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# Machine Learning for Climate-Smart Agriculture Adoption Among Smallholder Farmers: A Systematic Review

**Toyin Okebule**

toyin.okebule@futes.edu.ng

Federal University of Technology and Environmental Science, Iyin Ekiti

**Abiodun Oguntimilehin**

Federal University of Technology and Environmental Science, Iyin Ekiti

**Folasade O. Isinkaye**

Federal University of Technology and Environmental Science, Iyin Ekiti

**Femi Ajewole**

Federal University of Technology and Environmental Science, Iyin Ekiti

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# Abstract

Climate variability threatens agricultural productivity and food security, particularly among smallholder farmers who depend on climate-sensitive farming systems. Climate-smart agriculture (CSA) offers opportunities to improve agricultural productivity, strengthen climate adaptation, and, where possible, reduce greenhouse gas emissions. However, its adoption is influenced by farmers' socioeconomic circumstances, access to resources and extension services, institutional support, environmental conditions, and behavioral factors. Machine learning (ML) offers potential for supporting CSA through data-driven agricultural prediction and decision support, but its contribution to understanding and facilitating adoption requires further examination. This study systematically reviewed the application of ML to agricultural activities relevant to CSA adoption among smallholder farmers. Relevant literature was retrieved from Web of Science (WoS), and Google Scholar and synthesized thematically across five application areas: climate and weather prediction, crop and yield prediction, production risk assessment, soil, water and resource management, and CSA decision support. The review examined the ML approaches and data inputs used the integration of farmer and contextual factors, and the extent to which actual CSA adoption was considered. The synthesis revealed a gap between the technical applications of ML and its direct contribution to CSA adoption, particularly in the integration of socioeconomic, institutional, and behavioral factors, the consideration of farmers' differing circumstances, and the assessment of actual and sustained adoption. In response, the study proposes an integrated conceptual framework connecting farmer and contextual factors with ML applications, adoption prediction, observed adoption, and feedback. The framework provides a basis for future research into more context-sensitive, adoption-oriented ML approaches that can support CSA uptake and sustained use among smallholder farmers in Nigeria and beyond.


# 1. INTRODUCTION

Agriculture is the backbones of livelihood and food supply in Nigeria and in sub-Saharan Africa. However, it is gradually more vulnerable by climate inconsistency coupled with its effects. Omotoso and Omotayo [1] emphasized that climate change poses a serious threat to smallholder farmers in Nigeria. Smallholder farmers constitute the major producers that operate mostly under rain-fed conditions and this possess limited adaptive capacity. This makes them very vulnerable to climate-related threats. In Ekiti State and other agricultural communities, these challenges are usually caused by soil degradation, poor infrastructure, and limited access to timely advisory services. Climate-Smart Agriculture has advanced as an integrated approach that increases productivity, enhance adaptation to climate variability, and reduce green-house gas emissions where feasible. Ma and Rahut [2] proposed CSA that integrates agricultural productivity, adaptation and resilience to climate change, the study also considering mitigation where necessary and introduced to provide a pathway for maintaining food production in strengthening resilience to evolving climatic conditions.

The adoption of CSA practices among smallholder farmers is still very low across Nigeria and other countries. Adoption is not only influenced by a single determinant but by a complex interaction of

household, farm-level, institutional, and other factors. Mbanasor et al. [3] proposed CSA adoption among crop farmers in Southeast Nigeria thatis influenced by a combination of socioeconomic, institutional, farm and risk-related factors. The study combined 250 smallholder farmers in Nigeria so as to improved crop varieties, soil and water conservation, and cropping system adjustments that are interlinked and constitute part of a broader adaptation strategy rather than isolated choices. Mbossoh and Udoh [4] reviewed how farmers' choices of CSA practices are interconnected, they indicated that adoption decisions should be considered jointly rather than as isolated choices. Similarly, research among rice farmers in Osun State also revealed that socio-economic characteristics, access to institutional support, and risk-related considerations are influenced by both the decision to adopt CSA and the intensity of adoption. Studies from western Kenya established that 9,300 farmers' attributes resource endowments, farm conditions, access to extension services, and perceptions of climate and soil constraints have shaped the adoption patterns. Systematic reviews conducted across the region have documented more than fifty distinct CSA practices and over forty determinants of adoption, which can be grouped into farmer characteristics, farm attributes, economic factors, environmental conditions, and access to information. Among the recurring enablers are formal education, farming experience, larger farm size, availability of extension contacts, access to climate information services, and membership in farmer organizations. Oladele et al. [5] explained that extension contact, awareness of climate-related events, access to credit, perception, and association membership significantly influenced the adoption of CSA practices among agro-pastoralists in Sokoto State, Nigeria. On the other hand, frequently reported barriers include high labour demand, limited access to climate information, poor access to credit, technical complexity of practices, and inadequate institutional support. Conventional extension systems. However, central to disseminating CSA knowledge, usually fail to provide information that is timely, localized, and actionable for individual farming households, which reduces widespread uptake.

The limitations of conventional advisory approaches drew attention to digital and mobile agricultural technologies as complementary mechanisms for delivering climate-smart information to farmers. Mobile phone approach has increased in rural Nigeria; this provides a potential channel for bridging information gaps. However, actual utilization of mobile-based agricultural services is still a major constrained. Filusi et al. [6] demonstrated that farm size and farming experience were positively associated with mobile technology use for farming activities, while poor electricity supply and weak telecommunication infrastructure were major limitations. The study employed 376 cassava farmers in Ekiti State. However, high cost of devices and internet bundles, poor network connectivity, cost of airtime, and complexity of applications, which reduce effective access were reported in the study. Despite these constraints, some digital interventions have shown measurable impact. For instance, Abioye et al. [7] reported that the application of RiceAdvice among smallholder rice farmers in Nigeria were associated with substantial improvements in rice production. The RiceAdvice 's application was implemented as a digital decision support device, among 795 rice farmers in Ebonyi State and were integrated with a yield increase of approximately 1,907 kg/ hectare. This shows that utilizing digital advisory can improve productivity when it's appropriately deployed. Other emerging technology used includes smartphone-based systems for plant disease detection and management. Also, the platforms

for input recommendations. These studies demonstrated the importance of digital agriculture and also emphasized the persistent gap between access to technology and effective utilization for climate adaptation.

