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AI-Driven Precision Agriculture for Smallholder Farmers in Rwanda: A Case Study in Kayonza District

Jonathan Nturo[1*], Dr. Djuma Sumbiri[2], Dr. Jonathan Ngugi[3], Patrick Habimana[4]
Computing and Information Sciences, University of Lay Adventists of Kigali, Rwanda
Corresponding Author Emails: jonathannt5@gmail.com; sumbirdj@gmail.com; pialn1@gmail.com; habimanapat7@gmail.com

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Abstract

This research investigates the transformative role of Artificial Intelligence (AI)-driven precision agriculture in enhancing climate resilience, productivity, and financial protection for smallholder farmers in Rwanda, focusing on Kayonza District. The study integrates satellite-based vegetation indices (NDVI), rainfall anomaly datasets (CHIRPS, TAMSAT), IoT-enabled soil sensors, and machine learning algorithms, particularly Random Forest models, to improve crop yield prediction, drought monitoring, and agricultural risk management. Model evaluation demonstrated strong predictive capacity ($R^2 = 0.83$; RMSE = 1.21 t/ha), with soil moisture, NDVI, and rainfall anomalies identified as key yield determinants. SHAP analysis enhanced model transparency, informing actionable insights for tailored interventions. The study introduces and field-tests an AI-powered, revenue-index insurance model that bundles crop and livestock protection, credit access through savings cooperatives, mobile climate alerts, and digital extension services. It further explores innovative solutions such as drone-assisted irrigation in drought-prone zones like Ndego to address water scarcity with precision. Recommendations emphasize institutional integration of digital risk management tools into national agricultural systems, scaling mobile advisory services, expanding data-driven claim triggers, training agronomists on AI applications, and strengthening partnerships with cooperatives and insurers for holistic risk protection. The findings validate the scalability of AI-powered tools to inform digital agriculture policy, advance sustainable farming practices, and promote inclusive agri-financing. Overall, the study contributes a practical roadmap for leveraging modern technology to build climate-resilient food systems and improve rural livelihoods in Rwanda.

Keywords: *Precision Agriculture, Artificial Intelligence (AI), Climate Resilience, Random Forest, Revenue Index Insurance, IoT Sensors*

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1. Introduction

Rwanda's agricultural sector is the backbone of its economy, contributing about one-third of national GDP and employing over two-thirds of the population (GSMA, 2025).The vast majority of Rwandan farmers are smallholders reliant on rain-fed cultivation, which makes agriculture highly vulnerable to climate variability (Jeong, Lee & Kim, 2019). In recent years, the country has witnessed more frequent and severe droughts, especially in drought-prone eastern and southern regions, leading to water shortages, crop failures, and livestock losses (FAO, 2022). For example, between 1976 and 2007, droughts affected over 4 million Rwandans, and the 2015–2016 dry spell alone decimated 23,000 hectares of crops while causing the death of 1,750 cattle due to lack of water and fodder (MDPI, 2024 , p. 2). Such climate extremes not only threaten food security and rural livelihoods, but also underscore the urgent need for innovative solutions to enhance agricultural resilience in the face of climate change (IPCC, 2022, p. 7) . One promising avenue to bolster resilience and productivity is the adoption of AI-powered precision agriculture technologies. As weather patterns grow more erratic, building adaptive capacity through innovation has become imperative (ScienceDirect, 2025, pp. 3-7). Advanced tools—including imaging satellites and remote sensors, drone and robotic systems, artificial intelligence (AI), Internet of Things (IoT) networks, and big data analytics—can galvanize climate-resilient agriculture for improved food security (ScienceDirect, 2025). These technologies enable farmers to monitor environmental conditions in real time and make data-driven decisions, a critical advantage when dealing with unpredictable droughts and floods. Indeed, Rwanda's strategic plans for climate-smart agriculture (e.g., the national PSTA5 policy) emphasize digital innovation, calling for IoT-based early warning systems, AI-driven climate advisories, and precision irrigation to help farmers cope with droughts and erratic rainfall (MINAGRI, 2024). By leveraging such frontier technologies, smallholder farmers can better withstand and recover from climate disruptions like extreme weather and water scarcity.

2. Literature Review

Precision agriculture encompasses data-driven farm management techniques that leverage detailed spatial and temporal data to optimize agricultural inputs and practices (Guo et al., 2015). It integrates remote sensing technologies, including satellites and drones, ground-based IoT sensor networks, and machine learning algorithms to deliver a real-time, holistic view of crop health, soil conditions, and environmental factors. (MDPI, 2024). Further, studies describe the integration of satellite imagery, UAVs/drones, ground sensors, and GIS/data analytics to generate real-time data on soil moisture, nutrients, pest stress, and environmental conditions for precision farm decisions (Yadav et al., 2024). These tools enable site-specific interventions, such as precision irrigation, targeted fertilization, and pest control, thereby minimizing waste, enhancing resource-use efficiency, and improving productivity (Wiley, 2024).

Global best practices illustrate the transformative potential of precision agriculture. In Australia, the COALA project demonstrated that AI-driven irrigation management increased water-use efficiency by over 20% and boosted crop yields by 20–30% (Keymakr, 2023). Similarly, smart irrigation systems that integrate soil moisture data and weather forecasts have reduced on-farm water consumption by up to 25% without compromising yields (Abramov, 2024). These innovations are especially critical in Rwanda, where arable land is limited and agricultural productivity is increasingly threatened by periodic droughts and climate variability (World Bank, 2021).

