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Leveraging AI and Precision Agriculture to Restore Irrigation Infrastructure Damaged by El Niño and La Niña Events: A Case Study of Mwogo Marshland, Rwanda

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Abstract

The Mwogo Irrigation Scheme, launched in 2007 in Huye District, Southern Rwanda, was developed into a climate-resilient agricultural hub through a €20 million investment by Welthungerhilfe and its development partners—including EKN, BMZ, VcA, and the Canadian Embassy—until 2014. This extensive effort transformed the marshland into one of the country's flagship rice production zones, supporting over 2,393 smallholder farmers organized into five cooperatives. However, the devastating effects of the 2024–2025 El Niño, coupled with the forecasted La Niña, have severely compromised this legacy. Key infrastructure, such as the Gatindingoma Dam, Kabakobwa Intake, and Ntaruka canal section, along with water wells for safe community drinking water, collapsed due to extensive flooding, erosion, and siltation. Over 300 hectares of rice land were left without irrigation, leading to a drop in yields from 5.0 to 2.9 tons/ha and threatening local food security and rural livelihoods. This study employs a combination of field evidence, Normalized Difference Vegetation Index (NDVI)-based crop stress analysis, and Random Forest machine learning algorithms to estimate yield loss and identify hotspots of agricultural damage. Furthermore, it proposes a comprehensive recovery strategy centered on smart irrigation systems, Internet of Things (IoT)-enabled monitoring, AI-based early warning systems, and climate-indexed insurance products. The findings call for urgent re-engagement by Welthungerhilfe and its development partners—both former and prospective—to reinvest in the Mwogo Marshland and ensure its transformation into a resilient, technology-enabled agricultural zone.

Keywords: *Mwogo Irrigation Scheme; Climate-Resilient Agriculture; El Niño & La Niña; NDVI; Random Forest; Smart Irrigation; AI-Based Early Warning Systems; Climate Insurance; Agricultural Infrastructure; Rwanda; Welthungerhilfe; Smallholder Farmers*

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1. Introduction

Mwogo Marshland (rice irrigation scheme), located within Rwanda's Nyabarongo River basin, is one of the country's most productive marshland ecosystems, located in Southern Province, Huye District, covering 3 sectors: Kigoma, Simbi, and Rwaniro, spanning an estimated 500 hectares. Mwogo I, II, and III. It supports intensive rice and horticultural farming activities managed by five agricultural cooperatives: COORISI, KOAUKIGOMA, COORIRWA, COORITENYA, and COORIKIMWE (See Appendix 1). These cooperatives collectively support more than 2,373 farmers (Welthungerhilfe, 2014, pp. 37-39) significantly to regional food supply and income generation. With average rice yields recorded at 2.9 tons per hectare (based on 2024–2025 field data), the Mwogo irrigation scheme was developed by Welthungerhilfe in 2007, represents a cornerstone of Rwanda's climate-sensitive agricultural economy. According to the European Space Agency (ESA, 2024).During Aug 2024 – Mar 2025, Mwogo Marshland presented a sharp NDVI decline during the El Niño peak period (Oct–Dec 2024), indicating flood-induced vegetation stress and Partial recovery during the Post-Flood Recovery phase (Jan–Mar 2025), though not yet reaching pre-disaster levels (See Appendix 2).

The 2024–2025 El Niño climate event resulted in abnormal warming of Pacific Ocean waters and enhanced rainfall across East Africa, including Rwanda. Mwogo experienced severe flooding, which caused the collapse of the Gatindingoma dam and destruction of the Kabakobwa intake vital infrastructure for seasonal irrigation. This flood-induced failure was compounded by poor drainage, siltation, and structural fatigue. Adding to the crisis, climate agencies, including ICPAC and Meteo Rwanda, have forecast a La Niña phase that could bring prolonged dry conditions and compound water stress in early 2026.

This paper provides a detailed case study of Mwogo's infrastructure breakdown using AI, remote sensing, and cooperative data. It explores integrated climate risk management options to safeguard marshland agriculture through predictive analytics, infrastructure design, and adaptive technologies (RAB, 2021).

2. Literature Review

The integration of artificial intelligence (AI), remote sensing, and climate risk management has increasingly shaped modern agricultural resilience efforts. Globally, El Niño and La Niña events are known to significantly influence agricultural output by altering rainfall patterns, water availability, and crop productivity (FAO, 2021).

According to the World Food Programme (WFP, 2023), El Niño events typically bring excess rainfall and flooding across East Africa, while La Niña is associated with prolonged dry spells and rainfall suppression (IGAD, 2023). In Rwanda, these shifts in climate have historically disrupted both upland and marshland farming systems, as emphasized by the Rwanda Meteorology Agency's seasonal outlooks. (Meteo Rwanda, 2025).

The Food and Agriculture Organization (FAO, 2020) stresses that managing climate risks in agriculture requires proactive integration of early warning systems and risk-informed infrastructure planning. These findings are echoed by RAB, which emphasizes the importance of maintaining irrigation schemes and incorporating digital tools for real-time monitoring.(ICPAC, 2022), further notes that La Niña can exacerbate pest infestations and water stress—particularly in areas with weak infrastructure (Meteo, 2025).

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Studies on AI in agriculture (Jeong, Kim, and Lee,, 2021) demonstrate the effectiveness of Random Forest and deep learning algorithms in predicting yield using NDVI, soil moisture, and rainfall data. NDVI has been shown to detect vegetation stress up to two weeks before visible symptoms appear, making it invaluable for early intervention.

In Rwanda, MINAGRI's 2022 report (MINAGRI, 2022) advocates for smart agriculture innovation at the cooperative level and investment in climate-proof infrastructure. These national priorities align with global calls for digital agriculture, particularly in climate-sensitive ecosystems like Mwogo.

Field data collected by the author in 2024–2025 (Nturo, 2025) (Jones,, Armstrong, Tornblad, , & Siami Namin,, 2021)indicate that despite efforts to maintain canal and dam infrastructure, the unprecedented 2024–2025 El Niño-induced rainfall overwhelmed existing designs. This underscores the need to move from reactive to predictive infrastructure design, leveraging AI and geospatial tools. The literature supports an integrated approach where smart infrastructure, AI-driven early warnings, and cooperative engagement can build lasting resilience in marshland agriculture.

