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A predictive precision farming platform with online and offline weather-based advice for Nigerian farmers

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Abstract

Smallholder farmers make more than 90% of Nigeria's food supply but are largely excluded from AI-powered precision farming tools because of the low penetration of smartphones (less than 22%) and poor rural internet connectivity (less than 25%). This paper presents AgroCast, a dual-channel precision farming advisory platform that delivers weather-sensitive, crop-specific recommendations to Nigerian smallholder farmers regardless of their device type or connectivity status. The platform combines a web dashboard for internet-connected users with an Unstructured Supplementary Service Data (USSD) interface for basic feature phones and provides recommendations through Short Message Service (SMS). A total of 41,298 records were used to train crop yield prediction models for maize, rice, and soybean, using five machine learning algorithms using climate variables such as temperature, precipitation, and relative humidity as model inputs. The highest coefficient of determination (R^2) was obtained for XGBoost with 0.972, 0.963 and 0.960 for maize, rice and soybean, respectively, thus indicating that the climate-yield relationship in Nigerian agriculture is best captured by gradient-boosted ensemble methods. Google's Gemini Large Language Model (LLM) was used to generate contextualised farming advice, with a deterministic rule-based fallback mechanism to ensure uninterrupted output in the case of API unavailability. All the user journeys were evaluated, and both interfaces were able to provide weather-based recommendations. AgroCast proves that AI-powered yield forecasting, LLM-driven advisory content, and the dual-channel access can help overcome the digital divide in agricultural extension services and provide a scalable solution for AI-driven food security interventions in low-connectivity developing areas.

Keywords: Advisory system; Large language models; Machine learning; Precision agriculture; Smallholder farmers; USSD

1 Introduction

Agriculture remains the major source of employment for the Nigerian population, and it is the main source of livelihood for the rural population; serving as their source of food, income, and jobs. Although farming is an important industry in Nigeria, it is hampered by low productivity, environmental issues, and unpredictable weather. Traditional knowledge handed down through generations has helped many farmers make decisions over the past decades on planting, irrigation, and pest management. However, changes in weather patterns, prolonged dry seasons, soil erosion, and frequent outbreaks of pests and diseases have made farming in some areas of the country risky and challenging [1]. Precision agriculture has negated many of these issues in other regions of the world. Precision Agriculture (PA) is a contemporary approach in which 'precision' refers to the use of sensors, satellite imagery, and data processing to enable producers to make optimal decisions and take appropriate actions. PA will improve waste reduction, yields, and sustainability in farming by tailoring actions to the unique environment of each field or plant [2].

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In recent years, these systems have become more efficient through the implementation of Artificial Intelligence (AI) in Agriculture, where predictions of pest challenges, irrigation optimisation, and even the best planting time for a crop, based on historical data and weather forecasts, are possible [3]. However, in Nigeria, most of the tools are web or mobile applications, assuming ownership of a smartphone and a stable internet connection – which is not available for most Nigerians, with less than a third of rural dwellers having an internet connection and less than a quarter of the smallholder farmers having a smartphone [4]. Moreover, many farmers have only a rudimentary level of literacy and cannot work with complex technical language or unfamiliar interfaces. These barriers, instead of empowering farmers, have left many of them alienated from the innovations that would have help them. Hence, designing agricultural technologies appropriate to the socioeconomic and cultural context of smallholder farmers is critical to ensuring adoption and sustained use [5].

The majority of farmers still rely on intuition, radio prescriptions, and peer advice, which tend to be inflexible to their respective circumstances and not timely. This inability to access the relevant and localised information is a direct menace to livelihood and food security as climate change causes weather to be less predictable. Reducing this gap involves establishing systems that operate both online and offline, enabling farmers to access AI-based advice regardless of their internet connection. The other solution is to disseminate information through products that are more accessible to most farmers, such as Unstructured Supplementary Service Data (USSD) codes on basic mobile phones, while also offering sophisticated features for those with internet access. The study proffers a platform through which the precision farming hub uses AI to provide weather-sensitive recommendations, available online and offline, and accessible to smallholder farmers of Nigerian origin, that will cover the planting period, pest prevention, water and fertiliser use, and efficiency. Notably, the system will have two access modes through which two categories of farmers will access it: basic mobile phone farmers with no internet access and smartphone or internet-access farmers. The Food and Agriculture Organisation (FAO) observes that digital technologies applied to smallholder farming systems can increase productivity by 40% and reduce input waste by 25%; thus, the suggested tools are essential to achieving sustainable agricultural change in the developing world [6].