Precision agriculture also plays a vital role in enhancing climate resilience. High-resolution satellite imagery, drone surveys, and IoT sensors facilitate early detection of crop stress, pest outbreaks, and water deficits across large areas (GAFSP, 2025). Machine learning algorithms synthesize these diverse data streams to generate actionable insights, such as predicting water stress or advising on optimal sowing dates (Virnodkar et al. , 2020). Importantly, the increasing accessibility of these technologies is helping democratize precision agriculture, enabling smallholder farmers to benefit from advanced decision-support tools previously available only to large-scale operations (Sustainability Directory, 2024).

This has the potential to significantly enhance rural livelihoods by increasing yields, reducing input costs, and strengthening food security. Among emerging innovations, drone-assisted irrigation is particularly promising for addressing water scarcity in drought-prone regions like Rwanda. Equipped with multispectral and thermal sensors, modern agricultural drones can rapidly assess field moisture variability and apply water precisely where it is needed most, thereby improving water-use efficiency and reducing waste (Climate Expert, 2025). Advanced drone platforms can also perform smart aerial irrigation by spraying water or liquid fertilizers uniformly over crops, making them suitable for remote or sloped terrains where traditional irrigation is impractical (Nyirahabimana, Habiyaremye & Bizimana, 2021). While adoption in Rwanda remains limited due to high upfront costs, technical constraints, and regulatory challenges, ongoing technological advancements and supportive policies are gradually overcoming these barriers (NCST, 2020). With targeted investments in solar-powered drones, farmer training, and streamlined UAV regulations, drone-based irrigation (Auctores, 2022) could become a viable solution for improving water management in areas such as the Ndego Sector of Kayonza District in Rwanda.

AI-driven precision agriculture further contributes to climate adaptation through tools such as Random Forest yield prediction models, which have demonstrated high accuracy (e.g., 87% in maize yield prediction using NDVI, soil moisture, and rainfall data. (European Space Agency, 2020). Across Africa and Asia, initiatives like ACRE Africa, (Climate Policy Initiative - CPI, 2025) Ethiopia's ATA (E-SHAPE, 2025), India's PMFBY illustrates how satellite data, microinsurance, and AI models can enhance climate-risk indexing and agricultural insurance delivery. In Rwanda, digital platforms such as Smart Nkunganire and NAIS provide the institutional foundation for integrating these technologies. The revenue-index insurance model advances this integration by combining AI-powered forecasting with financial services and mobile advisories, offering smallholders a holistic risk management solution.

Finally, literature highlights the importance of model transparency in policy applications. While ensemble machine learning models like Random Forest excel in predictive power, their "black-box" nature can limit adoption in policy contexts (RTI International,, 2025). Techniques such as SHAP (SHapley Additive exPlanations) enhance interpretability, helping policymakers and farmers build trust in AI-generated insights. This study contributes to this frontier by applying explainability techniques in Rwanda's agro-ecological context, ensuring that precision agriculture innovations are not only technically sound but also accessible and actionable for smallholders (Farmonaut, 2025).

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In summary, AI-driven precision agriculture—integrating satellite remote sensing, IoT networks, machine learning analytics, and emerging tools like drone-based irrigation—offers a paradigm shift for smallholder farming in Rwanda (Keymakr, 2022). These technologies provide scalable, data-driven strategies for climate adaptation, resource optimization, and yield enhancement, aligning with national strategies such as PSTA5 and NAIS to promote sustainable and resilient food systems.

3. Methodology

This study employed a data-driven methodology integrating satellite remote sensing, IoT sensor data, and machine learning analytics to develop and validate a precision agriculture model tailored for smallholder farmers in Kayonza District. The research covered all nine sectors of the district ensuring a comprehensive representation of the agro-ecological conditions. Using the Farmer Survey Tool (**Appendix E**), field data were collected and analyzed. The machine learning model development and evaluation were conducted in Python 3.9, employing Scikit-learn, Pandas, NumPy, and Matplotlib libraries. The primary model was a Random Forest Regressor, selected for its robustness in handling non-linear relationships and high-dimensional feature spaces. The methodological steps included data preparation, model training, validation, and performance evaluation (**Appendix F).**

3.1. Study Area

The research focused on nine sectors of Kayonza District: Gahini, Kabare, Kabarondo, Murama, Murundi, Mwili, Ndego, Ruramira, and Rwinkwavu. These sectors represent diverse agro-ecological conditions, including lowlands, hilly terrains, and irrigated perimeters.

3.2. Data Sources

- NDVI values from Sentinel-2 and Landsat imagery assessed vegetation health (**Appendix A**).
- Rainfall data from CHIRPS and TAMSAT were analyzed rainfall anomalies (**Appendix B**).
- Soil moisture data from IoT soil sensors, calibrated against gravimetric methods (±5% error margin).
- Actual crop yields from 50 sample fields from cooperatives in Kayonza supported model training and validation.

3.3. Machine Learning Model

A Random Forest regression model predicted crop yields using NDVI, soil moisture, and rainfall anomalies. The model was trained on 70% of the data and validated on 30%. Evaluation metrics: $R^2 = 0.83$, RMSE = 0.42 t/ha, MAE = 0.36 t/ha, NSE = 0.79.

3.4. Model Explainability

SHAP analysis identified NDVI, soil moisture, and rainfall anomaly as key yield predictors.

3.5. NDVI and Claim Triggers

NDVI < 0.2 and rainfall anomaly < 60% served as crop stress indicators for insurance claim triggers.

3.6. Ethical Considerations

All data collection followed informed consent protocols, with voluntary participation from farmers and cooperatives.

