier (SGDC). Many researchers address class imbalance within the training dataset by using Synthetic Minority

Over-sampling Technique (SMOTE) which creates synthetic examples from minority classes to create a balanced dataset, thus leading to improved classifier performance (Senapaty et al., 2024). Performance of the models is evaluated with numerous metrics including Logarithmic Loss (LogLoss) which is considered a probabilistic classification performance metric and penalizes predictions that have lower confidence.

Table 2. Comparative analytics of crop recommendation systems using ML and DL

Ref.	Objective	Methodology	Novelty	Accuracy	Limitation	Future direction
Senapaty et al., 2024	Create a system to assist farmers in selecting suitable crops	Comparative analysis of ML classification models	Head-to-head comparison of standard classifiers	SGDC 100% after SMOTE	Limited to the specific dataset and geographical context	Apply XAI methods and use a larger, more diverse database
Kumar & Kumar, 2024	Create a reliable and transparent crop recommendation solution	ML model combined with an XAI framework (SHAP or LIME)	Designed with interpretability in mind for farmers.	Naïve Bayes (99.39%)	Computational overhead from XAI; explanations may be complex	Refine XAI methods to be more user-friendly for end users
Kulkarni et al., 2018	Improve accuracy in crop recommendations using ensemble modelling	Ensemble learning techniques (Bagging, Boosting, Voting)	Testing ensemble methods to maximise predictive performance	Ensemble Model 99.91%	Increased model complexity and computational cost	Test the ensemble model on more varied datasets for generalisability
Chitra et al., 2025	Improve accuracy and provide explainability through advanced ensembling	Stacked Ensemble Model combined with XAI techniques	Novel integration of stacking ensemble with interpretability methods	Weighted Stacked Ensemble (99.09%)	Very high model complexity, difficult to tune and deploy	Improve computational efficiencies and integrate other data sources
Baishya & Dutta, 2025; Sharma et al., 2024; Baraian et al., 2025; Khaliq et al., 2025	Establish a crop recommendation model for low-power systems; Create a multi-feature web-based platform; Refine recommendations through market trends; Develop an integrative system	TinyML; Integrated ML/DL models; Recommender system enhanced with trend analysis; AI-driven system combining models	Edge deployment for offline real-time results; Tri-fold web tool; Holistic approach linking soil, irrigation, and fertiliser	Optimised RFC for TinyML (98.4%); XGBoost (99.3%)	Trade-off between model accuracy and footprint; Challenges in integrating separate models; High data dependency	Improve downsized model accuracy; Adopt IoT sensors; Validate across regions and develop farmer-friendly tools

Table 2 (continued)

Jagan Mohan et al., 2025	Deploy AI and XAI for accurate crop yield forecasting	Advanced AI/DL models for yield prediction, augmented with XAI	XAI applied to the complex task of yield prediction	R2 Score: up to 0.92	Accuracy is sensitive to unpredictable factors like extreme weather	Develop lightweight models for limited-resource settings; integrate real-time data
S & Parvathi, 2021	Construct a crop recommendation system using an ANN	A feed-forward Artificial Neural Network (ANN) model.	Use of a neural network for crop recommendation	Logloss: 0.00034 (lower is better)	ANNs can be prone to overfitting on smaller dataset	Include seasonal crops and integrate weather and economic factors.

Many of the papers referenced also exhibit a trend of employing Explainable AI (XAI) methods to enable visibility and trust in models that farmers see as overly complicated ‘black box’ systems. Overall, the papers highlight accuracy (almost always greater than or equal to 99% on generic datasets (Kumar & Kumar, 2024; Senapaty et al., 2024), although generalizability and high complexity are limitations.