Interestingly, climate change has negatively impacted Nigeria, leading to environmental deterioration and harming its agriculture, as a result of people's use of fossil fuels, deforestation and bad farming practices. All of these have been extreme and characterised by erratic rainfall, extended dry seasons, and frequent floods, all of which have affected food production in the country during the last 20 years. The average temperature in Nigeria has been rising at 1.6°C since the 1980s [7], and desertification is progressing southward at the rate of 600 metres per year in the north of Nigeria. Categorically, over the past five years, more than one-quarter of the annual crop losses have been associated with climate-related events, including drought and flooding [8], and these challenges pose risks to food security and have a disproportionate impact on smallholder farmers as they are the largest proportion of producers and do not have the appropriate tools and information in time to adapt. Approximately, 80% of Nigerians are engaged in agriculture, and smallholder farmers produce more than 90% of Nigeria's food. However, crop losses due to lack of reliable production data are over 60% of the annual harvests, which is caused by the weather variability [9].

While some of these farming tools are already available in other parts of the world and have improved yields by as much as 30% and reduce input costs by approximately 20%, fewer than 25% of rural households in Nigeria have mobile internet, and less than 22% of smallholder farmers have a smartphone. To fill this void, the study is designed to create an AI-driven precision agriculture solution, providing farm-specific weather predictions and guidance through easy-to-use USSD codes and web services. The platform aims to facilitate productivity, minimise losses, and ensure food security by ensuring that data-driven insights reach all farmers in Nigeria.

2 Related Work

In Nigeria, Machine Learning (ML) based prediction models are reviewed systematically by [13] and in all the regional agronomic studies Random Forest and eXtreme Gradient Boosting (XGBoost) ensemble learning models were applied to model the variations of local datasets and actual maize crop yield response to changing climatic conditions and high structural predictability is achieved in all regional studies. Their research showed that these pipelines are well-adapted to non-linear relationships between the various characteristics of the local environment, and are unique. But the use of these pipelines on active digital platforms that are accessible to farmers is still limited. In Nigeria, for example, digital platforms such as Crop2Cash have shown the potential to link smallholder farmers with investors and inputs and markets through technological innovations, although not all these have been reported in a reproducible format or with ML pipelines.

Furthermore, Olam Nigeria employed an outgrower scheme in which they trained farmers, supplied rice inputs, and secured purchase agreements, but agents were the sole means they used to deliver the products [15]. Also, [16] reported that the sharing service by Hello Tractor included Internet of Things (IoT) systems that used Global Positioning System (GPS) to track the position of the machines, which then were combined with a digital bookings platform; the machines' purpose was to enhance access, not recommendations, for smallholder farmers in Nigeria. While the platforms did not offer transparency in AI reasoning, [17] suggested the improvement of AI reasoning and recommendations to be strictly adhered to. The developed solution, AgroCast. does just that in direct response to the needs of farmers by providing locally relevant recommendations, based on farmer-specific crop, yield forecast, and existing or current conditions, using outcomes of the farmers' LLM interactions with the serviced crops.

Consequently, weather forecasts were disseminated to farmers using USSD in Oyo, having shown that it is technically feasible [14], and [18] showed that structured agricultural innovation platforms enhanced farmer participation in West Africa. However, a significant challenge in Nigeria, with the diversity of regions and language, is the scaling-up of such platforms. Therefore, practical implementation of multilingual advisory systems that are based on Natural Language Processing (NLP) has shown enhanced farmer understanding but encountered continued difficulty scaling to multilingual areas, each with different languages and limited data for low-resource languages [19]. Importantly, the high accuracy rate above 90% reported for computer vision techniques [20][21] and the good performance of the ML-based yield prediction using climatic variables in the Nigerian agricultural settings [22] highlight the incredible potential of these AI techniques in agriculture through the use of smart phones or drones and only a minority of smallholder farmers can access it. Even though AgroCast does not have these capabilities, in the future they would be integrated into it.

3 Method

3.1 System Architecture

The system, AgroCast, is a web-based application with USSD capability, providing yield predictions and farming advice for specific crops both online and offline. The architecture consists of three layers: user interface layer (frontend), application layer (backend), and data layer (database), as shown in Figure 1.