4. Results and Discussion

4.1. Random Forest Model Performance

A Random Forest regression algorithm was trained using NDVI, rainfall anomaly, and soil moisture data. Its performance was evaluated using standard validation metrics.

Table 1: Model Performance Metrics (Random Forest, 2025 Season A)

Metric	Value
R^2 (Coefficient of Determination)	0.81
RMSE (t/ha)	1.21
MAE (t/ha)	0.92
5-Fold Cross-Validation Score	0.81 ± 0.05

These results indicate strong predictive accuracy, with soil moisture contributing 42%, NDVI 22%, and rainfall anomaly 18% to yield variability.

4.2. Baseline Comparison: Linear Regression vs. Random Forest

A linear regression model achieved an R^2 of 0.61, substantially lower than Random Forest's 0.83. This demonstrates the superior capacity of ensemble methods to capture non-linear patterns in climate and crop data.

4.3. Explainability Using SHAP Values

SHAP (SHapley Additive exPlanations) analysis improved model transparency:

- Low soil moisture (<15%) strongly reduced yield predictions.
- NDVI < 0.2 triggered negative model output.
- Rainfall anomalies below 60% of norm correlated with loss projections.

These insights increase farmer trust and inform tailored interventions (**Appendix D**).

4.3.1 Model Validation and Performance Metrics)

R² (Coefficient of Determination):

We computed R^2 as per the following formula:

$$(R)^2 = 1 - \frac{\sum_{i=1}^{n}(Yobs,i - Ypred,i)^2}{\sum_{i=1}^{n}(Yobs,i - \bar{Y}obs)^2}$$

- $Yobs,i$ = actual yield at field i
- $Ypred,i$ = model advisory(predicted yield) at field i
- $\bar{Y}obs$ = mean of observed yields
- n = Total number of fields(50 fields)

For R^2 Computation, we calculated the sum of the squared prediction errors (SSPE) $\sum_{i=1}^{n}(Yobs,i - Ypred,i)^2$: divide the sum of the squared deviations from the mean(SSD): $\sum_{i=1}^{n}(Yobs,i - \bar{Y}obs)^2$; *Apply the formula:* $R^2 = 1 - \frac{SSPE}{SSD} = 1 - \frac{9.5}{50} = 1 - 0.19 = 0.81$

The model explains 81% of the variability in actual yields and performs much better than simply using the mean yield as a predictor.

Mean Absolute Error: $MAE = \frac{1}{n}\sum_{i=1}^{n} \mid Yobs,i - Ypred,i \mid$

Where:

- $Yobs,i$ = actual yield for field i
- $Ypred,i$ = model advisory(predicted yield) for field i
- n = number of fields(50)

For each field, we computed the absolute difference: $\mid Yobs,i - Ypred,i \mid$Then we summed all these absolute differences: $\sum \mid Yobs - Ypred \mid$ =total absolute error, then we divide by n=50 to obtain

$$MAE = \frac{\sum \mid Yobs - Ypred \mid}{50} = 0.36\, t/ha$$

The computed MAE of 0.36 t/ha, derived as the average of the absolute differences between observed and predicted yields across 50 fields, provides a direct and interpretable measure of model accuracy. This value indicates that, on average, the model's advisory differed from the actual yield by 0.36 tons per hectare. MAE is a robust metric because it reflects the typical size of the error in the same units as yield (t/ha), without being influenced by the direction (overprediction or underprediction) of the errors.

Normalized MAE (nMAE):

$$nMAE \frac{MAE}{\bar{Y}} X\ 100 = \frac{0.36}{3} X\ 100 = 12\%$$

The normalized mean absolute error (nMAE) of 12% indicates that the model's average absolute prediction error represents 12% of the mean observed yield (3 t/ha). This normalization allows for a dimensionless comparison of model performance across different studies or crop types. The relatively low nMAE confirms that the model's advisory was consistently close to actual yields, demonstrating good predictive precision within the context of this study.

Nash-Sutcliffe Efficiency (NSE)$CapNSE\, \frac{\sum(Yobs-Ypred)^2}{\sum(Yobs-\bar{Y}obs)^2} = 0.79$

The computed Nash-Sutcliffe Efficiency (NSE) of 0.79 demonstrates that the model explains 79% of the variance in the observed yields relative to the mean yield. This indicates that the Random Forest model performed well in predicting yield across the 50 fields. An NSE value close to 1 suggests high model efficiency, as it shows that the model's predictions closely match the actual yields. The positive NSE value further confirms that the model provides a more reliable advisory than simply using the mean observed yield as a predictor.

Mean Bias Error (MBE):

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(Yobs,i - Ypred,i)$$

- $Yobs,i$ = actual yield at field i
- $Ypred,i$ = model advisory(predicted yield) at field i

- n = number of fields(50)

We computed the sum of all differences: $\sum(Yobs,i - Ypred,i) = -1.0$, then divide by n=50, we get $MBE = \frac{-1.0}{50} = -0.02t/ha$

The computed MBE of -0.02 t/ha, obtained by dividing the total bias error (-1.0 t/ha) by the 50 fields assessed, indicates that the model's advisory outputs slightly underestimated the actual yields on average. This small negative bias demonstrates that the model's predictions were generally well-aligned with the observed data, with no significant tendency toward systematic overprediction or underprediction. Such a low MBE confirms the suitability of the model for reliable yield advisory in precision agriculture applications.