Machine Learning has emerged as of one of the advanced mechanisms with the capacity to improve the application and precision of CSA support. Compared with conventional advisory that always delivers generic information, ML encourages the integration and analysis of large, heterogeneous datasets such as weather, soil, crop performance, and farmer-related variables to generate predictive insights and personalized recommendations. Noma and Babu [8] revealed the potential of incorporating socioeconomic, farm, agroecological, and climate-related variables into models for predicting CSA practices. Applications already documented include climate and weather forecasting, crop and yield prediction, production risk assessment, soil and water management, and CSA practice recommendation through decision support systems [9]. Nevertheless, existing studies have predominantly showed that agricultural prediction and recommendation accuracy with low attention to adoption of recommended practices by farmers [10]. Some models are evaluated based on technical performance metrics such as accuracy, F1-score, or root mean square error, but focus was not based on the adoption outcomes or behavioural change among farmers. To this, there is limited understanding to which ML methods can incorporate farmer and facilitate the transition from recommendation to actual adoption.

# 2. REVIEW METHODOLOGY

This study adopted a systematic literature review approach to examine how machine learning (ML) supports climate-smart agriculture (CSA) adoption among smallholder farmers. Relevant literature was searched in Web of Science (WoS), and Google Scholar using combinations of keywords and Boolean operators related to ML, CSA, smallholder farmers, technology adoption, and agricultural decision support. Studies were selected based on their relevance to the review objectives, without restricting the search to a predefined publication period. A standardized data extraction form was used to record publication details, study location and farming system, CSA practices addressed, ML algorithms, data inputs, farmer and contextual factors, adoption outcomes, and key findings. A narrative synthesis was conducted to accommodate differences in ML methods, CSA practices, and study contexts. Studies were grouped into five application areas: climate and weather prediction, crop and yield prediction, production risk assessment, soil, water and resource management, and CSA decision support. The synthesis examined how these applications could potentially support CSA adoption and the extent to which farmer characteristics, socioeconomic and institutional factors, environmental conditions, access to resources and extension services, and behavioral factors were incorporated into ML models rather than merely discussed as background. The findings informed the identification of research gaps and the development of a conceptual framework linking ML applications and adoption prediction with actual CSA adoption and feedback

# 3. EXISTING APPLICATIONS OF MACHINE LEARNING RELEVANT TO CSA

Studies shows that Machine Learning has been applied in different agricultural areas that are directly relevant to Climate-Smart Agriculture, although most studies were not originally designed to measure adoption as an outcome. Five dominant application areas stand out from the literature: climate and weather prediction, crop and yield prediction, production risk assessment, soil, water and resource management, and CSA practice recommendation and decision support.

## 3.1 Climate and Weather Prediction

Climate variability is another area of agricultural threat for smallholders in Nigeria and other parts of sub-Saharan Africa [11]. Machine learning is widely used to improve weather and seasonal forecasts which are critical for planting decisions, data application, and harvesting schedules. Several machine learning techniques have been implemented for rainfall prediction, drought forecasting, and early warning of severe climate and weather perdition. Danbatta et al. [12] established that the application of hybrid model incorporating with Artificial Neural Networks for rainfall forecasting in northern Nigeria showed potential in supporting agricultural planning and climate-resilience decisions. Some of these models integrate historical climate data, satellite observations, and atmospheric variables in generating predictions that can improve the precision of agricultural forecasts in Nigeria. For smallholder farmers in Ekiti State and other agricultural environments where there are delayed in rainfall and prolonged dry spells that can disrupt the traditional calendars. CSA support tool is foundational for accurate weather prediction because it enables timely decision-making on land preparation and planting. While most studies reported model performance metrics such as accuracy and root mean square error, which rarely assess whether farmers actually received or used the predictions to their farm practices adjustment.

## 3.2 Crop and Yield Prediction

Crop yield prediction is one of the most conventional applications of Machine Learning in agriculture. Machine learning algorithm such as XGBoost, Support Vector Machines, Random Forest, and ensemble methods, to mention a few have been utilized to predict crop yields under varying climatic and management scenarios. Some recent studies show that temperature, rainfall, soil characteristics, and vegetation indices are among the most frequently used features, while Random Forest, Gradient Boosting, Support Vector Machine, and deep learning models are widely applied for crop yield prediction [13], [14]. In Nigerian, where smallholders cultivate diverse crops such as cassava, rice, and maize are under heterogeneous conditions, crop yield prediction can support proactive planning and climate adaptation. Through anticipating low-yield seasons, farmers can adjust crop choices or adopt alternative CSA practices. Mbossoh and Udoh [4] found among 250 Nigerian smallholders that CSA practice choices were associated with factors such as access to credit, climate information, extension services, farm size, and farming experience.

## 3.3 Crop and Production Risk Assessment

Beyond yield prediction, Machine learning has been applied to predict production risks associated with climate shocks, pest outbreaks, and input failure. Risk assessment models combine biophysical and climatic data to identify vulnerable areas and estimate likelihood of crop failure or income loss. Such tools are relevant to CSA because they can inform insurance schemes, contingency planning, and targeted extension support. For example, Machine Learning-based risk maps can help extension agencies prioritize communities at higher risk of drought and flooding. Despite these advantages, literature reviewed shows that risk assessment outputs are rarely linked to farmer decision-making processes or to specific CSA recommendations that could mitigate identified risks.

## 3.4 Soil, Water and Resource Management

Soil fertility decline, water scarcity, and inefficient resource use are major constraints to CSA in smallholder systems. ML has been used for soil property mapping, soil fertility classification, irrigation scheduling, and water-use optimization. Sujatha and Jaidhar [15] reviewed ML-based approaches for soil fertility estimation and classification. Recent research has also examined ML applications in irrigation decision-making and smart irrigation systems [16], [17]. Models trained on soil test data, remote sensing imagery, and weather variables can generate site-specific recommendations for fertilizer application and water management. These practices align directly with CSA pillars of productivity and resource efficiency.

## 3.5 CSA Practice Recommendation and Decision Support

The most direct relevance of ML to CSA adoption lies in recommendation systems and decision support device that translate predictions into actionable advice for farmers. Noma and Babu [8] showed the potential of incorporating socio-economic and climate-related variables into Machine Learning models for predicting CSA practices to demonstrate the closer connection between ML prediction and farmers' adaptation decisions. Abioye et al. [7] reported that adoption of RiceAdvice substantially increased rice yields with an average of 1,907 kg/ha, while adoption decisions were influenced by factors which include training, extension access, smartphone ownership, and farming experience. Similarly, Ogungbemi and Filusi [19] reviewed that mobile technology utilization was influenced by socioeconomic capacity, perceived benefits, technology enablers, and infrastructural constraints, including electricity and network availability on 376 cassava farmers in Ekiti State. The study showed that smartphone-based applications for plant disease detection and management using image recognition and classification algorithms can help in early identification of biotic stresses and enabling timely intervention.