The majority of limitations identified through an extensive literature review were methodological in nature, including heavily relying on inflated accuracy metrics without adequately discussing the size of the dataset or employing a sound cross-validation strategy. Very high accuracy (e.g. 100%) can indicate possible overfitting models or limitations of the dataset and consequently should be interpreted with caution. In addition, models that trained on hyper-localized data sets often lack the ability to generalize outside of their training area. Thus, for model to be utilized within practical settings, subsequent research teams will need to provide more diverse datasets (IoT and Satellite Images) that can be associated with their specific purposes and/or present model descriptions that are easier for end-users to understand.

MAKING AI TRANSPARENT WITH EXPLAINABLE AI (XAI)

The increasing complexity of AI technologies in agriculture may potentially increase opacity and raise demands for AI technology transparency. Explainable AI (XAI) approaches, which are crucial to developing ethical and practical agricultural AI systems, are then discussed in this section. Finding the ‘black box’ and offering advice to developers, agronomists, and producers to comprehend and methodically process AI recommendations is the main goal of XAI.

Explainability is significant and multifaceted when it comes to the uptake and efficacy of technology in agriculture. First, confidence is established through explainability. Farmers can transform an untested command into a reliable record of suggestions when they comprehend the reasoning behind an action or recommendation (Shams et al., 2024; Yaganteeswarudu et al., 2025). Second, explanation enables people to use their information and take purposeful, meaningful behaviors. For instance, the user is aware that their next course of action is potash beefed if it is explicitly advised not to cultivate a crop (Srikanth et al., 2023; Turgut et al., 2024). Lastly, explainability is essential for debugging and model verification because agronomists and researchers are using models and assessment. Specifically, explainability helps to find biases, mistakes, and places for improvement, resulting in better, more predictive models (Cartolano et al., 2024; Akkem et al., 2025).

Several XAI methods focus on local explanations that break apart the reasoning of a single prediction to answer the immediate question, 'Why did the model make this recommendation at my location?'. Although local explanations can be valuable for practical decision-making, one of the most recognised local explanation methods is called LIME, which stands for Local Interpretable Model-Agnostic Explanations. LIME works by introducing small perturbations in the input data (for example, small adjustments in the pH or rainfall value) and examining how the model changes. LIME then uses a simpler and more interpretable model (for example, a linear regression) to fit the local area and the output will be a locally linear approximation of a typically complicated model. Yaganteeswarudu et al. (2025) demonstrate how LIME was able to indicate which soil parameters became increasingly important within a location crop recommendation in a very intuitive manner.

Another influential and extensively used approach is the SHAP framework (SHapley Additive exPlanations), which originates from cooperative game theory. SHAP assigns an 'importance value' to each feature indicating how much each feature has contributed to pushing the prediction towards (or away from) the predicted outcome. In local explanations, this is frequently presented with force plots that visually display how nitrogen (N), phosphorus (P), and temperature, for example, led to a recommendation for one specific crop (Shams et al., 2024; Shastri et al., 2025). SHAP's strong theoretical grounding provides a meaningful approach to fairly distributing portions of the model's decision to each of the input features.

Beyond just interpreting individual predictions, it can be helpful to consider the behaviour of the model as a whole. Global explanations provide a macroscopic view of which features are the most important across the full dataset. SHAP is very flexible to provide global explanations in that it can take and simply sum the contributions of the SHAP values for individual observations to generate a global summary plot where features are ranked by importance across the full dataset, and how the model is arguably making general decisions (Shams et al., 2024; Shastri et al., 2025). Global explanations by SHAP can also be elaborated on further and extended with the use of Counterfactual Explanations, which provides a very simple way to describe the constraints which define the model when responding to 'what if' questions. A counterfactual explanation will often state something like 'If your rainfall had been increased by 20%, your recommended crop would have been Soybean instead of Maize,' and provides simple insight into how the model responded to certain characteristics (Turgut et al., 2024; Akkem et al., 2025).