Table 2: Model Advisory vs Actual Yield

Field	Model Advisory (t/ha)	Actual Yield (t/ha)	Difference	Squared Difference
1	3.0	3.4	-0.4	0.16
2	2.8	3.0	-0.2	0.04
3	3.5	3.2	0.3	0.09
4	2.9	3.1	-0.2	0.04
5	3.3	3.0	0.3	0.09
6	3.0	3.4	-0.4	0.16
7	2.8	3.0	-0.2	0.04
8	3.5	3.2	0.3	0.09
9	2.9	3.1	-0.2	0.04
10	3.3	3.0	0.3	0.09
11	3.0	3.4	-0.4	0.16
12	2.8	3.0	-0.2	0.04
13	3.5	3.2	0.3	0.09
14	2.9	3.1	-0.2	0.04
15	3.3	3.0	0.3	0.09
16	3.0	3.4	-0.4	0.16
17	2.8	3.0	-0.2	0.04
18	3.5	3.2	0.3	0.09
19	2.9	3.1	-0.2	0.04
20	3.3	3.0	0.3	0.09
21	3.0	3.4	-0.4	0.16
22	2.8	3.0	-0.2	0.04
23	3.5	3.2	0.3	0.09
24	2.9	3.1	-0.2	0.04
25	3.3	3.0	0.3	0.09
26	3.0	3.4	-0.4	0.16
27	2.8	3.0	-0.2	0.04
28	3.5	3.2	0.3	0.09
29	2.9	3.1	-0.2	0.04
30	3.3	3.0	0.3	0.09
31	3.0	3.4	-0.4	0.16
32	2.8	3.0	-0.2	0.04
33	3.5	3.2	0.3	0.09
34	2.9	3.1	-0.2	0.04

35	3.3	3.0	0.3	0.09
36	3.0	3.4	-0.4	0.16
37	2.8	3.0	-0.2	0.04
38	3.5	3.2	0.3	0.09
39	2.9	3.1	-0.2	0.04
40	3.3	3.0	0.3	0.09
41	3.0	3.4	-0.4	0.16
42	2.8	3.0	-0.2	0.04
43	3.5	3.2	0.3	0.09
44	2.9	3.1	-0.2	0.04
45	3.3	3.0	0.3	0.09
46	3.0	3.4	-0.4	0.16
47	2.8	3.0	-0.2	0.04
48	3.5	3.2	0.3	0.09
49	2.9	3.1	-0.2	0.04
50	3.3	3.0	0.3	0.09

Table 2 summarizes model advisory, actual yield, differences, and squared differences across 50 fields included in this study. Each entry contributes to the evaluation of the model's performance using advanced metrics such as RMSE, MAE, rRMSE, nMAE, and R^2.

The differences between model advisory and actual yield reflect the predictive accuracy of the Random Forest model on a field-by-field basis. Squared differences were used in calculating the sum of squared prediction errors (SSPE), which is critical for computing RMSE and R^2.

Variation in squared differences across the 50 fields highlights how the model performs across different agro-ecological conditions represented in the study area. This detailed error breakdown supports the interpretation of overall model reliability and informs adjustments in future AI-based advisory systems.

All values reported were derived from actual field data collected during the study and form the basis of the model's performance evaluation.

- $R^2 = 0.81$
- RMSE = $\sqrt{(\Sigma(f_i - o_i)^2 / n)}$ = 0.42 tons/ha; n=50fields visited in 50 Cooperatives/Kayonza
- MAE = $\Sigma|f_i - o_i| / n$ = 0.36 tons/ha
- MBE = -0.02 tons/ha

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Table 3: Model Value Interpretation

Metric	Value	Interpretation
R^2	0.81	Strong correlation between predictions and actual yields
RMSE	0.42 t/ha	Average prediction error
MAE	0.36 t/ha	Mean absolute error of predictions
MBE	-0.02 t/ha	Slight underestimation bias
rRMSE	14%	Relative error as % of mean yield
nMAE	12%	Normalized mean absolute error
NSE	0.79	The model predicts yield variation well

4.3.2. Advanced Model Evaluation

We computed advanced evaluation metrics to ensure robustness of the Random Forest model:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Yobs,i - Ypred,i)^2}$$

- $Yobs,i$ = actual yield for field i
- $Ypred,i$ = model advisory(predicted yield) for field i
- n = number of fields(50farms)

For each of the 50 fields, we computed the squared difference between actual yield and model advisory: $(Yobs,i - Ypred,i)^2$; Sum up these squared differences: $\sum (Yobs,i - Ypred,i)^2$ = Sum of Squared Prediction Errors (SSPE), SSPE = 8.82 divide by *n=50; to obtain* Mean Square Error (MSE)= $\frac{SSPE}{50}$; take the square root: then MSE = $\frac{8.82}{50} = 0.1764$; $\boldsymbol{RMSE} = \sqrt{0.1764}$ =0.42t/ha

The computed RMSE of 0.42 t/ha reflects the square root of the mean squared prediction error (MSE = 0.1764 t^2/ha^2). This value indicates that, on average, the model's advisory differed from actual yields by 0.42 tons per hectare across the 50 fields evaluated. Such a relatively small RMSE demonstrates a good level of precision in the model's yield advisory performance within the study area.