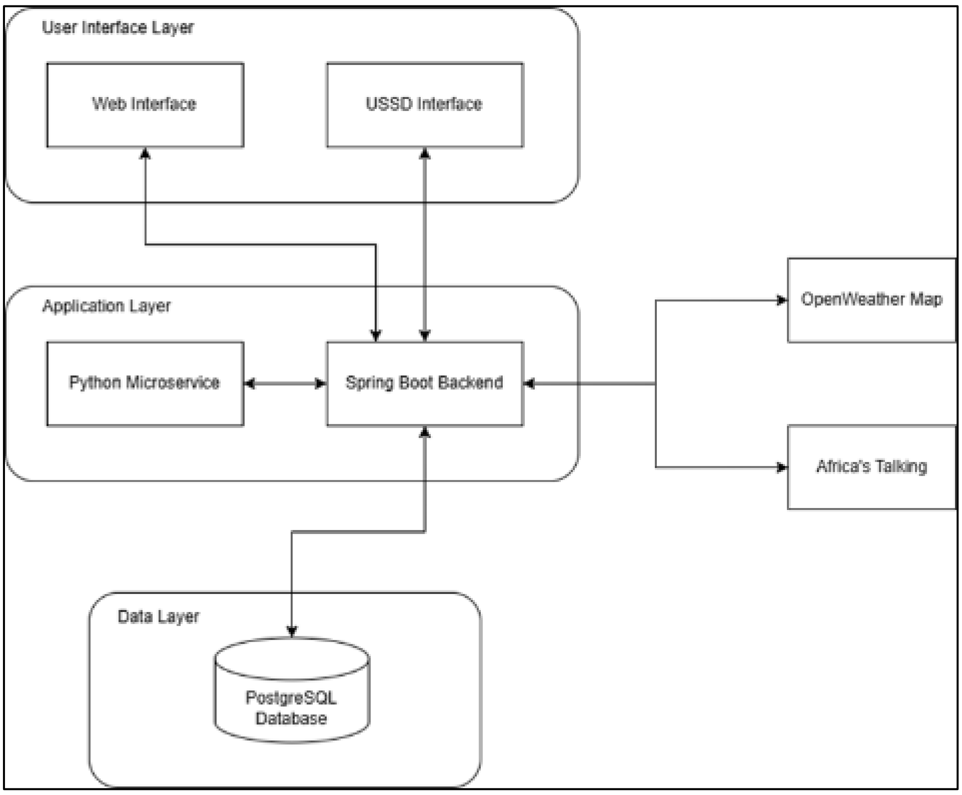

Figure 1 Architectural diagram of the proposed system

The system is broken down into layers such as:

- **User Interface Layer:** There are two access points on the system and one is the web interface designed to provide farmers who have internet access with interactive dashboards, weather forecasts, activity logs, and personalised recommendations. The USSD interface, on the other hand, is designed to be accessible to farmers who do not have internet access on their basic feature phones and mimics the basic functionality by using numbered menus and text messages. Both interfaces are integrated with the application layer.
- **Application Layer:** The system's business logic is implemented in this layer in two parts. The Spring Boot backend is the central server that receives requests from both interfaces, manages user and farm profiles, retrieves and localises weather forecasts from OpenWeatherMap, and provides outputs through Africa's Talking. Basically, Python microservice is responsible for generating AI advisory and crop yield prediction using Pandas, XGBoost, and Gemini models. It was intentionally detached from the backend since the machine learning ecosystem is Python-based, and separation enables models to be retrained and redeployed without impacting the primary application.
- **Data Layer:** Implemented using PostgreSQL, this layer stores user accounts, farm profiles, activity logs, verification tokens, training data, and the trained models in the database, and the relationships between the database tables provide data integrity and enable complex queries across the system.

3.1 Dataset

Two datasets were used for this study. Crop yield data for maize, rice, soybean, and wheat were obtained from the Data Integration and Analysis System (DIAS) in NetCDF format, covering the period 1981 – 2016. The second dataset was a Nigerian agricultural-climate indicators dataset containing historical climate variables and agricultural indicators from 1950 – 2023. From this dataset, only average temperature, precipitation, and relative humidity were used.. The crop yield data were spatially limited to Nigeria (latitude 4°N – 14°N and longitude 2°E -15°E) using the xarray library at a 0.5° grid resolution. The extracted records were converted into tabular format containing latitude, longitude crop type, year, and yield values. Crop yield records were then combined with climate data to create the final modelling dataset. The final modelling dataset consisted of 41,298 records for three crops after integration and cleaning, and the descriptive statistics are given in Table 1.