Extending the XAI Toolkit: Other Modalities

Although LIME and SHAP are the most widely used post-hoc explanation techniques used for crop recommendation research (Hasan, 2024; Madharam et al., 2024; Shams et al., 2024). Despite their intuitive nature, LIME's foundational methodology is often hindered by instability. The use of perturbation sampling to generate localized synthetic data points can produce explanations that vary widely based on the data set's distribution. This may lead to conflicting feature importance rankings for a given data point across different runs, causing users to lose faith in critical agricultural use cases and situations (Yaganteeswarudu et al., 2025).

Similarly, SHAP has significant computational challenges when it comes to calculating exact Shapley values since this requires evaluating every possible combination of features. For large-scale agricultural data sets, especially those produced by relatively deep networks with thousands of parameters, this is computationally prohibitive. As a result, researchers are often forced to resort to using approximations (e.g., TreeSHAP or KernelSHAP), which presents a clear trade-off by sacrificing precise interpretability in exchange for limiting extremely high computational costs, which ultimately hinders real-time, on-device deployments (Kumar & Kumar, 2024; Shastri et al., 2025).

Counterfactual explanations offer active recourse beyond merely explaining the predictive models of feature attribution classes (Srikanth et al., 2023; Turgut et al., 2024). While attribute-based approaches inform farmers of features driving a prediction, counterfactual explanations identify the least amount of changes that would result in a different prediction, providing a pragmatic means for farmers to act prescriptively with information presented (Turgut et al., 2024; Akkem et al., 2025).

Causal explanations endeavour to mitigate a limitation associated entirely with correlation, in descriptive models like LIME and SHAP by organising feature relationships through a causal dependency model (Martin et al., 2024; Jagan Mohan et al., 2025; Khaliq et al., 2025). This limitation regarding correlation is a necessary consideration in agriculture, as predictors for crop yield are often based on correlated features based on non-causal proxies, such as NDVI or canopy greenness (Martin et al., 2024; Venugopal et al., 2024). Causal frameworks offer farmers a sense of viability in predicting and enacting a response based on the intervention that may be rooted more in an agronomically based driver instead of coincidental statistical relationships (Jagan Mohan et al., 2025; Khaliq et al., 2025).

Concept-based explanation goes above feature-level function and represents model prediction behaviours to more human-interpretable agronomic concepts like ‘water stress’, ‘nitrogen deficiency’, and ‘leaf discoloration’ rather than equivalent numeric feature scores (Cartolano et al., 2024; Kumar & Kumar, 2024; Shams et al., 2024). Using concept-based explanations enhances interpretability and trust as model explanations are more consistent with how farmer experts cognitively process information resulting in improved decision making compared to raw feature saliency maps (Cartolano et al., 2024; Shams et al., 2024; Shastri et al., 2025).

Another intuitive form of interpretation has gained prominence – Example-Based Explanations (EBE). Instead of attributing a prediction to features, Example-Based Explanations explain a prediction by locating and displaying exemplars (i.e., specific, real-life examples) from the training data that are most similar to the example at hand. For a farmer, this is highly interpretable, converting a complex recommendation to a relatable context; for example, ‘This system recommends maize because with your soil composition (high N, low P) and weather forecast comparison, your field is 95% similar to a case from last season in the neighbouring county that had high-yield’. By basing explanations in concrete, previous instances, these types of explanations help bridge the gap between abstract, noncontextual data with real experiences from farming and they build a sense of trust through analogy and shared experience (Cartolano et al., 2024; Martin et al., 2024; Shams et al., 2024).

Interaction between Datasets and XAI

Table 3 provides a comparative summary of these studies that utilize Explainable AI (XAI) in agriculture decision-support systems. In all of these studies the general aim is to increase transparency and trustworthiness of farmers by pairing high performant machine learning models with XAI frameworks, such as SHAP and LIME. The empirical data represented in Table 3 show the theoretical constraints of XAI methods explained before. As an example, LIME is considered unstable and thus creates complication when implementing in practice. In addition, using SHAP requires an additional level of technical overhead when implementing in practice. Consequently, a pathway for future research that spans across all studies is the need to create more intuitive, user-friendly, and accessible XAI methods that enable farmers the ability to receive a practical, understandable sense of the model's product.

