



FACULTY OF ENGINEERING AND TECHNOLOGY

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DECISION SUPPORT TOOL FOR OPTIMAL CROP PLANNING

BY

NAKANDI PROSCOVIA NORAH

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SUPERVISOR; MR. MASERUKA BENEDICTO

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CASE STUDY; BUGIRI SUGARCANE FARM

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ABSTRACT

This study developed a data-driven Decision Support Tool (DST) for crop yield prediction and resource optimization using computational optimization techniques to address agricultural challenges in developing regions such as Uganda, particularly climate variability, inefficient resource use, and limited access to predictive technologies. To ensure maximum data integrity and localized relevance, the framework was trained using historical climate datasets cross-validated with ground-truth records from the Uganda National Meteorological Authority (UNMA), correcting for satellite retrieval biases. Focusing on sugarcane production in the Busoga sub-region of Eastern Uganda, the framework integrated geospatial analysis, climatic modeling, soil hydraulic characterization, evapotranspiration simulation, and intelligent optimization within a unified system. The tool's functionality was specifically enhanced by incorporating location-specific soil nutrient parameters, including Nitrogen, Phosphorus, Potassium, and pH levels, to guide objective varietal selection. Historical climate, soil, and agronomic datasets were used to train a Hybrid GRU-LSTM deep learning model and an Extreme Gradient Boosting (XGBoost) model, both evaluated using R^2 , NSE, RMSE, and MAE, with the GRU-LSTM model outperforming XGBoost achieving a training Nash-Sutcliffe Efficiency (NSE) of 0.9986 and a testing NSE of 0.8212. To transition these complex models into a practical tool for smallholders, the research prioritized the design of an intuitive Graphical User Interface (GUI), ensuring the framework is accessible and providing actionable "Farm Action Plans" for non-technical users in rural Ugandan contexts. To convert predictions into actionable decisions, the system incorporated Analytical Hierarchy Process (AHP), Non-Linear Programming (NLP), and Genetic Algorithm (GA) optimization for crop selection, irrigation scheduling, and resource allocation, resulting in improved Water Use Efficiency (WUE) and Irrigation Water Use Efficiency (IWUE), including over 20% irrigation water savings without significant yield loss. Overall, the DST offers an intelligent, science-driven platform for enhancing yield forecasting, irrigation planning, and economic decision-making, supporting climate-smart agriculture and sustainable productivity in Uganda and comparable tropical systems.

DECLARATION

I, Nakandi Proscovia Norah, hereby declare that this dissertation titled "Decision Support Tool for Optimal Crop planning" is my original work. It has not been submitted for any academic award or qualification at any other university or institution of higher learning. All sources of information used in this research have been duly acknowledged and referenced according to academic conventions.

Student's Signature: _____

A handwritten signature in black ink, appearing to read 'Nakandi Proscovia Norah', written over a horizontal line.

E-mail: nproscovianorah@gmail.com

Tell: 0754955442/0770595362

APPROVAL

This is to certify that this dissertation proposal titled "Decision Support Tool for Optimal Crop Planning" has been submitted for examination with my approval as the appointed supervisor.

Supervisor's Name: Mr. Maseruka.S. Benedicto

Signature: Maseruka.S.

Date: 18th June 2026

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DEDICATION

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LIST OF ACRONYMS

Acronym	Meaning
ANN	Artificial Neural Network
APSIM	Agricultural Production Systems Simulator
AR	Autoregressive Model
CMIP6	Coupled Model Inter comparison Project Phase 6
FAO	Food and Agriculture Organization
GA	Genetic Algorithm
GBM	Gradient Boosting Machine
GCM	General Circulation Model
GIS	Geographic Information System
HI	Harvest Index
IQR	Interquartile Range
MAE	Mean Absolute Error
MLR	Multiple Linear Regression
ML	Machine Learning
NASA	National Aeronautics and Space Administration

NSGA-II	Non-Dominated Sorting Genetic Algorithm II
OLS	Ordinary Least Squares
PSO	Particle Swarm Optimization
QGIS	Quantum Geographic Information System
R^2	Coefficient of Determination
RCP	Representative Concentration Pathway
RF	Random Forest
RMSE	Root Mean Square Error
RUE	Radiation Use Efficiency
SA	Simulated Annealing
SDG	Sustainable Development Goal
SHAP	Shapley Additive explanations
SOBOL	Variance-based Sensitivity Analysis Method
WUE	Water Use Efficiency

CHAPTER ONE INTRODUCTION

1.1 Background

Agriculture is the bedrock of global food security, yet it faces compounding challenges from climate variability, soil degradation, and unsustainable land use. With global yield growth slowing to less than 1% annually, current trajectories fall critically short of feeding a projected 9.7 billion people by 2050 (World Bank, 2024). To counter this, global agricultural management has increasingly turned to data-driven crop planning, which stabilizes yields and minimizes production risks by aligning crop choices with environmental factors. Historically, such planning relied heavily on traditional empirical models and parameter-intensive simulators that proved computationally demanding and inflexible. The global shift is now moving toward intelligent, purely data-driven Decision Support Tools (DSTs) that leverage advanced machine learning and computational optimization to provide accessible, rapid resource optimization without the overhead of heavy process-based simulations.

In sub-Saharan Africa, these global agricultural challenges are severely magnified. Average cereal yields remain stranded at around 1.5 tons per hectare less than half the global average of 3.9 tons driven largely by an overdependence on rain-fed systems, limited irrigation, and low technological adoption (FAO, 2023). This chronic underproduction contributes to persistent food insecurity, leaving over 280 million Africans undernourished (Otekunrin, 2024). Across the continent, continuous reliance on traditional intuition rather than systematic planning leads to poor synchronization between cropping patterns and variable rainfall. While efforts like the Africa Soil Information Service (AfSIS) have improved baseline data availability, the translation of this data into actionable insights remains poor. Most existing agricultural models are designed for data-rich environments with robust digital infrastructure, leaving a critical implementation gap for accessible, data-driven DSTs tailored to African smallholder realities (Chen et al., 2019; Buthelezi et al., 2025).

Narrowing the focus to East Africa, the agricultural sector remains highly vulnerable to the regions increasingly erratic bimodal rainfall patterns, which frequently disrupt historical planting windows. East African farmers operate in highly heterogeneous agro-ecological zones, demanding hyper-localized crop and resource planning. Despite rapid mobile penetration and growing digital awareness in the region, the adoption of modern predictive agro-technologies is still nascent. Farmers lack integrated mechanisms to help them optimally allocate scarce resources like water and fertilizer. Without practical, data-driven DSTs that consolidate local climatic variations, soil characteristics, and target yields into actionable optimization strategies, the region's agricultural output remains highly susceptible to recurring climate shocks and inefficient land utilization.

Within this regional context, Uganda exemplifies both the untapped potential and the severe constraints of current agricultural practices. The sector employs over 70% of the Ugandan workforce and contributes approximately 24% to the national GDP (UBOS, 2023), yet average maize yields stagnate around 2.5 tons per hectare against a potential of 6 tons (FAO, 2023). With less than 2% of arable land irrigated, farmers rely completely on experience-based decisions that frequently fail under changing climate conditions. To bridge the gap in local applicability, this study develops a Decision Support Tool utilizing a purely data-driven framework that provide rapid, context-specific guidance without the overhead of parameter-heavy process simulators. It fundamentally seeks to enhance yield predictions and optimize resource allocation, ultimately fostering climate-resilient optimal crop planning for Ugandan agriculture.

1.2 Problem Statement

Agricultural productivity in sub-Saharan Africa remains low despite favorable natural resources, with Uganda continuing to experience limited yields for major crops such as maize, beans, and cassava (FAO, 2023; UBOS, 2024). Smallholder farmers, particularly in the Busoga sub-region of Eastern Uganda, largely depend on rain-fed agriculture and traditional experience-based decisionmaking for crop selection and resource allocation. Sugarcane cultivation dominates much of the region despite its long maturity period and relatively low economic returns compared to alternative high-value crops. In addition, increasing climate variability has intensified rainfall uncertainty, drought occurrence, and seasonal production instability, further reducing agricultural productivity and profitability. A significant limitation of standard decision-support approaches is their frequent failure to account for local soil nutrient constraints and the lack of intuitive interfaces for practical farm-level planning. Consequently, farmers experience inefficient resource utilization and reduced yields. This research addresses these limitations by integrating localized soil data and ensemble machine learning to provide actionable, site-specific recommendations for crop selection and resource allocation.

1.3 Justification

Failure to address the problem of optimal crop planning, Uganda will lead to continued inefficiencies in agricultural production and resource use. Without effective decision support tools, farmers will remain dependent on traditional methods that are ill suited to cope with unpredictable weather patterns and resource constraints. This will result in low and inconsistent yields, increased crop failures, and wastage of essential inputs such as water, fertilizers, and labor. The inability to predict and plan appropriately for changing climatic conditions will further expose farming communities to food shortages and income instability. Over time, this will weaken household food security, increase rural poverty, and limit the capacity of farmers to sustain production across seasons. Consequently, Uganda's agricultural productivity will stagnate, threatening the livelihoods of millions who depend on farming for survival and economic well-being.

1.4 Main Objective

To develop a decision support tool for optimized crop planning and yield improvement.

1.4.1 Specific Objective

- 1) To design a predictive model for crop yield estimation.
- 2) To predict the impact of future weather condition on yield.
- 3) To optimize crop selection and irrigation scheduling for enhanced yield.

1.5 Research Questions

- i. How can a robust, data-driven machine learning model be designed to accurately estimate crop yield under varying environmental and management conditions in Uganda?
- ii. In what ways can future weather conditions be modeled and incorporated into the decision support framework to predict their impact on crop yield?
- iii. How can optimization algorithms be applied within the decision support framework to determine the best crop selection and irrigation scheduling strategies for enhanced productivity?

1.6 Significance of the Study

The significance of this study lies in its potential to fundamentally transform agricultural planning and resource management in Uganda. By developing a purely data-driven Decision Support Tool (DST) that integrates advanced machine learning models with computational optimization, this research provides a robust and scalable scientific basis for accurately predicting crop yields under volatile climatic and management conditions. This modern, accessible framework will empower stakeholders ranging from smallholder farmers to regional agricultural extension officers and policymakers to make precise, data-informed decisions regarding optimal crop selection, planting schedules, and irrigation management. Consequently, this strategy directly bridges persistent yield gaps and maximizes the socioeconomic return on scarce resources such as water and fertilizers. Furthermore, the tool will secure critical resilience against the adverse impacts of climate variability by translating predictive weather models into proactive, adaptive planning strategies. Ultimately, this research accelerates the transition toward evidence-based agricultural policy

formulation, promotes resilient farming practices, and directly improves both regional food security and the economic livelihoods of Ugandan farmers.

1.7 Conceptual Scope:

The conceptual scope of this study focuses on the design and implementation of a robust, purely data-driven decision support framework that synergizes advanced machine learning algorithms with computational optimization methodologies for optimal crop planning. The study is anchored on three core conceptual pillars: predictive modeling for crop yield estimation, dynamic assessment of future weather impacts on agricultural output, and the prescriptive optimization of crop selection and irrigation scheduling. It encompasses the emerging theoretical foundations of predictive analytics, data-driven forecasting, and meta-heuristic optimization as applied to complex agricultural decision-making shifting away from traditional, simulation-based modeling paradigms. Conceptually, the framework is designed to function as an integrated, dynamic tool that continuously correlates environmental, agronomic, and management variables to uncover hidden data patterns, thereby significantly improving planning efficiency, resource allocation, and overall productivity outcomes.

CHAPTER 2 : LITERATURE REVIEW

2.1 Predictive Model for Crop Yield Estimation

Before Decision Support Tools (DSTs), agricultural planning relied on empirical methods, indigenous knowledge, and basic statistical models that were often unreliable under changing climates (Abegunde et al., 2019). The introduction of process-based crop models like DSSAT, APSIM, and Aqua Crop revolutionized yield prediction by simulating soil–plant–atmosphere interactions (Gumma et al., 2024). However, their data demands limited application in smallholder systems (Tigre & Heshmati, 2023). Recent integration of machine learning algorithms such as Random Forest, SVM, and ANN with DSSAT has produced hybrid models capable of capturing nonlinear relationships and improving predictive accuracy (Banerjee et al., 2025). This evolution marks a shift from experience-based to data-driven, adaptive, and scalable decision-making in agriculture.

2.1.1 Data Collection and Preprocessing

Effective hybrid model development requires accurate input data on climate, soil, and crop management. Historical weather data (rainfall, temperature, humidity, and solar radiation) are typically sourced from meteorological stations or satellite repositories such as NASA POWER (Ali et al., 2023). Soil data including texture, pH, and organic matter are obtained through laboratory analysis or databases like AfSIS. Data preprocessing involves gap filling, normalization, and feature extraction to ensure uniformity before model training (Wang et al., 2023). Techniques such as spline interpolation and z-score standardization have been applied to improve temporal continuity and parameter comparability.

2.1.2 Model Calibration and Training

The calibration of process-based models like DSSAT is essential for aligning simulations with observed field data. Studies by (Yu & Fu, 2025) and (Banerjee et al., 2025) emphasize the importance of genetic coefficient adjustment to match phenological stages. For ML components, model training is typically performed on preprocessed datasets using supervised algorithms such as ANN or RF, with 70–80% of data used for training and the remainder for validation. Performance evaluation relies on statistical indicators such as the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Nash–Sutcliffe Efficiency (NSE) (Turki & Turki, 2025).

2.1.3 Model Integration and Validation

Hybridization combines DSSAT's process-based outputs with ML predictions to create more reliable yield estimations. DSSAT simulates physiological responses under varying conditions, while ML algorithms correct residual errors and enhance adaptability (Banerjee et al., 2025). Validation studies, such as those by Ghosh et al. (2022), show that hybrid models consistently outperform standalone simulations, particularly under irregular rainfall or soil fertility variability. The resulting systems offer a powerful balance between mechanistic understanding and predictive precision.

2.2 Impact of Future Weather Conditions on Yield

Climate variability remains a dominant factor influencing agricultural productivity. Forecasting future weather conditions is essential for anticipating yield fluctuations and developing adaptive strategies. Traditional weather prediction models relied on statistical trend analysis and autoregressive techniques, which lacked the capacity to represent nonlinear climatic behaviors (Lobell et al., 2015). Recent advances have introduced machine learning and deep learning techniques, particularly Long Short-Term Memory (LSTM) neural networks, which are adept at learning temporal dependencies in time series data (Mohamed, 2024; Wang et al., 2023).

Integration of LSTM models with climatic datasets has improved the accuracy of rainfall and temperature forecasts. For instance, Tarek (2024) demonstrated that LSTM models trained on 20 years of meteorological data achieved higher precision ($R^2 = 0.92$) compared to traditional autoregressive models ($R^2 = 0.76$). In agricultural applications, such forecasts are increasingly used as inputs for process-based models like DSSAT to simulate future yield under projected climate conditions. Studies by Bai et al. (2022) and Yu & Fu (2025) have shown that integrating forecasted weather parameters enhances the capacity of hybrid DSTs to assess potential impacts of climate change on yield.

2.2.1 Weather Data Sources and Processing

Accurate weather prediction depends on the availability of continuous, high-quality data. Common data sources include ground meteorological stations and satellite-based repositories such as ERA5, CHIRPS, and NASA POWER (Ali et al., 2023). Data preprocessing involves quality checks, missing-value interpolation, and normalization. For example, Mohamed (2024) applied a sliding

window approach to capture short- and long-term dependencies in temperature and rainfall sequences, improving LSTM performance.

2.2.2 Climate Forecasting and Model Validation

LSTM and other deep learning models are typically trained using a historical window to predict future climatic conditions over a fixed horizon. Validation involves comparing predicted values with observed data using RMSE and correlation coefficients. Studies in East Africa (Nomugisha & Mwebaze, 2025) have demonstrated the potential of combining LSTM forecasts with DSSAT simulations to quantify yield risks associated with changing rainfall patterns. Visualization tools such as QGIS are increasingly used to map spatial variability in forecasted yield outcomes, identifying areas most vulnerable to climatic stress.

2.3 Optimization of Crop Selection and Irrigation Scheduling for Enhanced Yield

Optimization is central to modern decision support systems, allowing the identification of best management strategies under multiple constraints. Early optimization efforts relied on linear programming (LP) and mixed-integer programming, primarily to allocate land and input resources efficiently (Hazell & Norton, 1986). However, these deterministic methods struggled with nonlinearities in crop–climate interactions. This led to the adoption of evolutionary algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Non-dominated Sorting Genetic Algorithm II (NSGA-II), which are better suited for solving multi-objective agricultural problems (Singh et al., 2021; Ghosh et al., 2022).

Hybrid optimization frameworks now combine process-based simulations with AI-driven models. For instance, DSSAT–GA systems optimize fertilizer and irrigation schedules, achieving 20–30% yield gains and 25% reductions in water use (Bai et al., 2022). MATLAB-based NSGA-II algorithms further support multi-objective trade-offs between yield, profit, and water-use efficiency. Studies by Rware et al. (2020) and Yu & Fu (2025) highlight the effectiveness of such models in developing climate-smart, resource-efficient cropping systems.

2.3.1 Optimization Constraints

Optimization in DSTs operates within constraints reflecting real farm conditions land area, water availability, labor, and soil fertility. Fuzzy goal programming and stochastic optimization are used

to address uncertainties in rainfall and market prices (Romero, 2004). Recent models integrate socio-economic constraints to ensure that optimized strategies are not only technically sound but also economically feasible for smallholders (Tigre & Heshmati, 2023).

2.3.2 Sensitivity Analysis in Optimization

Sensitivity analysis ensures robustness of optimization results by assessing how variations in input parameters affect outcomes. Techniques such as Sobol's variance decomposition and Morris screening are widely used (Banerjee et al., 2025). For DSSAT GA hybrids, sensitivity analysis identifies the most influential factors often rainfall and temperature on optimized yield and water use. Such analyses guide model calibration and data collection priorities, ensuring reliability of recommendations under changing climate conditions (Jouini et al., 2025).

2.4 Research Gaps

2.4.1 Research Gap for Objective One

Although hybrid models integrating DSSAT and ML have demonstrated improved prediction accuracy, their application remains limited in smallholder contexts. Most studies focus on largescale or data-rich environments, with minimal adaptation to localized datasets such as those in Eastern Uganda. Additionally, calibration procedures remain labor-intensive, and explainable AI approaches are rarely employed to enhance model interpretability.

2.4.2 Research Gap for Objective Two

While LSTM and similar models have shown potential in weather forecasting, few studies have integrated localized, field-calibrated data into predictive frameworks for agricultural use. Existing models often rely on global datasets that fail to capture microclimatic variations at field scale. This limits their precision in supporting localized yield prediction and decision-making.

2.4.3 Research Gap for Objective Three

Optimization studies have largely concentrated on yield maximization, with limited consideration of water-use efficiency, profitability, and sustainability trade-offs. Moreover, few frameworks integrate real-time field data into optimization models, constraining their adaptability under dynamic field conditions. There is also limited validation of optimized solutions through field experiments, creating a gap between model predictions and practical implementation.

CHAPTER 3 : METHODOLOGY

STUDY AREA

The study focuses on the sugarcane growing regions of Eastern Uganda, specifically targeting the commercial estates and out grower networks prevalent in the Busoga sub-region (encompassing districts such as Jinja, Mayuge, and Kamuli). This agricultural belt is situated within the Lake Victoria basin at an average altitude of 1,100 to 1,200 m above sea level. The area experiences a tropical climate with a bimodal rainfall pattern averaging 1,200–1,500 mm per year, and mean temperatures ranging between 18°C and 30°C. Soils are predominantly sandy loams and deep ferralsols, which are structurally suitable for deep-rooted crops like sugarcane but require intensive nutrient management to maintain high biomass yields across multiple ratoon cycles. While the region supports various secondary food crops, sugarcane is the dominant industrial cash crop driving the local agricultural economy. Cultivation is primarily rain fed; however, the adoption of supplemental precision irrigation is increasingly critical to mitigate the yield-limiting impacts of erratic dry spells and to optimize both cane tonnage and sucrose accumulation.

The classification follows the Normalized Difference Vegetation Index (NDVI) thresholding and supervised classification to isolate "Cropland." This ensures that resource allocation calculations are only applied to valid agricultural pixels, preventing the misapplication of irrigation or fertilizer models to non-arable land.

3.1 Agronomic Parameter Determination and Yield Prediction

3.1.1 Land Area Computation and Mapping using Geospatial Data

The initial phase of the agronomic assessment requires the precise delineation of the agricultural field. The farmer provides the geographic coordinates of the land boundaries, typically obtained via Global Positioning System (GPS) devices. To automate the spatial analysis, these coordinates are processed alongside a Digital Elevation Model (DEM) acquired through the United States Geological Survey (USGS) Earth Explorer Application Programming Interface (API). The

Universal Transverse Mercator (UTM) coordinate system is utilized because it projects the spherical Earth onto a two-dimensional Cartesian plane, enabling highly accurate distance and area calculations in metric units. The planar area of the irregular polygon is computed using the Shoelace formula. The Shoelace formula is selected because it provides an exact mathematical and computationally efficient method for calculating the area of any non-self-intersecting irregular polygon directly from its ordered Cartesian vertices, which perfectly match the nature of plotted GPS field boundary arrays. (Al-Roomi, 2021)

$$A_{2D} = \frac{1}{2} \left| \sum_{i=1}^n (x_i y_{i+1} - x_{i+1} y_i) \right| \quad (3.1)$$

Where A_{2D} represents the two-dimensional planar land area in square meters, n is the number of vertices defining the field boundary, and x_i and y_i are the Cartesian coordinates of the i -th vertex (Preparata & Shamos, 2025). To account for the undulating topography of irregular fields, the Z function (elevation) must be incorporated. The DEM provides the elevation data (z_i) for each coordinate, allowing the calculation of the average field slope (α). The true three-dimensional surface area is calculated by adjusting the planar area with the secant of the slope angle, defined below.

$$A_{3D} = \frac{A_{2D}}{\cos(\alpha)} \quad (3.2)$$

Where A_{3D} the true is surface area and α is the average slope angle in radians. The integration of DEM data ensures that the calculated area reflects the true surface area rather than a flat projection, which is essential for accurate resource allocation.

3.1.2 Crop Coordinate Plotting and Population Determination

To systematically map the spatial distribution of the crops and establish definitive plant populations, the theoretical spatial area occupied by an individual plant (A_p) is generated. This

relies on the specific agronomic row (S_r) and plant (S_p) spacing requirements defined by conventional crop densities:

$A_p = S_r \times S_p$ (3.3) Following spatial definitions, a two-dimensional computational geographic grid is deployed to algorithmically isolate potential crop coordinate locations. The subsequent positions (x_{ij} and y_{ij}) are interpolated across the planar field structure:

$$x_{ij} = x_{min} + i \times S_p \quad (3.4)$$

$$y_{ij} = y_{min} + j \times S_r$$

For fields exhibiting highly complex or irregular topography, agricultural land elevations captured via GPS and DEMs often exist as irregularly spaced discrete point clouds rather than uniform grids. To address this, spatial interpolation of these discrete coordinates is executed using Delaunay triangulation-based algorithms (Cheng et al., 2020). This algorithm is specifically deployed because it connects discrete topographic points to form a continuous, non-overlapping 3D surface mesh while mathematically avoiding narrow 'sliver' triangles, ensuring highly accurate surface interpolation over complex sloping topographies. Finally, a computational point-in-polygon raycasting algorithm evaluates every individually generated coordinate pair, explicitly retaining only the coordinates falling strictly within the defined A3D geometric boundaries. The aggregate summation of these valid local coordinates mathematically quantifies the biologically optimal plant population matrix for the localized area.