Table 1 Descriptive Statistics of the Final Modelling Dataset (n = 41,298)

Variable	Mean	Std	Min	Max
Latitude (°N)	9.33	2.43	4.25	13.75
Longitude (°E)	8.74	3.44	2.25	14.75
Yield (tons/ha)	1.40	1.04	0.00	10.17
Avg. Temperature (°C)	26.94	0.36	26.24	27.73
Precipitation	1088.21	88.74	866.06	1292.50
Relative Humidity (%)	57.86	1.39	54.37	60.34

3.2 Data Preprocessing

The data processing stages include:

- **Temporal alignment:** The agricultural-climate indicators dataset was 1950 – 2023, and the data was filtered to ensure it was consistent with the data sources, since the data used was only from 1981 to 2016, matching the time period of the crop yield data, before it was merged.
- **Climate Data:** Only average annual temperature, annual precipitation and relative humidity were selected from climate data. The three were selected as variables that are most directly associated to crop productivity but the other economic and agriculture indicator columns were not employed.
- **Column Renaming:** The raw DIAS files had “var” as the label for the crop yield variable, which can be confusing. It was renamed to ‘yield’ to make it clear what the target variable was before modelling.
- **Handling of missing values:** Rows in which Yield values were missing were removed from the dataset because the value to be predicted is Yield and there is a systematic bias in imputing missing values that will be added to the model training. In totality, there were 4,028 with missing values in the climate feature columns due to missing climate data at some grid points, and the arithmetic means of each column were used for the

imputation. The mean imputation was performed on the records that still contained missing values, and they were not included in the analysis. This two-step process was used to preserve as much of the training records as possible without adding in biased targets.
- **Data Integration:** The cleaned crop yield data and the cleaned climate data were integrated. The year column was used as the join key, and a left join was used to make sure that all yield records were included, and where available, climate values were added.
- **Feature Engineering:** Beyond the agronomic features, two sets of agronomic features were included to further enrich the data set beyond just raw climate features. A crop calendar was first developed; planting months and harvest months were assigned to each crop, based on known agronomic practice in Nigeria; maize (plant: May and harvest: September), rice (plant: June and harvest: November), soybeans (plant: June and harvest: October), and Wheat (plant: December and harvest: April). Second, agroclimatic rainy season labels were calculated based on latitude, with the intention to categorise each record's agroecological zone as follows: grid points below 7°N were assigned to the Southern Zone (March – October rainfall), while grid points between 7°N and 10°N were assigned to the Middle Belt Zone (April – October rainfall); and grid points above 10°N were assigned to the Northern Zone (May – September rainfall). These features are agronomic without the need for external reference data.
- **Wheat Exclusion:** Wheat records were excluded from the final modelling dataset, leaving maize, rice, and soybean as the crops used for analysis and model development.

3.3 Model Training and Evaluation

For the system training and evaluation, the following steps were taken:

- **Feature and target selection:** The five input features used for all models were latitude, longitude, average annual temperature, annual precipitation, and relative humidity. The engineered crop calendar and rainy-season fields were used to characterise the dataset, but these were not included as model input features. Since separate models were trained for each crop, the crop column became redundant as a direct predictor. Hence, it was also not included as a model input but the target variable was crop-yield in tonnes per hectare.
- **Crop-specific modelling:** Separate models were trained for each crop, and it is an agronomic reality that maize, rice and soybean have different climate-yield response curves. For example, rice has much higher thresholds for rainfall than soybean, which a pooled model would average out at the expense of the accuracy of each crop.
- **Train-test split:** The dataset was split into a training set (80%) and a test set (20%) using scikit-learn's train_test_split function. The same split ratios were used consistently for all three crops.
- **Models evaluated:** Five algorithms were trained and compared for each crop selected to represent a range of complexity from linear baselines to advanced gradient-boosted ensembles:
    - Linear Regression: a baseline capturing only linear relationships between climate variables and yield.
    - Decision Tree Regressor: max_depth=15, random_state=42.
    - Random Forest Regressor: n_estimators=100, max_depth=15, random_state=42, parallel training with n_jobs=-1.
    - XGBoost Regressor: n_estimators=200, max_depth=10, learning_rate=0.1, random_state=42.
    - LightGBM Regressor: n_estimators=200, max_depth=10, learning_rate=0.1, random_state=42.
- **Evaluation metric:** The coefficient of determination (R^2) was used to evaluate the model performance. It measures the proportion of variance in crop yield explained by the model. An R^2 score closer to 1.0 means the better the model fits the data; the closer the score is to 0.0, the worse the model fits the data. It is important to note that all the models in each crop iteration were trained on the same training partition and evaluated on the same held-out test partition, for a fair comparison.