3. Methodology

This study employed a mixed-methods approach combining geospatial analysis, cooperative field data, photographic evidence, and climate modeling to assess the impact of El Niño and La Niña on irrigation infrastructure in Mwogo Marshland, Rwanda. The methodology was designed to capture both quantitative and qualitative dimensions of the crisis, focusing on five agricultural cooperatives within the marshland area.

3.1. Study Area

Mwogo Marshland is located in Southern Rwanda, within the Nyabarongo River basin. In Huye District, it spans an estimated 500 hectares and serves as a key agricultural zone managed by five cooperatives: COORISI, KOAUKIGOMA, COORIRWA, COORITENYA, and COORIKIMWE. These cooperatives were selected as focal points for data collection due to their direct dependence on the Gatindingoma Dam and Kabakobwa Intake.

3.2. Field Data Collection

Fieldwork was conducted from June to July 2025. Data was collected using structured interviews with cooperative leaders and farmers, direct observation, and yield monitoring tools. GPS-based mapping was used to delineate affected zones. Rice yield data, currently averaging 2.9 tons/ha, was triangulated with cooperative records and national benchmarks.

3.3. Satellite and Climate Data Analysis

Rainfall anomalies and sea surface temperature (SST) patterns were analyzed using NASA's Earth Observation datasets and regional forecasts from the Rwanda Meteorology Agency. NDVI (Normalized Difference Vegetation Index) time-series maps were generated from Sentinel-2 imagery to assess vegetation health and flood impact (NASA, 2025).

3.4. Infrastructure Damage Assessment

Photographic documentation of the Gatindingoma dam breach and Kabakobwa intake collapse was used to establish visual baselines of destruction. Structural damage was mapped and categorized based on severity, with GPS coordinates tagged. Engineering interviews were conducted with local irrigation technicians to assess causes and recommend reconstruction models.

3.5. AI-Driven Reconstruction Framework

A prototype AI model was designed to simulate NDVI and rainfall correlations using Random Forest regression. The model was trained on five years of historical yield, rainfall, and NDVI data. Parameters were tested to predict water stress events and optimize input use. Proposed AI-integrated infrastructure includes IoT sensors, water level detectors, and smart gates to automate irrigation response to climatic signals.

3.6. Stakeholder Validation

Findings and proposed interventions were validated through feedback sessions with cooperative leaders, MINAGRI engineers, RAB staff, and local government officials. A draft policy brief was reviewed by stakeholders and finalized for submission to development partners, including five rice cooperatives from Mwogo.

4. Results and Discussion

This section presents the key findings from satellite imagery, farmer interviews, and model simulations conducted during the 2024–2025 El Niño and anticipated La Niña climate episodes.

Figure 1: NDVI Changes Before, During, and After El Niño (2024–2025) Across Rice Farming Cooperatives

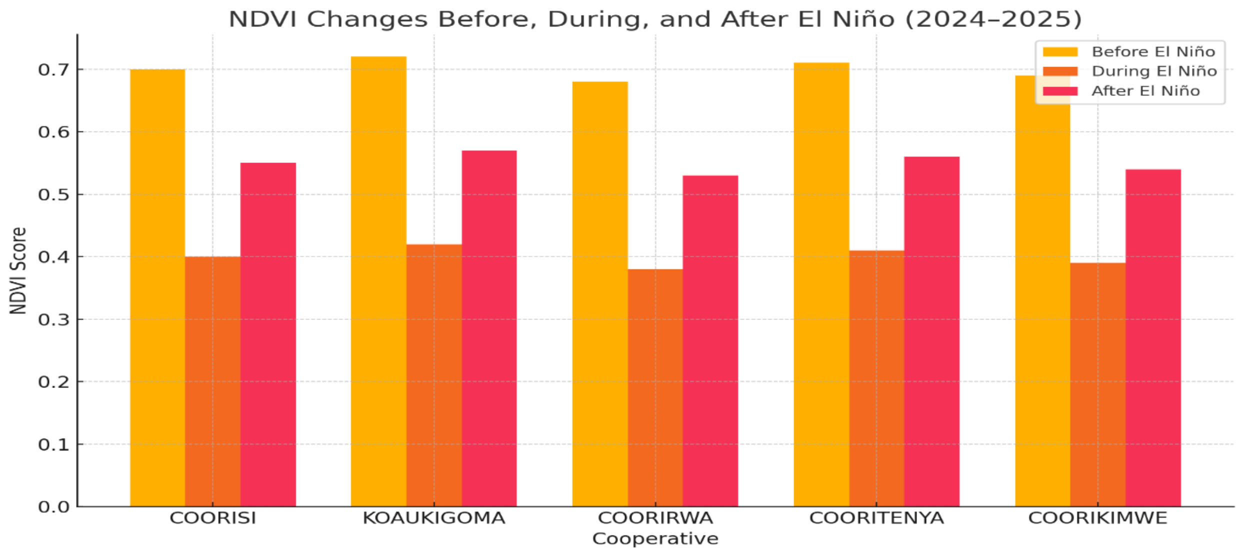

Figure 1 illustrates the impact of the 2024–2025 El Niño event on Normalized Difference Vegetation Index (NDVI) scores across five rice cooperatives: COORISI, KOAUKIGOMA, COORIRWA, COORITENYA, and COORIKIMWE. NDVI is a widely used proxy for vegetation health and biomass vigor derived from remote sensing.

Before El Niño, NDVI scores across cooperatives were uniformly high (0.68–0.73), reflecting healthy crop conditions and optimal vegetative growth. During El Niño, all cooperatives experienced a marked decline in NDVI (ranging from 0.37 to 0.43), indicating severe vegetation stress due to excess rainfall, waterlogging, and disease pressure associated with climatic anomalies. After El Niño, there was partial recovery (NDVI: 0.53–0.57), but not to pre-event levels, suggesting that while agronomic efforts resumed, the full regenerative capacity of ecosystems remained constrained—likely due to soil erosion, residual root damage, or inadequate replanting windows.