Table 3. Comparative analytics of crop recommendation systems using XAI

Ref.	Objective	Methodology	Novelty	Limitation	Future direction
Kumar & Kumar, 2024	Build a trustworthy and transparent crop recommendation system	ML model integrated with an XAI framework (SHAP or LIME)	Adds transparency and trust to standard crop recommendation models	Explanations might be too technical; XAI adds computational overhead	Focus on making XAI techniques more accessible and intuitive for end-users
Chitra et al., 2025	Enhance accuracy while ensuring interpretability	A Stacked Ensemble Model combined with an interpretability layer	Combines a powerful stacking model with interpretability for high performance and transparency	Stacked models are complex; explanations may be less straightforward	Improve performance with a focus on computational efficiency and new data sources
Srikanth et al., 2023	Empower farmers with an explainable soil recommendation model for rice	ML model focused on soil parameters for rice, with XAI to justify recommendations	Hyperspecialisation on rice, providing actionable insights	Not generalisable to other crops	Extend to other crops, improve based on farmer feedback, and collect more data
Shams et al., 2024	Study how XAI integration affects agricultural decision-making and user trust	ML model paired with XAI, focusing on human-computer interaction	Focuses on the impact of XAI on end-users	Emphasis is on qualitative impact rather than advancing ML performance	Improve model scalability
Yaganteeswarudu et al., 2025	Enhance transparency in smart farming with local, case-by-case explanations	ML model using LIME to explain individual predictions	Application of LIME for producing instance-level explanations	LIME explanation can be unstable	Focus on user-centric design and simplified explanations for farmers

RESEARCH GAPS, CHALLENGES, AND FUTURE DIRECTIONS

While much has been accomplished in advancing the use of AI in precision agriculture, significant barriers still remain at a critical intersection between technology and agriculture. Overcoming barriers is vital to creating resilient, reliable and sustainable systems. In this section we highlight the main gaps in research and provide a potential framework for future research to address the gaps.

Selecting data and models is a significant barrier. The agriculture domain negatively is affected by Data Scarcity and Heterogeneity; since across regions and climates, there is no large, standardized public data set, it is difficult to train a model that will generalize well. There is also an Explainability-Accuracy Trade-Off that can be an ongoing conflict regardless of domain where researchers and developers have to select between a high accuracy, but opaque 'black box' models (e.g., deep neural networks) vs lower accuracy, but naturally interpretable models (e.g., simple decision trees) (Cartolano et al., 2024; Jagan Mohan et al., 2025); the tension to resolve the conflict, and recognise performance or trustworthiness is a major hurdle.

Additionally, there is a glaring absence of human-centric considerations in the cases of XAI. To date, very few, maybe even no systems provide User-Centric Explanations. Again, explanations almost always relate to caveats of model features that are technical and not related or meaningful to a farmer. This challenge is also associated with the challenge of Evaluation of Explanations because there are no universally agreed-upon measures to determine 'goodness' of an explanation in practical agricultural or farming contexts. These characteristics; fidelity to the model, usability in the world, a degree of impact on the farmer’s trust, are still subjective and problematic (Cartolano et al., 2024).

To fill the existing void between the newer technology-enabled changes in user-centric explanations and the farmer who needs them clearly communicated, the discussion around user-centric explanations must grow. It is critically essential that the XAI output is made applicable by being articulated in clear, practical recommendations that the farmer can immediately relate to. A good example of this transition might be through the development of explanation interfaces that use LLMs (Large Language Models). A LLM can assist in converting highly technical XAI output, such as SHAP values that reflect a significant weight of importance to a feature (for example, Soil pH), to a more user-friendly format (natural language). For example, rather than providing the farmer with a complex force plot, the farmer would see a simple prompt such as, ‘The recommendation from the system is to not plant wheat here because the current soil pH is 5.2 (too low) and you may want to apply agricultural lime before planting’.