3.4 Large Language Model (LLM) Integration

After the yield prediction, a contextualised advisory layer was added, leveraging Google's Generative AI Application Programming Interface (API). The system tries to load models in order of their capabilities, Gemma 3 (27B, 12B, 4B, 1B) and then Gemini 2.0 Flash, to ensure graceful degradation if API constraints prevent the higher-capability model from being loaded. The recommendations are generated based on a structured prompt that includes four inputs: current weather conditions (temperature, rainfall, humidity), yield predicted by the ML, crop-specific agronomic parameters for Nigerian conditions, and farm size. The model provides a JavaScript Object Notation (JSON) object with a prioritised list of recommendations, optimal timing advice, yield assessment, and executive summary. Recommendations are classified into types (temperature, irrigation, pest and disease, fertiliser, planting, harvest, storage, or market) and given a priority level (critical, high, medium, or low).

Rate limiting is done through an exponential retry mechanism. If the system receives a 429 response, it extracts the retry delay from the response using regular expression (regex) and waits before retrying, up to 3 times. When the LLM is not available, a deterministic rule-based fallback is activated, which identifies threshold violations (e.g., temperatures below 18°C or above 35°C, humidity above 80%, and rainfall below 400mm or above 2000mm) and returns basic prioritised recommendations without relying on the LLM. However, errors are hidden from users when malformed responses trigger the same fallback.

3.5 USSD Interface Design

The USSD interface was built as a stateful, menu-driven application within the Spring Boot backend using Africa's Talking API, designed with two constraints at the protocol level: a 160-character response limit per screen and the statelessness of Global System for Mobile Communications (GSM) sessions in consideration. Its statelessness is managed by a server-side session store keyed by Africa's Talking's session identity (ID). The user enters an asterisk-delimited string of all previous inputs, which is then passed to the backend to be converted into an ordered array to determine the current depth of the menu and to retrieve the last input. Three multi-step conversation flows are supported: Registration flow (name, optional email), seven-step farm creation flow with inline validation, and two-step farm deletion flow. The verified users are those who have registered their phone numbers on the USSD system, and the passwords are replaced with hashed Universally Unique Identifiers (UUIDs), while the usernames are automatically generated from the phone numbers, thus hiding the management of credentials from the farmer. Recommendation delivery is separated from the USSD session because of the character limit. If a farmer asks for advice, the session ends immediately with a confirmation, and an asynchronous task fetches real-time weather data, calls the Python microservice for yield prediction and LLM-generated recommendations, and sends the output as an SMS via Africa's Talking API. If the ML service or SMS gateway is not available, a fallback error message is sent instead of a silent end.

4 Results

4.1 System Evaluation

For the system evaluation, the following criteria were used:

4.1.1 Model Accuracy

The five models trained across maize, rice, and soybean demonstrated a consistent performance hierarchy. Linear regression produced the weakest results across all three crops, with R^2 scores of 0.446, 0.258, and 0.320, respectively, confirming the relationship between crop yield and selected climate variables cannot be captured adequately by linear assumptions alone. Consequently, tree-based ensemble methods improved substantially on this baseline, with Random Forest achieving R^2 scores between 0.928 and 0.939, and XGBoost achieving the highest scores across all crops: 0.972, 0.963, and 0.960 for maize, rice, and soybean, respectively. Also, LightGBM performed competitively with XGBoost on soybeans (0.956) but marginally lower on maize and rice. The consistency of XGBoost's superiority across the three independently trained crop models provided stronger evidence for its suitability in this domain than a single crop evaluation would. Table 2 presents the R^2 scores for all fifteen model-crop combinations.