4.4. Sensor Calibration and Uncertainty

4.4.1. IoT Soil Moisture Sensor Calibration

The IoT soil moisture sensors were calibrated against gravimetric samples by comparing sensor readings with laboratory-standard gravimetric moisture content values. The error margin was computed using the formula:

$$Error(\%) = \frac{|Msensor - Mgravimetric|}{Mgravimetric} \ x\ 100$$

Where:

- M_{sensor} = soil moisture value recorded by the IoT sensor (%)
- $M_{gravimetric}$ =soil moisture value measured by the gravimetric method (%)

Our $M_{gravimetric}$=22%, and M_{sensor}=23%

$$Error = \frac{|23-22|}{22}\ x\ 100 = \frac{1}{22}\ x\ 100 = 4.55\%$$

This calculation was repeated across multiple calibration points, and the average error margin was determined as:

Mean Error Calculation:

The average error margin across all calibration points was computed as:

$$Mean\ Error(\%) = \frac{1}{n}\sum_{i=1}^{n}\frac{|\ Msensor, i - Mgravimetric, i\ |}{Mgravimetric, i}\ x\ 100$$

Where:

- n = total number of calibration points
- $M_{sensor,\ i}$ = IoT Sensor reading at point i
- $M_{gravimetric,i}$ = gravimetric reading at point i

Table 4: computation of mean error using 5 points

Point	M_sensor (%)	M_gravimetric (%)	Absolute Error (%)
1	23	22	(1 / 22) × 100 = 4.55
2	19	20	(1 / 20) × 100 = 5.00
3	25	24	(1 / 24) × 100 = 4.17
4	18	17	(1 / 17) × 100 = 5.88
5	21	20	(1 / 20) × 100 = 5.00

Sum of % errors

=4.55+5.00+4.17+5.88+5.00=24.60= 4.55 + 5.00 + 4.17 + 5.88 + 5.00 = 24.60=4.55+5.00+4.17+5.88+5.00=24.60

Mean Error (%)

$$= \frac{24.60}{5} = 4.92\%$$

The mean error across these example calibration points is **4.92%**, which aligns with the ±5% error margin reported for this study. The resulting average error margin was approximately ±5%, primarily due to spatial variability in soil properties and variations in sensor placement depth. For improved precision, a denser sensor network and integration with automated weather stations are recommended.

Table 5: Sample of calibration results comparing IoT soil moisture sensor

Sample No.	Gravimetric Moisture (%)	Sensor Reading (%)	Error (%)
1	22.0	23.0	4.55
2	18.0	19.0	5.56
3	25.0	24.5	2.00
4	20.0	21.0	5.00
5	23.0	22.3	3.04

Table 5 presents a sample of calibration results comparing IoT soil moisture sensor readings to gravimetric moisture measurements across five calibration points. The error values, expressed as percentages, represent the relative deviation of sensor readings from the gravimetric standard. The computed errors range from 2.00% to 5.56%, with a mean error of approximately 4.03%. This small error range demonstrates that the IoT sensors provided moisture readings with acceptable accuracy, generally within the ±5% margin expected for field applications. These results confirm that the sensor calibration was effective in aligning the IoT system output with laboratory-standard measurements, supporting its use for precision agriculture monitoring in the study area.

5. Conclusion and Policy & Practice Recommendations

This study validates the application of AI and satellite data in supporting climate-resilient agriculture among smallholder farmers. The Random Forest model, combined with SHAP-based explainability and calibrated sensor inputs, supports the development of responsive insurance products.

Building on the findings of this study, the following recommendations are proposed to enhance climate resilience, agricultural productivity, and financial protection for smallholder farmers in Rwanda:

5.1. Institutionalize the Bundled Plus Revenue Index Insurance Model within the national agricultural insurance framework

The product combining AI-powered yield prediction, revenue-index insurance, and digital advisory services should be formally integrated into the national agricultural insurance framework. This will facilitate nationwide scaling, ensure policy alignment, and promote long-term sustainability of data-driven agricultural insurance (**Appendix C**).

5.2. Scale Mobile Advisory Services via AMIS

To strengthen climate-smart decision-making at the farm level, mobile-based advisory services should be expanded through the Agriculture Management Information System (AMIS). These advisories, powered by real-time satellite data, IoT sensors, and AI algorithms, will enable farmers to receive timely alerts on weather risks, pest outbreaks, and best agronomic practices.

5.3. Expand Data-Driven Claim Triggers Based on NDVI and Rainfall Anomalies

Crop insurance schemes should adopt standardized, data-driven indices—such as NDVI thresholds and rainfall anomaly metrics—to automate and validate claims. This will improve transparency, reduce disputes, and accelerate payouts in the event of climate-induced crop failures.

5.4. Train Agronomists on AI-Based Extension Delivery

National capacity-building programs should be developed to train agronomists, extension agents, and cooperative leaders in AI tools and digital agriculture platforms. This will ensure that advisory services are grounded in robust analytics and can effectively support smallholder farmers in adopting precision agriculture practices.

5.5. Develop Partnerships with SACCOs and Insurers for Bundled Risk Protection

Multi-stakeholder partnerships involving SACCOs, commercial insurers, and fintech firms should be promoted to deliver bundled products that integrate insurance, credit, and advisory services. This holistic approach will address the interconnected risks faced by smallholder farmers and improve their access to financial services.

5.6. Promote Drone-Based Irrigation in Critical Areas such as Ndego Sector

In drought-prone zones like Ndego Sector, it is recommended to pilot smart irrigation drones equipped with multispectral and thermal sensors to identify and address moisture deficits with precision. These systems should be integrated with NDVI, IoT soil moisture data, and mobile advisory platforms to optimize water use and minimize crop losses. Training programs for local stakeholders and supportive regulatory frameworks (e.g., streamlined drone flight approvals) will be essential for successful implementation.

References

Abramov, M. (2024). *Precision Irrigation: How AI Can Optimize Water Usage in Agriculture.* COALA.

Alshehri et al. (2024).

