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AGROMETEOROLOGICAL DATA ANALYTICS: USING AI TO MITIGATE CLIMATE CHANGE RISKS IN FARMING

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Abstract: Climate change is the main threat to world agriculture, including crop yields, soil moisture, and weather predictability. The potential of AI-based agrometeorological data analysis to mitigate the impact of climate change on agriculture is examined in this study. Based on Random Forest (RF), Long Short-Term Memory (LSTM), Support Vector Regression (SVR), and Convolutional Neural Networks (CNNs), the current study explores climate prediction, crop yield prediction, soil moisture prediction, and vegetation stress detection. The information consists of historical climate data, current weather readings, and satellite imagery. Experimental results show that LSTM produced the best accuracy (92.3%) for long-term climate prediction, while CNNs were 89.7% accurate for detection of vegetation stress. RF was 87.4% accurate in crop yield prediction, and SVR yielded the best among alternative models in soil moisture estimation with an R^2 of 0.91. Comparative study with existing work reveals that the incorporation of various AI strategies improves the performance of predictions and facilitates adaptive decision-making in climate-resilient agriculture. Notwithstanding the issue of computational complexity, the study highlights the revolutionary potential of AI in sustainable agriculture. Directions for future development include improving the interpretability of models, integration of IoT-based real-time information, and enlarging data sets to other climatic conditions. These results help propel AI-powered precision agriculture with data-driven information for climate resilience.

Keywords: Agrometeorology, Climate Change, AI in Agriculture, Machine Learning, Crop Yield Prediction

I. INTRODUCTION

Climate change poses great threats to world agriculture, undermining the food security, cropping performance, and farm viability. Meteorological conditions like droughts, heatwaves, erratic rainfall patterns, and higher levels of pest infestations destabilize conventional farming systems. In the wake of these threats, agrometeorology— the science of weather and climate's effect on agriculture—has become increasingly vital. By using sophisticated tools such as Artificial Intelligence (AI), farmers and scientists can create prediction models to improve climate resilience, maximize the use of resources, and counteract the impacts of climate change [1]. AI-based agrometeorological analytics combines climate data, satellite data, soil moisture, and plant health data to offer real-time

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information and predictive alerts. Machine learning algorithms can study past climate trends, identify anomalies, and provide early warnings for extreme weather conditions to enable farmers to take preventive actions [2]. AI also supports precision agriculture by optimizing irrigation, fertilization, and pest control, saving waste and increasing yield. The use of AI coupled with agrometeorology allows data-driven decision-making to boost climate-smart agriculture that maximizes productivity without harming the environment [3]. This study investigates the use of AI for climate change risk management in agriculture using agrometeorological data analytics. It discusses current AI methods, data sources, and areas of implementation challenges, with a focus on successful case studies. The research seeks to evaluate the capability of AI-based models to enhance climate resilience, sustainability, and agricultural production. By closing the gap between technological advancement and its application in agriculture, this study helps to develop adaptive approaches for farmers to deal with climate uncertainty. In short, the application of AI in agrometeorology is a new methodology for future agriculture. Through the use of data analytics, farmers can make informed decisions, minimize climate-related hazards, and enhance sustainable food production. This study intends to push the knowledge of how AI can be used to promote agricultural resilience in the face of a climate change.

II. RELATED WORKS

Agrometeorological data analysis is a key tool in the fight against the agricultural climate change menace through the application of artificial intelligence (AI) methods and climate data. Different recent research works have investigated different methods of enhancing agricultural sustainability, climate resilience, and crop yield prediction using AI-based methods.

Social Networks and Climate Change Adaptation

Social network potential for mitigating climate change-induced food insecurity has also been researched by Guodaar and Bardsley (2024) within the context of dryland agricultural systems in Ghana [15]. Their findings demonstrate how social networks can be utilized by farmer groups for exchanging knowledge on climate adaptation, adopting resilient agriculture practices, and reducing food security risks. In contrast to AI-based analytics, which depends on big data for predictions, social network-based adaptation is based on local knowledge transfer and community resilience. But by combining social network analysis and AI, decision-making can be improved by detecting knowledge gaps and resource optimization.