Table 2 R^2 Scores for All Models Across Three Crops

Model	Maize R^2	Rice R^2	Soyabeans R^2
Linear Regression	0.446	0.258	0.320
Decision Tree	0.901	0.891	0.876
Random Forest	0.939	0.935	0.928
XGBoost	0.972	0.963	0.960
LightGBM	0.946	0.932	0.956

The result shows that XGBoost achieved the highest R^2 score for all three crops and was selected as the production model in each case. XGBoost as best-performing model for the three crops was serialised using Python's pickle library and deployed as part of the Python microservice, with model file sizes of 7.07 MB (maize), 7.40 MB (rice), and 5.42 MB (soybean). When the performance of the linear regression model and the tree-based models was compared, the significant performance gap confirmed that the climate-yield relationship in Nigerian agriculture is non-linear and that ensemble methods, particularly gradient boosting, are more effective than other machine learning methods used for the study.

4.1.2 System Reliability

The two-tier fallback architecture was tested in the event of an API failure. When the Gemini API was unavailable, the system triggered the rule-based fallback and sent out recommendations based on thresholds. Also, SMS outputs were sent to the users of the USSD service in both scenarios, which is a testament to the fact that the asynchronous delivery design works and was designed without regard to service availability.

4.1.3 Interface Evaluation

Both the web and USSD interfaces were evaluated on the main user journeys from registration through farm profile creation, weather retrieval, and recommendation delivery. While the web interface correctly rendered recommendations under live weather conditions, the USSD interface successfully finished all three conversation flows without session errors, and recommendation requests triggered SMS delivery within the expected processing time.

4.2 System Result

This section shows the output of the system developed, both the online and offline farming advisory systems.

4.2.1 The Result for the Online-Based Farming Advisory System

Figure 2 shows the creation of a farm account where you enter the farm name, location, crop and the size of the farm to be able to get recommendations.

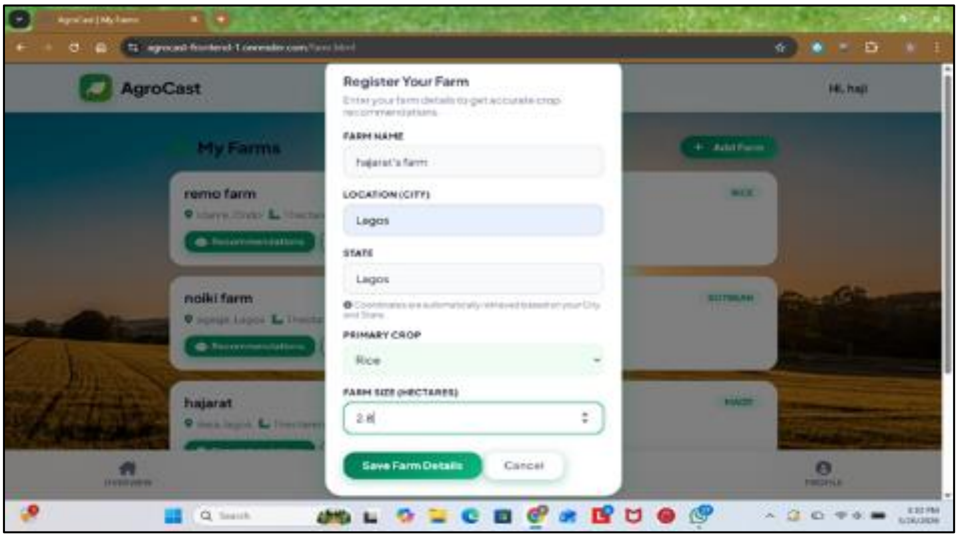

Figure 2 Creation of Farm Profile

Figure 3 shows the recommendations after entering the details and requesting the recommendations from the system.