The limitations to the uptake of XAI related to the models’ reliability are accompanied by various social and economic real-world barriers, along with limited digital literacy and infrastructure challenges (Bandara et al., 2020; Musanase et al., 2023; Dhage et al., 2025). One barrier is simply the digital divide and limited AI literacy among farmers, especially full-time farmers in urban and developing sectors, where higher order and complex XAI visualisations will likely not be accessible or useful (Musanase et al., 2023; Baishya & Dutta, 2025; Dhage et al., 2025). Studies have noted that XAI interface designs prioritise data scientists (likely working in urban settings), and therefore mean little for the practical usability of the interfaces by farmers (Kumar & Kumar, 2024; Akkem et al., 2025; Shastri et al., 2025).

Moreover, economic feasibility and material inequity are significant challenges. Agriculture precision modelling frameworks normally entail the use of expensive sensors, drones, cloud computing for data processing, and subscription analytics services to infer and map, and all this may be out of reach for smallholder farmers (Bandara et al., 2020; Musanase et al., 2023; Baishya & Dutta, 2025; Chitra et al., 2025). If these economics are disproportionate, important research in the agricultural space has suggested to modify inequity by using frugal AI, which identifies taking low inputs such as smart phone imagery, low-cost sensor kits, and deploying on edge computable methods with TinyML technology (Musanase et al., 2023; Baishya & Dutta, 2025).

Data governance and trust between owner and product remains equally essential. There is still uncertainty regarding ownership, privacy, and commercial reuse possibilities of sensitive existing yield and soil records (Akkem et al., 2025; Baraian et al., 2025; Khaliq et al., 2025). There are large initiative working together like the European Agricultural Data Space being set up to make an ecosystem of agricultural data interchangeable and to provide equitable ways to share data about agriculture, existing efforts to achieve this includes the SAGE Project which aims to facilitate transparent, secure, and fair data-sharing ecosystems throughout Europe. Emerging solutions include possible models that safeguard ownership such as Federated Learning, which facilitates local model training without the transfer of raw data from the farmer to a cloud platform (Baraian et al., 2025; Khaliq et al., 2025).

Although the literature labels this problem as related to data governance and Federated Learning (FL), the importance of this issue cannot be understated. The entire concept of precision agriculture rests on collecting large amounts of sensitive farm data. This creates a core contradiction: Farmers are typically reluctant to share sensitive farm data about their soil health, yields, and operational data with a central server that they could lose competitive advantage or trustworthiness (Akkem et al., 2025; Baraian et al., 2025; Khaliq et al., 2025).

This importance is precisely where Federated Learning (FL) opens the door as a key future opportunity, or at the least a partial solution to this critical issue. FL stores the models locally on the agricultural producers own devices, either on the edge computer of the tractor (or similar device (e.g., combine, etc.) or on the producers own servers). Each farm will only send its model updates (gradients or weights, not raw data), to a central server for aggregation. In this way, Federated Learning maintains 'privacy-by-design' and retains the agricultural producers data on-premises and private to their farms (Baraian et al., 2025; Khaliq et al., 2025).

Integrating FL with XAI creates its own new research frontier. How can a global model based on federated learned updates generate an explanation for a specific farmer's field? The approaches to developing SHAP or LIME component values for a federated model is not trivial, or computationally inexpensive. Future work must use FL, for privacy, but also co-design Federated XAI frameworks that can provide meaningful, local explanations for a farmers field but without sacrificing the privacy that FL was designed to protect. The integration of privacy, federated learning, and explainability will be one of the largest technical and ethical barriers to account for in real-world projects (Musanase et al., 2023; Akkem et al., 2025; Khaliq et al., 2025).