Recommendation systems characterized the relationship between Machine Learning and CSA adoption because they move beyond prediction to provide guidance on what, when, and how practice to adopt. However, even within this category, most evaluations focus on technical accuracy of recommendations rather than on actual adoption rates, sustained use, or behavioural change among farmers. The question of whether farmers continued using the recommended CSA practices has moved beyond the project period, and what factors influenced to continue use, is unaddressed. Machine learning has been extensively applied to climate prediction, crop yielding forecasting, risk assessment, soil and water

management, and decision support. These applications could potentially support CSA adoption by improving information quality, timeliness, and specificity. Currently, the existing body of work is off-center towards model development and performance evaluation, with less attention to integration of farmer realities and measurement of adoption outcomes. Table 1 summarizes the major application areas in which machine learning has been used. It highlights their main contributions to climate-smart agriculture (CSA) adoption. It also identifies the limitations that may affect the translation of ML-generated predictions and recommendations into practical farming decisions.

Table 1
Existing ML applications relevant to CSA adoption

| ML application area | Evidence from the reviewed studies | Potential contribution to CSA adoption | Identified limitation |
|---|---|---|---|
| Climate and weather prediction | Rainfall prediction, drought forecasting and early warning using ML models [10] | Supports planting decisions, farm planning and responses to climate variability | Model performance is commonly evaluated, while farmers' use of forecasts to adjust practices receives less attention |
| Crop and yield prediction | Yield prediction using climatic, soil and vegetation variables [11, 12] | Supports production planning, crop selection and consideration of alternative farming practices | Yield prediction does not directly establish whether farmers adopt recommended practices |
| Crop and production risk assessment | Identification of climate-related production risks and vulnerable areas | Supports risk-informed planning, contingency measures and targeted extension services | Risk predictions are not always connected to specific CSA recommendations or farmer decisions |
| Soil, water and resource management | Soil fertility estimation, classification and ML-based irrigation management [14–16] | Supports soil management, water conservation and efficient use of agricultural inputs | Recommendations may not adequately account for farmers' resources and implementation constraints |
| CSA practice recommendation and decision support | ML-based CSA practice prediction [17], RiceAdvice adoption and yield outcomes [18], and mobile agricultural technology use [19] | Supports practice selection, agricultural advice and timely farm-level interventions | Technical performance and immediate outcomes do not necessarily demonstrate adoption, sustained use or behavioral change |

# 3.6 Analysis of Existing ML Applications and Implications for CSA Adoption

As summarized in Table 1, existing ML applications can support CSA through improved climate information, crop yield forecasting, production risk identification, resource management, and agricultural decision support. The extent to which these applications support CSA adoption varies. Climate prediction, yield forecasting, and risk assessment primarily provide information for agricultural planning. The resource-management and recommendation tools can provide more direct guidance on the selection and implementation of CSA practices [10–18]. The reviewed studies also indicate a distinction between the technical performance of ML models and their contribution to farmers' adoption decisions. Although some applications provide actionable agricultural recommendations, farmers' ability and willingness to implement them depend on factors such as access to credit, climate information, extension services, appropriate infrastructure, and other socioeconomic conditions [13, 18, 19]. Consequently, accurate predictions and suitable recommendations do not necessarily translate into the adoption or continued use of CSA practices. An important gap, therefore, concerns the limited attention given to how ML applications influence actual CSA adoption, especially the initiation and continued use of recommended practices. Although existing studies reveal the capability of ML to improve agricultural predictions and decision support, further investigation is needed into how these capabilities can be applied to support context-specific adoption decisions among smallholder farmers. This gap provides a basis for examining the role of ML in CSA adoption, with particular attention to the agricultural, socioeconomic, and institutional conditions relevant to smallholder farmers in Ekiti State, Nigeria.

## 4. Treatment of Farmer Adoption in Existing Machine Learning Research

The major concerns of this study is not just whether Machine Learning is applied in agriculture, but the extent to which existing ML research considers the realities of smallholder farmers and their adoption contexts. The analysis is organized into five categories of adoption determinants that were consistently identified in empirical literature (farmer characteristics, socio-economic factors, environmental conditions, access to resources and extension services, and behavioural and decision-making factors). The key question is whether all these factors can actually be incorporated as features, variables, or design considerations within Machine Learning models.

# 4.1 Farmer Characteristics

The determinants of CSA adoption are farmer’sfeatures such as age, formal education, farming experience, and gender. Mbossoh and Udoh [4] proposed 250 smallholder farmers in Nigeria using farmer’s and farm’s characteristics, access to climate information, extension services, and other contextual factors influenced CSA practice choices. The study involved 9,300 farmers in western Kenya. Similarly, it indicated that farmer attributes, farm resources, and environmental perceptions influence adoption of agricultural practices. Ogungbemi and Filusi [6] reviewed on 376 cassava farmers in Ekiti State, and emphasized that the farming experience and farm size was associated with the use of mobile phones for agricultural information. The study suggested that farmer attributes can shape interaction

with digital tools. Most yield prediction, weather forecasting, and soil mapping models relied primarily on biophysical and climatic data such as rainfall, temperature, soil nutrients, and vegetation indices [11]–[16]. Demographic variables are discussed in the introduction section of this paper to justify the relevance of the study to smallholders, but they are excluded during model development and training. As a result, ML recommendations generated are generic and do not account for differences in literacy, experience, or capacity among farmers. This disconnection contributes to a gap between technical accuracy and practical adoptability.

## 4.2 Socio-Economic Factors

Socio-economic factors including farm size, household income, access to credit, labour availability, and market access are critical determinants of both adoption decision and intensity of adoption. Evidence from rice farmers in Osun State revealed that resource endowments significantly influence whether farmers adopt CSA practices and the extent of implementation. Small farm size and limited income often restrict ability to purchase improved seeds, fertilizers, and other inputs required to implement recommended practices, even when ML-based advisory suggests them. Abioye et al. [7] reported that adoption of mobile agricultural advisory technology was associated with significant yield gains among smallholder rice farmers, while farmer and technology-related characteristics also influenced adoption. The absence of socio-economic integration means that ML models may produce technically optimal but practically unfeasible recommendations for smallholders with limited resources.