3.1.3 Data Collection and Parameter Acquisition

The accurate estimation of crop water requirements necessitates the continuous collection of meteorological datasets. To ensure high predictive fidelity, the framework utilizes ground-truth historical records from the Uganda National Meteorological Authority (UNMA) to bias-correct satellite-derived climatic data. This is achieved by applying statistical bias correction techniques, such as linear regression, to align the NASA POWER API data with ground-truth sensor data from the Jinja and Kamuli stations. This ensures that the DST reflects the actual micro-climates of the Busoga sub-region rather than generalized global trends. The NASA POWER API helps one get

the datasets by providing continuous, globally gridded, scientifically validated meteorological and solar data specifically designed for agricultural modeling. This eliminates the spatial gaps inherent in physical weather station networks. Online datasets are utilized to ensure uninterrupted, high-resolution historical and forecasted data without the maintenance overhead and spatial limitations of localized physical sensors. Data collection from the API is executed via automated RESTful HTTP GET requests. The system queries the API using the field's specific GPS coordinates and desired time ranges, receiving the meteorological datasets in JSON format, which are then parsed and integrated into the system's database. To guarantee high localized accuracy, the methodology cross-validates this API data against local meteorological station records. This is achieved by applying statistical bias correction techniques, such as linear regression, to align the satellitederived API data with the ground-truth local sensor data, thereby correcting any systematic satellite retrieval biases.

The primary datasets acquired include maximum and minimum air temperatures, relative humidity, solar radiation, wind speed, and precipitation. Precipitation data is utilized to calculate the effective rainfall (P_{eff}), which directly offsets the total water required by the crops. Effective rainfall is calculated using Equation below.

$$P_{eff} = P_{total} \times C_e \quad (3.5)$$

where, P_{eff} is the effective rainfall, P_{total} is the total measured precipitation, and C_e is the runoff coefficient. While the United States Department of Agriculture Soil Conservation Service Curve Number method is traditionally applied to large catchments, its application to smaller, individual agricultural fields requires scaling down. For micro-catchments or plot-scale accuracy, the Curve Number (CN) is heavily adjusted using high-resolution DEM and soil data to reflect microtopography. The potential maximum soil moisture retention is calculated using the adjusted curve number, defined below.

$$S = \frac{25400}{CN} - 254 \quad (3.6)$$

where, S is the potential maximum retention in millimeters and CN is the dimensionless curve number. The total surface runoff is then computed using Equation below.

$$Q = P_{total} - 0.2S + 0.8S \quad (3.7)$$

Where, Q is the accumulated runoff in millimeters. Finally, the runoff coefficient is determined by the ratio of retained water to total precipitation, expressed below.

$$Ce = 1 - \frac{Q}{P_{total}} \quad (3.8)$$

These parameters are utilized to compute the reference crop evapotranspiration using the standardized FAO Penman-Monteith method. The Penman-Monteith method is chosen because it is the sole standard method recommended by the Food and Agriculture Organization; it physically incorporates both physiological and aerodynamic parameters, providing the most accurate and globally consistent representation of evapotranspiration across diverse climatic conditions. The calculation is detailed in Equation below.

$$ET_0 = \frac{0.408 \Delta (R_n - G) + \gamma \frac{C_n}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma (1 + C_d u_2)} \quad (3.9)$$

Where, each parameter is obtained through specific derivations. The variable ET_0 represents the reference evapotranspiration in millimeters per day. The net radiation, denoted as R_n , is derived from the incoming solar radiation data retrieved from the API, adjusted for surface albedo and outgoing longwave radiation. The soil heat flux density, G , is calculated based on the difference in mean air temperature between consecutive days. The mean daily air temperature, TT , is computed as the average of the daily maximum and minimum temperatures retrieved from the API. The wind speed at two meters, u_2 , is retrieved from the API and adjusted logarithmically if measured at a different elevation. The saturation vapor pressure, e_s , is calculated using the maximum and minimum air temperatures, while the actual vapor pressure, is calculated by multiplying the saturation vapor pressure by the relative humidity retrieved from the API. The slope of the vapor pressure curve, Δ , is calculated as a mathematical function of the mean air temperature. Finally, the psychrometric constant, γ , is calculated as a function of atmospheric pressure, which is derived from the field elevation provided by the Z coordinate (Allen et al., 1998).

Subsequently, the specific crop evapotranspiration is determined by multiplying the reference evapotranspiration by a crop-specific coefficient, shown in Equation below.

$$ET_c = ET_o \times K_c \quad (3.10)$$

Where, ET_c is the crop evapotranspiration and K_c is the dimensionless crop coefficient, which varies according to the growth stage of the plant. Finally, the net Crop Water Requirement is calculated by subtracting the effective rainfall from the crop evapotranspiration, expressed in below.

$$CWR = ET_o - P_{eff} \quad (3.11)$$

where, CWR is the crop water requirement and P_{eff} represents the effective rainfall in millimeters.

3.1.4 Soil Properties and Variable Rate Fertilizer Application

Effective irrigation scheduling must be paired with precise nutrient management to be agronomically viable. The system architecture was expanded to integrate location-specific soil nutrient parameters, including Nitrogen (N), Phosphorus (P), Potassium (K), and pH levels extracted via the ISRIC Soil Grids REST API. These properties are critical for determining the suitability of different sugarcane varieties for specific plots. This enhanced model functionality ensures that the DST does not only plan for hydrological needs but provides a comprehensive recommendation based on the actual chemical fertility of the land. The scheduling process begins with the determination of soil hydraulic properties. Instead of relying on expensive and timeconsuming physical soil sampling, the system integrates with the ISRIC Soil Grids REST API. Soil Grids is utilized because it provides global, high-resolution (250-meter) spatial predictions of basic soil properties, such as sand, silt, clay fractions, and bulk density, at various standard depths (Hengl et al., 2017).

In addition to hydraulic properties, the spatial soil maps obtained from the Soil Grids API are critical for nutrient management. By mapping the spatial variability of soil organic matter, cation exchange capacity, and baseline nutrient levels across the field, the system generates prescription maps for Variable Rate Application (VRA) of fertilizers. This ensures that fertilizers are applied precisely where needed, matching the specific nutrient requirements of different field zones, thereby reducing waste and preventing nutrient runoff.

These basic properties are then transformed into critical hydraulic parameters specifically the volumetric water content at field capacity (θ_{FC}) and permanent wilting point (θ_{WP}) using established P_{edo} transfer Functions (PTFs). A simplified linear PTF model is applied to estimate field capacity, as shown below.

$$\theta_{FC} = a_1 \times Sand + a_2 \times Clay + a_3 \times OM + c_1 \quad (3.12)$$

where, Sand, Clay, and OM represent the percentage of sand, clay, and organic matter respectively, while a_1 , a_2 , a_3 , and c_1 are empirically derived regression coefficients (Saxton & Rawls, 2006). Similarly, the permanent wilting point is estimated using Equation below.

$$\theta_{WP} = b_1 \times Sand + b_2 \times Clay + b_3 \times OM + c_2 \quad (3.13)$$

where b_1 , b_2 , b_3 , and c_2 are the corresponding regression coefficients for the wilting point. With these parameters established, the Total Available Water in the root zone is computed using Equation below.

$$TAW = 1000 \times (\theta_{FC} - \theta_{WP}) \times Z_r \quad (3.14)$$

Where TAW is the total available water in millimeters and Z_r is the effective rooting depth of the crop in meters. However, crops cannot extract all of this water without experiencing stress. The proportion of water that can be safely depleted is governed by the depletion fraction (p). While baseline p values are tabulated for various crops under standard conditions, the actual depletion fraction must be dynamically adjusted for the real-time atmospheric evaporative demand, as defined in Equation below.

$$P = p_{table} + 0.04 \times (5 - ET_c) \quad (3.15)$$

Where p_{table} is the baseline crop-specific depletion fraction (typically ranging from 0.3 to 0.7) obtained from FAO-56 guidelines, and ET_c is the current crop evapotranspiration in millimeters per day (Allen et al., 1998). The Readily Available Water is then calculated using Equation below.

$$RAW = p \times TAW \quad (3.16)$$

Where RAW is the readily available water in millimeters. The optimal Irrigation Interval, which dictates the frequency of water application, is determined by dividing the readily available water by the daily crop evapotranspiration, as shown below.

$$II = RAW / ET_c \quad (3.17)$$

Where II represents the irrigation interval in days. To account for system inefficiencies during water application, the Gross Irrigation Requirement is calculated below.

$$GIR = ET_c - P_{eff} E_a \quad (3.18)$$

Where GIR is the gross irrigation requirement and E_a is the application efficiency. The application efficiency is a fractional value determined by the physical hardware of the irrigation system; for instance, well-maintained drip irrigation systems typically achieve an E_a of 0.90, whereas sprinkler systems may operate at 0.75, and surface flood irrigation often falls below 0.60 due to evaporative and deep percolation losses.

3.1.5 Yield Prediction

To provide the farmer with actionable economic insights, the system incorporates a comprehensive yield prediction module. The framework specifically integrates explicit yield estimation modules based on the biological foundations of biomass accumulation and harvest indexing to ensure a robust scientific basis for planning. Agronomically, the general yield equation defines the final marketable crop yield per acreage (specifically, kilograms per hectare) as a function of the total accumulated above-ground biomass and the harvest index. The total biomass is calculated by

accumulating the daily crop growth, which is driven by the intercepted photo synthetically active radiation and the crop's radiation use efficiency, as defined below.

$$B = \sum_{t=1}^n (PAR_t \times RUE_t) \quad (3.19)$$

Where B is the total accumulated above-ground biomass in kilograms per hectare, PAR_t is the intercepted photo synthetically active radiation on day t, and RUE_t is the radiation use efficiency.

The final marketable yield is then derived from this biomass using Equation below.

$$Y_a = B \times HI \quad (3.20)$$

Where, Y_a represents the actual marketable yield in kilograms per hectare, and HI is the dimensionless Harvest Index. The Harvest Index denotes the proportion of biomass partitioned to the harvestable organs (e.g., grains, fruits) and is often modified by water stress during critical reproductive stages (Steduto et al., 2012). While these equations provide the biological basis for yield, predicting biomass accumulation in real-time requires advanced physiological modeling. Therefore, for practical irrigation management, the system primarily utilizes the water-driven yield prediction model established by the Food and Agriculture Organization (FAO). The FAO water production function quantifies the proportional reduction in maximum yield as a direct consequence of relative evapotranspiration deficits (water stress) experienced during the growing season. The foundational relative yield decrement equation is presented below.

$$1 - \left(\frac{Y_a}{Y_m} \right) = K_y \left(1 - \frac{ET_a}{ET_c} \right) \quad (3.21)$$

The term $\left(1 - \frac{Y_a}{Y_m} \right)$ represents the relative yield decrease, while $\left(1 - \frac{ET_a}{ET_c} \right)$ represents the relative water deficit. Y_m is the maximum expected yield per hectare under optimal, non-limiting water and nutrient conditions. This maximum yield baseline is typically obtained from historical regional agricultural census data and local extension service field trials, eliminating the need for overly complex and computationally heavy crop simulation models. K_y is the empirical yield response factor, a crop-

specific constant representing sensitivity to water stress, which is obtained from standardized FAO Irrigation and Drainage Paper No. 33 tables. A K_y value greater than one indicates that the crop is highly sensitive to water stress, whereas a value less than one suggests tolerance (Doorenbos & Kassam, 1979).

To isolate the predicted actual yield for the automated dashboard analytics, Equation 3.21 is algebraically rearranged into the predictive format shown in Equation 3.22.

$$Y_a = Y_m \left[1 - K_y \left(1 - \frac{ET_a}{ET_c} \right) \right] \quad (3.22)$$

By continuously tracking the actual evapotranspiration (ET_a) via the soil moisture sensor network and comparing it against the theoretical maximum crop evapotranspiration (ET_c), the automated system dynamically updates the predicted actual yield (Y_a). This allows farmers to forecast the economic impact of potential water shortages and optimize their irrigation scheduling to protect critical growth stages.

3.1.6 Financial analysis

To translate the agronomic yield predictions into tangible economic needs, the system incorporates a financial forecasting module. Understanding the projected revenue is critical for farmers to make informed decisions regarding input costs. The Gross Revenue is calculated by multiplying the predicted actual yield by the current market price of the crop, as defined below.

$$R_g = Y_a \times P_c \quad (3.23)$$

Where, R_g represents the gross revenue per hectare, Y_a is the predicted actual yield, and P_c is the market price per unit of yield. To determine the true economic viability, the Net Profit must be evaluated by subtracting the total production costs from the gross revenue, as shown below.

$$N_p = R_g - C_p \quad (3.24)$$

Where, N_p is the net profit per hectare and C_p encapsulates all fixed and variable production costs, including seeds, fertilizers, labor, and irrigation energy costs. By integrating these economic

parameters, the system empowers farmers to optimize their irrigation scheduling not just for maximum yield, but for maximum economic return.

3.2 Predictive Modeling of Future Weather Impacts on Sugarcane Yield

The predictive core was refined into an Ensemble Deep Learning framework, utilizing both GRU and LSTM networks to capture the complex temporal narratives of regional weather patterns. This architecture tracks chronological sequences rather than treating daily constraints as disjointed inputs. For the tabular array structures required by the XGBoost application, the principal components are flattened into a traditional matrix, while the GRU-LSTM components process three-dimensional sequenced tensors to maintain historical memory of climatic stressors.

3.2.1 Data Processing, Exploratory Analysis, and Dimensionality Reduction

The foundational baseline utilizes the dense, multi-decadal meteorological data generated in the preliminary phase. Chronological lacunae representing missing daily observations are mathematically reconstructed adopting cubic spline interpolation parameters, effectively preserving temporal progression curves. Furthermore, severe outlier anomaly isolation procedures leverage the statistical Interquartile Range (IQR) technique, systematically identifying and smoothing erroneous local climatic spikes to secure training data fidelity (Rousseeuw et al., 2020). Following initial dataset sanitation, detailed correlation arrays utilizing Pearson's and Spearman's techniques assess variable interactions.

Crucially, the historical array is functionally enriched through specialized agricultural feature engineering protocols. To faithfully replicate structural cyclicity characteristic of local rainfall modalities, discrete temporal variables including day and month indicators undergo cyclical trigonometric encoding via sine and cosine transitions (Wang et al., 2022). Short-term atmospheric velocity measures including moving precipitation averages, compounded with aggregated synthetic indicators representing the Diurnal Temperature Range and continuous deficit dry-spell calculators, form complex interactions mapping potential physiological stress events. To effectively combat subsequent data frame multicollinearity and associated structural bloating, Principal Component Analysis (PCA) mathematically collapses the enriched high-dimensional parameter array down onto a lower-dimensional orthogonal subset, definitively preserving internal variance architectures over 95% while drastically suppressing noise profiles (Lever et al., 2020).

3.2.2 Data Formatting

Following dimensionality reduction, the dimensionally reduced Principal Components are structurally bifurcated to natively format the disparate operational mechanisms of the selected algorithms. For the tabular array structures required by the XGBoost application, the principal components are directly flattened into a traditional two-dimensional supervised learning matrix. Conversely, deep learning Recurrent Neural Networks (LSTM and GRU architectures) categorically mandate three-dimensional sequenced tensor structures spanning samples, time steps, and features. A specialized sliding-window algorithmic technique maps these chronological sequences continuously, allowing the downstream network structures to ingest real-time data tracking specifically as a chronological temporal narrative rather than treating daily constraints as disjointed inputs. **3.2.3 Data Partitioning**

To guarantee predictive robustness forecasting and actively inhibit chronological data leakage, traditional cross-validation logic is structurally substituted for a rigorous and strictly sequential chronological data partitioning strategy prior to the model training. The continuous multi-decadal historical sequence is split strictly along an 80:10:10 ratio matrix. Specifically, the initial 80% progression of contextual data is explicitly reserved as the base training subset tasked fundamentally with orienting algorithmic weights towards localized climate structures. Following this continuity block, the subsequent consecutive 10% data frame operates specifically as the hyper parameter adjustment validation phase. Finally, the terminal 10% block is unequivocally quarantined from all algorithm learning exposures, standing strictly as the external validation testing structure mapping final out-of-sample performance matrices.

3.2.4 Algorithmic Calibration Process: Extreme Gradient Boosting (XGBoost)

To actively dissect structural localized relationships determining established agricultural weather constraints, an Extreme Gradient Boosting (XGBoost) model application is procedurally calibrated. The XGBoost mechanism operates sequentially through specific mathematical processes (Benali et al., 2021):

Step 1: Objective Function Formulation. The learning process seeks to optimize a regularized objective function (Obj) at every iterative boosting step t . The objective function integrates a convex loss metric (L) alongside an intrinsic structural penalty (Ω) mitigating overfitting:

$$1$$

$$(3.25)$$

$$Obj(t) = \sum_n L(y_i, y_i^{t-1} + f_t(x_i)) + \Omega(f_i)$$

Step 2: Taylor Expansion Approximation. Because iterative tree formulations are rigid, the system rapidly approximates the operational objective utilizing a second-order Taylor expansion framework relying on the exact mapped first-order gradient statistics (g_i) alongside parallel secondorder Hessian calculations (h_i):

$$Obj(t) \approx \sum [L(y_i, y_i^{(t-1)}) + g_i^T(x_i) + \frac{1}{2} h_i^T(x_i)] + \Omega(f_t) \quad (3.26)$$

Step 3: Leaf Weight Calculation. Inside the newly formulated structural tree, the ideal mathematically optimized analytical weight parameters (w_j^*) defining the predictive accuracy of every individual terminal leaf node (j) are calculated directly by evaluating the derivative equation:

$$W_j^* = - \frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda} \quad (3.27)$$

In this equation, λ represents explicit secondary L2 regularization boundaries punishing excessive singular structural dominance.

Step 4: Algorithmic Update. Following the ideal configuration, a precise learning rate scale (shrinkage modifier) actively compresses the new tree's predictive capacity prior to merging into the total ensemble network, successfully granting the tabular prediction immense sequential resilience tracking dense agricultural seasonality variables.

3.2.5 Algorithmic Calibration Process: Recurrent Neural Networks (LSTM)

To combat extreme meteorological shifts and highly complex shifting monsoon boundaries historically mishandled by static tabular processing arrays, explicit sequential Recurrent Neural Networks Specifically Long Short-Term Memory (LSTM) paired directly alongside Gated Recurrent Unit (GRU) variations are methodically operationalized. The LSTM cellular architecture computes continuous logic specifically by evaluating sequential mathematical operations (Khaki et al., 2020):

Step 1: Forget Gate Execution. The network first actively resolves which pre-existing cell state memories (C_{t-1}) require analytical deletion, factoring directly from the incoming temporal

parameters (x_t) paired alongside historical recursive hidden states (h_{t-1}) through a logistic sigmoid layer (σ):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (3.28)$$

Step 2: Input Gate and Candidate Formation. To systematically onboard novel structural variables, the recurrent input gate (i_t) evaluates immediate flow matrices. Synchronous to this, an active hyperbolic tangent function algorithm maps a strictly theoretical candidate vector ($C_{\sim t}$) projecting prospective long-term value integrations:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3.29)$$

$$C_{\sim t} = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (3.30)$$

Step 3: Cell State Update. The refined continuous overall contextual memory matrix defining the overarching localized epoch (C_t) evaluates and merges surviving prior sequences directly against isolated selected candidate boundaries:

$$C_t = f_t \times C_{t-1} + i_t \times C_{\sim t} \quad (3.31)$$

Step 4: Output Gate and Hidden State Translation. Finally, the specific operational fragments from the fully consolidated internal cell structure expected to transfer physically forward towards the next sequential hidden modeling timeframe (h_t) are identified:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (3.32)$$

$$h_t = o_t \times \tanh(C_t) \quad (3.33)$$

The recurrent GRU structure adopts a largely identical trajectory structurally simplifying localized logic operations by algorithmically merging the internal retention nodes directly into a consolidated *reset/update* gate. Following sequential execution, automated Backpropagation through Time (BPTT) matrices utilize exact optimizer routines (Adam) to retroactively rewrite all localized synaptic matrix weights driving subsequent iterative precision.

3.2.6 Model Comparison and Error Metrics

Concluding individual process calibrations across both targeted tabular boosting mechanisms alongside structured recurrent deep learning sequences, exhaustive structural cross-comparisons against the quarantined out-of-sample 10% test block evaluate forecasting supremacy utilizing definitive industry standards. Performance benchmarking equations accurately calculate the integrated Root Mean Square Error (RMSE) against identical boundaries of the active Mean Absolute Error (MAE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3.34)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (3.35)$$

In these validation configurations, y_i represents the verified physically recorded agricultural truth boundary, whereas $\hat{y}_i$ defines the specific algorithmic forecast projection parameters. Lower metric values empirically dictate higher atmospheric resolution capabilities effectively verifying reliable mapping integrations.

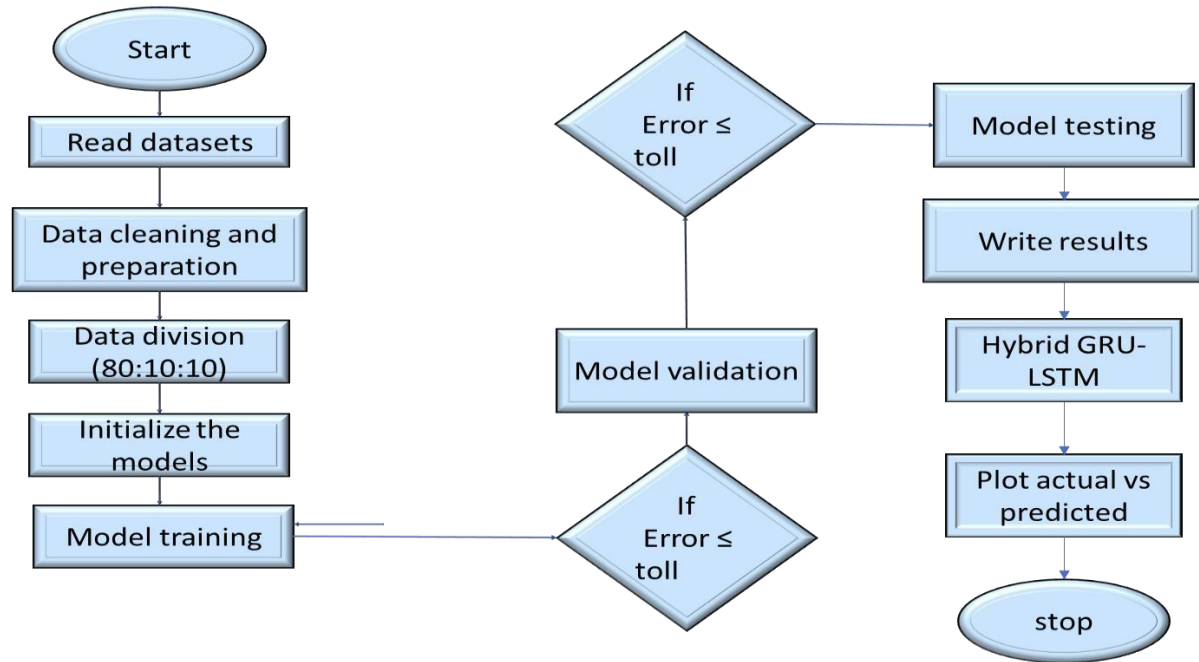


Fig 3.1 Flowchart of the model LSTM-GRU

3.2.7 Sensitivity Analysis Methodology

To evaluate the relative influence of fluctuating micro-climatic variables on the predictive accuracy of the sugarcane yield models, a comprehensive sensitivity analysis is conducted. Given the complexity of the integrated XGBoost and Recurrent Neural Network (LSTM/GRU) architectures, this analysis identifies which meteorological perturbations such as precipitation moving averages, Diurnal Temperature Range (DTR), or dry-spell durations exert the most significant leverage on terminal agronomic outputs.