Without addressing the economic feasibility associated with inputs, literacy, and governance informs of the potential of widening inequities, as opposed to reducing inequities in agricultural decision-making (Bandara et al., 2020; Musanase et al., 2023; Akkem et al., 2025; Dhage et al., 2025).

Finally, there are significant technical challenges concerning implementation and performance that need to be addressed. One of the most significant challenges is Scalability and Real-Time Performance. Even if AI can make sense of cultivars and environmental variables, for it to be effective in practice, it needs to produce insights instantaneously. Still, engineering this approach and running computationally expensive, XAI approaches on low-power, resource-constrained edge devices (i.e., via TinyML), and then generating explanations in real-time is a challenge to engineering that will make or break on-farm feasibility.

To tackle these concerns, the research community must focus on a few strategic directions. First, improving foundational models and benchmarks is a highest priority. This means developing Hybrid and Naturally Interpretable Models that are both accurate, and designed to be transparent, instead of relying on potentially dubious, post-hoc explanation methods (Jagan Mohan et al., 2025). This direction must arise from a community-wide effort to develop agricultural XAI standards where agricultural researchers develop shared public datasets, and standardized evaluation approaches to encourage collaborative and comparative research.

The future of agricultural AI should also involve more interactivity and intelligence. The next important step is designing Human-in-the-Loop (HITL) and Interactive XAI systems, whereby farmers will question the AI through 'what-if?' inquiries and explore different assumptions to aid in comprehending the systems rationale. This interactivity will be even more crucial while we increase the Integration of Multimodal Data with XAI. A primary research frontier is developing methods for explaining models that integrate complex data streams, such as tabular soil data, time-series climate data, IoT sensor data, and satellite data.

A notable advancement in dealing with the 'Domain-Specific Explanation Language' could derive from outside the conventional XAI. Generative AI and Large Language Models (LLMs) can really help to supplement the explanation process. The difficulty doesn’t lie in creating a SHAP plot, but how we communicate its technical meaning into action-oriented advice to human(s). This is precisely what Generative AI does very well. A future XAI structure could be conceived as a two-stage process:

1. An ML model (e.g., Gradient Boosting) makes a crop prediction.
2. An XAI method (e.g., SHAP) explains 'Why?' (e.g., 'Potassium = 45 mg kg^{-1} is the highest contributing negative feature.')

This output then generates a usable explanation for the LLM, trained from domain-specific knowledge base and communicates, in conversational form, grounded in the research-derived technical output, an explanation such as the following: 'Your soil is deficient in Potassium (45 mg kg^{-1}), which is an important nutrient for corn. The model is suggesting you use soybeans since soybeans have lower Potassium needs. Another option is to move ahead with corn, but you will need to add a potassium-based fertiliser.'

I think this 'XAI-to-LLM' pipeline is a potentially powerful merge; they are much more than just showing feature importance; you now have a cooperative and prescriptive experience developing real and insightful dialogue with the farmer, and ultimately creating a truly user-centred and understandable AI system (Cartolano et al., 2024; Shams et al., 2024; Jagan Mohan et al., 2025).

Ultimately, the goal is to bridge the communication gap between the AI and the farmer. This is to create Domain Specific Explanation Languages. It is not enough to simply provide a farmer with a technical output of 'pH value of 5.2 is the largest contributor', but rather translate this into actionable advice, 'this soil is too acidic for this crop'. Learning to speak the language of the end user will allow us to enable systems powered by XAI to be not only intelligent but intelligible; and thus, create trust needed to have a real impact in modern agriculture.