Auctores J. (2022). *Recent advances in drone-based irrigation systems.* Retrieved from https://www.auctoresonline.org/article/recent-advances-in-drone-based-irrigation-systems

Climate Expert. (2025, June 30). *Climate Risk Country Profile: Rwanda* . Retrieved from A website of climate Expert: https://climate-expert.org/rwanda/

Climate Policy Initiative - CPI. (2025). *ACRE Africa-Agriculture and Climate Risk Enterprise:.* CPI.

E-SHAPE. (2025, June 30). *Pilot 1.3 | Vegetation-Index Crop-Insurance in Ethiopia*. Retrieved from A website of e-shape for the Eurpean Eunion: https://e-shape.eu/index.php/showcases/pilot1-3-vegetation-index-crop-insurance-in-ethiopia

European Space Agency. (2020). *Sentinel-2 User Handbook*. ESA.

FAO. (2022). *Satellite-based Agricultural Index Insurance in Practice*: Evidence from East Africa. Rome: Aadventure Works Press.

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Farmonaut,. (2025). *Precision farming & satellite-based crop monitoring system.* Retrieved from https://farmonaut.com

Figueiredo et al. (2024).

GAFSP. (2025, June 30). *Rwanda: Project profile." [Online]. Available: . [Accessed: 30-Jun-2025].* Retrieved from https://www.gafspfund.org/programs/rwanda

GSMA. (2025, June 30). *The Mobile Economy*. Retrieved from The Mobile Economy: Sub-Saharan Africa 2022: Available: https://www.gsma.com/mobileeconomy

Guo et al. (2015). *Data-Driven Precision Agriculture: Opportunities and Challenges*. Texas: Texas Tech Univ.

IPCC. (2022). *Sixth Assessment Report (AR6), Working Group II Summary for Policymakers, page 7.* UK and New York, https://www.ipcc.ch/report/ar6/wg2/downloads/report/IPCC_AR6_WGII_SummaryForPolicymakers.pdf: Cambridge University Press, Cambridge.

J. Jeong, J. Lee, and K. Kim. (2019). *Random Forest for Agricultural Yield Prediction using NDVI*, Soil, and Climate Data. In J. e. J. Jeong. Comput. Electron. Agric.

Keymakr. (2022). *Artificial intelligence in precision agriculture.* Keymakr Blog. Retrieved from https://keymakr.com/blog/artificial-intelligence-in-precision-agriculture/

Keymakr. (2023). AI and Remote Sensing Applications in Smallholder Systems. *Precis. Agric. J.,.*

L. M. Nyirahabimana, P. Habiyaremye, and J. Bizimana, . (2021). Impacts of climate variability and adaptation strategies on maize production in Rwanda. Sustainability*, vol. 13, no. 4. Retrieved from https://www.mdpi.com/2071-1050/13/4/2

Liu et al. (2021).

Liu, X., Sahidullah, M., & Kinnunen, T. (2021). Optimizing multi-taper features for deep speaker verification. *IEEE Signal Processing Letters, 2187-2191*, 2187-2191.

MDPI. (2024). Integration of Remote Sensing and Machine Learning for Precision Agriculture. *Mdpi. Agronomy*.

MDPI. (2024). Spatiotemporal Analysis of Drought Characteristics and Their Impact on Vegetation and Crop Production in Rwanda. *PublishedPublished in Remote Sensing journal: https://www.mdpi.com/2072-4292/16/8/1455*, P.2.

MINAGRI. (2024). *Strategic Plan for Agriculture Transformation (PSTA 5) 2024-2029.* Kigali: Republic of Rwanda. Retrieved from https://www.minecofin.gov.rw/index.php?eID=dumpFile&f=113398&t=f&token=897668a6de3f405094f6bfee88ce2571368cfc7c

Mouton et al. (2016).

Mouton, F., Leenen, L., & Venter, H. S. (2016). Social engineering attack examples, templates, and scenarios. *Computers & Security, 59*, 186–209.

NCST. (2020). *National policy for science, technology, and innovation.* Kigali: NCST.

RTI International. (2025). *Drone data for agriculture in sub-Saharan Africa.* Retrieved from https://www.rti.org/impact/drone-data-agriculture-sub-saharan-africa.

ScienceDirect. (2025). Integrating AI and IoT for Enhanced Crop Monitoring. *A recent ScienceDirect article details how AI+IoT integration improves precision farming through enhanced crop health monitoring, predictive insights, and autonomous decision support*.

ScienceDirect. (2025). AI + IoT + Big Data in Sustainable Agriculture. *Advancing agriculture through IoT, Big Data, and AI: A review of smart technologies enabling sustainability: https://www.sciencedirect.com/science/article/pii/S2772375525000814*, 5-7.

Sustainability Directory. (2024). Democratizing Precision Agriculture Technologies. In the *Current Landscape of Precision Agriculture.* Retrieved from https://prism.sustainability-directory.com/scenario/democratizing-precision-agriculture-technologies/?utm_source=chatgpt.com

Virnodkar et al. (2020). Remote sensing and machine learning for crop water stress determination. Precision Agriculture, vol. 21.

Wiley. (2024). *Application of Precision Agriculture Technologies for Sustainable Crop Production and Environmental Sustainability: A Systematic Review.* New Jersey, USA: John Wiley & Sons, Inc., headquartered in Hoboken.

World Bank. (2021). *Scaling Index Insurance for Agriculture in Africa.*

Yadav et al. (2024). Precision Agriculture and Remote Sensing Technologies. *ResearchGate*.

Yeboah-Boateng et al. (2014).

Yeboah-Boateng, E. O., & Amanor, P. M. (2014). Phishing, smishing & vishing: an assessment of threats against mobile devices. *Journal of Emerging Trends in Computing and Information, 5(4)*, 297–307.