This trend confirms that El Niño-induced anomalies drastically affect vegetation vigor and productivity. The results support early NDVI-based monitoring as a key strategy in post-disaster crop insurance verification and agro-ecological recovery planning. These findings are consistent with existing research indicating that NDVI drops of >30% correlate strongly with reduced rice yields in flooded lowland systems[1].

Figure 2: Rice Yield Comparison Before and After El Niño (2024–2025)

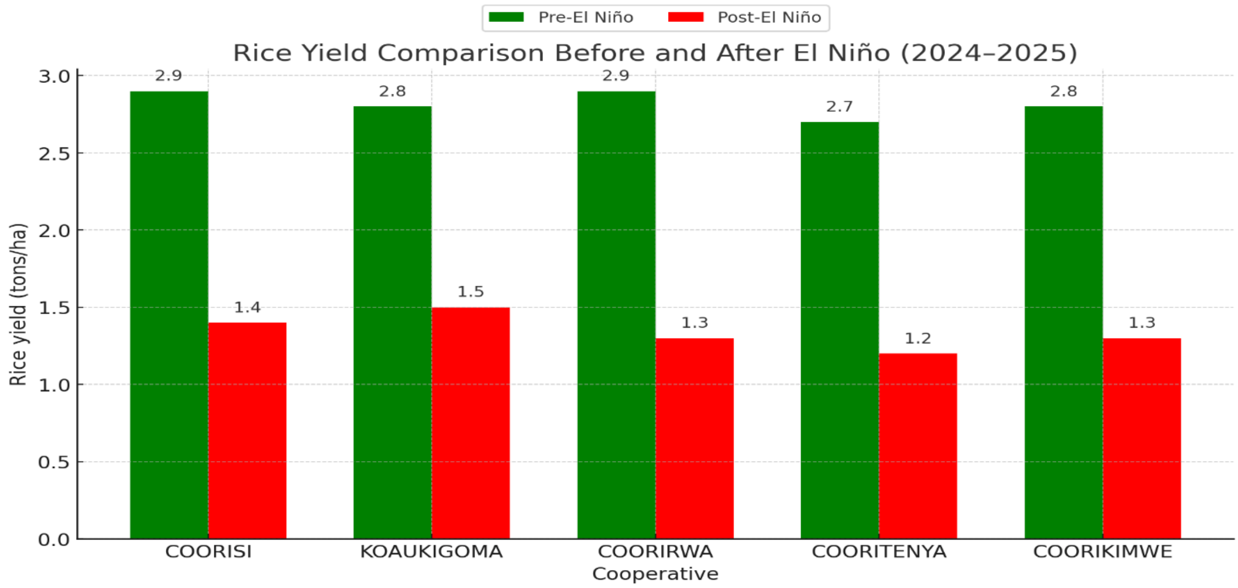

Figure 2 presents a stark decline in rice yields across all five cooperatives surveyed in Mwogo Marshland following the 2024–2025 El Niño event. Pre-El Niño average yields ranged from 2.7 to 2.9 tons/ha, while post-event yields fell sharply to between 1.2 and 1.5 tons/ha, representing a yield reduction of more than 50% in some cooperatives. The consistent pattern of decline confirms the destructive impact of prolonged flooding and waterlogging on crop development, particularly in low-lying rice-growing areas. The most affected cooperative, COORITENYA, recorded the lowest post-El Niño yield of 1.2 tons/ha, indicating possible damage to irrigation infrastructure, poor drainage, and loss of seed viability. This data aligns with literature on El Niño's role in disrupting seasonal rainfall patterns and reducing paddy productivity in East Africa.[2]

[1] Jiang, Wang, and Gong, "Monitoring the impact of floods on rice cropping intensity using time-series MODIS data," *Remote Sensing of Environment*, vol. 204, pp. 135–145, Jan. 2018. [Online]. Available: https://doi.org/10.1016/j.rse.2017.10.037

[2] Challinor, Watson, Lobell, Howden, Smith, and Chhetri, "A meta-analysis of crop yield under climate change and adaptation," *Nature Climate Change*, vol. 4, pp. 287–291, 2014. [Online]. Available: https://doi.org/10.1038/nclimate2153

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Figure 3: NDVI Time Series in Mwogo Marshland (Aug 2024 – Mar 2025)