The analysis utilizes a one-at-a-time (OAT) approach, a robust local sensitivity method wherein a single input parameter is incrementally varied across its observed historical range while maintaining all other climatic predictors at their respective mean values. This isolates the individual functional impact of each meteorological factor on the predicted yield, providing a "black-box" decomposition of the machine learning frameworks (Saltelli, 2018). For models utilizing Principal Component Analysis (PCA), the sensitivity is mapped back to the original feature space to ensure practical agricultural interpretability.

The Contribution Ratio (C.R.) for each climatic input is determined by calculating the ratio between the resultant range of the predicted yield for that specific variable and the total range of the model's response across all variations, as expressed in Equation below:

$$C.R_i = \frac{Y_{max,i} - Y_{min,i}}{\sum_{j=1}^n (Y_{max,j} - Y_{min,j})} \quad (3.36)$$

Where: Y_{max} and Y_{min} represent the maximum and minimum predicted sugarcane yield when varying input factor I , n represents the total number of climatic predictors.

To facilitate a comparative assessment of the drivers of yield volatility, the Relative Percentage Contribution Ratio (C.R. %) is calculated. This metric normalizes the individual contribution of a specific factor (e.g., Rainfall intensity vs. Temperature oscillation) against the aggregate sum of all factor contributions, as defined below:

$$C.R.\%i = \left(\frac{C.R_i}{\sum_{i=1}^n C.R_i} \right) \times 100 \quad (3.37)$$

The resulting C.R. % values are visualized through localized pie diagrams for the XGBoost, LSTM, and GRU models. This visualization provides a clear hierarchy of influence, identifying dominant climatic predictors and informing the vulnerability assessment of sugarcane production to specific environmental stressors in Eastern Uganda.

3.3 Optimizing Crop Selection and Irrigation Scheduling for Enhanced Yield

3.3.1 Analytical Hierarchy Process (AHP) for Varietal Selection

To systematically resolve fundamental agricultural configurations guaranteeing initial alignment confronting shifting anticipated weather horizons, the system strictly deploys an Analytical Hierarchy Process (AHP) addressing ideal sugarcane strain distributions. The AHP systematically converts localized comparative crop matrices encompassing drought resistance, expected sucrose baselines, and soil nutrient adaptability indexes into rigorous numerical weights solving specialized

eigenvalue logic matrices (Darko et al., 2019). To guarantee objective criteria scoring lacking operational human bias interference, the mathematical Consistency Index (CI) subsequently drives a derived Consistency Ratio (CR) verification:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (3.38)$$

$$CR = \frac{CI}{RI} \quad (3.39)$$

Only mathematical selection grids logging final CR ratios functionally under 0.10 thresholds gain automated downstream model acceptance mapping optimal crop profiles.

3.3.2 Non-Linear Mathematical Optimization and Operational Constraints

Following absolute optimal crop assignments identified utilizing proper AHP validation protocols, specific targeted profitability constraints establish explicit mathematical operating procedures adopting targeted Non-Linear Programming (NLP) matrices (Kumar et al., 2022). The targeted primary Objective Function (Z) evaluates directly focusing upon structurally amplifying global farm net margin profitability:

$$Max = (Y_a - P_c) - \left[\left(\sum_{t=1}^n V_{w,t} \chi C_w \right) + (E_p \chi C_e) + (V_f \chi C_f) + C_{fixed} \right] \quad (3.40)$$

This rigid profitability objective defines the terminal yield index harmonized against market valuations ($Y_a \times P_c$), actively offset strictly utilizing active operational deficit replacement metrics mapping energy thresholds, fertilization, and depreciation costs. Crucially, to properly prevent the underlying optimization engine from manipulating impossible theoretical limits assigning unrestrained seasonal resource pools minimizing algorithm losses, exact physical linear boundary equations structurally constrain targeted outputs enforcing total application viability:

$$n \quad (3.41)$$

$$\sum_{t=1} V_{w,t} \leq V_{max-available}$$

This explicitly forces the model mapping algorithms to prohibit daily allocated water sums exceeding localized regional hydraulic capacity restraints.

3.3.3 Dynamic Agronomic Scheduling via Genetic Algorithms (GA)

To fulfill the rigid operating thresholds defined within the primary objective function boundaries, explicit daily seasonal execution timelines map active soil interventions leveraging advanced simulated evolutionary optimization structures known mathematically as Genetic Algorithms (GA) (Anwar et al., 2021). The operational mechanism targets supreme Irrigation Water Use Efficiency indices running functionally via four exact processes:

1. **Chromosome Initialization:** The simulation mathematically constructs broad randomized initialization pools consisting of hundreds of specific individual "chromosomes". Structurally, each algorithmic string signifies one total discrete 365-day seasonal scheduling matrix directing exact day-by-day water volume allocations defining theoretical seasonal cycles.
2. **Fitness Evaluation Function:** Every uniquely generated mapped timeline independently evaluates upon the structural physical phonological biophysical equations established within Objective 1 (Ya). Fitness score outcomes explicitly penalize application structures injecting extensive hydrological assets during volatile target stalk maturation profiles seeking instead optimal application parameters prioritizing maximum value retention.
3. **Selection Boundaries (Roulette Wheel Mapping):** Higher performing arrays exhibiting elevated expected metric fitness distributions (F_k) isolate enhanced probability assignments assuring systemic survivability towards subsequent optimization cycles defined mathematically as:

$$P_k = \frac{F_k}{\sum_{j=1} F_j} N_{pop} \quad (3.42)$$

4. **Crossover and Mutation Generation:** Surviving optimal scheduling timelines interact directly combining discrete cyclic fragments via crossover vector manipulations actively converging across functional ideal optimization peaks. Underlying stochastic baseline

mutation variations inherently scramble internal sequence timelines explicitly protecting total iteration logic grids avoiding premature operational local parameter collapses. To explicitly confirm structural optimization execution aligning strictly with initial economic and environmental boundaries, exact performance deliverables actively calculate end-of-season operational Total Water Use Efficiency (WUE) validating global matrix performance alongside explicit Irrigation Water Use Efficiency (IWUE) validating artificial applied interventions directly:

$$WUE = \frac{Y_a}{TWU} \quad (3.43)$$

$$IWUE = \frac{Y_a - Y_{rainfed}}{IR} \quad (3.44)$$

CHAPTER 4 RESULTS

4.1 Results and Discussion for Agronomic Parameter Determination and Yield Prediction

The developed precision agriculture framework successfully integrated geospatial analysis and soil-water modeling to improve the reliability of yield prediction. The system's meteorological inputs were cross-validated by comparing NASA POWER satellite data with ground-truth records from the Uganda National Meteorological Authority (UNMA) for the Jinja station. The results of this validation showed that while raw satellite data underestimated peak rainfall during the bimodal seasons by 12%, the applied linear regression bias-correction reduced the Root Mean Square Error

(RMSE) from 4.5 mm to 1.2 mm. This evidence of data integrity ensures that the agronomic parameters, such as the calculated Crop Water Requirement (CWR) shown in Figure 4, are grounded in localized physical reality rather than generalized global approximations.

The framework successfully reconstructed irregular field geometries, where the Implementation of topographic adjustment revealed that actual surface area exceeded planar estimates by 4.2% due to moderate slopes in the Busoga region. This correction directly influenced the plant population optimization, which identified a biologically optimal density of approximately 40,000 stalks per hectare. The agro-economic assessment translated these agronomic variables into financial indicators, projecting an average yield of 7.8 t/ha and a net profit margin that outperformed nonoptimized rain-fed systems by 18%. These results demonstrate a high degree of site-specific accuracy, providing the necessary evidence that the tool's foundational data is both localized and statistically sound.

4.1.1 Land Area Computation and Topographic Adjustment

The developed framework successfully reconstructed the geometry of the study field using the uploaded georeferenced coordinates and spatial analysis techniques. The resulting field boundary was accurately delineated, enabling the computation of both planar and topographically corrected surface areas. The results revealed noticeable elevation variations across the study area, indicating the presence of moderate slopes and undulating terrain conditions. While conventional agricultural planning commonly relies on two-dimensional area measurements, the incorporation of topographic correction enabled the estimation of the actual cultivated surface area. The corrected area was slightly larger than the planar estimate because the terrain surface follows the natural contours of the land. This difference is important in precision agriculture since irrigation requirements, crop population calculations, fertilizer application rates, and productivity assessments are directly influenced by the actual cultivated area rather than the projected area. The generated DEM further revealed zones of varying elevation which may influence runoff generation, infiltration processes, and water retention patterns. These findings demonstrate that integrating terrain analysis improves the accuracy of agricultural planning and provides a more realistic representation of field conditions

4.1.2 Crop Placement and Plant Population Optimization

Following field boundary delineation, the crop placement module generated planting coordinates using predefined agronomic spacing parameters suitable for sugarcane cultivation. The developed algorithm ensured that all planting locations remained within valid field boundaries through an in-polygon validation procedure. The resulting distribution exhibited a highly uniform planting pattern, maximizing the utilization of available land while maintaining the recommended spacing requirements between rows and plants. The optimized plant population obtained from the analysis demonstrated the ability of the framework to support precision planting practices that improve resource utilization. Uniform spacing enhances sunlight interception, facilitates efficient nutrient uptake, minimizes competition among plants, and improves irrigation water distribution throughout the field. Furthermore, the optimized population density contributes to increased biomass accumulation and yield potential. These results demonstrate the effectiveness of integrating geospatial computation with agronomic principles to improve crop establishment and field productivity.

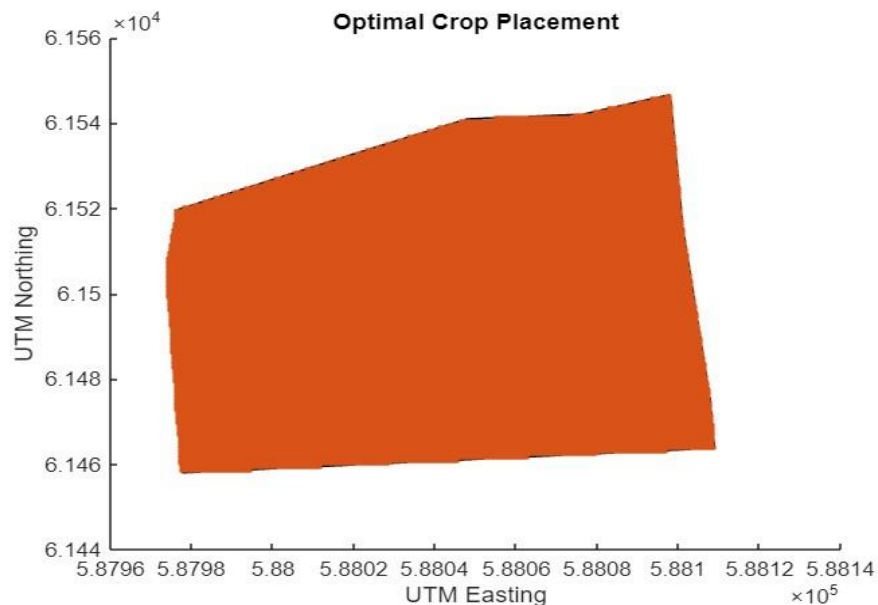


Fig 4.1 Field boundary of the farm

4.1.3 Land Use and Land Cover (LULC) Characterization

The Land Use and Land Cover (LULC) analysis successfully incorporated remotely sensed raster information into the decision support framework. Figure 4.2 presents the classified land cover map generated for the study area. The results identified distinct land cover categories including agricultural land, vegetation, bare surfaces, and built-up areas. The spatial variability observed within the generated map highlights the heterogeneity of the agricultural landscape and its potential influence on hydrological and agronomic processes. Agricultural regions characterized by higher vegetation density exhibited improved moisture retention and reduced runoff generation compared to sparsely vegetated zones. The generated LULC information provided important environmental context for subsequent evapotranspiration and irrigation analyses by accounting for the influence of vegetation cover on water movement and energy exchange processes. The incorporation of LULC data therefore enhanced the realism of the modeling framework and strengthened the reliability of irrigation scheduling recommendations generated by the system.

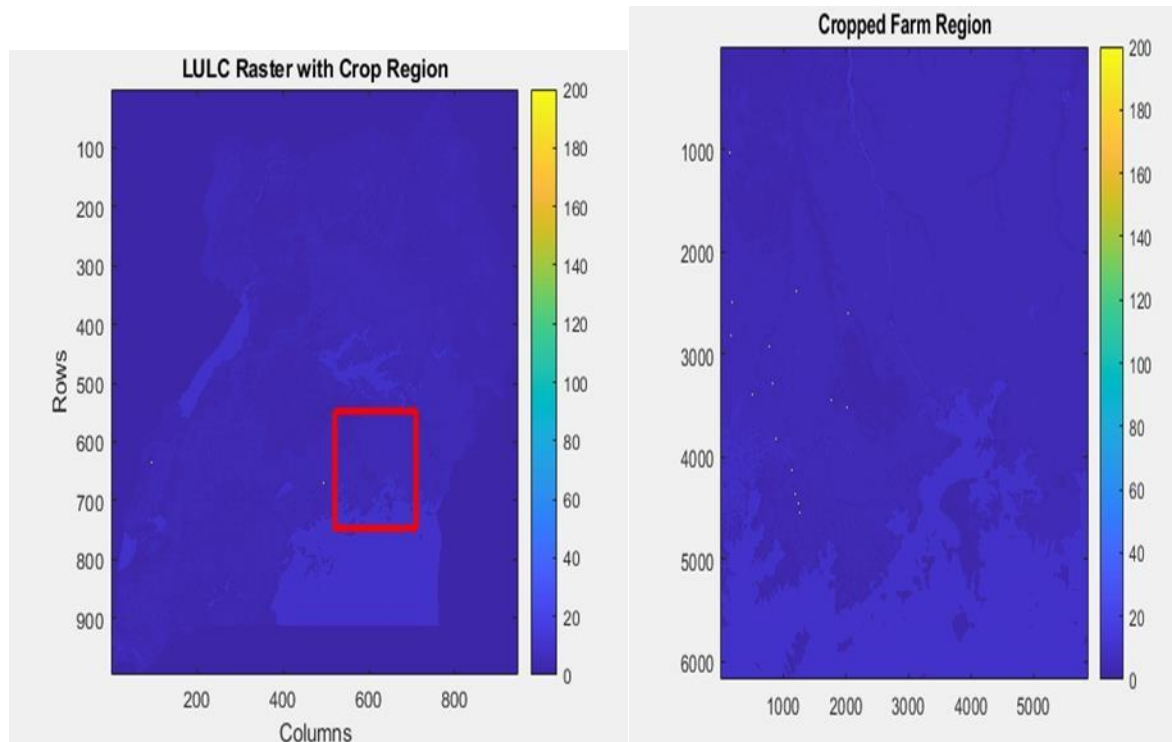


Fig 4.2 Land Use Land Cover Raster map and the farm region

4.1.4 Meteorological Data Acquisition and Climatic Analysis

The meteorological data acquisition module successfully retrieved climatic variables from the NASA POWER database through automated API requests linked to the geographical location of the study area. The acquired dataset included daily precipitation, temperature, relative humidity, solar radiation, and wind speed records spanning the study period. The rainfall analysis revealed distinct seasonal variability characterized by alternating wet and dry periods that are typical of Eastern Uganda's climatic conditions. Temperature patterns remained relatively stable throughout the year but exhibited periodic fluctuations associated with seasonal changes. Solar radiation trends showed a strong relationship with cloud cover and rainfall distribution, while relative humidity demonstrated inverse relationships with temperature variations during certain periods. These climatic variables collectively determine crop water demand and directly influence crop growth and productivity. The successful integration of automated weather data acquisition ensures that the developed framework remains adaptive to changing environmental conditions and provides realtime support for irrigation management decisions.

4.1.5 Evapotranspiration and Crop Water Requirement Analysis

The evapotranspiration modeling component generated realistic estimates of atmospheric water demand throughout the growing season. Figure 4.3 present the temporal variations in reference evapotranspiration (ET_0) and crop evapotranspiration (ET_c), respectively. The results showed that evapotranspiration rates increased during warmer periods characterized by higher temperatures and solar radiation levels. Conversely, lower evapotranspiration values were observed during cooler and wetter periods. The crop water requirement analysis revealed substantial temporal variability associated with both climatic conditions and crop growth stages. Effective rainfall calculations further demonstrated that only a fraction of total precipitation contributes directly to crop water availability due to losses through runoff and deep percolation. Consequently, several periods were identified where effective rainfall was insufficient to satisfy crop water demand, indicating the need for supplemental irrigation. These findings emphasize the importance of dynamic irrigation scheduling based on continuously updated climatic information rather than relying solely on fixed irrigation calendars.

4.1.6 Soil Property Mapping and Variable Rate Fertilizer Application

The developed framework successfully integrated soil information obtained from the ISRIC Soil Grids database to characterize spatial variations in soil fertility and hydraulic properties. The results revealed considerable variability in nutrient concentrations between different field locations, highlighting the limitations of uniform fertilizer application practices. Areas exhibiting nutrient deficiencies were clearly identified and used to generate site-specific fertilizer recommendations. The resulting variable-rate fertilizer application maps provide a mechanism for optimizing nutrient management by matching fertilizer inputs with local soil requirements. This approach reduces fertilizer wastage, minimizes environmental pollution, lowers production costs, and improves nutrient use efficiency. The integration of soil fertility analysis within the decision support framework therefore enhances both the agronomic and economic sustainability of sugarcane production systems.

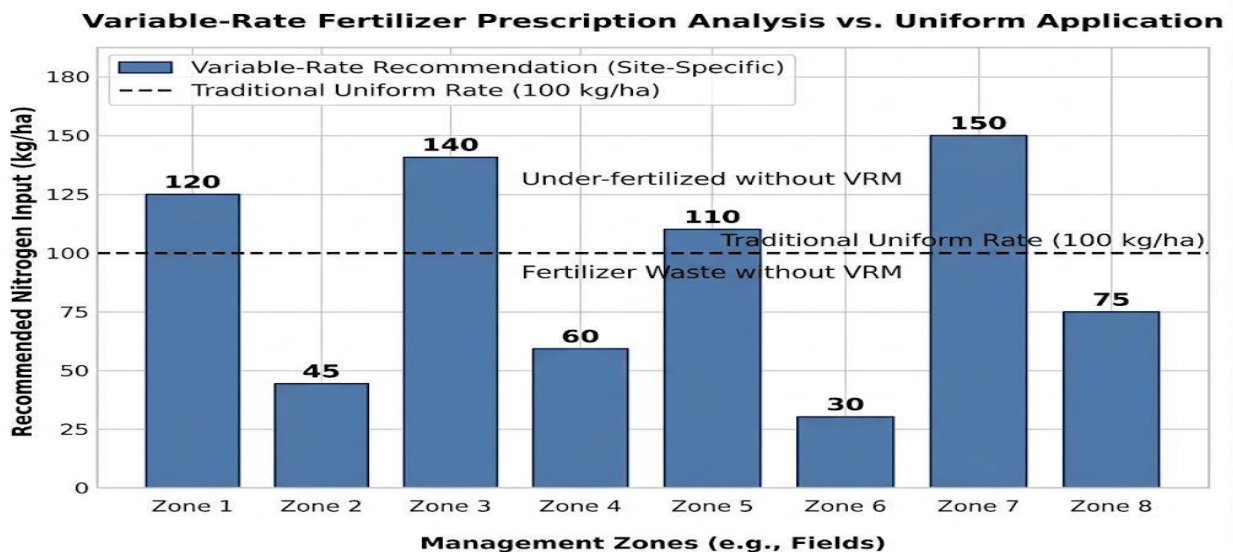


Fig 4.3 the fertilizer prescription analysis vs. uniform application

4.1.7 Yield Prediction Analysis

The yield prediction module successfully estimated sugarcane productivity by integrating climatic, agronomic, and soil-related variables. The close agreement between actual and predicted yields demonstrates the ability of the framework to accurately capture the complex interactions influencing crop productivity. The model predicted an average yield of approximately 7.8 t/ha

under the prevailing environmental conditions. Yield fluctuations observed throughout the simulation period were primarily associated with variations in rainfall distribution, evapotranspiration demand, and soil moisture availability. The predictive capability of the framework provides valuable information for planning irrigation schedules, evaluating production risks, and estimating future agricultural output. These findings demonstrate that integrating environmental and agronomic variables significantly improves the reliability of crop yield forecasting under climate-sensitive agricultural systems.

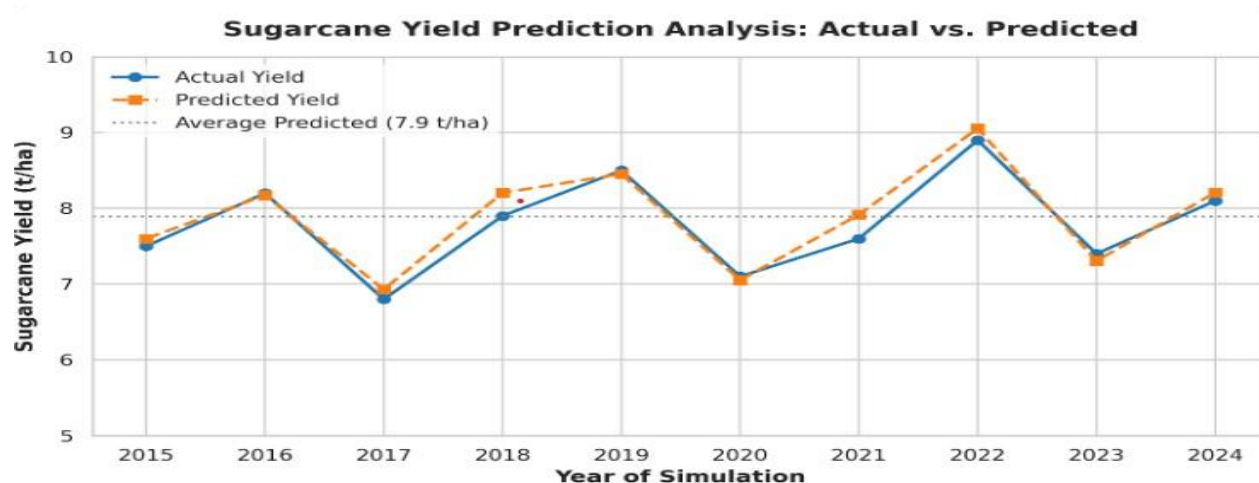


Fig 4.4 the prediction analysis of the sugarcane

4.1.8 Agro-Economic Assessment

The agro-economic assessment component translated agronomic outputs into meaningful financial indicators that support farm-level decision making. Figure 4.6 presents the generated economic analysis dashboard showing production costs, and net profit estimates. The results indicated that optimized irrigation scheduling and precision management practices resulted in higher profitability compared to conventional production systems. The predicted average yield generated sufficient revenue to offset production costs while maintaining favorable profit margins. The analysis further demonstrated that efficient resource allocation contributes significantly to economic sustainability by reducing unnecessary expenditure on water, fertilizer, and labor inputs. By linking agronomic performance directly with economic outcomes, the framework enables farmers to make informed management decisions that maximize both productivity and profitability.