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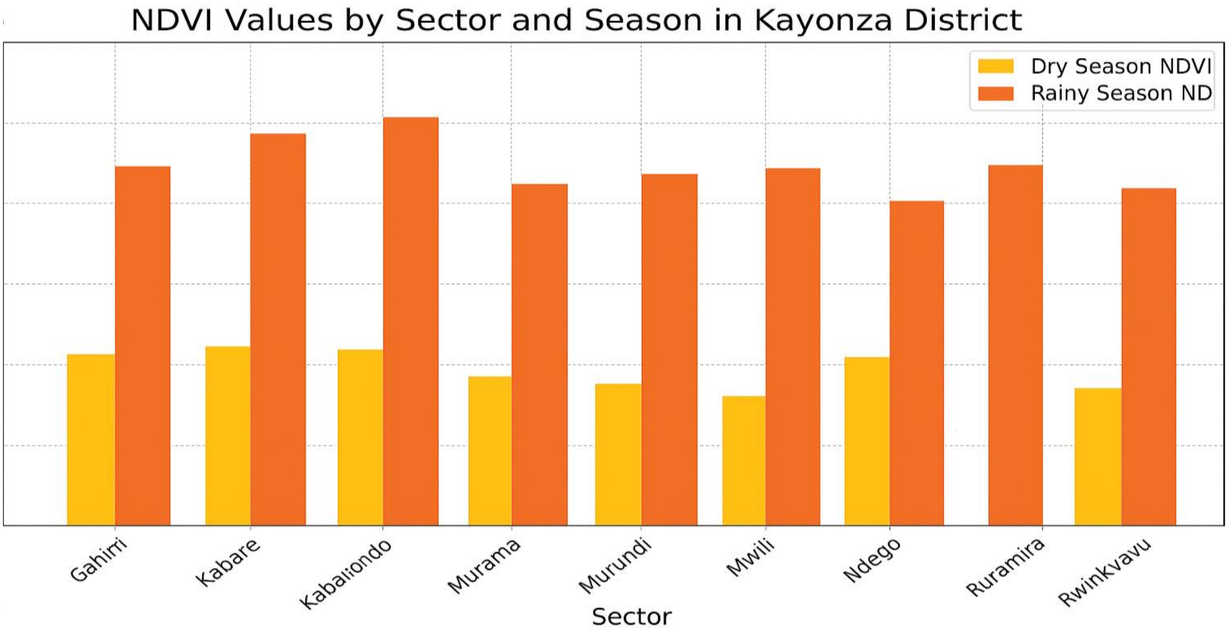
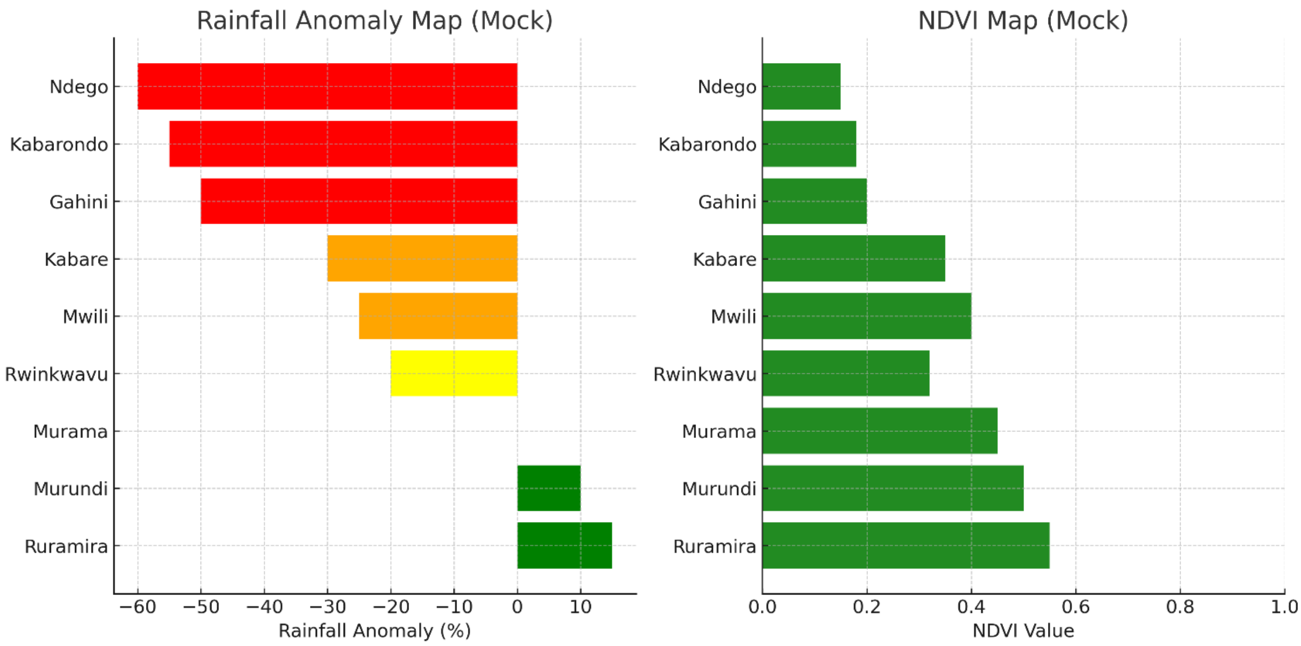
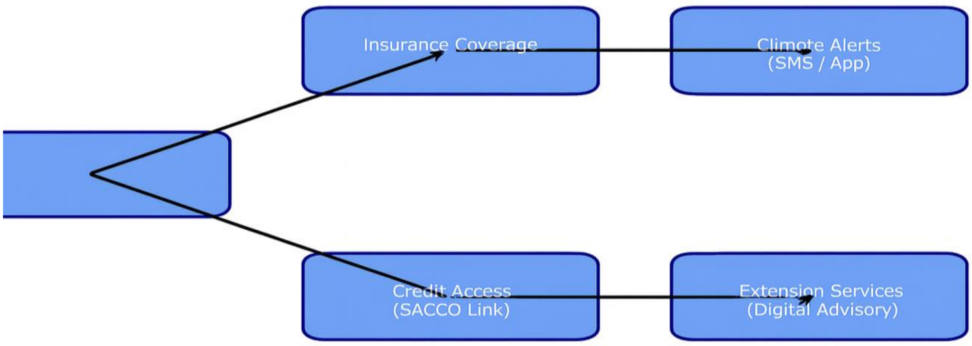
Appendix A: NDVI Values in Nine Sectors