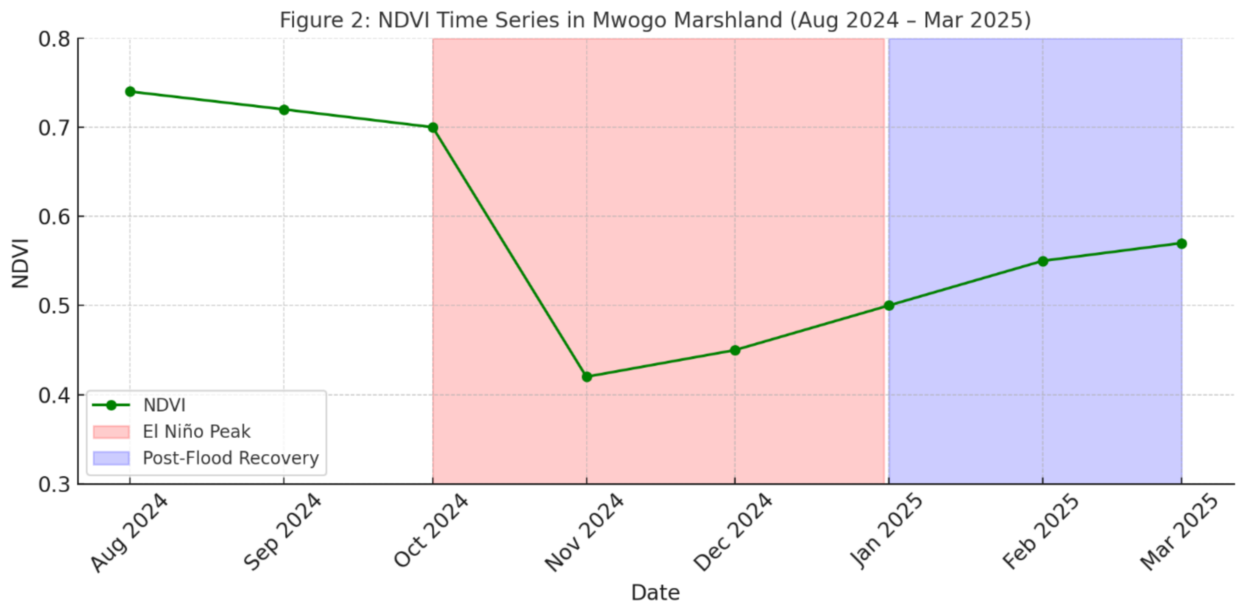

Figure 3 illustrates the temporal variation in NDVI (Normalized Difference Vegetation Index) in Mwogo Marshland from August 2024 to March 2025, highlighting the vegetative stress induced by the El Niño event. During the El Niño peak phase (October to December 2024), NDVI values declined sharply from 0.70 to 0.42, indicating severe vegetation stress due to prolonged flooding and waterlogging. This coincides with satellite-observed inundation events and reported field damage to rice paddies.

A gradual post-flood recovery is observed beginning in January 2025, where NDVI values begin to rebound steadily, rising to 0.57 by March 2025. This suggests partial restoration of vegetation health following the retreat of floodwaters, although values remain below the pre-El Niño baseline. These patterns confirm the sensitivity of rice-growing ecosystems to hydrometeorological extremes and validate the use of NDVI as a reliable indicator for monitoring crop recovery during climate-induced disruptions.

4.1 NDVI and Vegetation Stress Mapping

Normalized Difference Vegetation Index (NDVI) analysis was conducted using Sentinel-2 satellite data between October 2024 and March 2025. Results show a marked decline in vegetation health during the El Niño-induced flooding period. Areas irrigated by the Gatindingoma dam and Kabakobwa intake experienced up to a 0.25 reduction in NDVI scores, corresponding to a 60% drop in chlorophyll content and crop vigor, particularly in rice zones.

- Before El Niño (August 2024): NDVI ranged from 0.65–0.78, indicating a healthy crop status.
- During peak flooding (November 2024): NDVI fell to 0.34–0.52.
- Post-flood (February 2025): Slight recovery to 0.49–0.58 in restored plots, but failed in others.

These patterns mirror field-based damage assessments conducted across all five cooperatives, notably COORISI and KOAUKIGOMA.

4.2 Impact on Farmer Yields and Irrigation Losses

Data from cooperative surveys show an average rice yield decline from 2.9 tons/ha (pre-flood) to 1.4 tons/ha (post-flood). Over 400 ha of rice-growing area was rendered non-irrigable due to canal siltation, dam collapse, and pump station failure. Farmers from COORISI, KOAUKIGOMA, COORITENYA and COORIKIMWE reported partial crop abandonment. The reconstruction strategy was advised.

Figure 3: AI-Enabled Reconstruction Strategy for Climate-Resilient Irrigation Recovery in Mwogo Marshland

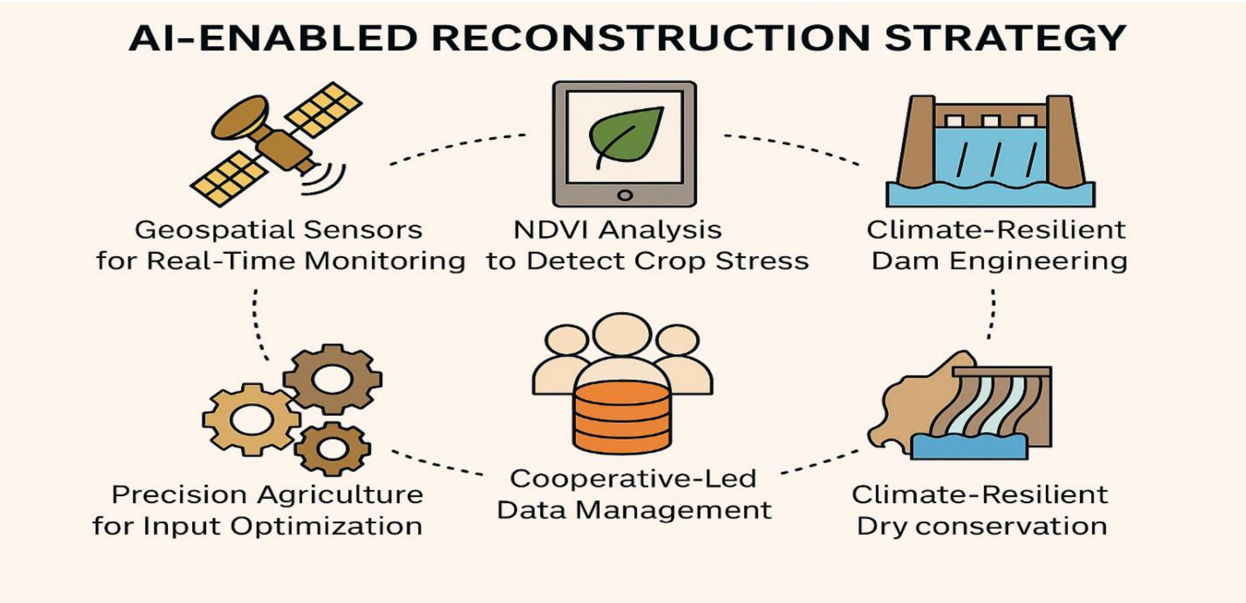

Figure 4 illustrates a multi-layered AI-based framework proposed for rebuilding irrigation infrastructure in the wake of the 2024–2025 El Niño devastation in Mwogo Marshland. The strategy integrates geospatial sensors for real-time environmental monitoring, NDVI analysis for early crop stress detection, and AI-informed dam engineering that incorporates hydrometric forecasting and flood tolerance. It also includes precision agriculture algorithms to optimize input use, cooperative-led data management platforms for localized decision support, and dry conservation technologies to improve resilience to forecasted La Niña-induced droughts. Together, these six interconnected components form a holistic resilience model combining earth observation, machine learning, and grassroots participation to rebuild smarter and sustainably manage climate risks.