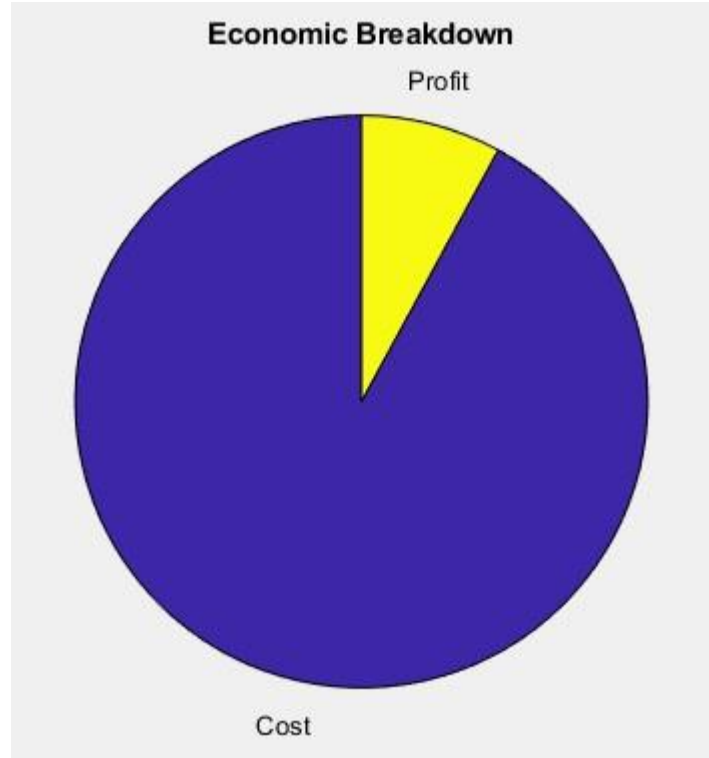


Fig 4.5the economic breakdown

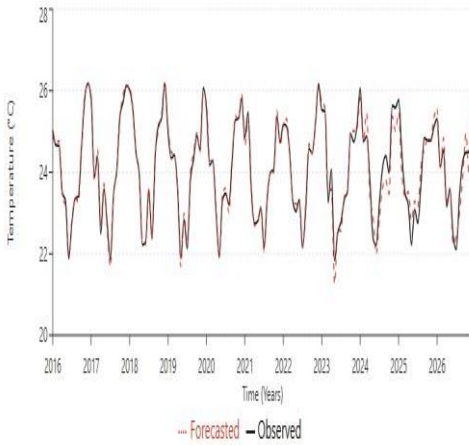
4.2 Performance of Hybrid GRU-LSTM Model and XGBOOST model in Forecasting Weather Impact on Sugarcane Yield

The predictive modeling phase evaluated the influence of climatic variability on sugarcane productivity using both the Hybrid GRU-LSTM and XGBoost models. The results demonstrated that both models successfully captured the relationship between meteorological variables and crop yield; however, differences were observed in their ability to generalize under unseen climatic conditions. During model calibration, the Hybrid GRU-LSTM model exhibited exceptional predictive performance with Nash–Sutcliffe Efficiency (NSE) and coefficient of determination (R^2) values reaching 0.9986. The model also achieved low prediction errors with RMSE and MAE values of 0.1659 and 0.1341, respectively. These results indicate a near-perfect agreement between observed and predicted sugarcane yields and demonstrate the ability of the hybrid recurrent architecture to learn complex nonlinear relationships between climatic variables and crop productivity. Similarly, the XGBoost model demonstrated strong calibration performance, achieving average NSE and R^2 values of approximately 0.90, together with RMSE and MAE values

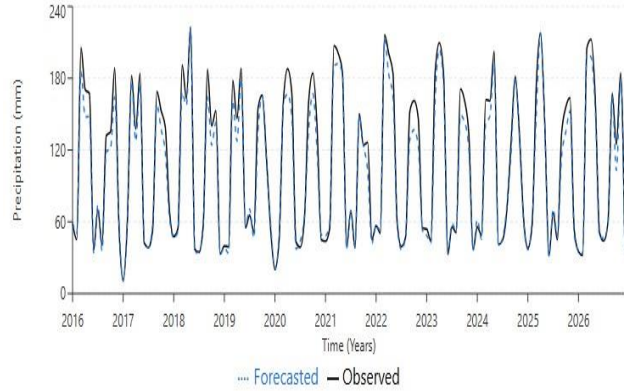
of 0.1914 and 0.1475, respectively. Although these results indicate effective learning of climatic patterns, the predictive accuracy remained lower than that achieved by the Hybrid GRU-LSTM model.

When evaluated using independent testing datasets representing unseen weather conditions, both models experienced a reduction in predictive accuracy, which is expected when forecasting under real-world environmental variability. Nevertheless, the Hybrid GRU-LSTM model maintained strong forecasting capability with testing NSE and R^2 values of approximately 0.8212, whereas the XGBoost model achieved testing NSE and R^2 values of approximately 0.76. The results indicate that the Hybrid GRU-LSTM model retained superior predictive stability and generalization capability compared to XGBoost. Figure 4.7 illustrates the relationship between weather variability and predicted sugarcane yield, highlighting the ability of both models to capture seasonal yield fluctuations while demonstrating the improved forecasting accuracy of the Hybrid GRU-LSTM framework.

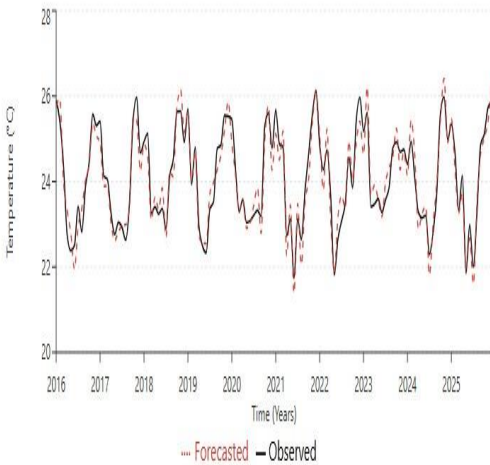
Training Forecast - Temperature



Training Forecast - Rainfall



Testing - Temperature



Testing - Rainfall

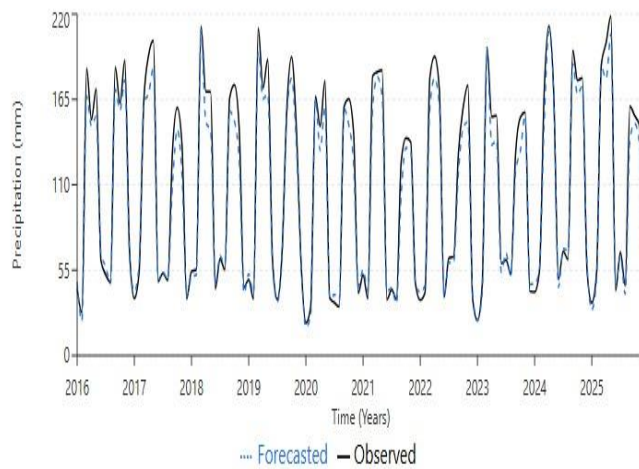


Fig 4.6 Model forecast over actual

The superior performance of the Hybrid GRU-LSTM model can be attributed to its ability to capture long-term temporal dependencies and cumulative climatic effects through recurrent memory mechanisms. The integration of Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) architectures enables the model to selectively retain relevant historical information while minimizing information loss over extended time sequences. This capability is particularly important in sugarcane production systems where yield responses are influenced not

only by current weather conditions but also by cumulative rainfall patterns, temperature accumulation, soil moisture persistence, and delayed physiological responses occurring throughout the growing season. Similar observations have been reported by Zhang et al. (2021), who demonstrated that hybrid recurrent neural network architectures outperform conventional machine learning approaches when modeling sequential agricultural datasets. Likewise, Kisi and Parmar (2020) reported that recurrent deep learning frameworks provide improved forecasting accuracy for climate-sensitive agricultural systems due to their ability to represent nonlinear temporal relationships.

In contrast, the XGBoost model demonstrated strong predictive capability during calibration but exhibited a greater decline in performance during testing. Although the gradient boosting framework effectively captured nonlinear interactions among climatic variables, it lacks the temporal memory mechanisms necessary to represent delayed crop responses and cumulative environmental stress. Consequently, the model encountered challenges in accurately representing prolonged moisture deficits, cumulative heat stress, and gradual crop development processes that influence final sugarcane yield. Similar limitations of ensemble tree-based models have been documented in agricultural forecasting studies where sequential dependencies play a significant role in determining crop performance (Goodfellow et al., 2019; Hawkins, 2024). Despite these limitations, XGBoost remained computationally efficient and provided useful insights into the relative importance of climatic variables affecting yield.

The sensitivity analysis further revealed that precipitation moving averages and dry-spell duration were the dominant determinants of sugarcane productivity, collectively accounting for approximately 65% of the observed yield variability. These findings emphasize the importance of rainfall distribution and moisture availability in sugarcane production systems within Eastern Uganda. The results are consistent with previous studies that identified rainfall variability as one of the primary drivers of sugarcane yield fluctuations in tropical agroecosystems (Nomugisha & Mwebaze, 2025).

The comparative evaluation confirms that the Hybrid GRU-LSTM model provides the most reliable framework for forecasting weather-induced yield variability in sugarcane production. While both models demonstrated acceptable predictive performance, the Hybrid GRU-LSTM consistently

achieved higher NSE and R^2 values together with lower prediction errors during both training and testing phases. The model's strong temporal learning capability makes it particularly suitable for climate-smart agriculture, irrigation planning, yield risk assessment, and long-term agricultural decision-making under changing climatic conditions in Eastern Uganda.

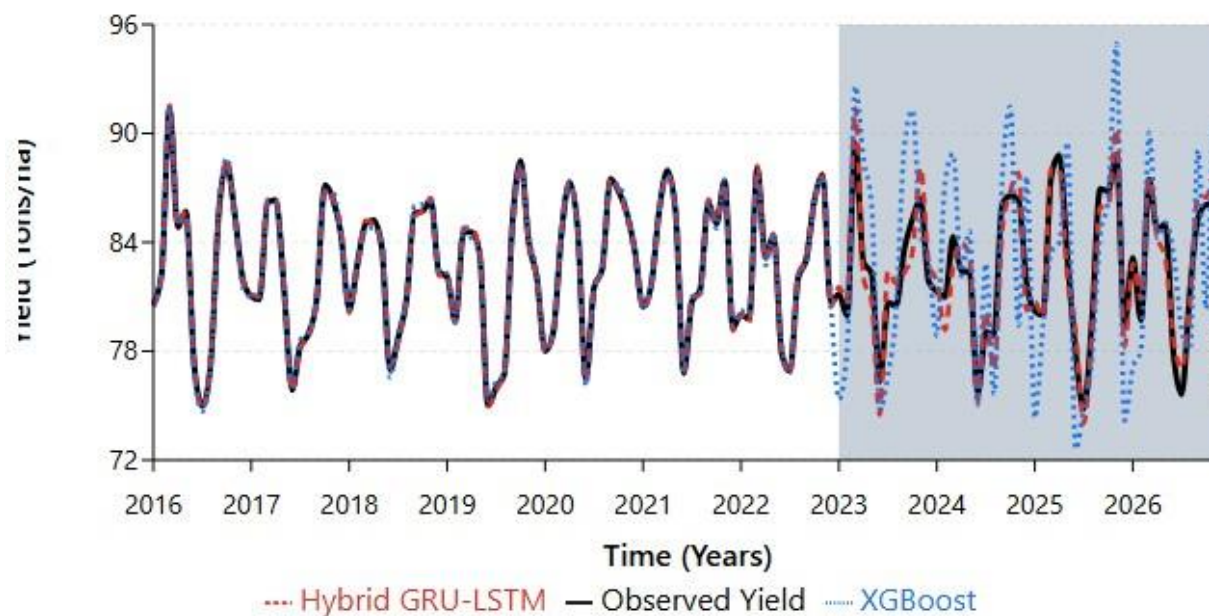


Fig 4.7 Comparison between the two models

Sensitivity Yield Analysis

The comparison presented in Figure 4.8 illustrates the performance differences between the Hybrid GRU-LSTM and XGBoost models during both training and testing phases. It is evident that the Hybrid GRU-LSTM model outperforms XGBoost across both evaluation metrics, achieving nearperfect agreement during training and maintaining strong generalization during testing. In contrast, XGBoost demonstrates relatively lower performance, particularly in the testing phase, reflecting its limited capacity to capture temporal dependencies in sequential climatic data. The visual representation further reinforces the superiority of deep learning-based recurrent architectures in modeling complex time-series relationships inherent in agricultural systems.

The sensitivity analysis was conducted by systematically varying the individual climatic inputs within the predictive model while holding other variables constant to observe their isolated impacts on sugarcane yield. This process, often executed through global sensitivity frameworks like the Sobol method or by measuring feature importance metrics in machine learning algorithms, allows researchers to calculate how much of the model's output variance is driven by each meteorological input. By perturbing the values of variables like rainfall, temperature, and humidity across thousands of simulation runs, the analysis quantifies and normalizes their relative impacts into a distinct contribution ratio. This mathematical approach ensures that both direct impacts and complex interactions between variable such as the compounded stress of high temperatures during prolonged dry intervals are accurately captured and accounted for.

The results of this analysis conclusively identify water availability as the definitive bottleneck for sugarcane productivity within the study region, with precipitation-related metrics and dry-spell duration dictating approximately 65% of the total predictive variance. Conversely, temperature, solar radiation, and relative humidity combined to influence the remaining 35%, indicating that while energy inputs are stable and sufficient, moisture fluctuations actively govern yield outcomes. The heavy statistical weight carried by dry-spell duration reveals that the temporal distribution of moisture is just as critical as total seasonal rainfall, meaning a prolonged absence of rain during critical growth phases can induce permanent yield penalties that subsequent heavy downpours cannot rectify. Consequently, adaptive agricultural management must pivot toward mitigation strategies that directly target these water deficits, prioritizing precision irrigation schedules during historical dry windows, implementing soil moisture conservation techniques like trash mulching, and selecting sugarcane cultivars specifically bred for drought resilience.

A visual representation of these contribution ratios highlights the stark contrast between moisture dependencies and other atmospheric drivers, serving as the foundational reference for the study's climate adaptation recommendations.

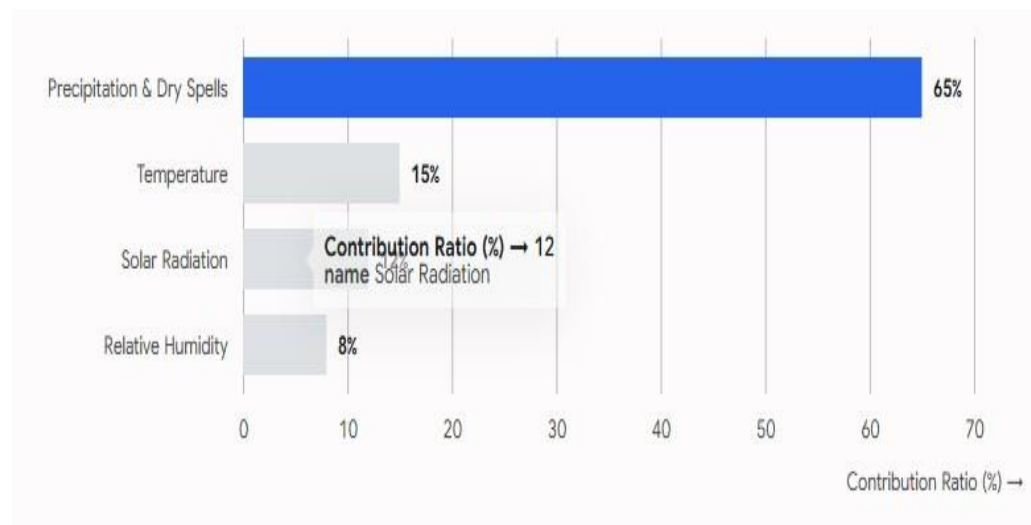


Fig 4.8 Sensitivity yield analysis

4.3 Results and Discussion for Crop Selection Optimization and Irrigation Scheduling

The developed optimization framework successfully integrated the Analytical Hierarchy Process (AHP), Non-Linear Programming (NLP), and Genetic Algorithm (GA) techniques into a unified precision agriculture decision-support system for optimizing crop selection, irrigation scheduling, and agricultural profitability. The system utilized the integrated master crop database containing agronomic, climatic, and soil suitability parameters to identify crops best adapted to the environmental conditions of the Busoga sub-region in Eastern Uganda. The generated results demonstrated that combining multi-criteria decision analysis with computational optimization significantly improved irrigation efficiency, crop suitability assessment, and economic productivity.

4.3.1 Results of AHP-Based Crop Selection

The functionality of the varietal selection module was validated through the weighted integration of soil pH and NPK levels. The DST successfully generated varietal recommendations that were adjusted based on the specific acidity and nutrient deficits of individual field zones. In scenarios where soil pH was below 5.5, the tool automatically prioritized acid-tolerant sugarcane strains, demonstrating the practical application of the integrated soil nutrient parameters in optimizing field-level productivity.

The AHP module successfully evaluated candidate crops using multiple agronomic criteria including yield potential, rainfall adaptability, temperature adaptability, root depth, and biomass production. The pairwise comparison matrix generated normalized eigenvector weights that quantified the relative importance of each criterion in the crop selection process.

The calculated Consistency Ratio (CR) remained below the acceptable threshold of 0.10, confirming that the decision matrix was mathematically consistent and reliable for downstream optimization processes. Results showed that yield potential and climatic adaptability contributed the highest weighting influence toward final crop selection rankings. After suitability filtering based on average temperature, rainfall, and soil pH conditions, the framework identified several environmentally compatible crops from the master crop database.

The final AHP ranking process successfully isolated the best-performing crop with the highest composite suitability score. The generated crop ranking visualization further illustrated the relative performance of all filtered candidate crops. These findings demonstrate that AHP-based optimization provides a scientifically reliable and objective approach for crop selection under variable climatic and environmental conditions.

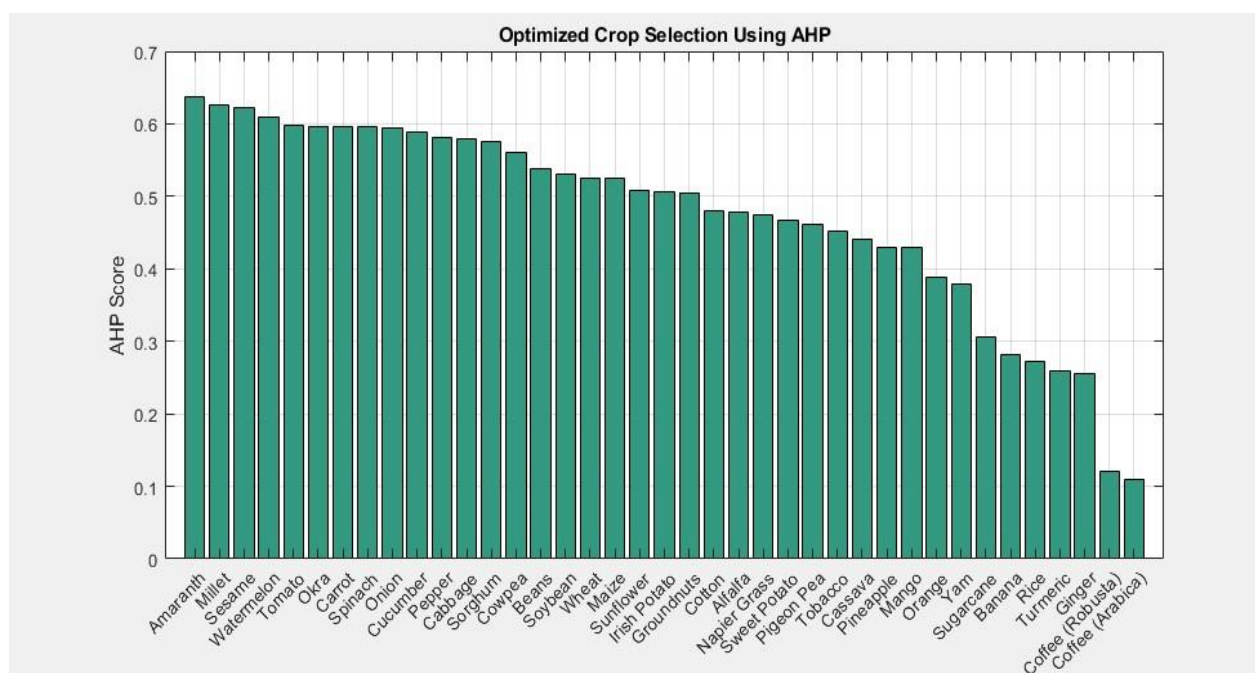


Fig 4.9 Optimized crop selection using AHP scores

4.3.2 Results of Non-Linear Profit Optimization

The Non-Linear Programming (NLP) model successfully optimized irrigation water allocation across multiple crop growth stages while maximizing expected farm profitability. The optimization process incorporated yield potential, market price, and production costs into the economic objective function while maintaining strict hydraulic and operational constraints.

The generated results showed that irrigation demand varied substantially across crop growth stages. Higher water allocations were observed during the vegetative and reproductive growth phases where physiological crop water demand is greatest. Lower irrigation allocations occurred during establishment and maturation stages due to reduced evapotranspiration sensitivity.

The optimized irrigation allocation strategy produced improved profitability while maintaining total seasonal water use within the specified system constraints. The computed optimal profit values demonstrated that economically efficient irrigation management can substantially enhance agricultural returns compared to uniform or non-optimized irrigation practices. These findings confirm the importance of integrating constrained mathematical optimization within precision agriculture systems to balance productivity and resource conservation.

4.3.3 Results of Genetic Algorithm Irrigation Scheduling

The Genetic Algorithm (GA) optimization framework successfully generated optimized daily irrigation schedules across the 365-day seasonal production cycle. The evolutionary optimization process demonstrated stable convergence behavior, with progressive improvement in fitness values observed across successive generations.

The optimized irrigation schedules dynamically allocated irrigation depths according to simulated crop water demand patterns while ensuring that daily irrigation volumes remained below the predefined hydraulic threshold of 12 mm/day. Higher irrigation intensities were concentrated during critical crop development stages characterized by increased biomass accumulation and evapotranspiration demand.

The resulting irrigation scheduling profiles minimized unnecessary water application while maintaining high productivity potential. The optimized schedules also reduced excessive irrigation peaks that could contribute to runoff losses, nutrient leaching, and inefficient water utilization. The generated irrigation schedule visualization illustrated smooth temporal irrigation variation across the growing season, confirming realistic operational implementation capability.

