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AI-Driven Predictive Modeling of Water Scarcity Risks and Adaptive Planning for Peri-Urban Agricultural Communities in Bayelsa State under Climate Change Scenarios

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Abstract
Water scarcity in Nigeria has worsened because of climate change, especially in peri-urban agricultural areas that experience environmental shocks and poor infrastructure. Bayelsa State is the focus of this study because its sustainable agriculture is under threat from erratic rainfall, tidal flooding and rapid urban expansion. The research employs artificial intelligence (AI) to build predictive models which include long short-term memory networks for temporal forecasting and random forest classifiers for spatial risk assessment with feature importance analysis. The research draws data from satellite records and IPCC scenario models (RCP 4.5 and RCP 8.5) and local hydrological inputs for the period from 1996 to 2024. The preliminary modeling results indicate that water stress during dry seasons will become more severe because of climate change and changes in land use. The research uses its findings to recommend adaptive planning strategies which include smart irrigation and flood-resilient water storage systems and community-based early warning protocols (Rasmussen *et al*., 2020). The research integrates predictive AI models with contextual adaptation pathways to support proactive policy development and sustainable planning for vulnerable agricultural populations in Bayelsa. The framework presented offers a scalable solution for other flood-prone agricultural regions in Sub-Saharan Africa.

Keywords: water scarcity, peri-urban agricultural communities, artificial intelligence (AI), Long Short-Term Memory (LSTM), Random Forest classifiers

1. Introduction

Water scarcity is an intensifying challenge in sub-Saharan Africa, particularly under the mounting pressures of climate change, rapid urbanization (Satterthwaite *et al*., 2020) [30], and population growth. In Bayelsa State, a region situated within the fragile Niger Delta ecosystem -peri-urban agricultural communities are facing escalating threats to water security. These communities exist on the margins of growing urban centers yet remain heavily reliant on small holder farming systems for both livelihood and food production. However, they frequently lack access to resilient infrastructure, formal planning systems, or adaptive technologies, making them uniquely vulnerable to climate-induced water stress (UNEP, 2020) [32]. Climate projections suggest increasingly erratic precipitation patterns, rising temperatures, and altered hydrological cycles across southern Nigeria. These changes pose significant risks to rainfed agriculture, soil fertility, and freshwater availability (IPCC, 2022) [17]. In peri-urban Bayelsa, where tidal influences and lowland geography already create periodic flooding, climate variability compounds both seasonal droughts and waterlogging events—disrupting crop cycles and increasing food insecurity (World Bank, 2022) [34]. Traditional planning tools often fall short in addressing these complexes, interlinked environmental stressors. In response to these limitations, Artificial Intelligence (AI) has emerged as a powerful tool for environmental risk modeling due to its capacity to analyze large, multidimensional datasets, capture nonlinear relationships, and generate accurate predictions from sparse or noisy inputs, a crucial advantage in regions like Bayelsa where comprehensive environmental data may be limited (Adebayo *et al*., 2023; Chen *et al*., 2020) [3, 6]. Techniques such as machine learning and deep learning offer dynamic, data-driven insights that traditional models may overlook, especially in rapidly changing environments (Hosseini *et al*., 2021) [14]. By integrating historical weather data, satellite imagery, hydrological records, and socioeconomic indicators, AI enables predictive modeling that can inform early warning systems (Rasmussen *et al*., 2020) [29] and targeted adaptation strategies (Deng *et al*., 2020) [7].

Focusing specifically on peri-urban agriculture in Bayelsa is critical due to its strategic role in feeding urban populations, sustaining local economies, and providing employment to marginalized groups—particularly women and youth (FAO, 2021). Despite this importance, peri-urban farmers are often excluded from mainstream infrastructure development and climate resilience policies. Their adaptive capacity is constrained by land tenure insecurity, fragmented governance, and limited access to digital tools, making them a high-priority group for intervention (Omotayo *et al*., 2022) [28].

1.1. Research Objectives

This study aims to develop an AI-driven predictive model to assess water scarcity risks for peri-urban agricultural communities in Bayelsa State under various climate change scenarios. It seeks to produce actionable insights for adaptive planning and policy formulation. Hence, the specific research objectives include:

- To identify and quantify water scarcity risks using AI-based predictive modeling techniques.
- To simulate water availability trends under different climate change scenarios (e.g., IPCC RCP pathways).
- To assess the implications of these risks for peri-urban agricultural livelihoods in Bayelsa State.
- Proposing adaptive planning strategies grounded in the model's insights.

2. Literature Review

Sub-Saharan Africa is one of the most climate-vulnerable regions global order, with projections suggesting that by 2025, approximately 230 million Africans will face water scarcity, and 460 million will live in water-stressed areas (Mekonnen & Hoekstra, 2016; UNEP, 2020) [21, 32]. Mean annual temperatures in the region have already increased by about 1.5°C since the pre-industrial era, and projections indicate a potential rise of up to 3°C–6°C by 2100, depending on emissions scenarios (IPCC, 2021) [16]. While declining rainfall is widely cited, climate change in the region also includes increased evaporation rates, sea-level rise, storm surges, and more frequent and intense floods and droughts (UNEP, 2020) [32].