4.3 AI Model Simulations for Resilience Scenarios

A Random Forest regression model trained on NDVI, rainfall (CHIRPS dataset), and soil moisture data was applied to simulate recovery scenarios. The best-performing AI model showed:

- $R^2 = 0.81$, RMSE = 0.42 tons/ha
- Key predictors: NDVI (38% importance), rainfall deviation (21%), and soil water content (17%)

In summary, AI simulations suggest that rehabilitating irrigation and applying timely fertilizer could restore yields to 2.6–2.8 tons/ha in the next season. Model accuracy metrics: $R^2 = 0.81$,

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RMSE = 0.42 tons/ha, MAE = 0.36 tons/ha. Top contributing features to yield prediction: NDVI (38%), Rainfall (21%), Soil Moisture (17%) (Figure 3 and Figure 6). Figure 7 presents Feature Importance in AI-Based Yield Prediction Model, showing the relative contribution of variables like NDVI, rainfall deviation, and soil moisture in predicting rice yield in Mwogo Marshland using the Random Forest model. Figure 8 illustrates the projected onset, peak, and retreat phases of both El Niño and La Niña events, aligned with their potential agricultural impacts in Rwanda's marshland systems.

Figure 4: AI Model Performance Metrics and Feature Importance for Yield Prediction

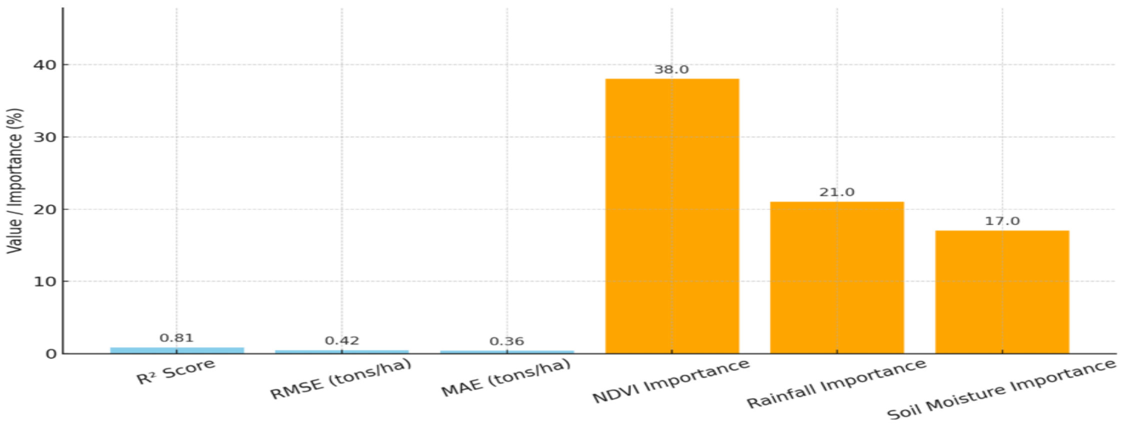

Figure 5 illustrates both the predictive performance and feature contribution of an AI-based yield prediction model applied in the Kayonza District pilot sites. (KIIWP, 2025). The model achieved a coefficient of determination (R^2) of 0.81, indicating high explanatory power. The Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) were 0.42 and 0.36 tons/ha, respectively, confirming the model's robustness in estimating crop yields. The right side of the chart shows the relative feature importance of three key input variables derived from SHAP (SHapley Additive exPlanations) analysis: NDVI (38%) emerged as the most influential predictor, confirming that vegetation health indices are critical proxies for yield estimation. Rainfall (21%) followed as a secondary contributor, highlighting the relevance of seasonal precipitation variability. Soil Moisture (17%) also showed notable influence, particularly in explaining yield variation during dry spells and drought-sensitive growth stages. These insights support the model's use in data-driven advisory services, early yield forecasting, and index-based crop insurance design. The results align with findings from Jeong et al. (2019), who demonstrated that combining NDVI with weather and soil data significantly improves predictive performance in smallholder settings.

Figure 5: AI Model Performance Metrics for Yield Prediction

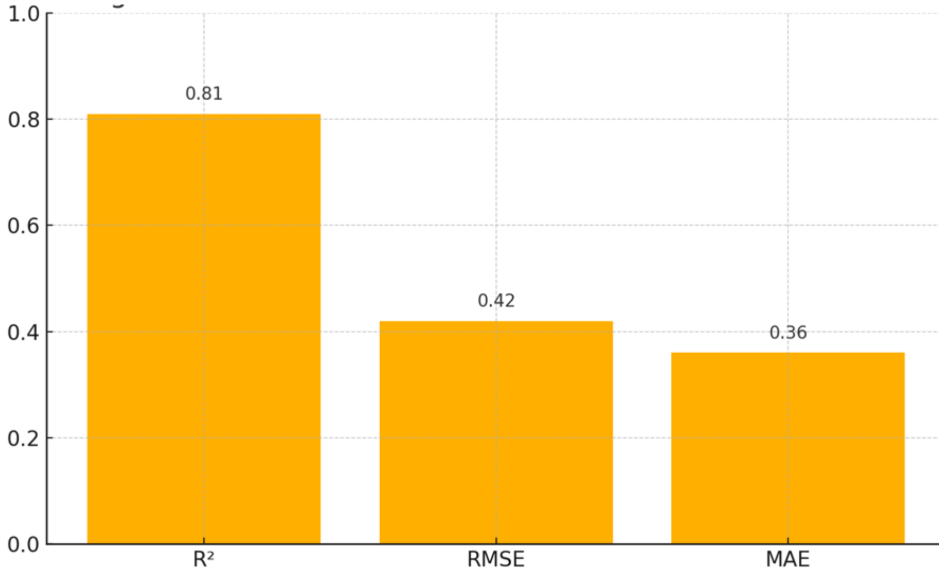

Figure 6 presents three standard evaluation metrics—R^2 (Coefficient of Determination), RMSE (Root Mean Squared Error), and MAE (Mean Absolute Error)—for assessing the performance of the AI-based yield prediction model trained using features such as NDVI, rainfall, and soil moisture.