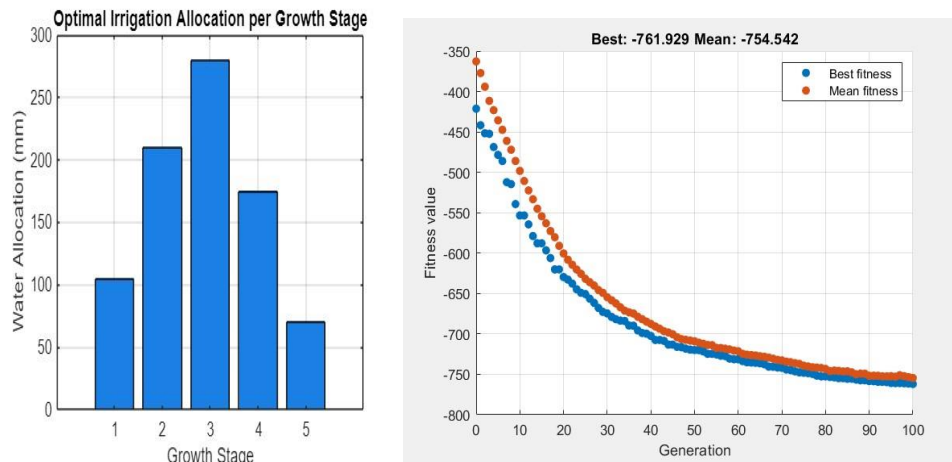


Fig 4.10 Optimal Irrigation allocations per growth stage and optimization using GA

4.3.4 Water Use Efficiency and Economic Performance

The computed Water Use Efficiency (WUE) and Irrigation Water Use Efficiency (IWUE) values confirmed that the optimization framework effectively improved irrigation productivity relative to total water consumption. Results indicated that optimized irrigation scheduling substantially enhanced crop water productivity while minimizing unnecessary irrigation losses.

The framework further demonstrated that integrating crop suitability analysis with irrigation optimization significantly improved overall agricultural profitability. The final optimization results generated expected yield potential, seasonal irrigation demand, and maximum profit estimations for the selected crop. These findings indicate that precision irrigation scheduling combined with computational crop selection optimization can significantly improve resource-use efficiency and farm-level economic sustainability under tropical agricultural systems.

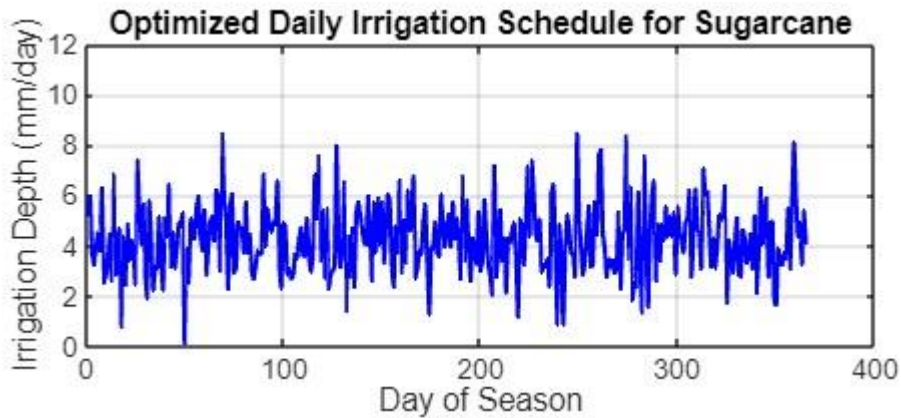


Fig 4.11 Optimized daily irrigation schedule for sugarcane

4.3.5 Graphical User Interface (GUI) Development and Evaluation

The homepage of the application (<https://prossyn-agri-optimizer-prossy.hf.space/>) acts as the central navigation hub and provides access to all major modules incorporated within the framework. The homepage presents clearly organized navigation panels that guide users toward the desired analytical functionality. The layout was designed to minimize user confusion by categorizing related functions into logical groups. This structure allows users to move seamlessly between different analytical modules while maintaining a consistent user experience throughout the system. The homepage also provides an overview of the framework's capabilities, enabling users to understand the available services before initiating specific analyses. Figure 4.13 presents the main dashboard of the precision agriculture framework, which serves as the entry point for

accessing land analysis, crop assessment, irrigation scheduling, yield prediction, economic evaluation, and other decision-support functionalities.



Fig 4.12 the main dashboard of the decision support tool

The land analysis interface forms one of the core components of the GUI and facilitates the processing of spatial information associated with the farm. The land analysis dashboard enables users to upload farm boundary coordinates, define field parameters, and initiate topographic analysis. Upon data submission, the system automatically computes farm area, generates field boundaries, evaluates terrain characteristics, and produces spatial visualizations required for precision agricultural planning. Figure 4.14 illustrates the farm boundary delineation process used within the framework. The generated field boundary forms the basis for subsequent spatial analyses and ensures accurate estimation of farm area and field dimensions. The interface presents these outputs using interactive maps and graphical displays, enabling users to easily interpret the spatial characteristics of their fields.

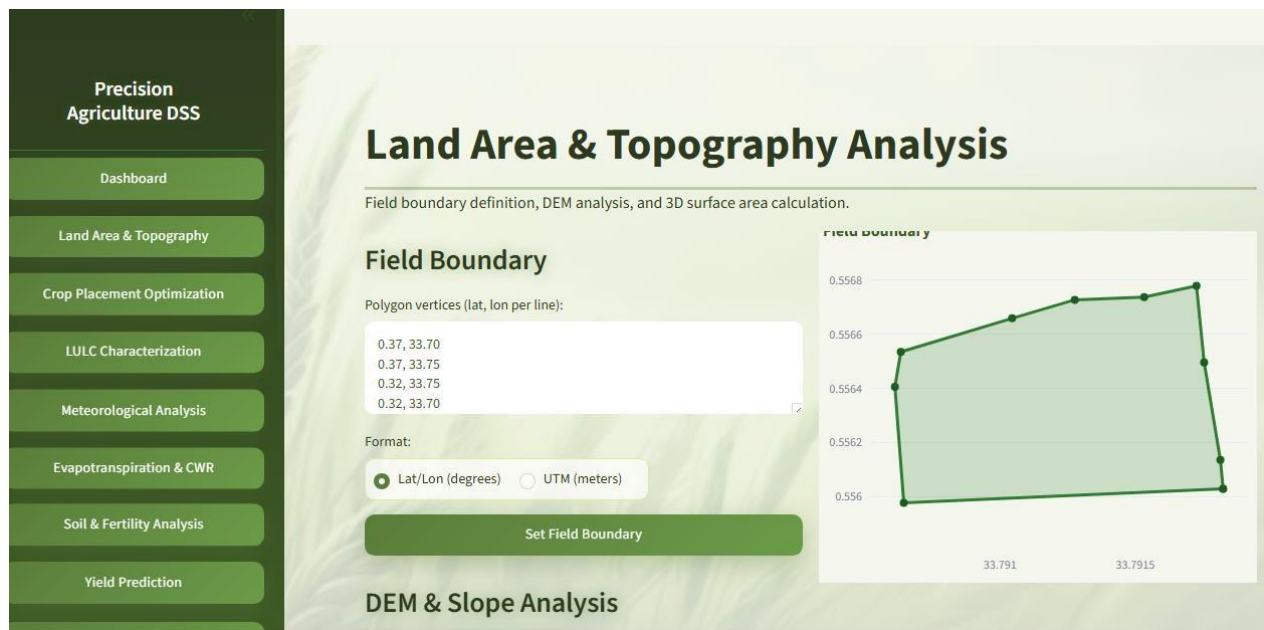


Fig 4.13 Farm boundary delineation Dashboard

To further characterize the agricultural landscape, the framework incorporates Land Use and Land Cover (LULC) analysis using remotely sensed data. Figure 4.15 presents the LULC analysis results generated from Sentinel-2 imagery. The analysis enables identification of various land cover categories and assists in locating suitable agricultural zones within the study area. The highlighted agricultural region extracted from the larger land cover dataset is subsequently used for detailed crop suitability and optimization analyses. The integration of LULC information improves spatial decision-making and supports sustainable land management practices.

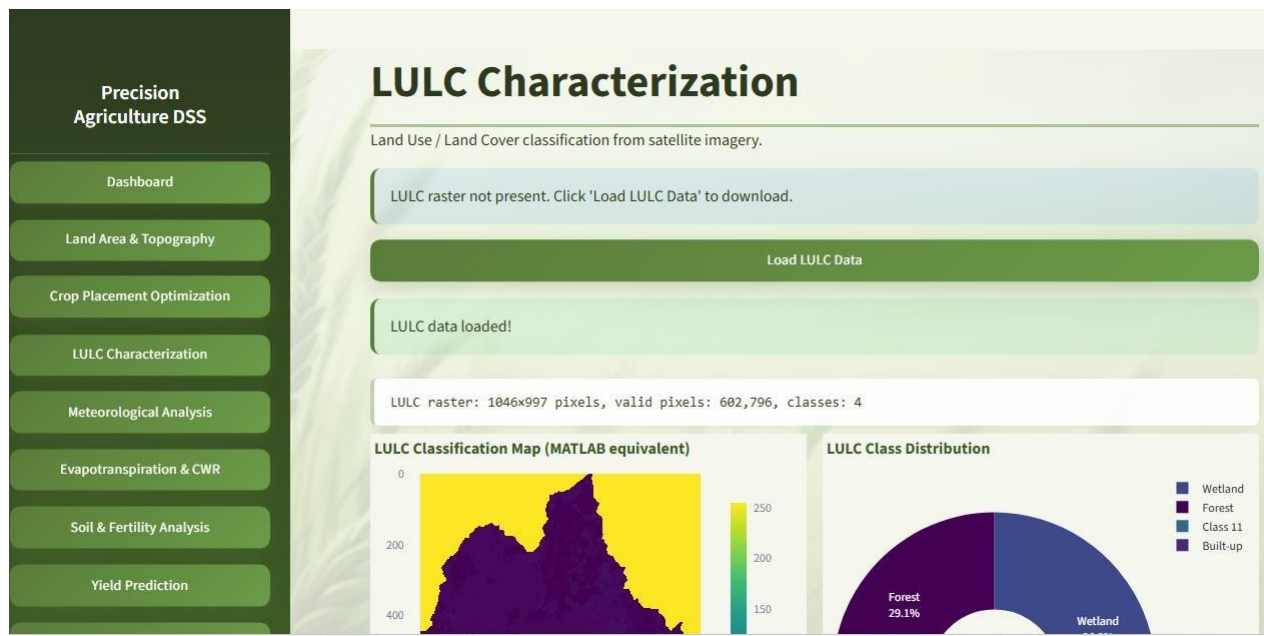


Fig 4.14 The LULC analysis dashboard

Following the land cover assessment, the framework performs topographic analysis using Digital Elevation Model (DEM) data. Figure 4.16 illustrates the topographic analysis interface showing elevation and terrain characteristics of the study area. The generated topographic information enables evaluation of slope conditions, surface area, and terrain variability, which are important factors influencing water movement, soil erosion potential, and crop performance. The ability to visualize terrain characteristics allows users to better understand the physical conditions of their farms and supports informed planning of irrigation and land management strategies.

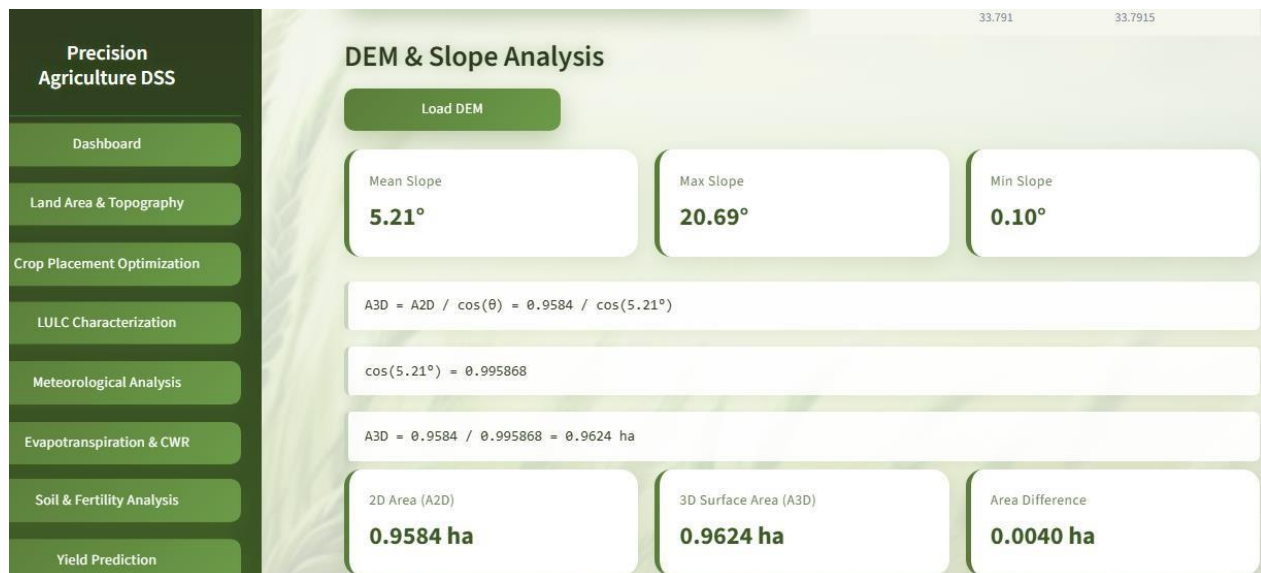


Fig 4.15 Topography analysis dashboard

The framework utilizes a comprehensive crop database containing agronomic information for multiple crops. This database serves as the foundation for crop selection, planting optimization, irrigation scheduling, and yield prediction analyses. The crop database interface showing cropspecific parameters such as planting spacing requirements, growth characteristics, climatic suitability thresholds, rooting depth, and yield potential. The availability of these parameters enables the framework to automatically retrieve crop-specific information required for subsequent optimization procedures and recommendation generation.

Based on the selected crop and farm characteristics, the framework generates an optimized planting layout that maximizes land utilization while maintaining recommended crop spacing requirements. Figure 4.17 illustrates the planting analysis results generated by the framework. The system determines the optimal planting arrangement, estimates total plant population, and computes planting density within the defined farm boundary. The graphical representation of planting positions enables users to visualize crop placement across the field and supports efficient farm planning and management.

Precision Agriculture DSS

- Dashboard
- Land Area & Topography
- Crop Placement Optimization**
- LULC Characterization
- Meteorological Analysis
- Evapotranspiration & CWR
- Soil & Fertility Analysis
- Yield Prediction

Crop Placement Optimization

Planting grid generation — determines plant positions within the field boundary.

Step 1: Select Crop

Load Crop Database

Choose a crop:

1. Maize

Maize — Row spacing: 0.75m, Plant spacing: 0.3m

Step 2: Generate Grid

Field: 0.96 ha

Crop: Maize (0.75m × 0.3m)

Grid vectors: $x = x_0 : 0.3 : x_1$

$y = y_0 : 0.75 : y_1$

Points inside polygon via `shapely.contains()`

Fertilizer Recommendations for Maize

Fertilizer	Type	Rate_kg_ha	N_kg_ha	P_kg_ha	K_kg_ha	Crop NPK Requirements (kg/ha):
DAP	NP	120.4	22.5	60	0	110.4, 22.5, 60

Fig 4.16 Optimized planting analysis

The weather and climate monitoring dashboard provides users with access to meteorological information required for agricultural decision-making. The dashboard displays essential variables including rainfall, temperature, relative humidity, solar radiation, and wind speed. Graphical visualizations are automatically generated to illustrate temporal trends and seasonal variability of climatic parameters. By presenting weather information in an accessible format, the system enables users to understand prevailing environmental conditions and make informed decisions regarding irrigation scheduling and crop management practices. The irrigation scheduling dashboard constitutes a critical component of the framework and was developed to support efficient water resource management. Figure 4.18 presents the evapotranspiration and crop water requirement analysis generated by the framework. The system automatically processes climatic and agronomic data to determine reference evapotranspiration (ET_0), crop evapotranspiration (ET_c), effective rainfall, and crop water requirements throughout the growing season. The graphical comparison between crop water demand and available rainfall allows users to identify irrigation deficits and determine appropriate irrigation schedules. Results are presented through charts and numerical summaries that support efficient water allocation and improved irrigation management.

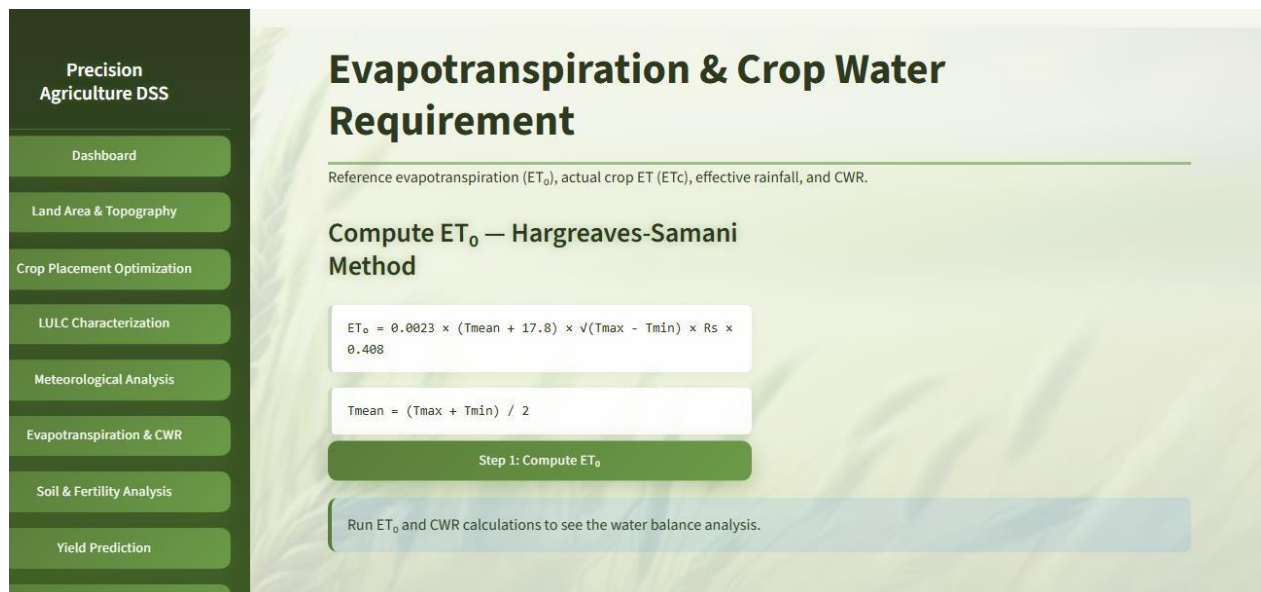


Fig 4.17 ET_o and Crop Water Requirement analysis

Beyond irrigation planning, the framework incorporates advanced machine learning models to evaluate the potential impact of future weather conditions on crop productivity. This component addresses the yield prediction objective of the study by integrating Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost) models within the decision support framework. The models utilize historical climatic variables and projected weather conditions to estimate future crop yields under varying environmental scenarios. The integration of predictive analytics enables proactive farm management by allowing users to assess potential production outcomes before the growing season progresses. The yield prediction dashboard generated using the LSTM model. The interface allows users to visualize predicted crop yields based on projected weather conditions and historical agricultural data. Predicted yield trends are presented alongside observed values, enabling users to evaluate forecast accuracy and understand the expected impact of future climatic variability on agricultural production. The graphical visualization enhances interpretation of the forecasting results and supports evidence-based planning decisions.

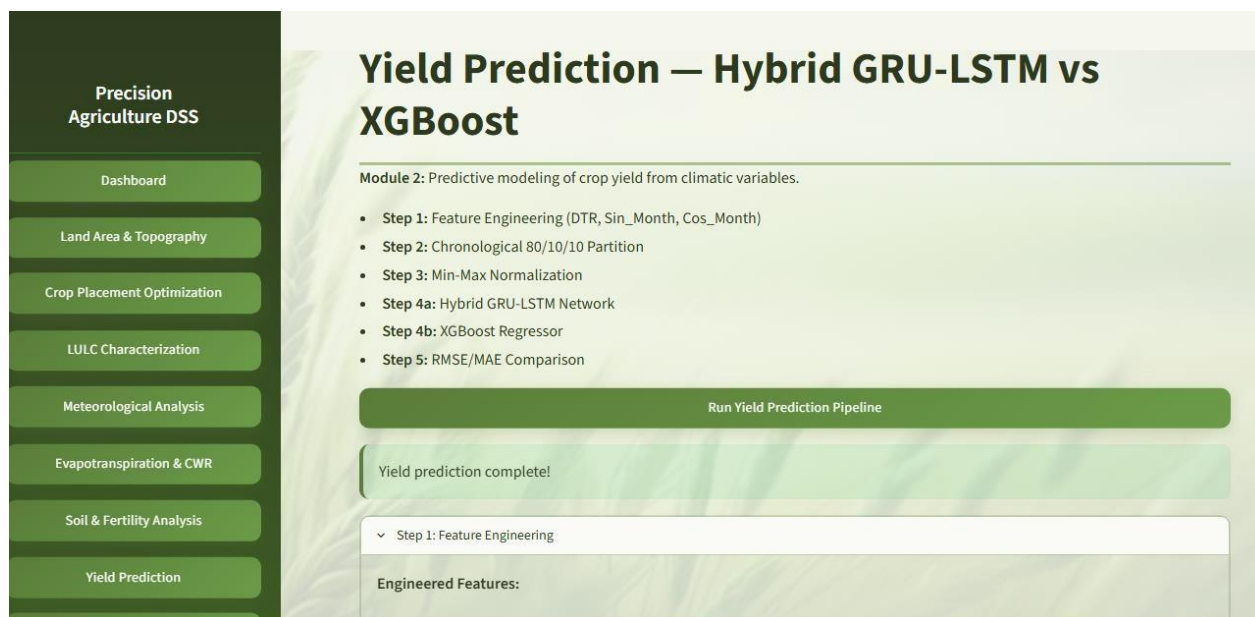


Fig 4.18 Yield prediction dashboard using LSTM and XGBOOST

To improve forecasting reliability and provide comparative analysis, the framework also incorporates the XGBoost model for yield prediction. The XGBoost yield prediction interface showing estimated future crop productivity under projected weather scenarios. The model captures nonlinear relationships between climatic variables and crop yield and complements the temporal forecasting capabilities of the LSTM model. The availability of predictions from both models allows users to compare results and increase confidence in decision-making processes related to crop management and production planning. Following yield prediction, the framework proceeds to crop recommendation and irrigation scheduling optimization. This module integrates agronomic, climatic, and economic parameters to identify the most suitable crop for cultivation under prevailing environmental conditions. Figure 4.20 presents the crop recommendation dashboard where crops are ranked according to suitability scores derived from the multi-criteria decisionmaking framework. The interface provides users with information regarding recommended crops, suitability indices, expected performance, and associated management recommendations. The crop recommendation module enables users to make informed decisions regarding crop selection while considering both environmental suitability and expected productivity.