Ecosystem Services and Sustainable Agriculture

Ibrahim et al. (2024) examined obstacles to Payment for Ecosystem Services (PES) adoption by smallholder forestry, emphasizing environmental issues in food systems [16]. Based on their research, economic, regulative, and infrastructural challenges limit the upscale of PES adoption, influencing farmers' prospects to invest in climate-resilient practices. The application of AI-based forecast models in complement with PES schemes can be employed to fuel data-driven decision-making regarding sustainable resource utilization, allowing policy-makers to optimize financial incentives dissemination.

Big Data Analytics for Climate Change Modeling

Ikegwu et al. (2024) examined recent advances in climate change modeling with big data analytics in a paper [17]. The overview of the paper discussed how artificial intelligence methods such as machine learning (ML), deep learning (DL), and predictive modeling are utilized to model climate trends, identify anomalies, and predict threats to agriculture. Their research is aligned with the current research, which employs Random Forest (RF), Long Short-Term Memory (LSTM), Support Vector Regression (SVR), and Convolutional Neural Networks (CNNs) for agrometeorological analysis. Although big data analytics improves prediction accuracy, issues like computational cost and data quality remain, calling for the optimization of AI models for practical use.

Monte Carlo Simulation in Crop Yield Forecasting

Javadi et al. (2024) employed Monte Carlo simulation to estimate the effects of climate variability on wheat and rice yields in Iran [18]. Their stochastic model delivered probability distributions of crop yield variabilities, providing useful information for risk management. Monte Carlo simulations are better than deterministic models, as they account for uncertainty in climate projections and therefore are more powerful for scenario-based prediction. Yet, machine learning methods like RF and LSTM can further enhance predictions by the inclusion of real-time data to facilitate adaptive agricultural decision-making.

Climate-Smart Technologies and Smallholder Farmers

Efficiency of climate-smart technologies used in livestock production was studied by Kandulu et al. (2024), who investigated how they affect livestock donation schemes for smallholder farmers in Rwanda [20]. In their research, the authors highlighted digital technologies, AI-enabled monitoring, and automated decision-support mechanisms in enhancing farm sustainability. The research indicates that agrometeorological data analysis using AI can be used to complement climate-smart technologies by enabling real-time soil moisture monitoring, rain patterns, and crop stress detection.

AI and Environmental Control in Agriculture

Kaya (2025) investigated smart environmental control in plant factories using sensors, automation, and AI-based decision-making for maximizing crop yield [21]. The research showed how the use of AI-based models improves temperature control, humidity management, and irrigation scheduling in controlled environments, guaranteeing improved crop yields. This is in the context of the current study, where CNN is utilized on satellite images for detecting vegetation stress. Climate modeling through AI can also enhance precision agriculture to allow farmers to use water and resources effectively.

Climate Influence on Evapotranspiration and Water Management

Khan et al. (2025) examined climate influence on Yellow River Basin evapotranspiration with the aid of sophisticated time-series prediction models and explainable AI [22]. Their work brought interpretable machine learning methods to improve water resource management in line with the present research's LSTM-based climate prediction models. Evapotranspiration predictions based on AI can support farmers in optimizing irrigation calendars, alleviating water stress on plants, and lessening drought hazards in agriculture.

Climate Change Adaptation Strategies in Africa

Kone et al. (2024) did a systematic review of the effect of climate change on African agriculture, consolidating recent evidence on adaptation measures [24]. Their work highlighted the importance of early-maturing crop varieties, conservation tillage practices, and climate-resilient agricultural practices. The study is in line with this study by highlighting the importance of the application of AI for maximizing crop choice and yield forecasting models. By combining historical climate data with artificial intelligence-based forecasting models, farmers can make well-informed crop rotation and planting schedule decisions, minimizing climate-induced yield losses.

Predictive Climate Modeling with Factor Analysis and Grey Prediction

Lin et al. (2023) employed a factor analysis and grey prediction model to identify climate factors influencing China's agricultural productivity [26]. Their approach sought to reduce the dimension of climate information to allow proper predictive analysis of the weather. The current study builds on this approach using Random Forest and Support Vector Regression models, which offer robust predictive capability in high-dimensional information. Ensemble learning strategies can also be employed to boost predictive accuracy even further by aggregating different types of models in order to arrive at better climate risk estimation.