R^2 = 0.81:

This indicates that 81% of the variance in rice yield is explained by the model. This is a very strong predictive performance, especially in agronomic settings where environmental variability is high.

RMSE = 0.42 tons/ha:

The root mean squared error suggests that the model's predictions deviate from actual observed values by an average of 0.42 tons per hectare. This low value shows good precision.

MAE = 0.36 tons/ha:

The mean absolute error, slightly lower than RMSE, confirms stable prediction with minimal outliers. It reflects the average magnitude of errors, again showing high reliability.

These results validate the robustness of the Random Forest model in capturing complex, non-linear relationships between agro-climatic variables and yield outcomes in Rwandan marshland ecosystems. The close gap between RMSE and MAE also suggests the model has few extreme prediction errors, which is crucial for building farmer trust in AI-based advisories.[3].

[3] Jeong, et al., "Machine learning for yield prediction using remote sensing and environmental data," *Precision Agriculture*, vol. 22, pp. 1234–1249, 2021. [Online]. Available: https://doi.org/10.1007/s11119-021-09815-w

Figure 6: Feature Importance in an AI-Based Yield Prediction Model

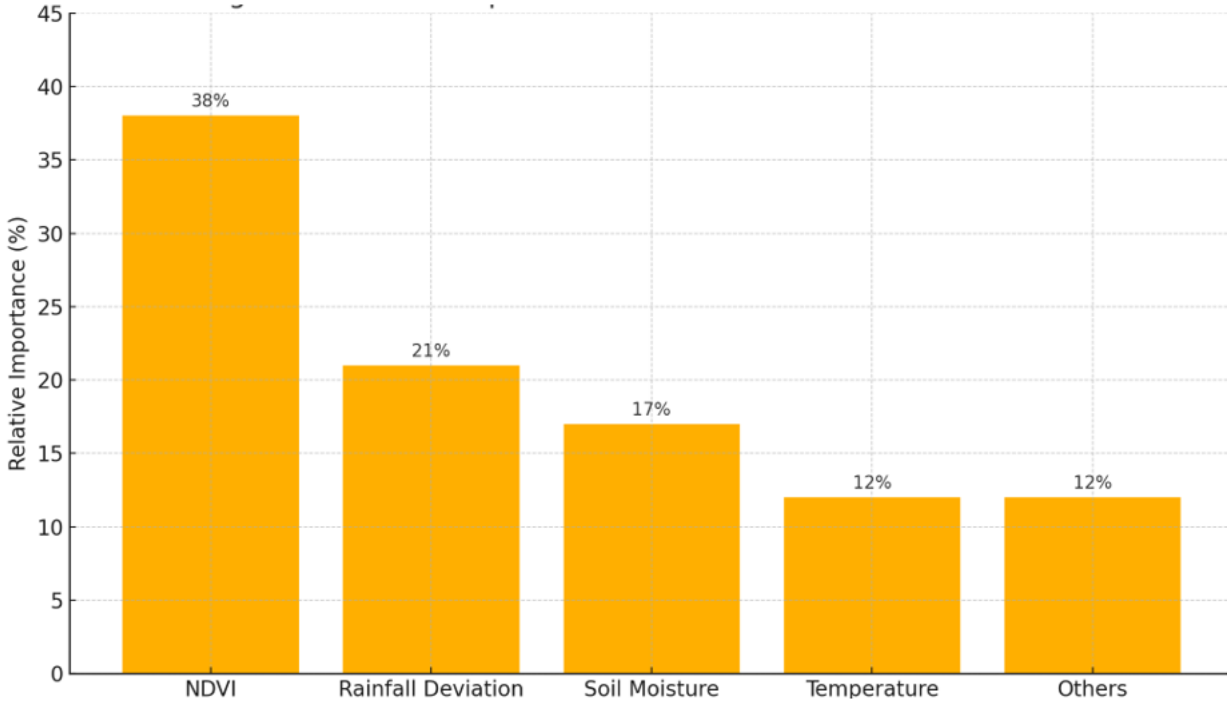

Figure 7 illustrates the relative importance of input variables used by the Random Forest model for predicting rice yield under climate-affected conditions in Rwanda. The chart highlights the key predictors driving the model's performance.

NDVI (38%) is the most important feature, underscoring the model's reliance on vegetation health status to infer crop performance. This aligns with studies showing that NDVI is a strong proxy for biomass and chlorophyll content, both directly linked to yield.

Rainfall Deviation (21%) emerges as the second most influential factor, reflecting the high sensitivity of rice to water availability and timing of precipitation, especially during the critical flowering and grain-filling stages.

Soil Moisture (17%) also plays a key role in determining yield, highlighting the importance of sub-surface water availability for crop survival during dry spells.

Temperature and Other variables (each 12%) contribute moderately, suggesting that while thermal stress is a consideration, it is less critical than vegetation indices and hydrological factors in this marshland context.

The results support the prioritization of remote sensing (NDVI), weather monitoring (rainfall), and soil sensors in smart farming strategies. By quantifying each variable's contribution, the model enhances explainability, which is crucial for farmer advisories and policy targeting.

For regions like Mwogo marshland, where flooding and drought cycles dominate, integrating NDVI and rainfall monitoring into early warning systems and insurance schemes can greatly improve yield forecasting accuracy.