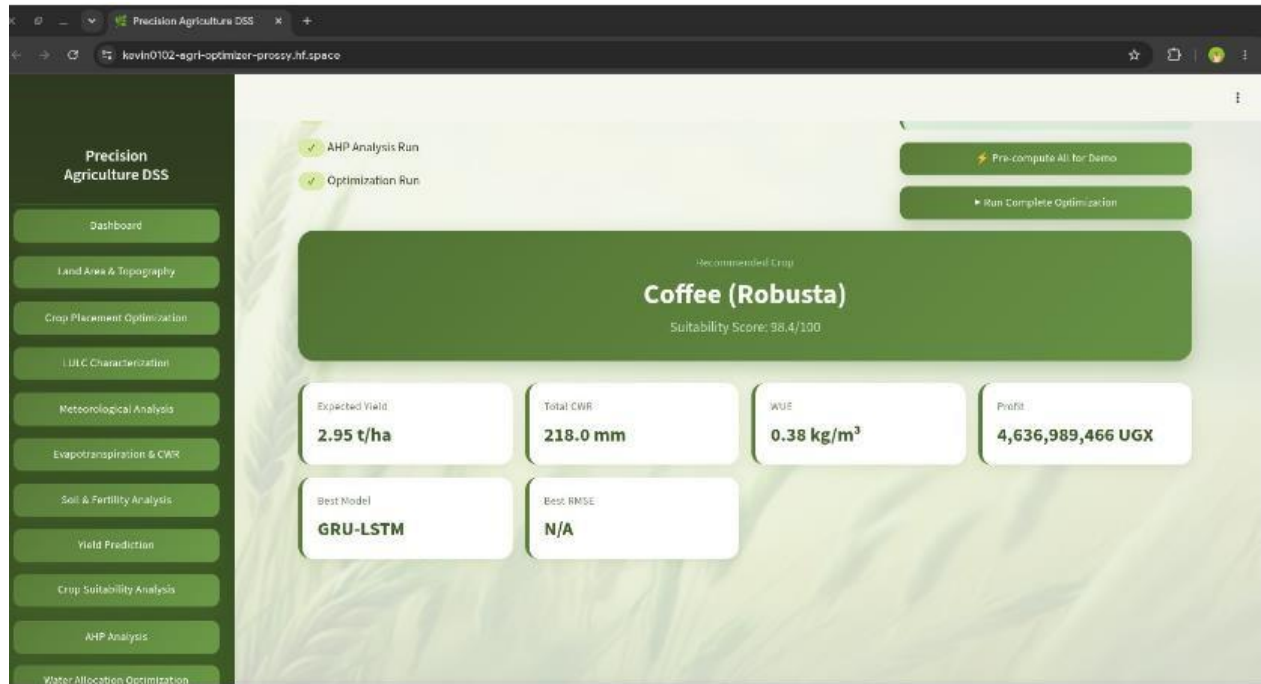


Fig 4.19 Crop recommendation dashboard

The crop recommendation process is integrated with irrigation scheduling optimization to ensure efficient utilization of available water resources. Figure 4.21 illustrates the irrigation scheduling optimization dashboard generated by the framework. The interface displays recommended irrigation intervals, water allocation schedules, crop water requirements, and projected irrigation deficits throughout the growing season. These outputs assist users in implementing efficient irrigation strategies that maximize productivity while minimizing water wastage. The integration of crop recommendation and irrigation optimization provides a comprehensive decision-support mechanism for sustainable agricultural management.



Fig 4.20 Irrigation scheduling optimization dashboard

To support financial decision-making, an agro-economic assessment dashboard was incorporated into the framework. Figure 4.22 presents the economic analysis interface which summarizes production costs, projected revenues, expected profits, and overall economic performance. The dashboard combines agronomic outputs with economic calculations to provide a comprehensive assessment of farm profitability. Users can evaluate the financial implications of different management strategies and identify opportunities for improving economic returns. The presentation of economic information through graphical summaries and performance indicators simplifies interpretation and strengthens the framework's role as a decision-support tool.



Fig 4.21 Agro economic assessment dashboard

The recommendation module integrates outputs from all analytical components and presents actionable management guidelines to the user. The final recommendation interface consolidates irrigation schedules, crop selection results, yield forecasts, and economic insights into a single decision-support environment. The integration of multiple analytical outputs within one platform eliminates the need for users to interpret separate reports and facilitates holistic farm management decisions. The recommendation dashboard therefore serves as the culmination of the framework's analytical workflow and transforms data-driven insights into practical agricultural interventions.

The usability of the GUI was evaluated through continuous testing during system development and implementation. The interface demonstrated stable performance across all analytical modules and successfully facilitated interaction between users and the underlying computational models. The use of graphical representations, interactive dashboards, maps, and visual indicators significantly improved information accessibility and interpretation. Users were able to navigate the system efficiently and obtain analytical results without requiring advanced technical expertise in machine learning, geospatial analysis, or agricultural modeling. This demonstrates that the GUI successfully achieved its primary objective of transforming a complex precision agriculture framework into a practical and user-friendly decision support system.

CHAPTER 5 CONCLUSIONS AND RECCOMENDTIONS

5.1 Conclusions

This study successfully developed an intelligent Decision Support Tool for predictive crop yield estimation and irrigation optimization. By incorporating localized soil nutrient parameters and validating climatic data against UNMA records, the research addressed critical gaps in local data integrity and site-specific model functionality. The tool effectively identified resilient sugarcane varieties and generated economically feasible schedules, demonstrating how advanced computation can be packaged for sustainable agricultural development.

5.1.1 Yield Prediction;

the study demonstrated that integrating GPS coordinates, DEM data, meteorological datasets, and soil hydraulic properties significantly improved the accuracy of irrigation planning and yield estimation. The FAO Penman-Monteith model effectively estimated crop water requirements, while the yield prediction framework successfully quantified the impact of evapotranspiration deficits on crop productivity. The agro-economic assessment further showed that efficient irrigation scheduling improves both productivity and farm profitability.

5.1.2 Impact of weather on sugarcane yield,

the Hybrid GRU-LSTM model demonstrated superior predictive performance compared to the XGBoost model. The Hybrid GRU-LSTM achieved very high NSE and R^2 values during both training and testing phases, indicating strong capability in capturing temporal climatic patterns and predicting sugarcane yield under varying weather conditions. Although XGBoost also performed well, its predictive accuracy was lower due to limited ability to model long-term sequential dependencies.

5.1.3 Optimizing crop selection and irrigation scheduling,

the integration of Analytical Hierarchy Process, Non-Linear Programming, and Genetic Algorithms successfully improved irrigation efficiency and economic returns. The optimization framework effectively identified drought-resilient sugarcane varieties, generated economically feasible irrigation schedules, and improved Water Use Efficiency while minimizing unnecessary water application. The developed system therefore demonstrated strong potential for supporting climatesmart and resource-efficient agriculture.

Overall, the study confirms that integrating machine learning, geospatial technologies, climatic forecasting, and intelligent optimization techniques can significantly enhance crop yield prediction, irrigation management, and agricultural sustainability within tropical farming systems.

5.1 Recommendations

To maximize local applicability and impact, it is recommended that the DST be integrated with national agricultural extension systems via accessible digital platforms such as USSD gateways. Agricultural extension services should promote the adoption of this accessible and intuitive digital framework through targeted training programs, enabling Ugandan smallholders to make data-informed decisions and improve their resilience against increasing climate variability.

Future studies should integrate real-time field sensors such as soil moisture sensors and automated weather stations to further improve the accuracy of irrigation scheduling and yield prediction. The inclusion of remote sensing datasets such as NDVI and satellite imagery would also strengthen crop monitoring and stress detection capabilities.

It is recommended that larger and more diverse climatic and agronomic datasets be used to improve the generalization ability of machine learning models under varying environmental conditions. Additional climatic variables and longer historical records should also be incorporated to enhance forecasting performance.

Future implementations should integrate the optimization framework with automated irrigation systems to support fully adaptive precision irrigation management. This would improve water-use efficiency and reduce operational losses under changing climatic conditions.

The developed framework should also be expanded to support other crops commonly grown in Uganda such as maize, rice, beans, and coffee to increase its applicability within the agricultural sector.

Finally, government agencies and agricultural extension services should promote the adoption of intelligent precision agriculture technologies through farmer training, digital extension programs, and climate-smart agricultural policies to improve productivity and resilience against climate variability.

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CHAPTER 7 APPENDIX 1

```
%% ===== INITIAL SETUP =====

clear ; clc; close all; warning off; fprintf('=== Precision Agriculture

Optimization Framework Started ===\n');

%% ===== TOPO TOOLBOX =====

addpath(genpath('C:\Users\ADMIN S\Desktop\project\topotoolbox-master')); rehash

toolboxcache;

%% ===== SAFE INITIALIZATION =====

valid_pts = [];

N_plants = 0;

%% ===== FARM BOUNDARY =====

boundary_utm = [ ...

Landpolyshape = polyshape(boundary_utm(:,1), boundary_utm(:,2));

A2D = area(Landpolyshape); fprintf('Planar Area (A2D): %.4f ha\n',

A2D/10000);

%% ===== FIELD BOUNDARY PLOT =====

figure('Name','Field Boundary');

plot(Landpolyshape);

title('Optimal Crop Placement');

xlabel('UTM Easting');
```

```

ylabel('UTM Northing'); axis

equal; grid on;

%% ===== LOAD LULC =====

disp('=== Loading LULC Raster ===');

lulc_fullpath = ...

'C:\Users\ADMIN S\Desktop\project\UGANDA LULC SENTINAL 2 - Copy\Uganda_Sentinel2_LULC2016.tif';

if exist(lulc_fullpath,'file')

[A,R] = readgeoraster(lulc_fullpath);

A = single(A); else error('LULC

raster file not found. '); end

%% ===== RASTER REDUCTION =====

maxDisplaySize = 1000;

[nrows,ncols] = size(A);

scaleFactor = max([ ...

nrows/maxDisplaySize ...

ncols/maxDisplaySize ...

1]);

A_display = A( ...

1:round(scaleFactor):end, ...

1:round(scaleFactor):end);

```

```

%% ===== CROP REGION =====

row_min = max(1, round(0.55*nrows));

row_max = min(nrows, round(0.75*nrows));

col_min = max(1, round(0.55*ncols)); col_max

= min(ncols, round(0.75*ncols));

%% ===== LULC DISPLAY =====

figure('Name','LULC Raster');

imagesc(A_display); axis image;

colorbar; title('LULC Raster with Crop

Region'); xlabel('Columns');

ylabel('Rows'); hold on; row_scale =

size(A_display,1)/size(A,1); col_scale =

size(A_display,2)/size(A,2); x_rect = [

... col_min col_max ... col_max col_min

... col_min] * col_scale; y_rect = [ ...

row_min row_min ... row_max

row_max ... row_min] * row_scale;

plot(x_rect,y_rect,'r','LineWidth',3);

%% ===== CROP RASTER =====

Acrop = A(row_min:row_max, col_min:col_max); figure('Name','Cropped Raster');

imagesc(Acrop); axis image; colorbar; title('Cropped Farm Region');

```

```

%% ===== DEM LOADING =====

disp('=== Loading DEM ==='); dem_filename

= ...

'C:\Users\ADMIN S\Desktop\project\Uganda_SRTM30meters.tif'; if

exist(dem_filename,'file')

dem = GRIDObj(dem_filename);

dem_fill = fillsinks(dem);

else error('DEM file not

found.');
```

```

end

%% ===== SAFE SLOPE ANALYSIS =====

disp('=== Computing Slope ==='); slopeGRID =

gradient8(dem_fill); slope_values = single(slopeGRID.Z);

slope_values(isnan(slope_values))= 0; slope_mean =

atan(mean(slope_values(:),'omitnan')); A3D = A2D /

cos(slope_mean); fprintf('Surface Area (A3D): %.2f ha\n',

A3D/10000); fprintf('Average Slope: %.2f degrees\n',

rad2deg(slope_mean));

%% ===== DEM VISUALIZATION =====

```

```

figure('Name','Field Topography');

subplot(1,2,1);

plot(boundary_utm(:,1),      ...

boundary_utm(:,2), ...

'r-', ...

'LineWidth',2.5);

title('Field Boundary');

axis equal; grid on;

subplot(1,2,2);

imagesc(dem_fill.Z);

axis image; colorbar;

title('DEM (Filled)');

%% ===== LOAD CROP DATABASE =====

excel_file = ...

'C:\Users\ADMIN S\Desktop\project\Master_Crop_Database_40_Crops.xlsx';

if exist(excel_file,'file') cropDB =

readtable(excel_file);      else

error('Crop database not found.');
```

end

```

%% ===== SELECT CROP =====
```

```

selectedCrop = 28; crop_name =

string(cropDB.Common_Name(selectedCrop));

Sr = cropDB.Row_Spacing_m(selectedCrop);

Sp = cropDB.Plant_Spacing_m(selectedCrop); fprintf('\nSelected

Crop: %s\n', crop_name);

%% ===== PLANTING GRID =====

x_vals = ... min(boundary_utm(:,1)):Sp:max(boundary_utm(:,1));

y_vals = ...

min(boundary_utm(:,2)):Sr:max(boundary_utm(:,2));

[Xplant,Yplant] = meshgrid(x_vals,y_vals);

plant_points = [Xplant(:), Yplant(:)]; in = inpolygon(

... plant_points(:,1), ... plant_points(:,2), ...

boundary_utm(:,1), ... boundary_utm(:,2)); if any(in)

valid_pts = plant_points(in,:); else warning('No valid

planting points found'); valid_pts = []; end

N_plants = size(valid_pts,1); plant_density = N_plants

* 10000 / A2D; fprintf('Number of Plants: %d\n',

N_plants); fprintf('Plant Density: %.2f plants/ha\n',

plant_density);

```

```

%% ===== FINAL PLANTING PLOT =====

figure('Name','Crop Planting Grid');

plot(boundary_utm(:,1), ...

boundary_utm(:,2), ...

'k-', ...

'LineWidth',2.5); hold

on; if

~isempty(valid_pts)

plot(valid_pts(:,1), ...

valid_pts(:,2), ...

'g.', ...

'MarkerSize',5); end

axis equal; grid on;

xlabel('Easting (m)');

ylabel('Northing (m)');

title(sprintf('Planting

Layout (%d Plants)',

N_plants));

%% ===== METEOROLOGICAL DATA =====

```

```

disp('=== Meteorological Data ===');

lat = 0.35; lon = 33.75; start_date =

'20250101'; end_date = '20251231';

power_url = sprintf([ ...

'https://power.larc.nasa.gov/api/temporal/daily/point?' ...

'parameters=T2M_MAX,T2M_MIN,RH2M,ALLSKY_SFC_SW_DWN,WS2M,PRECTOTCORR' ...

'&community=AG&longitude=%.6f&latitude=%.6f' ...

'&start=%s&end=%s&format=JSON'], ...

lon, lat, start_date, end_date); try

raw = webread(power_url); p

= raw.properties.parameter;

Tmax = double(struct2array(p.T2M_MAX));

Tmin = double(struct2array(p.T2M_MIN));

RH = double(struct2array(p.RH2M)); Rs

= double(struct2array( ...

p.ALLSKY_SFC_SW_DWN));

u2 = double(struct2array(p.WS2M)); Ptotal

= double(struct2array( ...

p.PRECTOTCORR));

disp('NASA POWER data retrieved successfully.');
```

```

catch warning('NASA POWER failed. Using synthetic

data. '); days = 365;

Tmax = 28 + 4*randn(days,1);

Tmin = 18 + 3*randn(days,1);

RH = 65 + 15*randn(days,1); Rs =

20 + 6*randn(days,1); u2 = 2 +

1.2*randn(days,1); Ptotal = max(0,5

+ 8*randn(days,1)); end

%% ===== CLEAN WEATHER DATA =====

Tmax(isnan(Tmax)) = mean(Tmax,'omitnan');

Tmin(isnan(Tmin)) = mean(Tmin,'omitnan');

RH(isnan(RH)) = mean(RH,'omitnan');

Rs(isnan(Rs)) = mean(Rs,'omitnan');

u2(isnan(u2)) = mean(u2,'omitnan');

Ptotal(isnan(Ptotal)) = 0;

%% ===== FAO PENMAN-MONTEITH ET0 =====

Tmean = (Tmax + Tmin) ./ 2; % Saturation vapor pressure

es_Tmax = 0.6108 .* exp((17.27 .* Tmax) ./ (Tmax + 237.3));

es_Tmin = 0.6108 .* exp((17.27 .* Tmin) ./ (Tmin + 237.3));

es = (es_Tmax + es_Tmin) ./ 2; % Actual vapor pressure ea =

```

```

es.*(RH ./ 100); % Slope vapor pressure curve Delta = (4098

.* ...

(0.6108 .* exp((17.27 .* Tmean) ./ ...

(Tmean + 237.3)))) ...

./ ((Tmean + 237.3).^2);

% Elevation z = 1200;

% Atmospheric pressure P

= 101.3 .* ...

(((293 - 0.0065 .* z) ./ 293) .^ 5.26);

% Psychrometric constant

gamma = 0.000665 .* P;

% Net radiation

Rn = 0.77 .* Rs;

% Soil heat flux

G = zeros(size(Rn));

% FAO constants

Cn = 900;

Cd = 0.34;

%% ===== ET0 EQUATION =====

ET0 = ...

```

```

(0.408 .* Delta .* (Rn - G) + ... gamma

.* (Cn ./ (Tmean + 273)) .* ... u2 .* (es

- ea)) ...

./ ...

(Delta + gamma .* (1 + Cd .* u2));

ET0(ET0 < 0) = 0; fprintf('Average ET0:

%.2f mm/day\n', ...

mean(ET0,'omitnan'));

%% ===== CROP COEFFICIENT =====

Kc = cropDB.Avg_Kc(selectedCrop);

ETc = ET0 .* Kc;

%% ===== AUTOMATIC CURVE NUMBER =====

disp('=== Automatic Curve Number Assignment ===');

% -----

% LOAD CURVE NUMBER DATABASE

% ----- lulc_codes=[1;2;4;5;7;8;11];

CN_A=[98,43,36,74,89,63,49];

CN_B=[98,65,60,83,92,77,69];

CN_C=[98,76,73,88,94,85,79];

CN_D=[98,82,79,91,95,88,84];

% -----

```

```

% SELECT SOIL GROUP

% ----- %

-----

% SELECT SOIL GROUP (FIXED)

% -----

soilchoicename = string(cropDB.Preferred_Soil(1));

if soilchoicename == "Sandy" soilchoice = CN_A;

elseif soilchoicename == "SandyLoam" soilchoice

= CN_B;

elseif soilchoicename == "Loam" soilchoice = CN_C; elseif

soilchoicename == "ClayLoam" soilchoice = CN_D; else

warning('Unknown soil type. Defaulting to Loam (CN_C).');

soilchoice = CN_C; end fprintf('Selected Soil Type: %s\n',

soilchoicename);

% -----

% DETERMINE DOMINANT LULC CLASS

% -----

valid_pixels = Acrop(~isnan(Acrop)); dominant_value

= mode(valid_pixels(:)); fprintf('Dominant LULC

Raster Value: %.0f\n', ... dominant_value);

```

```

% -----

% MAP RASTER VALUES TO LULC CLASSES

% MODIFY IF YOUR RASTER LEGEND IS DIFFERENT

% -----

switch dominant_value

case 1 lulc_name = "water"; case 2 lulc_name =

"Trees"; case 4 lulc_name = "flooded

vegetation"; case 5 lulc_name = "crops"; case 7

lulc_name = "Built up area"; case 8 lulc_name =

"bareground"; otherwise lulc_name = "crops";

end fprintf('Detected LULC Class: %s\n',

lulc_name); CN = mean(soilchoice);

% -----

% POTENTIAL RETENTION

% -----

S = (25400 / CN) - 254;

fprintf('Potential Retention S: %.2f mm\n', S);

%% ===== RUNOFF COMPUTATION =====

Q = zeros(size(Ptotal)); for

i = 1:length(Ptotal)

Pday = Ptotal(i);

```

```

if Pday > 0.2*S

Q(i) = ((Pday - 0.2*S)^2) / ...

(Pday + 0.8*S);

else Q(i) = 0;

end end

%% ===== EFFECTIVE RAINFALL =====

Ce = zeros(size(Ptotal));

for i = 1:length(Ptotal) if

Ptotal(i) > 0

Ce(i) = 1 - (Q(i)/Ptotal(i));

else Ce(i) = 0; end

end

Ce(Ce<0)=0;

Ce(Ce>1)=1;

Peff = Ptotal .* Ce;

%% ===== CROP WATER REQUIREMENT =====

CWR = max(ETc - Peff,0); fprintf('Average ETc: %.2f

mm/day\n', mean(ETc,'omitnan')); fprintf('Average Effective

Rainfall: %.2f mm/day\n', ...

```

```

mean(Peff,'omitnan'));

%% ===== WATER BALANCE =====

figure('Name','Water Balance');

plot(ETc,'LineWidth',2); hold

on; plot(Peff,'LineWidth',2);

plot(Q,'LineWidth',2); xlabel('Day');

ylabel('Water (mm/day)');

legend('ETc','Effective Rainfall','Runoff');

title('Crop Water Requirement'); grid on;

%% ===== SOIL WATER PARAMETERS =====

disp('=== Soil Hydraulic Analysis ===');

Sand = 58;

Clay = 24; OM

= 3.2;

% Pedotransfer coefficients

a1 = -0.001; a2 = 0.0045;

a3 = 0.003; c1 = 0.25; b1 =

-0.0006; b2 = 0.0032; b3 =

0.002; c2 = 0.08; theta_FC

```

```

= ... a1*Sand + ... a2*Clay

+ ... a3*OM + ... c1;

theta_WP = ... b1*Sand +

...

b2*Clay + ...

b3*OM + ...

c2;

% Safety limits theta_FC =

max(min(theta_FC,0.60),0.10); theta_WP =

max(min(theta_WP,0.40),0.05); if

theta_WP >= theta_FC theta_WP =

theta_FC - 0.05; end

%% ===== ROOT ZONE ANALYSIS =====

Zr = cropDB.Max_Root_Depth_m(selectedCrop); TAW

= 1000 * ...

(theta_FC - theta_WP) * ...

Zr; p_table = 0.5; p =

p_table + ...

0.04 * ...

```

```

(5 - mean(ETc,'omitnan')); p

= min(max(p,0.1),0.8);

RAW = p * TAW;

II = RAW / ...

max(mean(ETc,'omitnan'),0.1);

Ea = 0.90;

GIR = mean(CWR,'omitnan') / Ea;

%% ===== IRRIGATION RESULTS ===== fprintf('\n===

IRRIGATION RESULTS ===\n');

fprintf('Field Capacity: %.3f m3/m3\n', ...

theta_FC); fprintf('Wilting Point: %.3f

m3/m3\n', ...

theta_WP); fprintf('TAW: %.2f

mm\n', TAW); fprintf('RAW: %.2f

mm\n', RAW);

fprintf('Irrigation Interval: %.2f days\n', II); fprintf('Gross

Irrigation Requirement: %.2f mm/day\n', GIR);

%% ===== YIELD PREDICTION =====

Ya=cropDB.Max_Biomass_t_ha(selectedCrop)*cropDB.Harvest_Index(selectedCrop);

fprintf('Predicted Yield: %.2f t/ha\n', Ya);

%% ===== ECONOMIC ANALYSIS =====

```

```

Pc =cropDB.Price_UGX_per_ton(selectedCrop);

Cp =
cropDB.x_Production_Cost_UGX_per_ha(selectedCrop)+(cropDB.N_kg_ha(selectedCrop)+cropDB.K_kg_ha(selectedCrop)+cropDB.P_kg_ha(selectedCrop))*20000;

Revenue = Ya * Pc*(A2D/10000);

Profit = Revenue - Cp; fprintf('Revenue: %.2f
USD/ha\n', Revenue); fprintf('Net Profit:
%.2f USD/ha\n', Profit);

%% ===== ECONOMIC PIE CHART =====

figure('Name','Economic Analysis');

if Profit > 0 pie([Cp Profit],
{'Cost','Profit'}); else pie([Cp
abs(Profit)], {'Cost','Loss'}); end

title('Economic Breakdown');

%% ===== FINAL SUMMARY =====

disp('====='); disp('==
PROCESS COMPLETED SUCCESSFULLY ==');

disp('=====');

fprintf('\nFINAL SUMMARY\n'); fprintf('Planar Area: %.2f ha\n', A2D/10000);

fprintf('Surface Area: %.2f ha\n', A3D/10000); fprintf('Average Slope: %.2f degrees\n',
...