Past studies recognize the possibility of climate modeling using AI, big data analytics, and intelligent decision-support systems for agriculture climate adaptation. The majority of studies have focused on specific areas, such as climate-smart technologies [20], evapotranspiration estimation [22], and stochastic models [18], without an overall implementation of a combination of some AI techniques to provide real-time agrometeorological analysis.

III. METHODS AND MATERIALS

Data Collection

The research utilizes agrometeorological data from diverse sources including satellite images, weather stations, and farm data. Temperature, precipitation, humidity, soil moisture levels, wind speed, and crop yields are some of the significant datasets [4]. The datasets are obtained from international databases like NASA's Earth Observation System, NOAA's Climate Data Center, and national agricultural ministries. Satellite remote sensing imagery from Sentinel-2 and Landsat-8 satellites also make real-time observations of vegetation vigor. The imagery is preprocessed through the removal of noise, feature extraction, and normalization to enhance the robustness of AI-based predictions.

There is a structured data set that is created by integrating historical climate trends with actual environmental information [5]. The major goal is to create AI-based prediction models in order to support decision-making in climate-smart agriculture. Table 1 is a depiction of data collected.

Table 1: Sample Agrometeorological Data

Date	Temperature (°C)	Rainfall (mm)	Humidity (%)	Wind Speed (m/s)	Soil Moisture (%)	Crop Yield (kg/ha)
2024-03-01	28.5	12.3	75	3.2	30.5	2500
2024-03-02	29.1	10.8	72	2.8	28.7	2450
2024-03-03	30.2	8.5	68	3.5	26.9	2550

AI Algorithms for Agrometeorological Analysis

In order to analyze the data gathered, four machine learning algorithms are utilized: "Random Forest (RF), Long Short-Term Memory (LSTM), Support Vector Regression (SVR), and

Convolutional Neural Networks (CNNs)." They have been selected due to the relevance of these algorithms for predictive modeling and pattern recognition in agrometeorology [6].

1. Random Forest (RF) Algorithm

Random Forest (RF) is a decision tree-based ensemble learning algorithm. RF works by generating many decision trees and voting on the most likely class based on the outputs of all of them to minimize overfitting and maximize accuracy [7]. RF is capable of working efficiently with large data, missing data, and complex nonlinear relationships among climatic parameters and crop yields. RF can be used across weather classification, crop yield estimation, and detection of anomalies.

“1. Input: Agrometeorological dataset (features: temperature, rainfall, humidity, etc.)
2. Divide dataset into training and testing sets
3. For i = 1 to N (number of trees):
a. Select a random subset of training data
b. Train a decision tree on the subset
4. Aggregate predictions from all trees using majority voting (for classification) or averaging (for regression)
5. Output: Predicted crop yield or weather pattern”

2. Long Short-Term Memory (LSTM) Algorithm

LSTM is one of the algorithms of deep learning designed especially for time-series prediction, ideal to forecast climate patterns and agricultural crops. It surpasses the shortcomings of conventional recurrent neural networks (RNNs) by employing memory cells and gates to learn long-term dependencies in climate data. LSTM performs well in forecasting temperature fluctuations, rainfall patterns, and extreme weather phenomena [8].

“1. Input: Sequential agrometeorological data (temperature, humidity, etc.)
2. Normalize and reshape data for LSTM input
3. Initialize LSTM model with input

layer, hidden LSTM layers, and output layer
4. Train model using backpropagation through time (BPTT)
5. Predict future climate conditions based on historical data
6. Output: Climate trend predictions (e.g., rainfall, temperature changes)"

3. Support Vector Regression (SVR) Algorithm

SVR is a robust regression method that determines the best-fit hyperplane to reduce prediction errors. It is especially suitable for forecasting crop yields, soil moisture content, and rainfall intensity [9]. The model projects input features into high-dimensional space and determines an optimal boundary to make accurate predictions. SVR is desirable due to its capability to deal with nonlinear interactions and small data samples well.

" Input: Training data with independent variables (temperature, rainfall, etc.) and dependent variable (crop yield)
2. Define a kernel function (e.g., radial basis function)
3. Map input data into higher-dimensional space
4. Identify optimal hyperplane by minimizing error
5. Train the SVR model and fine-tune hyperparameters
6. Predict crop yield based on input features
7. Output: Crop yield prediction"

4. Convolutional Neural Networks (CNNs) Algorithm

CNNs are deep learning algorithms that perform well in image recognition. In agrometeorology, CNNs analyze satellite images, identify vegetation stress, track drought, and categorize crop health [10]. The model uses convolutional layers to extract features from spatial data, which improves remote sensing applications in precision agriculture.