## 4.3 Environmental Conditions

Environmental factors such as rainfall, temperature, degraded soil, farm location, and others are better integrated than socio-economic elements in the Machine Learning Model (MLM). This is evident from the fact that environmental factors are easily accessible from weather stations, satellite images, and soil sensors. Additionally, environmental factors are used as input variables in MLMs for climate predictions, yield forecasts, and management of the agricultural environment [10]–[16]. However, environmental factors are poorly localized and contextualized in the MLM. For instance, the models are trained using national and regional data and not localized information about various farm clusters. This limits their ability to capture variations in smaller-scale localizations such as the Ekiti State farms and other regions in the south-western part of Nigeria. Furthermore, environmental factors are treated as mere input features in agricultural MLMs and not as contextualization factors that farmers use to interpret the risks in their environment. The integration of environmental factors in the decision support system for precision farming, therefore, remains partially achieved since they are used to predict yields, recommend interventions, and manage the farmland environment. However, farmers do not engage these factors to interpret their environment and act according to their experiences and indigenous knowledge about the environmental risks in their locality.

## 4.4 Access to Resources and Extension Services

The presence and availability of resources and institutional support, including extension contact, climate information services, membership to farmer organizations, electricity, and telecommunication

infrastructure, was found to be a key enabler to CSA adoption. Ogungbemi and Filusi [6] explicitly identified inadequate electricity and telecommunication infrastructure as important factors in the low uptake of mobile technologies by cassava farmers in Ekiti State, alongside the costs of both data and devices. These findings indicate that access to resources and institutional support can act as mediating factors to whether farmers can access and adopt ML-based advisory.

Although most ML studies postulate that access to resources and institutional support is near-universal, the studies operate in controlled environments with good digital infrastructure and ignore the limitations in access to resources in rural Nigerian communities. Similarly, extension services, which could be used as a conduit to deliver ML-based advisory to smallholder farmers with poor digital literacy, are rarely considered as part of the adoption framework of ML-based advisory systems. The same neglect is evident in the consideration of factors such as farmer group membership as a potential mediating factor on CSA adoption or as a conduit for introducing innovations such as ML-based advisory.

## 4.5 Behavioral and Decision-Making Factors

Behavioral and decision-making factors such as risk attitudes trust in technological innovations, perceived complexity of practices and past experiences with innovations are key drivers and predictors of adoption behavior. Studies on CSA adoption suggest that farmers were more likely to adopt a certain practice when they perceived specific benefits, ease of use, and fit within their farming system (and not necessarily on the basis of some superior technological properties). Risk aversion could make farmers dismiss recommendations that require high input costs at first, despite possible long-term benefits. In the literature on machine learning, behavioral factors are hardly considered at all. ML methods are mostly optimized for accurate predictions, while little attention is paid to the role of such factors in the decision making of farmers. Trust, usability, and acceptance of recommendations are not typically assessed, more so, for decision support tools that aim to be directly used by farmers: the focus is on yield outcomes or model performance, rather than on behavioral response, attitude toward adoption, and long term use of the recommended practices. Indeed, Noma and Babu [8] demonstrated how various socioeconomic, farm related, agroecological, and climate related variables could be integrated into a machine learning pipeline for prediction of CSA practices, but this does not necessarily imply that farmers will adopt and continue using these practices.

In addition, although farmer and contextual factors are extensively discussed in the background justification of the ML-related literature, their incorporation as features or design elements in ML approaches is minimal. Of these factors, environmental conditions were most commonly integrated, followed by farm attributes, whereas socio-economic, institutional access and behavioural factors were excluded. This can partly explain the apparent gap between the technical performance of ML approaches in experimental settings reported by the reviewed literature, and the overall lack of reported widespread adoption by Nigerian smallholders or similar settings.

# 5.0 EVIDENCE GAPS AND RESEARCH OPPORTUNITIES

The synthesis of existing literature on Machine Learning applications relevant to Climate-Smart Agriculture reveals several critical gaps that limit the translation of ML advances into actual adoption among smallholder farmers. While Section 4 established the limited incorporation of farmer and contextual factors, this section focuses specifically on what is missing in current research and where future opportunities lie, particularly concerning the shift from recommendation to adoption.

Figure 1 presents a synthesis of the major evidence gaps identified in the reviewed literature and the corresponding research opportunities discussed in the following section. It illustrates the transition from existing machine learning applications that emphasized on prediction and technical performance, towards approaches that explicitly consider farmer circumstances, personalized recommendations, and actual CSA adoption outcomes.

# 5.1 Limited Adoption-Oriented ML Models

A major gap identified is the scarcity of ML models that are explicitly designed with adoption as a primary outcome rather than as a secondary implication. Most reviewed studies focus on improving prediction tasks such as rainfall forecasting, yield estimation, or disease detection, with model evaluation based on technical metrics like accuracy, precision, F1-score, or root mean square error. Few studies develop models that predict likelihood of adoption, intention to adopt, or sustained use of CSA practices. For example, while the RiceAdvice tool applied among 795 rice farmers in Ebonyi State demonstrated yield gains of approximately 1,907 kg per hectare, its evaluation centered on productivity impact rather than on adoption determinants or long-term uptake [7]. Similarly, smartphone-based disease detection tools are assessed based on classification accuracy rather than on whether farmers adopted the recommended management practices. This orientation means that current ML research is largely technology-centric rather than adoption-centric, leaving unanswered questions about what drives farmers to adopt ML-supported CSA recommendations in real farming contexts such as Ekiti State.

# 5.2 Limited Integration of Farmer and Contextual Factors

As discussed in Section 4, the integration of farmer and contextual factors into ML models remains minimal. Socio-economic variables such as access to credit, farm size, labour availability, and income level, which were found to influence adoption among 250 smallholder farmers in Nigeria and rice farmers in Osun State, are rarely encoded as features [4]. Institutional factors such as extension contact, access to climate information, and membership in farmer organizations, which were identified as enablers among 9,300 farmers in western Kenya, are similarly absent from model design. Environmental factors are included more frequently, but often at coarse resolution that does not capture plot-level heterogeneity. This limited integration results in models that generate agronomically optimal recommendations that may not be socio-economically feasible or institutionally supportable for resource-constrained smallholders. Future research opportunities therefore lie in developing hybrid models that fuse biophysical data with household survey data, extension records, and infrastructure indicators such as electricity availability and telecommunication coverage, which were reported as significant barriers among 376 cassava farmers in Ekiti State [6].