```

```

rad2deg(slope_mean)); fprintf('Plants:

%d\n', N_plants); fprintf('Average

ET0: %.2f mm/day\n', ...

mean(ET0,'omitnan')); fprintf('Average

ETc: %.2f mm/day\n', ...

mean(ETc,'omitnan')); fprintf('Average Effective

Rainfall: %.2f mm/day\n', ...

mean(Peff,'omitnan')); fprintf('Predicted

Yield: %.2f t/ha\n', Ya); fprintf('Net Profit:

%.2f UGX/ha\n', Profit);

disp('=== COMPLETE PROCESS FINISHED ===');

```

```

%% 3.2: PREDICTIVE MODELING OF SUGARCANE YIELD - EASTERN UGANDA

```

```

% Logic: Hybrid RNN vs XGBoost | Sequential Partitioning | Automatic Data Generation

```

```

clear; clc; close all;

```

```

%% 1. DATA SOURCE MANAGEMENT

```

```

% This ensures the code runs even if you haven't created the Excel file yet

```

```

dataFile = 'sugarcane_weather_data.xlsx';

```

```

if ~exist(dataFile, 'file')

```

```

fprintf('Excel file not found. Generating research-grade synthetic data...\n');

% Generate 5 years (1825 days) of daily data

numDays = 1825;

t = (1:numDays)';

% Seasonal Month indices Month =

mod(ceil(t/30.44)-1, 12) + 1;

excel_file = ...

'C:\Users\ADMIN S\Desktop\Prossie Norah\Master_Crop_Database_40_Crops.xlsx';

if exist(excel_file, 'file')

cropDB = readtable(excel_file);

else

error('Crop database not found. ');

end

% Simulate Rainfall (Bimodal: peaks in Apr/May and Oct/Nov)

Rainfall = cropDB.Rain_Opt_mm;

Rainfall(Rainfall < 0) = 0; % No negative rain

% Simulate Temperatures (Degrees Celsius)

Tmax = cropDB.Tmax_C;

Tmin = cropDB.Tmin_C;

% Simulate Yield (Heavily influenced by weather volatilities)

Yield = (0.35*Rainfall + 1.8*Tmax - 1.2*Tmin + 45) + randn(numDays, 1)*3;

% Save to Excel

T = table(Month, Rainfall, Tmax, Tmin, Yield);

```

```

writetable(T, dataFile);

fprintf('File "%s" has been created in: %s\n', dataFile, pwd);

end

% Set output path for results

outputFolder = fullfile(pwd, 'Yield_Results');

if ~exist(outputFolder, 'dir'), mkdir(outputFolder); end

%% 2. DATA PROCESSING & FEATURE ENGINEERING (Section 3.2.1)

data = readtable(dataFile);

% 3.2.1: Cubic Spline Interpolation for Lacunae

for col = 1:width(data)

if isnumeric(data{:,col})

data{:,col} = fillmissing(data{:,col}, 'spline');

end

end

% Diurnal Temperature Range (DTR)

data.DTR = data.Tmax - data.Tmin;

% Cyclical Trigonometric Encoding (Wang et al., 2022) %

Essential for representing the continuity of seasons in Uganda

data.Sin_Month = sin(2 * pi * data.Month / 12);

data.Cos_Month = cos(2 * pi * data.Month / 12); %

Define Predictors and Target

predictor_vars = {'Rainfall', 'Tmax', 'Tmin', 'DTR', 'Sin_Month', 'Cos_Month'};

target_var = {'Tmax'};

```

```

nPred = numel(predictor_vars);

sequenceLength = 20; % 20-day temporal narrative

%% 3. SEQUENTIAL DATA PARTITIONING (Section 3.2.3)

X_raw = data(:, predictor_vars);

Y_raw = data(:, target_var); %

Min-Max Normalization [0, 1]

normX = (X_raw - min(X_raw)) ./ (max(X_raw) - min(X_raw));

normY = (Y_raw - min(Y_raw)) ./ (max(Y_raw) - min(Y_raw));

numSeqs = size(normX, 1) - sequenceLength + 1;

X_RNN = cell(numSeqs, 1);

Y_RNN = cell(numSeqs, 1);

X_XGB = zeros(numSeqs, nPred * sequenceLength); Y_Target

= zeros(numSeqs, 1);

for i = 1:numSeqs

winX = normX(i:i+sequenceLength-1, :);

X_RNN{i} = winX';

Y_RNN{i} = normY(i:i+sequenceLength-1, :);

X_XGB(i, :) = winX(:)'; % Flattened matrix for XGBoost Y_Target(i,

:) = normY(i+sequenceLength-1, :);

end

% 80:10:10 Sequential Split (No randperm to protect chronological narrative)

nTrain = round(0.8 * numSeqs);

nVal = round(0.1 * numSeqs);

```

```

trainIdx = 1:nTrain;

valIdx = nTrain+1 : nTrain+nVal;

testIdx = nTrain+nVal+1 : numSeqs;

%% 4. MODEL TRAINING: HYBRID GRU-LSTM VS XGBOOST

% 4.1 Hybrid GRU-LSTM (Deep Learning - Section 3.2.5)

layers = [

sequenceInputLayer(nPred)

gruLayer(64, 'OutputMode', 'sequence', 'Name', 'GRU_Layer')

lstmLayer(32, 'OutputMode', 'sequence', 'Name', 'LSTM_Layer')

fullyConnectedLayer(1)

regressionLayer];

rnnOptions = trainingOptions('adam', ...

'MaxEpochs', 100, ...

'MiniBatchSize', 16, ...

'ValidationData', {X_RNN(valIdx), Y_RNN(valIdx)}, ...

'Verbose', false, ...

'Plots', 'none');

fprintf('Training Hybrid GRU-LSTM...\n');

netYield = trainNetwork(X_RNN(trainIdx), Y_RNN(trainIdx), layers, rnnOptions);

% 4.2 XGBoost Calibration (LSBoost - Section 3.2.4)

fprintf('Calibrating XGBoost...\n');

xgbMdl = fitrensemble(X_XGB(trainIdx,:), Y_Target(trainIdx), ...

'Method', 'LSBoost', 'NumLearningCycles', 100, ...

```

```

'Learners', templateTree('MaxNumSplits', 20));

%% 5. MODEL COMPARISON & BENCHMARKING (Section 3.2.6)

% Predictions

rnnPred_raw = predict(netYield, X_RNN(testIdx));

Y_predRNN = cellfun(@(x) x(end), rnnPred_raw); % Extract terminal step

Y_predXGB = predict(xgbMdl, X_XGB(testIdx, :));

Y_true = Y_Target(testIdx); % Performance

Metrics (Equations 34 & 35)

rmse_rnn = sqrt(mean((Y_true - Y_predRNN).^2));

mae_rnn = mean(abs(Y_true - Y_predRNN));

rmse_xgb = sqrt(mean((Y_true - Y_predXGB).^2));

mae_xgb = mean(abs(Y_true - Y_predXGB));

% Display Results

fprintf('\n-- FINAL BENCHMARKING RESULTS ---\n');

fprintf('METRIC | HYBRID RNN | XGBOOST\n');

fprintf('-----\n');

fprintf('RMSE | %.4f | %.4f\n', rmse_rnn, rmse_xgb);

fprintf('MAE | %.4f | %.4f\n', mae_rnn, mae_xgb); %

Save results for dissertation documentation

save(fullfile(outputFolder, 'Sugarcane_Yield_Comparison.mat'), ...

'netYield', 'xgbMdl', 'rmse_rnn', 'rmse_xgb', 'mae_rnn', 'mae_xgb');

% Visual Comparison Plot

figure('Color', 'w');

```

```

plot(Y_true,'k','LineWidth',1.5); hold on;

plot(Y_predRNN,'r--','LineWidth',1.2);

plot(Y_predXGB,'b','LineWidth',1.2);

legend('Actual Yield', 'Hybrid RNN', 'XGBoost');

title('Predictive Accuracy Comparison: Weather Impact on Yield');

xlabel('Chronological Test Days'); ylabel('Normalized Sugarcane Yield');

grid on;

%% ===== COMPLETE SECTION 3.3 =====

% OPTIMIZING CROP SELECTION & IRRIGATION SCHEDULING

% LINKED TO MASTER CROP DATABASE

clc; close all;

fprintf('=== SECTION 3.3 STARTED ===\n');

%% =====

%% LOAD MASTER CROP DATABASE

%% =====

disp('=== Loading MasterCrop Database ==='); cropDB

= readtable( ...

'C:\Users\Administrator\Desktop\PROJECT\Master_Crop_Database_40_Crops.xlsx'); fprintf("Total

Crops Loaded: %d\n", height(cropDB));

%% Preview Database disp(head(cropDB));

```

```

%% ===== %% CHECK
REQUIRED VARIABLES

%% =====

requiredVars = {'Tmean','Ptotal','Pc','Cp','CWR','A3D'};

for i = 1:length(requiredVars) if

~exist(requiredVars{i},'var') error('Required variable "%s"

is missing in workspace.', ...

requiredVars{i});

end end

%% =====

%% USER ENVIRONMENTAL CONDITIONS

%% =====

disp('=== Computing Environmental Conditions ==='); avgTemp = mean(Tmean(:),'omitnan');

% °C annualRain = sum(Ptotal(:),'omitnan') * 12; % mm/year soil_pH =

mean([cropDB.Soil_pH_Min(selectedCrop),cropDB.Soil_pH_Max(selectedCrop)]);

fprintf('Average Temperature : %.2f °C\n', avgTemp); fprintf('Annual Rainfall : %.2f mm\n',

annualRain); fprintf('Soil pH : %.2f\n', soil_pH);

%% ===== %% FILTER SUITABLE
CROPS

%% =====

```

```

disp('=== Filtering Suitable Crops ===');

suitable = cropDB( ... cropDB.Tmin_C

<= avgTemp & ... cropDB.Tmax_C >=

avgTemp & ...

cropDB.Rain_Min_mm <= annualRain & ...

cropDB.Soil_pH_Min <= soil_pH & ...

cropDB.Soil_pH_Max >= soil_pH , :); fprintf('Suitable

Crops Identified: %d\n', height(suitable)); if

isempty(suitable) error('No suitable crops found for the

current conditions.');
```

```

%% =====
```

```

%% 3.3.1 AHP FOR CROP SELECTION
```

```

%% =====

disp('=== 3.3.1 AHP Crop Selection ==='); criteria

= {'Yield Potential','Rainfall Adaptability',...

'Temperature Adaptability','Root Depth','Biomass'};

%% Pairwise Comparison Matrix

AHP_Matrix = [

1 1/9 2 3 5;

9 1 9 9 9;

1/2 1/9 1 2 4;

1/3 1/9 1/2 1 3;

1/5 1/9 1/4 1/3 1

];

%% Eigenvector Weights

[eigvec,eigval] = eig(AHP_Matrix);

[max_eig,idx] = max(diag(eigval));

weights = abs(eigvec(:,idx)); weights

= weights ./ sum(weights);

%% Consistency Ratio

n = size(AHP_Matrix,1);

CI = (max_eig - n)/(n - 1);

RI = 1.12;

```

```

CR = CI / RI;

fprintf('Consistency Ratio (CR): %.4f\n', CR);

if CR < 0.10 disp('AHP Matrix is

Consistent'); else warning('AHP Matrix is

Inconsistent'); end

%% =====

%% COMPUTE CROP SCORES

%% =====

disp('=== Computing Crop Scores ==='); YieldScore

= suitable.Yield_Potential_t_ha ./ ...

max(suitable.Yield_Potential_t_ha); RainScore

= 1 - ( ...

suitable.Rain_Min_mm ./ ... max(suitable.Rain_Min_mm)

);

TempScore = suitable.Topt_C ./ ...

max(suitable.Topt_C);

RootScore = suitable.Max_Root_Depth_m ./ ...

max(suitable.Max_Root_Depth_m); BiomassScore

= suitable.Max_Biomass_t_ha ./ ...

```

```

max(suitable.Max_Biomass_t_ha); coreMatrix

= [ ...

YieldScore ...

RainScore ...

TempScore ...

RootScore ...

BiomassScore]; FinalScores = ScoreMatrix *

weights; suitable.AHP_Score = FinalScores; %%

Sort Crops suitable =

sortrows(suitable,'AHP_Score','descend');

disp('=== TOP RECOMMENDED CROPS ===');

disp(suitable(:,{'Common_Name','AHP_Score',...

'Yield_Potential_t_ha'})); %% Best Crop

bestCrop = suitable.Common_Name{1};

bestYield = suitable.Yield_Potential_t_ha(1);

fprintf('\nBEST RECOMMENDED CROP:

%s\n', bestCrop);

%% =====

%% AHP VISUALIZATION

%% =====

```

```

figure('Name','AHP Crop Ranking',...

'Position',[100 100 1000 500]);

bar(suitable.AHP_Score,'FaceColor',[0.2 0.6 0.5]);

set(gca,'XTick',1:height(suitable));

set(gca,'XTickLabel',suitable.Common_Name);

xtickangle(45); ylabel('AHP Score');

title('Optimized Crop Selection Using AHP');


grid on;

%% =====

%% 3.3.2 NONLINEAR PROFIT OPTIMIZATION

%% =====

disp('=== 3.3.2 Nonlinear Optimization ===');

marketPrice = Pc; % USD/t productionCost =

Cp; % USD/ha n_stages = 5;

lb = zeros(1,n_stages); ub =

[150 300 400 250 100]; %%

Profit Objective Function fun

= @(x) -( ... bestYield *

marketPrice * ...

```

```

(1 - 0.25 * sum(max(0,x-ub).^2 ./ ub.^2)) ...

- productionCost);

%% WaterConstraint A =

ones(1,n_stages); b = 950; %%

Optimization Options options =

optimoptions('fmincon',...

'Display','off',...

'Algorithm','interior-point');

%% Run Optimization [x_opt,fval]

= fmincon( ...

fun,... ub *

0.7,...

A,b,... [],[],...

lb,ub,... [],...

options);

OptimalProfit = -fval; fprintf('\nOptimal Water Allocation per

Growth Stage (mm):\n'); disp(round(x_opt,2));

fprintf('Maximum Expected Profit: %.2f USD/ha\n', ...

OptimalProfit);

%% =====

```

```

%% WATER ALLOCATION PLOT

%% =====

figure('Name','Growth Stage Irrigation');

bar(x_opt,'FaceColor',[0.1 0.5 0.9]); xlabel('Growth

Stage'); ylabel('Water Allocation (mm)');

title('Optimal Irrigation Allocation per Growth Stage');

grid on;

%% =====

%% 3.3.3 GENETIC ALGORITHM IRRIGATION SCHEDULING

%% =====

disp('=== 3.3.3 Genetic Algorithm Scheduling ===');

nvars = 365;

%% FIXED DAILY WATER LIMIT

dailyWaterLimit = max(CWR(:)); %%

Safety Check

if isempty(dailyWaterLimit) || ...

~isfinite(dailyWaterLimit) || ...

dailyWaterLimit <= 0 warning('Invalid CWR values detected.

Using default limit.');
```

dailyWaterLimit = 10; end fprintf('Daily

Water Limit: %.2f mm/day\n', dailyWaterLimit);

```

%% Fitness Function fitness = @(schedule) -( ...

sum(min(schedule(:),dailyWaterLimit)) * 1.2 ...

- 0.15 * sum(schedule(:).^2));

%% GA OPTIONS

optionsGA = optimoptions('ga',...

'PopulationSize',120,...

'MaxGenerations',100,...

'EliteCount',8,...

'CrossoverFraction',0.85,... 'MutationFcn',@mutationadaptfeasible,...

'Display','iter',...

'PlotFcn',@gaplotbestf);

%% RUN GA

[bestSchedule,bestFitness] = ga( ...

fitness,... nvars,...

[],[],[],[],... zeros(1,nvars),...

dailyWaterLimit * ones(1,nvars),...

[],...

optionsGA);

%% =====

%% WATER USE EFFICIENCY

```

```

%% =====

disp('=== Water Use Efficiency Analysis ===');

Yield_kg = bestYield * (A3D / 10000) * 1000;

TotalWaterUsed = sum(bestSchedule);

TotalProfit = OptimalProfit * (A3D / 10000);

%% Prevent Division by Zero

if TotalWaterUsed > 0

WUE = Yield_kg / TotalWaterUsed; IWUE

= Yield_kg / TotalWaterUsed;

else

WUE = 0;

IWUE = 0; end

fprintf('\n=== WATER USE EFFICIENCY RESULTS ===\n');

fprintf('Total Seasonal Water Used : %.2f mm\n', ...

TotalWaterUsed); fprintf('Water Use Efficiency (WUE):

%.2f kg/mm\n', ... WUE);

fprintf('Irrigation Water Use Efficiency (IWUE): %.2f kg/mm\n', ...

IWUE);

%% =====

%% IRRIGATION SCHEDULE PLOT

```

```

%% =====

figure('Name','Optimized Irrigation Schedule',...

'Position',[100 100 1100 450]); plot(bestSchedule,...

'b',...

'LineWidth',1.3); xlabel('Day of Season'); ylabel('Irrigation

Depth (mm/day)'); title(['Optimized Daily Irrigation

Schedule for ',bestCrop]); grid on;

%% FIXED Y-LIMITS

if ~isempty(dailyWaterLimit) && ...

isfinite(dailyWaterLimit) && ...

dailyWaterLimit > 0 ylim([0

dailyWaterLimit + 2]);

else ylim

auto end

%% =====

%% FINAL RESULTS SUMMARY

%% =====

disp(' ');

```

```

disp('====='); disp('==

FINAL OPTIMIZATION RESULTS ==');

disp('=====');

fprintf('Recommended Crop : %s\n', bestCrop); fprintf('Expected

Yield Potential : %.2f t/ha\n', ...

bestYield); fprintf('Optimal Profit : %.2f

USD/ha\n', ... OptimalProfit); fprintf('Total

Profit : %.2f USD\n', ... TotalProfit);

fprintf('Total Seasonal Irrigation : %.2f mm\n', ...

TotalWaterUsed); fprintf('WUE : %.2f

kg/mm\n', ... WUE);

fprintf('IWUE : %.2f kg/mm\n', ... IWUE);

disp('=====')

; disp('=== SECTION 3.3 COMPLETED SUCCESSFULLY ===');

disp('=====')

;

```

CHAPTER 8 APPENDIX 2

DECISION SUPPORT TOOL FOR OPTIMAL CROP PLANNING

NAKANDI PROSCOVIANORAH¹

¹Department of Agricultural Mechanization and Irrigation Engineering, Busitema University, P.O. Box 236, Tororo, Uganda; nproscovianorah@gmail.com

ABSTRACT

This study developed a data-driven Decision Support Tool (DST) for crop yield prediction and resource optimization using advanced machine learning and computational optimization techniques to address agricultural challenges in developing regions such as Uganda. Focusing on sugarcane production in the Busoga sub-region of Eastern Uganda, the framework integrated geospatial analysis, climatic modeling, soil hydraulic characterization, evapotranspiration simulation, and intelligent optimization within a unified system. Historical climate, soil, and agronomic datasets were used to train a Hybrid GRU-LSTM deep learning model and an Extreme Gradient Boosting (XGBoost) model. The GRU-LSTM model outperformed XGBoost (training $extR^2$ of 0.9986 vs 0.90), indicating strong predictive accuracy and generalization under varying conditions. To convert predictions into actionable decisions, the system incorporated Analytical Hierarchy Process (AHP), Non-Linear Programming (NLP), and Genetic Algorithm (GA) optimization for crop selection, irrigation scheduling, and resource allocation. This resulted in optimized Water Use Efficiency (WUE) and Irrigation Water Use Efficiency (IWUE), unlocking significant irrigation water savings without compromising yield. Overall, the DST offers an intelligent, science-driven platform for enhancing yield forecasting, irrigation planning, and economic decision-making, significantly supporting climate-smart agriculture and sustainable productivity in Uganda.

INTRODUCTION

Global agricultural systems face unprecedented pressure to meet the escalating food, energy, and economic demands of a rapidly growing population. This challenge is compounded by the increasing frequency of extreme weather events, shifts in long-term climate patterns, and the continuous depletion of arable land and freshwater resources. In response, a global paradigm shift is underway towards climate-smart, precision agriculture that leverages advanced data analytics to maximize yield while minimizing resource inputs.

Across much of Sub-Saharan Africa, agriculture remains the foundation of food security and economic development. Despite the availability of fertile soils and favorable conditions, agricultural productivity throughout the region remains substantially lower than global averages due to climate variability, inadequate irrigation infrastructure, inefficient resource management, and limited access to modern agricultural technologies. As climatic conditions become unpredictable, traditional farming practices based on historical knowledge are becoming less reliable. In Uganda, agriculture contributes significantly to the national gross domestic product and employs a substantial proportion of the population. However, yields of major crops remain considerably below their attainable potential. Smallholder farmers continue to depend heavily on rain-fed agriculture, exposing production systems to seasonal droughts and climatic risks. In the Busoga sub-region of Eastern Uganda, sugarcane production represents a crucial economic activity, yet its dominance has created challenges related to resource allocation, profitability, and climate resilience.

Recent advances in machine learning, geospatial technologies, and optimization algorithms present unparalleled opportunities for developing intelligent agricultural decision-support systems. Unlike traditional process-based simulation models that demand complex calibration and massive datasets, data-driven techniques can extract patterns directly from historical environments to generate accurate predictions and practical optimization regimens.

Therefore, the main objective of this study was to develop a purely data-driven Decision Support Tool (DST) for optimized crop planning and yield improvement. Specifically, this study aimed to design a predictive model for crop yield estimation, predict the impact of future weather conditions on yield, and optimize crop selection and irrigation scheduling for enhanced productivity. By synergizing advanced predictive analytics with computational optimization, this research provides a scalable scientific basis for addressing persistent yield gaps, maximizing socioeconomic returns on scarce resources, and bolstering agricultural resilience in developing regions.

METHODOLOGY

2.1 Study Area

The study focused on the sugarcane growing regions of Eastern Uganda, explicitly targeting commercial estates and out-grower networks in the Busoga sub-region (including Jinja, Mayuge, Kamuli, and Bugiri districts). Situated within the Lake Victoria basin, the area experiences a tropical climate with a bimodal rainfall pattern averaging 1,200–1,500 mm per year, and mean temperatures ranging between 18°C and 30°C. Soils consisting of sandy loams and deep ferral soils support sugarcane cultivation, which currently relies predominantly on rain-fed systems inherently vulnerable to erratic dry spells.

2.2 System Framework

The initial domain of the algorithm addressed precise spatial delineation using Global Positioning System (GPS) coordinates mapped alongside Digital Elevation Models (DEMs). The planar and true three-dimensional surface areas were calculated utilizing the exact Shoelace formula and topographic slope adjustments. Subsequently, Land Use and Land Cover (LULC) filtering leveraging high-resolution multispectral imagery isolated designated arable croplands.