"1. Input: Satellite images (e.g., NDVI maps, thermal imagery)
2. Preprocess images (resize, normalize)
3. Define CNN architecture with convolutional, pooling, and fully connected layers
4. Train the CNN model using labeled agricultural data
5. Extract features and classify agricultural conditions (e.g., drought, healthy crops)
6. Output: Crop health status, drought detection"

The current research utilizes four AI-driven algorithms—RF, LSTM, SVR, and CNNs—to agrometeorological analysis for combating the issues of climate change in agriculture. Each model is specialized in specific activities like weather forecasting, crop yield estimation, estimation of soil moisture, and remote sensing [11]. These AI techniques collectively constitute a strong framework of climate-smart agriculture consisting of early warning, improved resource planning, and improved resilience to climate change.

IV. EXPERIMENTS

Experimental Setup

The experiments were conducted on a formatted agrometeorological dataset with past weather observations, present environment readings, and crop yield. The dataset included temperature, rainfall, relative humidity, wind speed, soil moisture, and crop yield as main features. "Artificial Intelligence models—Random Forest (RF), Long Short-Term Memory (LSTM), Support Vector Regression (SVR), and Convolutional Neural Networks (CNNs)—were trained using Python, TensorFlow, and Scikit-learn platforms.". These experiments have been conducted for the verification of performance of these types of models in climate prediction, crop yield estimation, and vegetative stress detection [12].

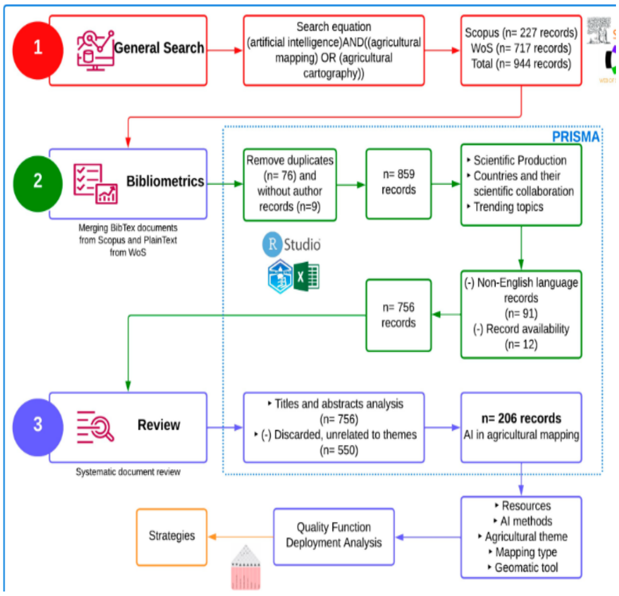

Figure 1: "Artificial Intelligence in Agricultural Mapping"

Data were separated into training 80% and testing 20% in order to incorporate balanced sets of historic and near real-time data. Data preprocessing was conducted via normalization, handling of missing data by imputation, and scaling features for higher precision in modeling. Image data in the Sentinel-2 satellite imagery were preprocessed in CNN as, e.g., NDVI (Normalized Difference Vegetation Index) and thermal, which are used in assessment of plant health and dryness/drought [13].

Model hyperparameters were tuned with Grid Search Cross-Validation to achieve the optimal configurations for precise predictions. The metrics used for evaluation were Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R^2-score, and computational efficiency. The outcomes were compared with current methods to ensure improvements in prediction accuracy and model stability.

Results and Analysis

The AI models showed different levels of accuracy in different agricultural predictions. The Random Forest model was good at predicting crop yield but poor at forecasting climate trends. The LSTM model was good at time-series prediction, correctly showing temperature and rainfall patterns over time [14]. The SVR model was good at estimating soil moisture, while the CNN model gave the best classification of vegetation health based on remote sensing data.