## 5.3 Limited Personalization of CSA Recommendations

Another issue discovered from the integration of machine learning (ML) into climate-smart agriculture (CSA) is the limited attention given to the specific need of individual farmers. Many advisory systems actually provided similar recommendations to farmers within the same region but with little consideration for variation in farm conditions, available resources, or willingness for adoption. For example, farmers living in the same community may be advised to apply the same quantity of fertilizer, even when their plots are differ in soil quality, cultivated area, purchasing power, and access to farm inputs. Such recommendations may not adequately address individual circumstances, potentially reducing farmers' confidence in the advice and their willingness to implement it. Agricultural mobile services would therefore benefit from information that reflects local conditions and the realities of individual farm users. Machine learning techniques, including farmer clustering, recommendation algorithms, and adaptive learning could support this process by identifying some of the differences among farmers and adjusting the advice gradually. However, their application to personalized CSA advisory services still remains an area for further investigation. Combining farmer profiles with plot-level information and feedback on previous recommendations could help develop advisory systems that respond to changing farm conditions and farmers' practical needs.

## 5.4 Comparative Analysis of Reviewed Studies

Table 1 summarizes representative studies according to their principal focus, geographical context, analytical approach and major limitation.

Table 1
Comparative overview of selected studies on CSA adoption and digital agricultural technologies

| Study | Primary focus | Context | Method/technology | Major limitation |
|---|---|---|---|---|
| c and Udoh [8] | CSA practice choice and uptake | Nigeria | Multivariate Probit | Does not develop a digital recommendation system |
| Ogungbemi et al. [6] | Mobile technology utilization | Ekiti, Nigeria | Factor analysis, regression, FGDs | Focused on cassava production |
| Abioye et al. [7] | Mobile agricultural advisory | Ebonyi, Nigeria | RiceAdvice and PSM | Rice-specific and based on an existing application |
| Izuogu et al. [19] | CSA implementation | Nigeria | Literature synthesis | No primary system or predictive model |
| Ojo et al. [20] | CSA adoption intensity | Osun, Nigeria | Econometric analysis | Rice- and state-specific |
| Otitoju et al. [21] | CSA technologies | Nigeria | Literature review | No primary empirical system evaluation |
| Finizola et al. [22] | CSA adoption drivers | Africa | Systematic review | Broad geographical scope |
| Agyekum et al. [23] | CSA benefits and barriers | West Africa | Systematic review | Heterogeneous evidence |
| Ma and Rahut [24] | CSA adoption and impacts | Multiple contexts | Evidence synthesis | No single locally validated dataset |
| Porciello et al. [25] | Digital agricultural services | LMICs | Systematic scoping review | Limited evidence on climate-resilience outcomes |
| Adamu et al. [26] | Agricultural technology adoption | Plateau, Nigeria | Logit, adoption index, factor analysis | Potato-specific |
| Fawole and Aderinoye-Abdulwahab [27] | CSA adoption and productivity | Nigeria | Conceptual/empirical synthesis | No digital intervention |

Finizola eSilva et al. [28] conducted a systematic review on factors that are affecting climate-smart agriculture adoption among smallholder farmers majorly, in Africa. The study's analysis covered socioeconomic, institutional and farm-related influences across different agricultural settings. The study also indicated that access to information on farming resources and institutional support can shape the farmers' readiness to adopt climate-smart practices. However, the study failed to provide the countries and farming systems which can adopt this system based on the factors identified.

Another study in [29] implemented a PRISMA-guided systematic on 33 different studies that were retrieved from Scopus and Web of Science. The study reviewed the use of climate information services among smallholder farmers in Africa. The findings shows that education, ICT literacy, agricultural advisory services and access to livelihood resources were factors influencing farmers' responsiveness and use of climate information. More so, the review explained how forecasts can support agricultural adaptation but study did not develop a predictive machine-learning model or report model-accuracy scores.

Agyekum et al. [23] conducted a systematic review on 12 studies which were identified through Science Direct, Web of Science and Scopus. The study explored climate-smart agriculture practices, its benefits and the factors affecting adoption across West African farming systems. Education, age, gender, extension services and access were considered as relevant considerations. The reviewed studies also associated adoption with potential improvements in soil fertility, crop yields, income and resilience to climate variability. Nevertheless, limited climate information, high labour costs and inadequate financial and institutional support continued to hinder adoption.

In a study [19] published research on the implementation of climate-smart agriculture practices in Nigeria. The study focused on existing literature to examine practices and challenges within Nigerian farming systems rather than sourcing for a new crop dataset or training a machine-learning model. The review provided a basis for understanding the national context and identifying factors that may affect implementation. However, quality of the literature examined, and crop-specific prediction accuracy was not its primary outcome.

The author in [30] examined how digital agricultural technology influences climate-smart agriculture decisions among smallholder farmers in sub-Saharan Africa. The review considered technologies such as remote sensing, geographic information systems, the Internet of Things and artificial intelligence across different crops and farming environments. The study emphasized the importance of connecting digital tools with farmers' practical decisions and adoption needed based on certain factors. Nevertheless, the study failed to establish a common measure of effectiveness, Infrastructure, resources and local conditions.

Rurii et al. [31] conducted the PRISMA-ScR framework usig 54 empirical studies, addressing climate-smart agriculture adoption and its relationship with productivity, food security and resilience in African farming systems. The review identified research gaps relating to gender, behavioural influences, livestock systems and variations in local farming conditions. Its broad coverage provides a useful overview of existing studies. However, the author considered qualitative-only studies which may have limited range of farmers' experiences as represented.

The study in [32] analyzed 50 peer-reviewed studies published between 2003 and 2023 to investigate climate-smart agriculture adoption among maize farmers in sub-Saharan Africa. The study used a three-stage screening process and the Mixed Methods Appraisal Tool (MMAT) to assess study quality. Their review showed that adoption rates of 56.7% in Eastern Africa, 43.2% in Southern Africa and 38.9% in

Western Africa. This Analysis showed the differences suggestion of adoption which varies across regional and socioeconomic settings and the figures were synthesized from existing research.

Alobwede and Nzengya [33] examined the relationship between climate-smart agriculture adoption and food security among smallholder farmers. The study focused on agricultural practices and socioeconomic outcomes with adoption, rather than the performance of a predictive algorithm on a single crop dataset. This perspective is relevant because the value of climate-smart agriculture extends beyond production methods to farmers' livelihoods and access to food., However, applying these technologies to smallholder agriculture may be difficult where there are lack of internet connectivity

In [34], reviewed research published between 2017 and 2026 on the use of artificial intelligence in precision agriculture. The review considered applications of machine learning in crop monitoring, agricultural resource management and technology adoption across different farming environments. The study demonstrates the effect of AI-based tools to assist farmers in making more informed production decisions. However, applying these technologies to smallholder agriculture may be difficult where there are limited internet connectivity, computing facilities and reliable agricultural data.