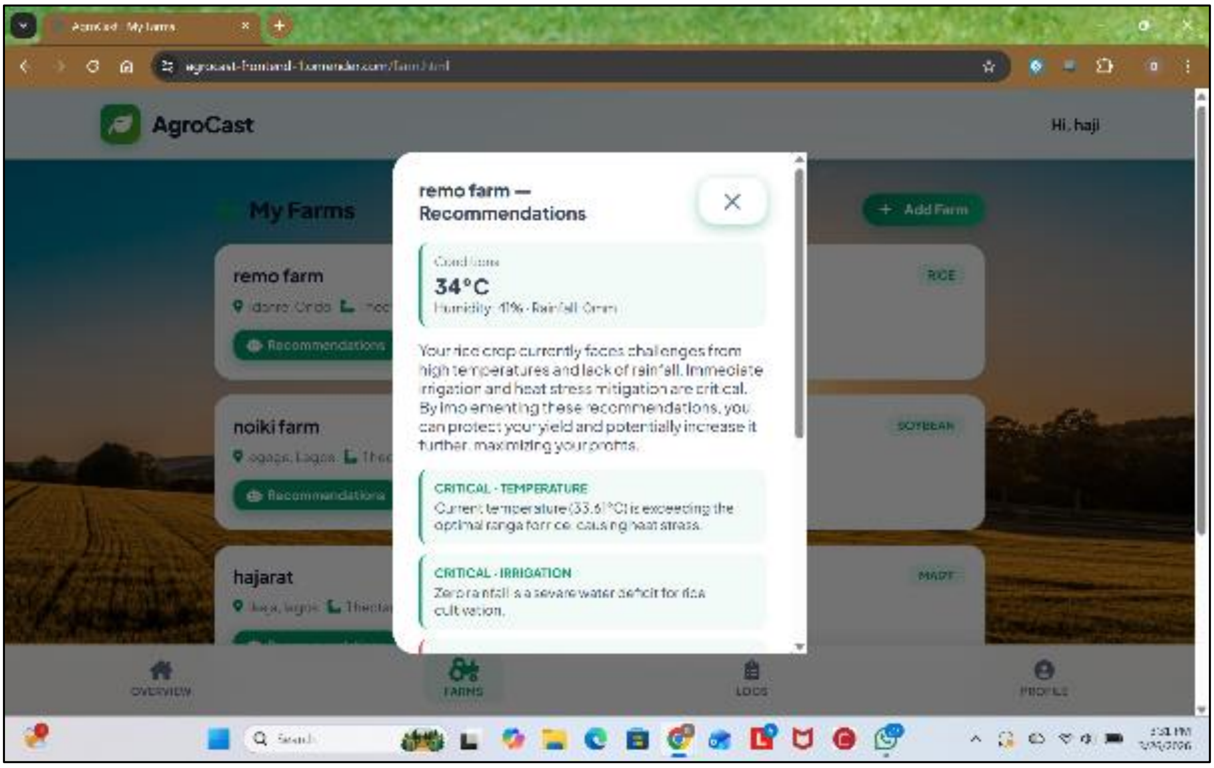

Figure 3 Recommendation Pop-Up

4.2.2 The Result for the Offline-Based Farming Advisory System

We used Africa's talking to create a service code and channel, and a callback URL (that the backend uses to communicate with Africa's Talking API). The recommendations are sent via SMS due to session limits, and figure 4 shows the recommendations received by the farmer via USSD delivered to the SMS.