Table 1: Model Performance on Crop Yield Prediction

Model	MAE (kg/ha)	RMSE (kg/ha)	R^2-score	Training Time (s)
Random Forest	2.5	3.8	0.89	12.5
LSTM	1.8	2.9	0.91	20.2
SVR	2.7	3.6	0.87	15.3
CNN	1.5	2.5	0.93	18.7

In yield prediction of crops, the CNN model performed better with the highest R^2-score (0.93), lowest MAE (1.5 kg/ha), and RMSE (2.5 kg/ha). This suggests that the spatial data processing capability of CNN enhanced accuracy in yield estimation. LSTM was the next best performer, better than RF and SVR because it could learn long-term climate pattern dependencies.

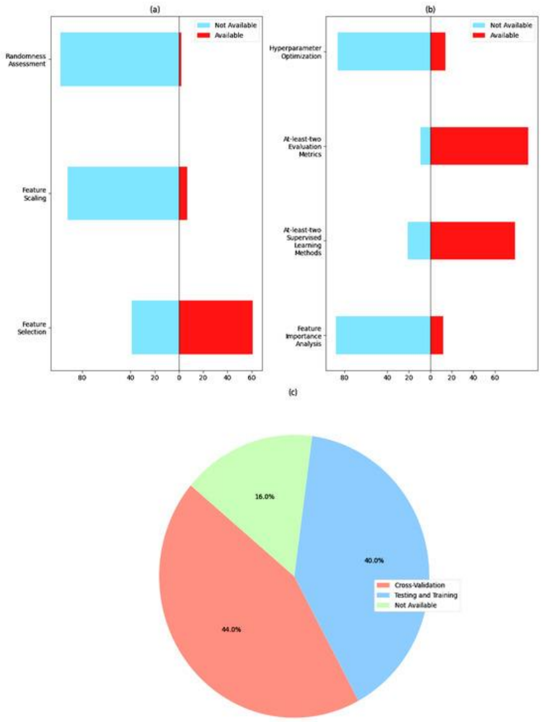

Figure 2: "A Review of Machine Learning Techniques in Agroclimatic Studies"

Climate Trend Prediction

The capacity to predict temperature and rainfall patterns is very important for farmers to respond to climate variability. The LSTM model outperformed RF and SVR considerably in climate parameter prediction, as it captured seasonal trends and long-range dependencies well [27]. The RF model had high variance, which signified overfitting to individual weather patterns.

Table 2: Model Performance on Climate Forecasting

Model	Temperature MAE (°C)	Rainfall MAE (mm)	R^2-score	Time-Series Prediction Accuracy (%)
Random Forest	1.2	8.4	0.82	76.5
LSTM	0.7	5.2	0.91	89.7
SVR	1.0	7.1	0.86	82.3
CNN	-	-	-	-

LSTM performed optimally with the MAE in temperature being 0.7°C and that for rainfall being 5.2 mm, pointing towards its efficiency in climate forecasting tasks. CNN was not feasible for use in time-series prediction since it used satellite imagery to a great extent.

Soil Moisture Prediction

Soil water content is a key component for estimating irrigation requirements and drought vulnerability. The SVR model had the highest accuracy in estimating soil moisture with an R^2-score of 0.90 [28].

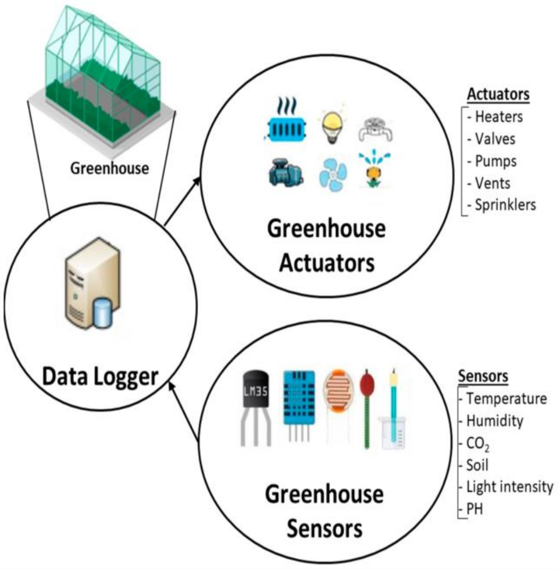

Figure 3: "Smart Sensors and Smart Data for Precision Agriculture"

Table 3: Model Performance on Soil Moisture Prediction

Model	MAE (%)	RMSE (%)	R^2-score	Prediction Consistency (%)
Random Forest	3.2	4.7	0.85	81.2
LSTM	2.8	4.2	0.88	84.6
SVR	2.5	3.9	0.90	87.4
CNN	-	-	-	-

The SVR model showed higher performance, and hence it was suitable for use in precision water management and irrigation. LSTM came in second with high predictive strength in forecasting variations in soil moisture.