Sukriadi et al. [35] conducted a PRISMA-based systematic literature review of 496 articles on machine-learning applications in rural and resource-constrained agricultural environments. The reviewed studies addressed crop monitoring, disease detection and irrigation management. The study explained several deep learning and machine learning models, including convolutional neural networks (CNN), support vector machines (SVM) and long short-term memory networks (LSTM). Nevertheless, these techniques offer different ways to analyze agricultural data. These practical implementation in rural communities may be affected by implementation costs and inadequate technical infrastructure.

Another author in [14] examined studies on crop-yield prediction between 2017 and 2024. The review covered diverse crops and datasets, with temperature, soil characteristics and vegetation-related variables that are frequently used as prediction inputs. Random Forest, Linear Regression and Gradient Boosting were common ML models, while CNN and LSTM featured among the deep-learning techniques. The study provides an overview of approaches that were used for yield estimation, although differences in datasets, input variables and evaluation procedures show direct comparisons between the results difficult presented.

Jabed and Murad [36] reviewed crop-yield prediction using machine learning and deep learning methods. The study employed 68 studies on machine-learning methods and applied 47 studies on deep learning. The reviewed research considered different crops and variables, including rainfall, temperature, soil characteristics, humidity and vegetation indices. The review relevant environmental and agricultural information on estimating yield. Nevertheless, the major concern lies on geographical differences and difficulties integrating prediction systems into everyday farm management.

In a study [14] considered commonly used input variables, modeling approaches and evaluation measures on a single original dataset. Vegetation indices such as NDVI and EVI, rainfall and temperature

were among the features considered for predictors. Random Forest, CNN and LSTM were also identified among the methods employed. RMSE and MAE were common measures for evaluating prediction performance. However, differences in crop types, data sources and experimental procedures make it difficult to identify one algorithm as the best choice for all agricultural setting.

Another author in [37] reviewed 60 studies published between 2014 and 2024 on soil-moisture forecasting. The research covered approaches using historical sensor readings, weather observations and irrigation-related information across different agricultural environments. Accurate soil-moisture estimates can help farmers plan irrigation, reduce unnecessary water use and manage crop-water requirements. The review also drew attention to differences in how forecasting models are developed and evaluated. Without consistent methods and evaluation procedures, comparing the reliability of models across studies remains challenging.

Fares et al. [38] investigated applications of artificial intelligence for predicting crop performance on drought and water-stress condition using different 32 studies from an initial pool of 438 records. The study covered different crops and incorporated weather, soil, crop, irrigation and remote-sensing information. Random Forest, Gradient Boosting, ANN and CNN were among the models examined for estimating yield and crop responses to water problems. However, this method may support drought assessment and irrigation planning but weak generalization across environments that can reduce the practical reliability.

In a study [39] reviewed applications of machine learning and deep learning in crop-yield estimation and food-grain quality assessment. The review demonstrates the impact of intelligent computational methods. However, the study does not establish the quality, diversity and availability of study's datasets.

The reviewed studies show that CSA adoption is influenced by socioeconomic, institutional, financial, and technological factors. However, most studies are geographically or commodity specific, while less attention has been given to integrating CSA adoption factors with personalized digital agricultural solutions. This highlights a gap in the development of practical, context-specific digital tools to support CSA adoption among smallholder farmers.

## 5. Research Gaps Identified in the Literature

# 5.1 Overemphasis on Model Performance Rather than Actual Adoption Outcomes

A common development noticed in all the reviewed articles is that the emphasis is placed on the performance of the model rather than the extent to which it is adopted and actually improves smallholder farmers' livelihood. The conducted research focuses on enhancing the performance of different machine learning algorithms, including Random Forest, Support Vector Machine, XGBoost, Artificial Neural Networks, and ensemble techniques, as well as comparing their performance. However,

there are a limited number of studies that attempt to assess the farmer's adoption of the tested methods and techniques. Although it is essential to ensure that the chosen algorithm performs at its best, its high accuracy rate does not necessarily mean that it will be beneficial for the farmers' livelihood. For instance, a model with an accuracy rate of 95% that advises farmers on the most capital-intensive practices may not be useful as a model with an accuracy rate of 80% that advises farmers on adopting less capital-intensive practices. Moreover, the adoption, dis-adoption, and adaptation of CSA practices after the end of the intervention are rarely considered in the reviewed articles. This indicates the need to assess ML-supported CSA systems using both technical and outcome-based measures, including adoption rate, intensity of use, sustained application, farmer satisfaction, productivity improvement, and changes in resilience.

## 5.2 What is Missing: Focus on Actual CSA Adoption

A key gap in the existing literature is the limited focus on actual CSA adoption as an outcome of machine learning applications. Current studies demonstrate what ML can predict or recommend, but provide less evidence on whether these recommendations lead to adoption among smallholder farmers. The transition from ML-based recommendations to actual adoption involves several stages, including awareness, access, trust, trial, and sustained use, all of which are influenced by farmer characteristics and contextual factors. Addressing this gap requires the development and evaluation of adoption-oriented ML approaches that integrate socioeconomic and institutional variables, personalize recommendations to farmers' circumstances, and assess adoption outcomes alongside predictive performance. Relevant evaluation measures should include adoption rates, intensity of use, continued application, farmer satisfaction, and associated productivity and resilience outcomes. Generally, the reviewed literature highlights a gap between the technical capabilities of ML applications and their contribution to actual CSA adoption among smallholder farmers. Further research should examine how ML can support adoption decisions by accounting for farmer circumstances, resource constraints, and local agricultural conditions among smallholder farmers in Ekiti State, Nigeria.

# 6. CONCEPTUAL FRAMEWORK AND FUTURE RESEARCH AGENDA

A a result of these gaps identified and the adoption determinants documented in the study. This study proposes a concise conceptual framework that illustrates how future Machine Learning research could effectively address CSA adoption among smallholder farmers. The framework is designed to bridge the disconnect between technical Machine Learning capability and actual farmer adoption by systematically integrating farmer and contextual factors into the ML pipeline and by shifting evaluation focus from prediction accuracy to adoption outcomes. Figure 1 shows the proposed framework consisting of four interconnected components that represent the pathway from farmer realities to CSA adoption through ML.

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between technical Machine Learning capability and actual farmer adoption by systematically integrating farmer and contextual factors into the ML pipeline and by shifting evaluation focus from prediction accuracy to adoption outcomes.