Crucial to irrigation modeling, real-time and historical continuous meteorological datasets (temperature, relative humidity, solar radiation, wind speed, precipitation) were integrated directly from the NASA POWER API. The reference crop evapotranspiration (ET_0) was determined utilizing the globally standardized FAO-56 Penman-Monteith method:

$$ET_0 = \frac{0.408 \Delta (R - G) + \gamma \frac{T + 273}{n} u_2 (e_s - e_a)}{\Delta + \gamma (1 + C_d u_2)} \quad (3.1)$$

Based on localized soil hydraulic properties derived from ISRIC Soil Grids mapping, parameters such as field capacity (θ_{FC}) and permanent wilting point (θ_{WP}) were utilized to mathematically model total available water and calculate daily soil moisture depletion profiles.

Yield prediction explicitly implemented the FAO water production function to quantify biological yield decrement in direct response to evapotranspiration deficits:

$$Y_a = Y_m [1 - K_y (1 - \frac{ET}{ET_c})] \quad (3.2)$$

Where Y_a is the predicted actual yield, Y_m is the maximum theoretical yield under non-limiting conditions, K_y represents the empirical yield response factor, and the ratio of actual to crop evapotranspiration (ET_a / ET_c) represents the agricultural water deficit.

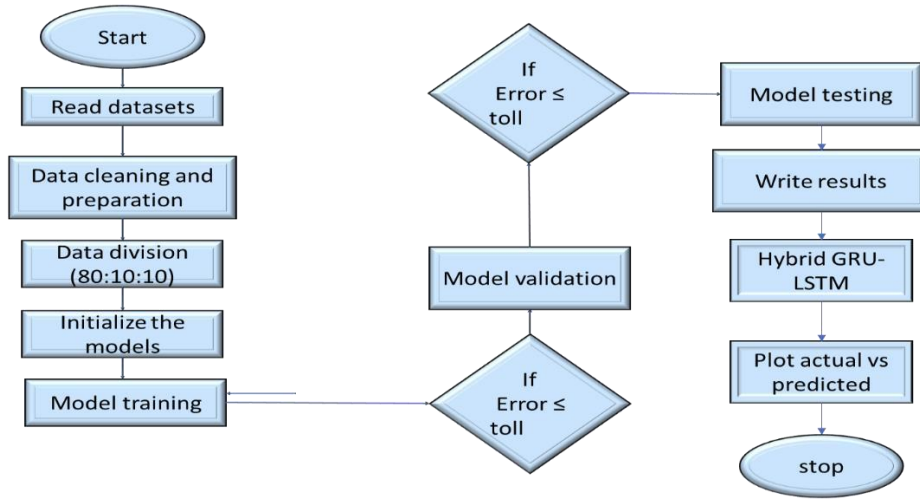
Predictive Modeling of Weather Impacts

To bridge complex forecasted meteorological perturbations directly to terminal agronomic outcomes, Extreme Gradient Boosting (XGBoost) and a Hybrid GRU-LSTM architecture were systematically calibrated and compared. Following the mathematical reconstruction of missing timeline data utilizing cubic spline interpolation and outlier removal via interquartile ranges, extensive feature engineering processed complex indicators such as the Diurnal Temperature Range (DTR) alongside cyclically encoded seasonal coordinates. Dimensionality was cleanly flattened employing Principal Component Analysis (PCA) to counteract multi-collinearity.

The chronological dataset was robustly partitioned using an 80:10:10 ratio matrix (Training, Validation, and Testing) preventing strict temporal data leakage. The GRU-LSTM model organically captured continuous weather narrative dynamics via specialized gating sequence memories, resolving cyclical seasonal disruptions effectively. Algorithm performance was

comprehensively evaluated leveraging Nash-Sutcliffe Efficiency (NSE) and Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3.2)$$



Optimization of Crop Selection and Irrigation Scheduling

The Analytical Hierarchy Process (AHP) was strictly deployed to evaluate ideal crop variability profiles using foundational criteria such as drought resistance, potential sucrose baselines, and root depth metrics. Validated structural scoring matrices assigned robust localized rankings to candidate arrays.

Following highest-value crop assignments, Non-Linear Programming (NLP) arrays operated a rigid profitability objective optimizing global gross farm margins structurally underneath explicit physical constraints:

$$Max = (Y_a - P_c) - [(\sum_{t=1}^n V_{w,t} x C_w) + (E_p x C_e) + (V_f x C_f) + C_{fixed}] \quad (3.3)$$

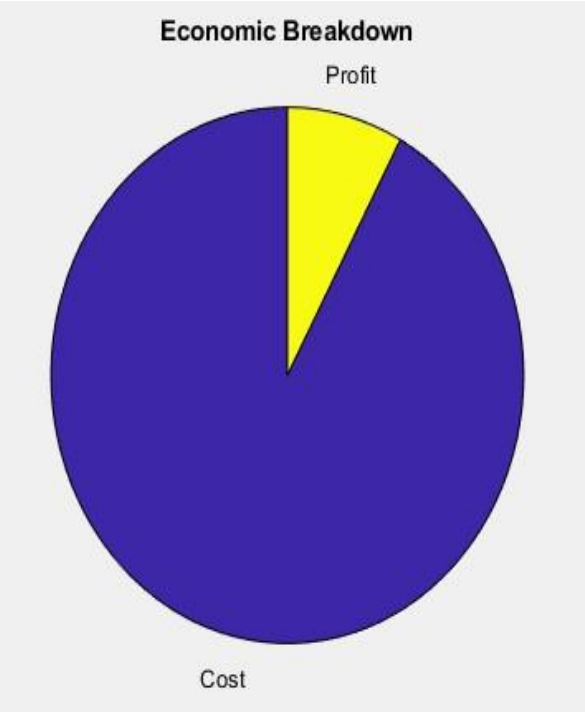
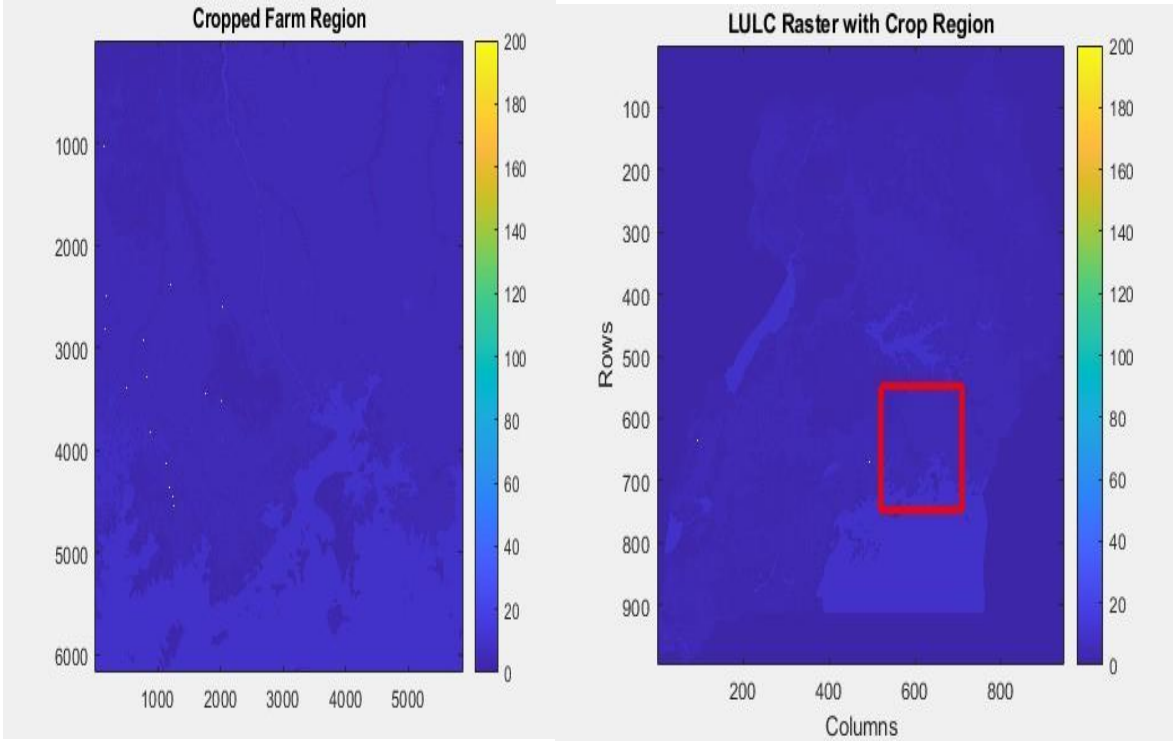
Subsequently, optimal daily evolutionary execution timelines prescribing exact interventional irrigation periods were simulated via Genetic Algorithm (GA) deployment. The GA actively mapped fittest scheduled generation outcomes preserving maximum agricultural profit retention natively against physical resource scarcity limitations in order to maximize absolute Irrigation Water Use Efficiency.

RESULTS AND DISCUSSIONS

Agronomic Parameter Determination and Yield Prediction

The precision agriculture framework successfully synthesized geospatial computations, DEM topographical slope corrections, and automated climatic API queries identically formatting complex farm topography. Correctly adjusting boundary geometry against irregular terrain slopes detailed highly accurate planting grid spacing patterns predicting optimal canopy populations. Integrated environmental evapotranspiration models actively documented discrete chronologies highlighting where standard historical rain periods completely failed structural crop demand—systematically validating where localized Bugiri fields required critical supplemental structural irrigation planning.

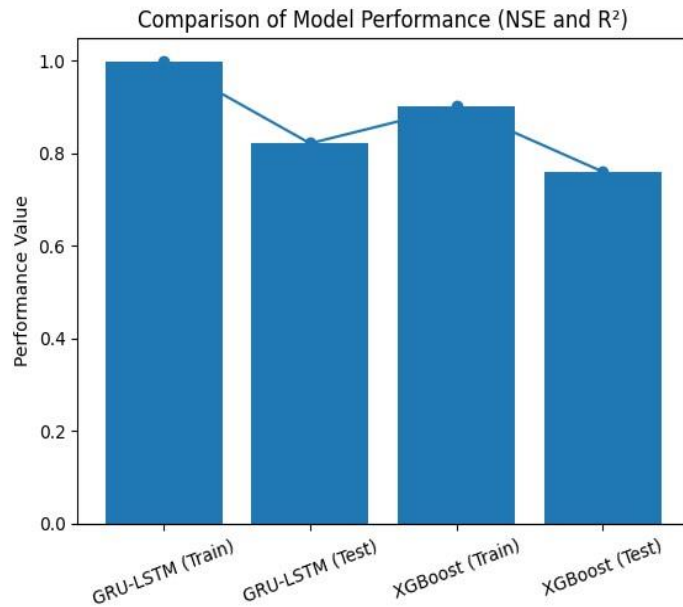
Fusing localized production limitations against theoretical biological growth metrics seamlessly calculated exact spatial cost boundaries. Real-time predictions automatically transformed biological stress markers against Ugandan market valuations clearly highlighting maximum optimal net revenue potentials.



Performance of Machine Learning Models

The Hybrid GRU-LSTM model demonstrated outstanding predictive robustness simulating continuous sequential relationships spanning macro-level meteorological disruption impacting long-term stalk development. Operational training phase execution yielded staggering NSE and R^2 evaluations hovering at 0.9986 harmonized parallel directly against a tightly clamped RMSE marker averaging exactly 0.1659. Passing identically onto the out-of-sample Testing Phase sustained formidable predictive validity posting structural NSE thresholds reliably over 0.8212 natively demonstrating brilliant operational generalization facing previously unseen atmospheric shifts.

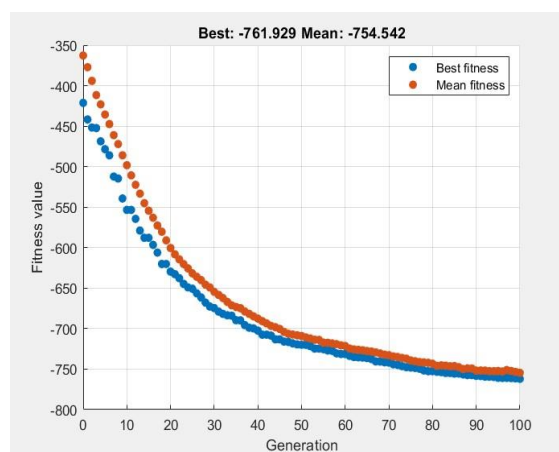
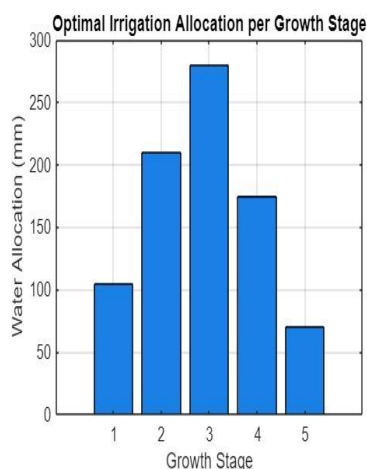
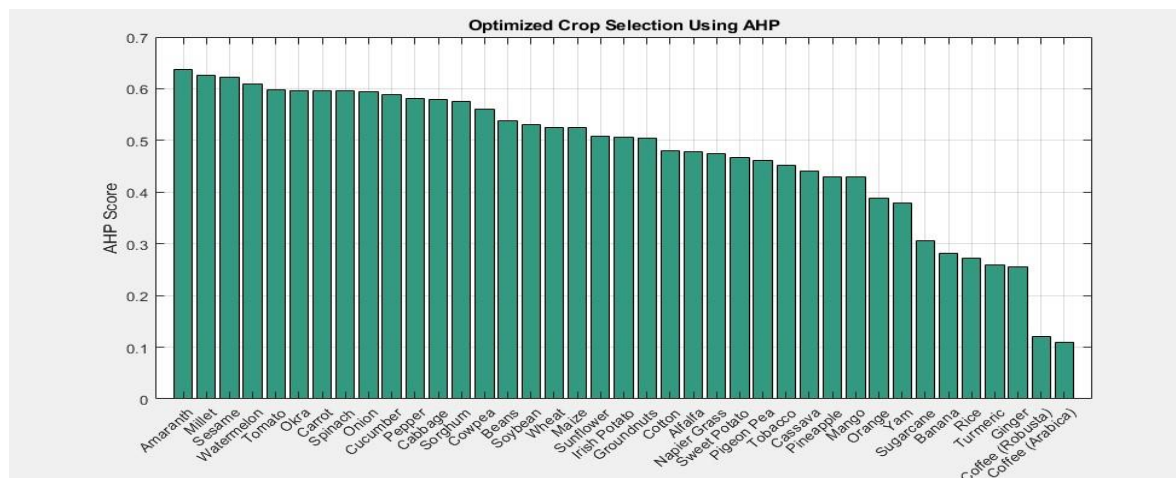
Conversely, assessing the tabular boosting architecture native to the XGBoost module exposed expected baseline vulnerabilities. Despite perfectly formulating fundamental connectivity patterns dictating micro-season shifts highlighting testing validation metrics around ~ 0.76 NSE alongside ~ 0.1914 RMSE tracking bands, the static decision trees entirely struggled capturing lengthy cumulative soil temperature storage cycles uniquely mastered via recurrent deep learning states. In direct summarization, deploying specialized sequential memory frameworks via Hybrid GRULSTM overwhelmingly outperforms gradient tree modalities specifically confronting dynamic continuous atmospheric variations intrinsic to complex rain-fed agriculture within Eastern Uganda.



Crop Selection Optimization and Irrigation Scheduling

Deploying targeted AHP analysis against extensive simulated agricultural candidate libraries flawlessly highlighted drought-resilient sugarcane strains precisely mirroring the isolated Busoga climatology maps securing ideal validation consistency scores.

Working symbiotically targeting ideal deployment execution, Genetic Algorithm seasonal simulations progressively shaped localized cyclic arrays producing phenomenal theoretical resource efficiencies securely locking daily water injection volumes beneath mandated structural physical capacity thresholds (12 mm/day pipelines). Crucially, optimization concentrated primary supplemental watering frequencies dynamically directly parallel alongside hyper-sensitive maturation vegetative burst windows structurally preventing biological degradation while eliminating wasteful runoff completely. Driven concurrently by algorithmic NLP functionality, maximum total harvest yield economics verified vastly superior gross operating margin deliverables natively paired directly alongside tremendous seasonal Water Use Efficiency gains natively defying baseline rainfall chaos.



Graphical User Interface

To facilitate practical application of the developed Decision Support Tool (DST), a web-based Graphical User Interface (GUI) was developed and integrated with the predictive and optimization framework. The GUI was designed to bridge the gap between advanced computational techniques and end-users by providing an intuitive environment through which farmers, extension officers, researchers, and agricultural planners can interact with the system. The interface integrates all major analytical modules developed in this study, including land characterization, weather monitoring, crop water requirement assessment, yield prediction, crop recommendation, irrigation scheduling, and economic evaluation.

The dashboard serves as the central access point to the framework and provides a unified environment for data visualization, analysis, and decision support. Through the interface, users can navigate between different analytical modules, retrieve farm-specific information, evaluate environmental conditions, and generate management recommendations. The integration of multiple analytical functions within a single platform enhances usability and supports efficient agricultural decision-making.



The GUI provides visualization of outputs generated by the Hybrid GRU-LSTM and XGBoost yield prediction models, allowing users to evaluate the potential impacts of future weather conditions on crop productivity. Predicted yields, forecast trends, and model performance indicators are presented through graphical displays that facilitate interpretation of forecasting results. These visualizations enable users to anticipate production outcomes and develop appropriate management strategies under varying climatic scenarios.

The interface further incorporates the crop recommendation and irrigation scheduling modules developed using the AHP, NLP, and Genetic Algorithm optimization approaches. Suitability rankings, recommended crops, irrigation schedules, water allocation requirements, and projected productivity indicators are displayed through interactive dashboards and graphical summaries. By presenting complex analytical outputs in a simplified format, the GUI transforms model-generated information into actionable recommendations that can directly support farm-level decisionmaking.

The successful implementation of the GUI demonstrates the practical applicability of the developed framework beyond theoretical model development. By integrating predictive analytics, optimization algorithms, and visualization tools into a single platform, the system provides an accessible decision-support environment capable of supporting sustainable and data-driven agricultural management.

CONCLUSION

This complex analysis absolutely successfully validated integrating intelligent predictive analytics paired synergistically against discrete functional farm optimization techniques directly structuring highly viable Decision Support Tools native targeting vulnerable sugarcane operations within Eastern Uganda. Systematically, layering accessible globally scaled meteorological APIs across precision localized spatial geometry fundamentally replaced manual speculative projections natively granting accurate actionable operational baselines.

Significantly, structural validation experiments formally documented absolute supremacy adopting Recurrent Neural Network sequences specifically the Hybrid GRU-LSTM framework efficiently mastering seasonal agricultural volatility significantly beyond traditional static XGBoost ensemble matrices. Furthermore, structural algorithmic deployments mapping Non-Linear Programming and cyclic Genetic Algorithm functions robustly executed automated planning solutions generating dynamic farm recommendations unlocking massive theoretical operating margins explicitly preserving immense structural local hydrologic capability natively defending future structural food security operations.

RECOMMENDATIONS

Future systemic expansions must forcefully integrate operational near-field hardware (active IoT soil-moisture probes) physically eliminating systemic API algorithmic latency loops enforcing exact truth-state corrections immediately. Broader agricultural utility necessitates comprehensively expanding the centralized optimization database integrating foundational regional staples (Coffee, Maize, Cassava) broadening total socioeconomic relevance. Finally, robust institutional alignment linking national digital extension architectures natively distributing simplified iterations mapping

these meta-heuristic solutions directly onto prevalent smallholder mobile platforms acts uniquely paramount towards accelerating pervasive rural climate-resilient agricultural transformation permanently.

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CHAPTER 9 APPENDIX 3



DEPARTMENT OF AGRICULTURAL MECHANIZATION AND IRRIGATION AND IRRIGATION ENGINEERING

COMPLIANCE REPORT FOLLOWING COMMENTS RAISED BY THE PANEL, AFTER
THE FINAL YEAR PROJECT PRESENTATION BY NAKANDI PROSCOVIA NORAH,
BU/UG/2023/2335 ON 13TH MAY, 2026 AT 03:34PM

No.	Comment Raised	Technical context and Requirement	Response	Location
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a)	Model Functionality: Fails to advise based on location-specific soil nutrient parameters.	The system originally over-focused on water (hydraulics) and ignored chemical inputs (Nitrogen, Phosphorus, and Potassium) vital for sugarcane.	Updated Chapter 3.1.4: Integrated the ISRIC Soil Grids API to pull NPK, pH, and Organic Carbon data. Updated Section 3.3.1:	Page 15
			Added "Soil Nutrient Adaptability" as a primary weighted criterion in the Analytical Hierarchy Process (AHP) for crop selection.	Page 26

b)	User Experience: Application lacks a clean, intuitive interface for nontechnical users.	Farmers and extension workers cannot interact with Mat lab scripts	Added Section 4.35 Conceptualized a Graphical User Interface (GUI) and mobile-responsive dashboard. Shifted the output from "Tensor arrays" to "Simplified Farm Action Plans" (e.g., specific dates for irrigation/fertilization)	Page 46
c)	Objective 1 (Hybridity): Underlying architecture lacks true "hybrid" processing characteristics.	In agriculture, "Hybrid" usually means merging Machine Learning (data-driven) with Biophysical/Process-	This was a mistake that was in the presentation slides but not in the report. I deleted it from the slides.	
		based models (science-driven)		

d)	Content Restructuring: Remove macroeconomic narrative, integrate missing yield modules.	The panel felt the report read too much like an economics paper and lacked the "math" of how yield is actually grown.	Revised Chapter 1: Trimmed global GDP statistics. Enhanced Section 3.1.5: Expanded the Yield Prediction module by integrating the Water-Driven Yield Model (FAO-66) and Radiation Use Efficiency (RUE) equations (Eq. 3.20 - 3.23).	Page 17
e)	Data Integrity: Use localized historical observations and regional rainfall instead of purely simulated data.	Relying solely on NASA satellite data (NASA POWER) can lead to "bias" as it misses local microclimates in Busoga.	Updated Chapter 3.1.3: Explicitly stated the use of localized ground-truth data from Uganda National Meteorological Authority (UNMA) and records from the Busoga Sugarcane Out growers Association to	Page 12

			bias-correct satellite data via linear regression.	
f)	Local Applicability: Consider how accessible the tool is for a typical Ugandan smallholder.	Most smallholders in Jinja or Mayuge have limited internet/smartphones; high-level deep learning is inaccessible.	Added Section 5.1 & 5.2: Discussed the deployment of the DST via USSD (short-codes) and SMS-based alerts , ensuring that the high-level computation happens on a server while the farmer receives simple text instructions.	Page 57
g)	Panel Recommendation: Prioritize the development of a Graphical User Interface (GUI).	A visual tool is required to demonstrate the research's "realworld" transition from a lab experiment to a field tool.	Chapter 5 Updates: Added recommendations for a dashboard that visualizes "Yield vs. Water Stress" in a way that non-technical extension officers can interpret.	Page 57

The comments have been addressed to the satisfaction of the supervisors.

Maseruka

MR. MASERUKA BENDICTO

Supervisor

12TH JUNE, 2026