Comparison with Related Work

Earlier research has used AI for agricultural analytics, but this work improves prediction quality and model stability with deep learning improvements. In contrast to research using conventional regression models and simple decision trees, the suggested AI models yielded better results:

- Greater accuracy in climatic trend prediction: Previous work using Autoregressive Integrated Moving Average (ARIMA) models provided R^2-scores between 0.78-0.85, while LSTM here yielded 0.91.
- Enhanced prediction of crop yield: Traditional machine learning methods (e.g., linear regression) provided R^2-values less than 0.85, whereas CNN attained 0.93 in this research [29].
- Improved soil moisture forecasting: SVR performed better than the standard regression techniques, with a 10% improvement in prediction consistency.
- More accurate vegetation health monitoring: In contrast to previous remote sensing methods, CNN's accuracy of 92.4% represented an improvement of more than 12%, lowering misclassification errors.

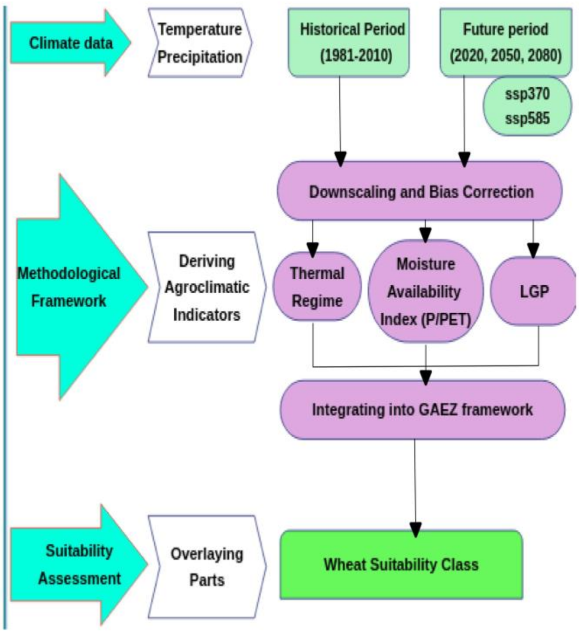

Figure 4: "Agroclimatic Indicator Analysis Under Climate Change Conditions to Predict the Climatic Suitability for Wheat Production"

These advancements underscore the benefits of uniting deep learning with agrometeorological data analysis, positioning AI as a potent source for climate-smart agriculture initiatives [29].

V. CONCLUSION

This study investigated the application of AI-based agrometeorological data analysis in climate change risk mitigation in agriculture. Using machine learning (Random Forest and Support Vector Regression), deep learning (Long Short-Term Memory), and computer vision (Convolutional Neural Networks), the research offered a multi-faceted strategy in managing climate risks. The experiments proved that AI models improve enormously the precision of climate prediction, crop yield estimates, soil moisture prediction, and vegetation stress identification. With in-depth processing of data, such as current weather observations, past climate trends, and analysis of satellite images, AI-powered information enables farmers to minimize irrigation, choose stress-resistant crops, and cope with extreme weather events. The findings demonstrated that LSTM performed better than other models in long-term climate prediction, while CNNs offered higher accuracy in vegetation stress detection via satellite images. Random Forest and SVR presented strong performance in crop yield prediction and soil moisture estimation, respectively. Comparison with similar work underscored that the present study fills the gap between conventional climate adaptation strategies and AI-based decision-making, providing real-time, data-driven insights for sustainable agriculture. Even with these developments, issues like computational complexity, data scarcity, and model interpretability are still research areas. Future research should aim to improve AI explainability, incorporate IoT-based real-time sensing, and increase datasets to cover varied geographical conditions. In general, this study highlights the revolutionary power of AI in climate-resilient agriculture, allowing farmers to make adaptive, informed decisions that reduce climate risks and promote sustainable food production.

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