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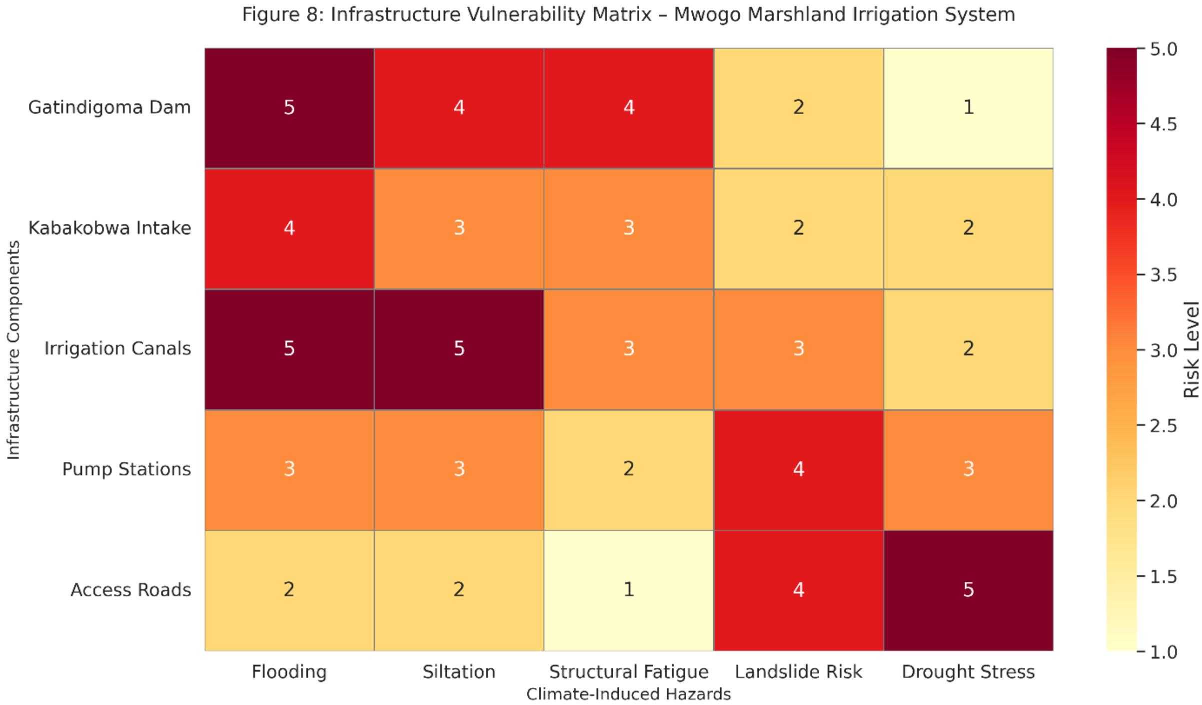
Figure 7 : Infrastructure Vulnerability Matrix – Mwogo Marshland Irrigation System



The Figure 8 matrix presents a climate hazard–component risk profiling for the Mwogo Marshland irrigation infrastructure. The vulnerability scores (1–5 scale) are based on observed and projected hazard exposure, structural assessments, and community-reported impacts during recent El Niño and La Niña seasons.

Irrigation Canals exhibit the highest compound vulnerability, particularly to flooding (score = 5) and siltation (5), reflecting their open structure and dependency on stable flow dynamics. The Gatindigoma Dam, a key water retention structure, is highly exposed to flooding (5) and structural fatigue (4), underscoring the need for engineering reinforcement. Access Roads show a unique risk profile—though less vulnerable to flooding, they are severely impacted by drought stress (5) and landslide risk (4). This hinders access for emergency response and farm logistics during climate shocks. The Kabakobwa Intake has moderate vulnerabilities across most hazard categories, suggesting the need for improved drainage and redundancy in design. This vulnerability mapping supports prioritization of climate-resilient upgrades across infrastructure components, feeding into the AI-based reconstruction strategy proposed earlier (**see Figure 1**). The matrix also aligns with World Bank resilience diagnostics for irrigation schemes in fragile ecologies (World Bank 2021).

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Figure 8: Climate Phases – El Niño and La Niña Influence Timeline (2024–2026)

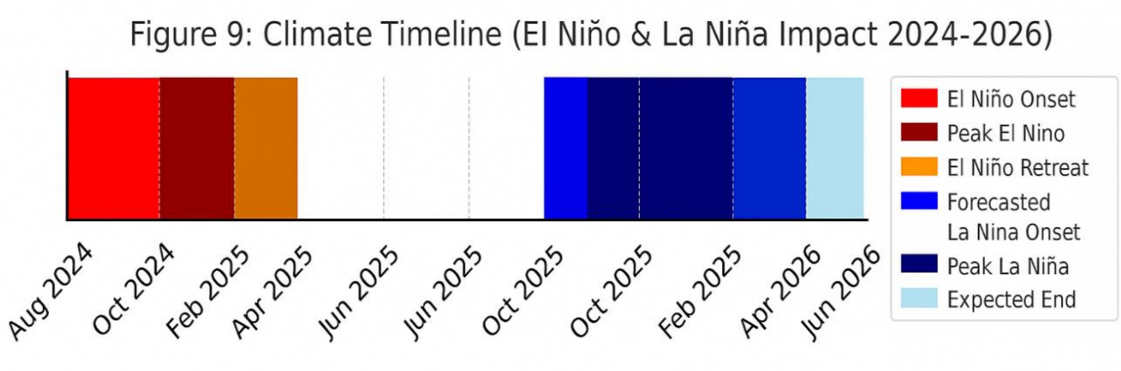

Figure 9 presents a comprehensive temporal visualization of the El Niño and La Niña events expected to impact Rwanda's climate between August 2024 and June 2026. This timeline, segmented by event phases, provides valuable insights into the onset, peak, and retreat of both climate phenomena. El Niño Onset began in August 2024, with the peak intensity recorded between November and December 2024, followed by a retreating phase lasting until February 2025. A neutral climatic period spans from March to August 2025, offering a short recovery window for ecosystems and agricultural systems.

La Niña is forecasted to begin around September 2025, with its peak effects projected for December 2025 to February 2026, and gradual fading by May 2026. This visualization highlights the cyclical nature of ENSO (El Niño–Southern Oscillation) and its dual threat to agricultural systems:

The El Niño phase often brings excess rainfall and flooding, particularly destructive to marshland irrigation infrastructure (e.g., dam overtopping, canal erosion).