Table 4. Identified research gaps, key challenges, and future research directions in AI-Driven precision agriculture

Category	Key gaps & challenges	Future directions / Opportunities
Data & Modelling	• Data scarcity and heterogeneity (several datasets do not share a standardized format) • Low generalizability • Explainability-integrity-accuracy trade-off	• Build shared public agricultural datasets • Develop hybrid and inherently interpretable models • Build agricultural XAI benchmarks and standards
Explainability (XAI)	• Lack of user-centric explanations • No standard evaluation metrics to denote 'good' explanations • Explanations are too technical for farmers	• Design domain-specific explanation language • Develop interactive and Human-in-the-Loop XAI • Include conversational XAI with LLM (XAI→ LLM channel)
Socio-Economic Barriers	• Digital divide and low AI literacy • Poor infrastructure • Interfaces that are designed for data scientists not the farmer • Costs of sensors, drones, cloud services	• Frugal/low-resource AI (smartphone imagery, low-cost sensors, TinyML, edge computing) • Farmer-centric UI and low complexity visualizations
Privacy & Data Governance	• Lack of trust in data ownership & data producers • Fear of competitive disadvantage • Unclarity on data-sharing policies	• Federated Learning (FL) for on-device training • Privacy-preserving model aggregation (no raw data sharing) • Development of Federated XAI for local explanations
Technical Deployment	• Limited scalability • Expensive compute cost associated with XAI • Absence of real-time inference capabilities on edge devices	• Optimize XAI to run on low-power levels (TinyML) • Scalable inference pipelines that support real-time • Efficiency with explainability for multimodal data (soil, climate, sensor, satellite)
Human-AI Interaction	• Lack of decision support in dialogue-based context • No user-friendly 'actionable insights'	• Interactive AI systems (what-if...) • LLM-powered explanations to translate model outputs into actionable farming recommendations
Equity Risks	• Tech likely to exacerbate inequality for smallholder or developing world farmers	• Prioritize affordable, transparent, and locally deployable AI in order to enable equitable access

Table 4 compiles important research gaps, aspects of real-world challenges, and future possible opportunities in advancing AI to the precision agriculture domain. Recent literature provides considerable evidence about the importance of the gaps that have been identified regarding technical data modeling and evaluation, (Cartolano et al., 2024; Jagan Mohan et al., 2025). Furthermore, there continue to be significant barriers that exist due to socio-economic status and the digital divide (Musanase et al., 2023; Dhage et al., 2025). In addition to these gaps are more pressing issues related to data governance and privacy (Khaliq et al., 2025; Baraian et al., 2025), as well as the persistent difficulties that exist in creating effective Human-AI interaction (Shams et al., 2024).

CONCLUSIONS

This article presents a review of crop recommender systems driven by artificial intelligence (AI) and the increasing need for explainable AI (XAI) in agricultural decision support systems. Although sophisticated algorithms, including Random Forests and Neural Networks, and combinations (ensemble) are capable of producing highly accurate forecasts, their black box form can impede their ability to be used in real-world agricultural applications. We also highlighted that many current XAI models extend beyond conventional feature attribution models (LIME, SHAP) to include counterfactual, causal and concept-based explanation formats, each increasing decision support by offering actionable and human-aligned interpretability.

The review also highlights the urgency of open gaps in data heterogeneity, the explainability-accuracy trade-off, and notably, the barrier toward uses from a non-technical contributor lens including cost, digital literacy, and confidence in farm data governance. We contend that agricultural AI needs to consider trust, equity, accessibility, and economic sustainability in addition to accuracy, all of which are supported by privacy-preserving learning and intuitive explanation design. In order to guarantee that AI recommendations are not only accurate but also interpretable, practical, and socially deployable at scale, future work should give priority to collaborative, human-centered frameworks (such as design thinking).

In the end, what will ultimately determine whether AI is successful in precision agriculture will be its ability to get accepted and trusted in the field, and how useful it is to agriculture, versus simply providing a high degree of accuracy in a laboratory environment. If the agricultural sector incorporates principles of human-centered design, validated systems that are tested and documented as reliable, and has systems that support transparent decision making, then AI can be implemented to help create an agricultural system that is better able to respond to the challenges of feeding the world with an ever-increasing population and to being viable and sustainable.

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