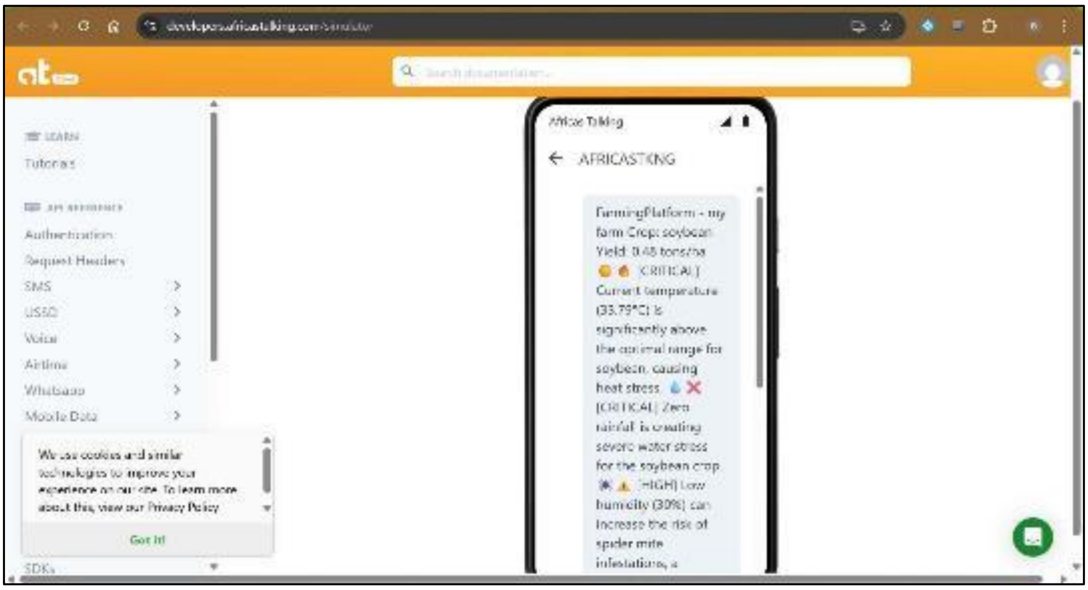

Figure 4 SMS Recommendation

5 Discussion

The experimental results demonstrated that the ensemble learning models performed better than the traditional regression model in predicting crop yield. Among all the models evaluated, XGBoost achieved the highest R^2 scores for maize, rice, and soybean, with values of 0.972, 0.963, and 0.960, respectively. This means that the model could learn the relationship between the climatic variables (such as temperature, precipitation, and humidity) and the crop yield values well enough. Notably, Linear regression had the lowest accuracy in all the crops, while Random Forest and LightGBM were outstandingly performing. Both the web and USSD interfaces were able to successfully deliver weather-based farming recommendations. The web application enabled farmers with internet capable devices to have access to interactive dashboards, weather forecasts, activity logs, and personalised recommendations, while farmers with basic mobile phones received recommendations via the USSD and SMS channels. This is a proof that the platform was able to cut down on the accessibility gap between internet-enabled and offline farmers.

The use of the Gemini Large Language Model (LLM) enhanced the recommendation aspect of the system by providing more detailed and context-sensitive pieces of farming advice based on the forecast yield and weather data gathered. The recommendations included irrigation, fertiliser application, pest and disease control, and harvesting and marketing recommendations. As the LLM service was not available in certain scenarios, the fallback system also implemented a rule-based recommendation system for basic recommendations. The proposed platform brings together yield prediction using machine learning, weather-based advisory services, and dual online and offline access in a single system, which is superior to the existing systems discussed in related works. A lot of systems currently in use are dependent on the smartphone, internet connectivity, costly hardware, or small-scale deployments of the pilot systems. Notably, these limitations were overcome by the developed system, which also allows for web and USSD interaction with Nigerian smallholder farmers.

5.1 Limitations

Although successful, there were some system limitations to the study. While carrying out the design, development, and testing phases of this advisory platform, a few technical and practical flaws were faced:

- Lack of real-time: The study used historical climatic data from 1981 to 2016 and did not currently include real-time input from soil sensors in the IoT network, or multi-language support for advising.
- Scarcity of localised datasets: Finding highly accurate, historically consistent agricultural and weather datasets specific to deep rural Nigerian zones proved incredibly difficult, forcing the AI to occasionally work with broader regional data rather than hyper-local farm statistics.
- Network Dependency & USSD Timeouts: Highly unstable telecommunications networks in deep rural areas occasionally interrupted the real-time retrieval of weather data from the APIs and sometimes caused the USSD sessions to time out before the farmer could finish reading the menu.
- USSD Character Constraints: Communicating deeply nuanced, AI-generated farming advice via USSD was incredibly difficult due to the strict 160-character limit.
- AI model retriction: The AI model had to be heavily restricted to force it to spit out highly condensed, stripped-down summaries rather than detailed explanations.
- API Data vs Physical Sensors: Because the platform currently relies on third-party weather APIs (like OpenWeatherMap) rather than physical IoT soil moisture sensors planted directly in the farmer's field, the micro-level accuracy of the soil-based advice was occasionally generalised to the regional level instead of the exact farm plot.

Further enhancements could include soil monitoring with IoT, translation capabilities using local dialects, and computer vision capabilities for crop disease detection in real-time.

6 Conclusion

In conclusion, the development and deployment of the AI-powered precision farming platform were completed with resounding success. The system met its primary objectives, resulting in a highly centralised, secure, and inclusive tool that directly addresses the food insecurity and climate anxiety that have traditionally plagued Nigerian agriculture. By deploying this dual-channel digital solution, local smallholder farmers no longer have to rely purely on guesswork or outdated radio broadcasts to rightly plan their seasons. Regardless of their digital literacy or internet access, the process of receiving critical crop advice, logging farm profiles, and tracking weather warnings is now intelligent, extremely fast, and completely democratised to improve agricultural practises among farmers, particularly those in Nigeria.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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