Figure 2 shows the proposed framework consisting of five interconnected components that represent the pathway from farmer realities to CSA adoption through ML and the associated explanation of each component.

Farmer, Farm and Contextual Factors: The first component comprises farmer characteristics, farm conditions, socioeconomic and institutional factors, and environmental conditions. Farmer characteristics include age, education, farming experience, preferences, and attitudes towards risk. Farm factors include farm size, crop type, soil conditions, and existing production practices. Socioeconomic and institutional factors include income, access to credit, labour availability, extension services, and access to agricultural information. Environmental factors include rainfall, temperature, soil characteristics, and climate-related risks. These factors provide the contextual information needed to understand both the suitability of CSA practices and the circumstances under which farmers may adopt them. Their inclusion can help address the limitation of models that generate recommendations based primarily on the biophysical data without adequately considering farmers' resources and constraints.

Machine Learning-Based Analysis: The second component in Fig. 2 uses ML techniques to analyze the relationships between the input factors and CSA-related decisions. These combined the relevant agricultural, environmental, and farmer-level data, ML models that could identify the patterns associated with practice suitability and adoption. Depending on the research objective and available data, separate models may be developed to recommend appropriate CSA practices and estimate the likelihood or intensity of their adoption. The important of this component lies not simply in improving predictive performance, but in examining how multiple factors jointly relate to farmers' decisions. Model development should therefore be considered for data quality, local relevance, interpretability, and the availability of sufficient observations to represent different farmer circumstances.

CSA Recommendation and Adoption Prediction: The third component translates the model outputs into two related but distinct forms of decision support. The recommendation component identifies CSA practices that may be suitable for a farmer's production conditions and available resources. The adoption prediction component estimates the likelihood that the farmer will adopt a particular practice, based on patterns learned from relevant adoption data. These outputs can complement each other. For example, a practice may be ergonomically suitable but less likely to be adopted where farmers lack credit, labour, inputs, or extension support. Identifying this distinction could assist the researchers and agricultural advisers to consider the best practices, and what constraints may need to be addressed to facilitate adoption. Adoption predictions should be treated as estimates instead of definitive explanations of individual farmers' decisions.

**Actual Adoption of CSA Practices**: The fourth component in Fig. 2 focuses on farmers' actual decisions to adopt and implement recommended practices. Adoption is influenced by more than the technical

suitability of a recommendation; it also depends on affordability, accessibility, perceived benefits, trust, local knowledge, and available institutional support. More so, ML-generated recommendations should be evaluated against the observed adoption behavior rather than assumed to lead automatically to implementation. Future studies should distinguish between awareness, intention to adopt, initial adoption, intensity of use, and continued application. These outcomes would provide a more complete assessment of whether ML-supported decision-making contributes to CSA adoption among smallholder farmers.

Feedback and Model Improvement: The last component establishes a feedback relationship between adoption outcomes and the preceding stages of the framework. It provides information on farmers' decisions, implementation experiences, constraints, and feedback that can be used to evaluate recommendations and identify areas where the models or advisory approaches require improvement. Where suitable data become available, the models may be updated to reflect changing environmental conditions and farmers' circumstances. This feedback component makes the framework iterative instead of being a one-way process. It also provides a basis for evaluating the framework using both technical measures and practical outcomes, such as adoption, continued use, farmer satisfaction, and relevant productivity or resilience indicators.

# 6.2 Future Research Agenda

Building on the research gaps identified in Section 5 and the proposed conceptual framework, the four key priorities for future research are proposed:

Development of adoption-oriented ML models: Future studies can create machine learning models that will clearly measure how likely the farmers will adopt CSA and determine how strong the adoption is crop yield or weather should only be focused. It means gathering information about the choices farmers make. Consideration should also be about the farmers, their farms and the environment around them when building effective models. This will help to make sure the models are accurate.

Integration of heterogeneous data sources: Future research should integrate biophysical data with socioeconomic, institutional and behavioral information to provide a more comprehensive understanding the farmers' circumstances and adoption decisions. Evidence from studies in Osun State and western Kenya highlights the relevance of the socioeconomic factors in CSA adoption, supporting the need to incorporate these factors into ML-based methods [40 and 41].

Personalization and co-design of CSA recommendations: Future machine learning methods should include farmer preferences, feedback and participatory design. This will help to make sure the recommendations system fit conditions, affordable and work with current farming methods. This is very imperative when dealing with problems like cost and complexity, which have been reported in Ekiti State. Now machine has advanced to identify crop diseases and suggest treatments. These can help to build more flexible and farmer-focused decision-support tools [40 and 41].

Adoption-focused evaluation and feedback: Beyond measures, future evaluations should try to include accuracy and root mean square error (RMSE) and how farmers can actually use the tools and the effectiveness of the recommendations system and the impact on farming. It is therefore imperative machine learning-based that will help farmers to keep using climate- agriculture practices.

# 7. Conclusion

This systematic review examined how machine learning (ML) supports climate-smart agriculture (CSA) adoption among smallholder farmers. It focuses on the integration of farmer and contextual factors and the transition from recommendations to actual adoption. The findings show that ML has been applied to climate and weather prediction, crop and yield forecasting, production risk assessment, resource management, and agricultural decision support. However, existing research predominantly emphasizes predictive performance. The integration of farmer-level determinants, personalized recommendations, and actual adoption outcomes are underexplored. The key contribution of the study is the identification of the gap between ML's technical capabilities and its potential to support actual CSA adoption. It advances an integrated conceptual framework that connects farmer, farm, socioeconomic, institutional and environmental factors with ML-based CSA recommendations, adoption prediction, observed adoption, and feedback for model refinement. The framework provides a basis for moving beyond technology-centered approaches towards farmer-responsive, adoption-oriented ML research by distinguishing between recommending suitable practices and predicting whether farmers are likely to adopt them. Future studies should empirically validate this framework, integrate heterogeneous data sources, and evaluate adoption, continued use and relevant livelihood outcomes alongside predictive performance. This direction could strengthen the practical contribution of ML to sustained CSA adoption, climate adaptation and food security among smallholder farmers in Nigeria and beyond.

# Declarations


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### CONFLICT ON INTEREST

The authors declared that there is no conflict of interest.

### ETHICS, CONSENT TO PARTICIPATE, AND CONSENT TO PUBLISH DECLARATIONS

Not applicable.