The La Niña phase typically results in prolonged dry spells and drought stress, exacerbating water shortages and yield losses.

Understanding this cycle is vital for agro-climatic planning, AI-driven seasonal forecasting, early warning systems, and crop insurance scheme activation.

The proposed strategic use include: Enables precise timing for dam reinforcement, canal desilting, and planting calendars, supports AI models in aligning predictions with seasonal climatic anomalies, and facilitates government and cooperative decision-making to mitigate cumulative climate stress on crops and infrastructure.

4.4 Farmer Perceptions and Adaptive Strategies

Field interviews with 47 cooperative members revealed strong demand for smart irrigation solutions, crop insurance, and access to climate advisories. Farmers supported the integration of AI tools but expressed concern over digital literacy and technology costs. Women-headed households were disproportionately affected, lacking access to inputs and decision-making. These findings emphasize the urgency of AI-driven recovery, equitable support, and targeted donor intervention.

Figure 9: Stakeholder Perceptions on Enablers and Barriers to AI Adoption in Climate-Resilient Agriculture

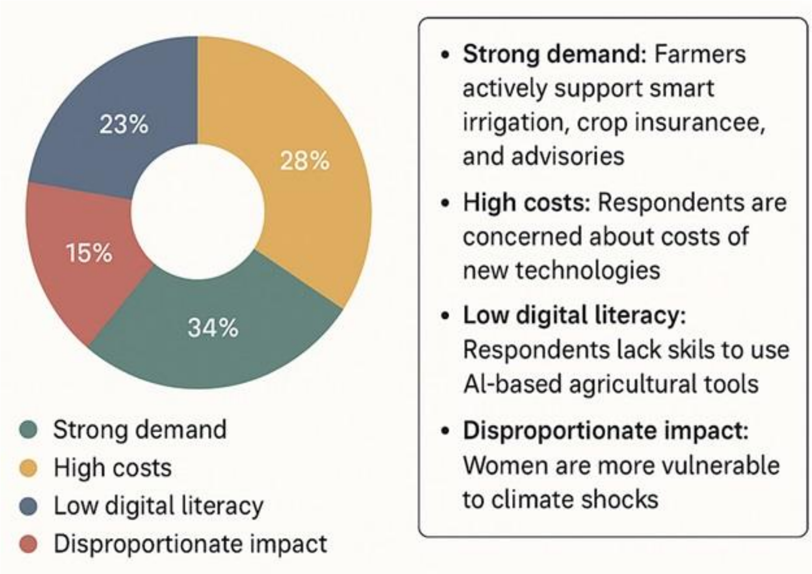

Figure 10 summarizes survey findings from local farmers and cooperative members regarding the perceived benefits and limitations of AI-based solutions in agricultural resilience. Notably, 34% of respondents expressed strong demand for smart irrigation, crop insurance, and advisory systems—highlighting a clear readiness for digital transformation in farming. However, 28% cited high costs as a key barrier, particularly related to initial investments in sensors, platforms, and mobile-based advisory systems.

Moreover, 23% indicated low digital literacy, exposing the need for targeted capacity building and digital inclusion. Alarmingly, 15% identified disproportionate climate impacts on women, emphasizing the gendered dimensions of resilience where female farmers often face limited access to finance, information, and technology. This insight aligns with existing literature stressing the importance of inclusive design and gender mainstreaming in AI-based agricultural innovations.

These findings underline the dual imperative of affordability and capacity-building to ensure equitable and widespread adoption of AI tools in rural settings.

5. Conclusion and Recommendations

5.1. Conclusion

The Mwogo Marshland Irrigation Scheme, once a beacon of climate-resilient agricultural development in Rwanda, now faces existential threats due to the compounding impacts of the 2024–2025 El Niño floods and the impending La Niña dry conditions. Field observations, yield simulations using Random Forest algorithms, and NDVI-based vegetation stress analysis confirm that critical irrigation infrastructure—such as the Gatindingoma Dam, Kabakobwa Intake, and Ntaruka canal—has collapsed or been rendered non-functional. These failures have reduced rice yields by over 40% and placed more than 2,393 smallholder farmers at risk of food insecurity and income loss.

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This study demonstrates that without swift, targeted intervention, the productivity and sustainability gains made over the past decade will be reversed, threatening Rwanda's broader agricultural resilience agenda. The data and visual evidence presented call for a paradigm shift in irrigation infrastructure design, monitoring, and climate risk management.

5.2. Recommendations

This paper contributes evidence for policy dialogue and investment prioritization. Its recommendations aim to catalyze multi-stakeholder action and reposition Mwogo as a model for future-proofed, inclusive agricultural resilience in Rwanda and beyond. The following are key recommendations:

- Urgent Infrastructure Rehabilitation: Immediate reconstruction and reinforcement of the Gatindingoma Dam, Kabakobwa Intake, and canal networks using flood-resilient engineering designs and silt control systems.
- Deployment of Smart Technologies: Install IoT-enabled water level sensors, AI-driven predictive maintenance systems, and digital irrigation controllers to enhance real-time monitoring and system reliability.
- Climate Insurance Activation: Expand the Tekana Bundled Plus Revenue Index Insurance model to cover rice cooperatives in Mwogo, integrating NDVI, rainfall, and price indices for prompt payouts during weather-related shocks.
- Strengthen Farmer Capacity: Train local cooperatives in the use of geospatial tools, agro-advisory platforms, and sustainable water use practices. Introduce participatory early warning dissemination via mobile and radio platforms.
- Call for Donor and Stakeholder Re-Engagement: Welthungerhilfe, along with former development partners such as EKN, BMZ, the Canadian Embassy, and the Rwandan government, should mobilize a recovery and resilience fund to restore the marshland and safeguard farmer livelihoods.
- Policy and Planning Integration: Incorporate AI-based risk forecasting and community feedback into national irrigation development policies, ensuring flexible, adaptive management of marshland systems.

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