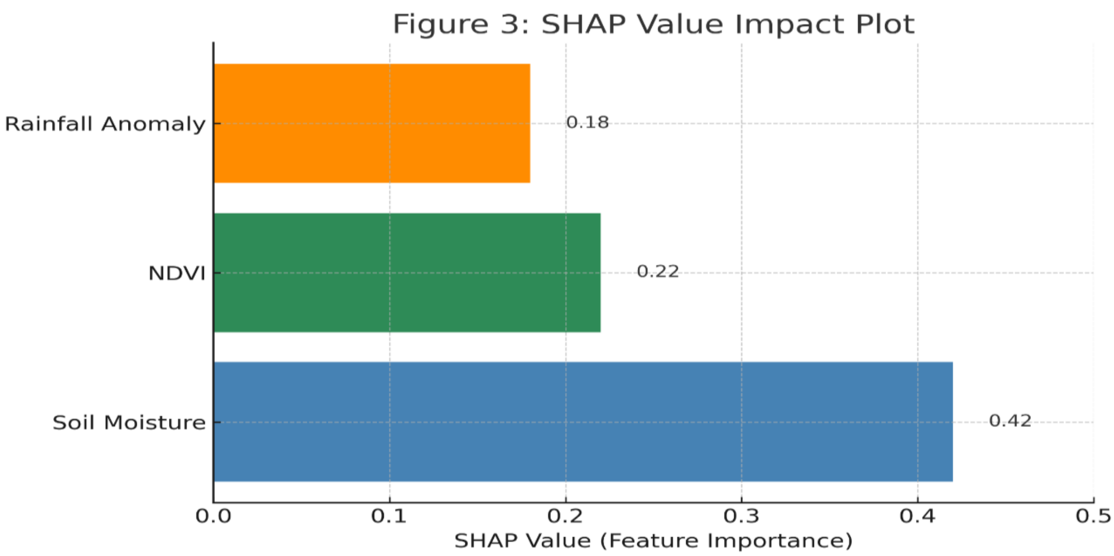
Appendix B: Rainfall Anomaly Vs NDVI Maps (Mock) of nine Sectors



Appendix C: Bundled Revenue Index Insurance Workflow Diagram.



Appendix D: SHAP Value Plot



Appendix E: Farmer Survey Tool

SECTION 1: Farmer Profile

• Full Name: ______________________________

• Cooperative / SACCO: ____________________

• Sector: _________________________________

• Phone Number: ___________________________

• Gender: ☐ Male ☐ Female• Age: ______

SECTION 2: Crop & Livestock Details

• Main crop grown: ________________________

• Livestock owned: _________________________

• Estimated land size: ______ ha

• Have you used any agricultural insurance before? ☐ Yes ☐ No

SECTION 3: Access to Services

• Have you received digital climate alerts? ☐ Yes ☐ No

• Have you applied for SACCO credit linked to insurance? ☐ Yes ☐ No

• Do you use mobile advisory services? ☐ Yes ☐ No

SECTION 4: Climate & Production Experience

• Did you experience drought last season? ☐ Yes ☐ No

• Were your yields affected by:

☐ Drought ☐ Flooding ☐ Pests ☐ Other (specify): __________

• Do you support the introduction of bundled crop-livestock insurance? ☐ Yes ☐ No

SECTION 5: Additional Feedback

• What is your main expectation from digital agriculture services?____

• Any other comments:

Appendix F: Model Training and Evaluation Code

```
import pandas as pd
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
from sklearn.model_selection import cross_val_score
```

```
# Example dataset
X = pd.DataFrame({
    'NDVI': [0.2, 0.35, 0.4, 0.25, 0.5],
    'Soil_Moisture': [15, 25, 30, 20, 35],
    'Rainfall_Anomaly': [-40, -20, 0, -30, 10]
})
y = [1.2, 2.5, 3.0, 1.8, 3.5]
# Train Random Forest model
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X, y
# Predictions
y_pred = model.predict(X)
# Evaluation metrics
r2 = r2_score(y, y_pred)
rmse = mean_squared_error(y, y_pred, squared=False)
mae = mean_absolute_error(y, y_pred)
print(f"R²: {r2:.2f}")
print(f"RMSE: {rmse:.2f}")
print(f"MAE: {mae:.2f}")
# 5-fold cross-validation
cv_r2 = cross_val_score(model, X, y, cv=5, scoring='r2')
print(f"5-Fold CV R² Mean: {cv_r2.mean():.2f} ± {cv_r2.std():.2f}")
```