### AUTHOR CONTRIBUTIONS

Toyin Okebule: Conceptualization, methodology, literature search, screening of studies, and original manuscript writing. Abiodun Oguntimilehin: Literature review, and validation. Folasade O. Isinkaye: Supervision, validation, and critical review of the manuscript. Femi Ajewole: Review, and editing of the manuscript. All authors reviewed and approved the final version of the manuscript.

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42. Authors’ Profiles

# Figures

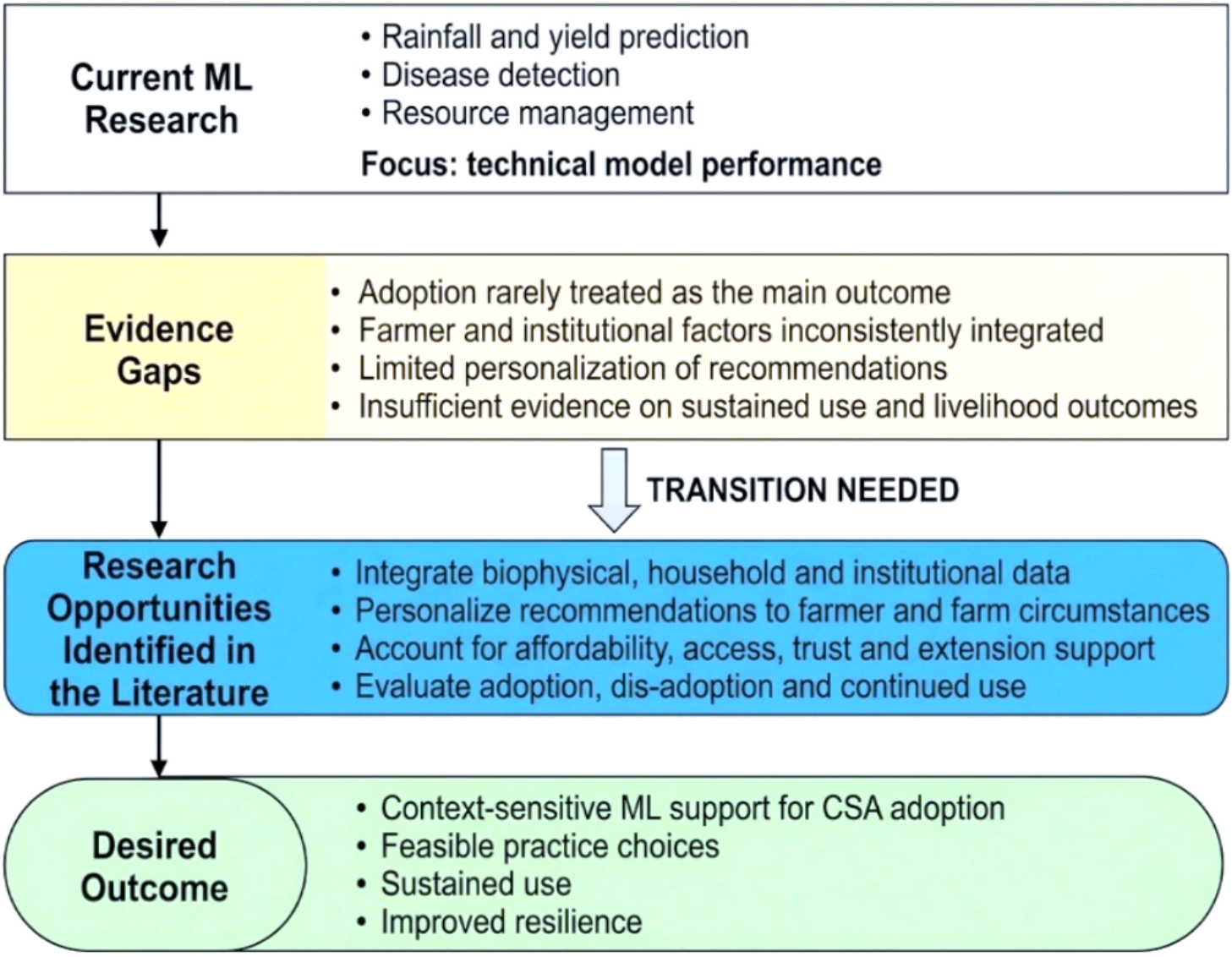



**Figure 1**

*Research gaps and opportunities for transitioning from existing machine learning applications to adoption-oriented climate-smart agriculture.*

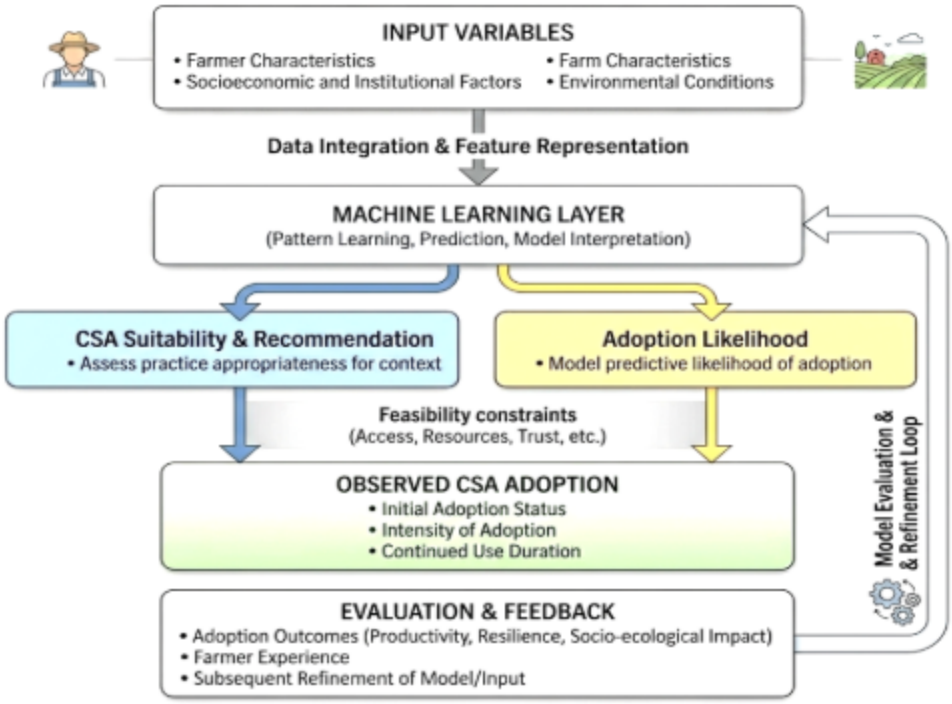



**Figure 2**

*Conceptual Framework for ML-Based CSA Adoption*

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