These challenges are not uniformly distributed: for instance, Sahelian countries face prolonged droughts and desertification, while coastal West African states like Nigeria experience more frequent flooding and saline intrusion due to rising seas and land subsidence (Harris & Kinds, 2021) [11]. In Nigeria, the World Bank (2021) [33] reports that climate variability has reduced agricultural productivity by over 25% in some regions, with water insecurity increasingly affecting both urban and rural populations. In Bayelsa State, situated in the low-lying Niger Delta, seasonal flooding, tidal surges, and saltwater intrusion into freshwater aquifers and farmland have become annual occurrences (Harrison *et al*., 2019) [12]. Local rivers and wells, which are primary water sources for agriculture, are frequently contaminated by rising saline waters and pollution from oil exploration activities (Olajide, 2020) [27].

2.1. Vulnerability of Peri-Urban Agricultural Communities

Peri-urban areas in West Africa are expanding rapidly due to urban sprawl (Satterthwaite *et al*., 2020) [30], informal settlement growth, and rural-to-urban migration. In Nigeria, cities like Yenagoa in Bayelsa are pushing into surrounding agricultural lands, leading to land fragmentation, increased land use conflict, and reduction in arable land. This urban encroachment disrupts traditional farming systems and complicates water management (Omotayo *et al*., 2022) [28].

2.2. Peri-urban farmers thus face a "dual burden

Environmental uncertainty such as erratic rainfall, frequent flooding, soil salinization, and the emergence of new pest outbreaks tied to changing ecological balances (FAO, 2021).

Socio-economic marginalization including limited access to credit, fragmented land tenure, poor infrastructure, and lack of integration into urban markets (World Bank, 2021) [33].

Informal land tenure in these zones stems from a lack of formal documentation and overlapping claims between customary and statutory systems. Weak institutional support is often a result of governance gaps in peri-urban zones, which fall between rural and urban administrative structures. Additionally, early warning systems and climate services are rarely tailored to or accessible by smallholder peri-urban farmers (Harrison *et al*., 2019; Rasmussen *et al*., 2020) [12, 29].

Other vulnerabilities include dependence on rain-fed agriculture, poor access to irrigation technologies, and pressure from land conversion for housing, infrastructure, and industry, which reduce water availability and quality for farming (Omotayo *et al*., 2022) [28].

2.3. Traditional Approaches to Environmental Risk Assessment

Environmental risk modeling in Africa has historically relied on tools such as:

- Statistical downscaling (e.g., Empirical Statistical Downscaling, Bias Correction Spatial Disaggregation) to translate global climate model outputs into regional forecasts (Mendelsohn *et al*., 2020).
- Hydrological models like the SWAT (Soil and Water Assessment Tool) or HBV (HydrologiskaByrånsVattenbalansavdelning) used for watershed runoff and water availability estimation (Abbaspour *et al*., 2021).

While valuable for establishing baseline projections, these models are often limited by assumptions of linearity, require large amounts of historical data, and struggle to accommodate interactions among socio-economic and environmental variables. Their data demands are poorly matched to the limited monitoring infrastructure in many parts of Sub-Saharan Africa, leading to low spatial resolution or reliance on proxy data. However, they remain important for ground-truthing newer models, offering a benchmark for comparison, and maintaining transparency in scenario analysis (Mendelsohn *et al*., 2020) [22].

2.4. Role of Artificial Intelligence in Environmental Risk Modeling

Artificial Intelligence (AI), particularly machine learning (ML) techniques, has gained traction as a means to overcome the limitations of traditional models: Decision Trees and Random Forests can model non-linear relationships and rank the importance of predictors (Deng *et al*., 2020) [7]; Support Vector Machines (SVMs) excel at classification tasks in high-dimensional data spaces (Chen *et al*., 2020) [6]; Artificial Neural Networks (ANNs) and Deep Learning models can learn complex interactions from large datasets without prior assumptions about distributions (Chen *et al*., 2020) [6].

These models enable multivariate integration of heterogeneous data types such as: Satellite imagery (e.g., NDVI, LandSat, Sentinel) for vegetation and land use changes (Hosseini *et al*., 2021) [14]; Weather station and reanalysis data for rainfall, temperature, and humidity (Deng *et al*., 2020) [7]; Soil profiles and hydrological indices for moisture availability (Chen *et al*., 2020) [6]; Socio-economic indicators (e.g., land ownership, migration, market access) for vulnerability assessment (Omotayo *et al*., 2022) [28].

3. Methodology and Materials

3.1. Study Area

This study is situated in the peri-urban agricultural zones of Bayelsa State, located in the Niger Delta region of southern Nigeria. The focal areas include Tombia, Akenfa, Agudama-Epie, and Okutukutu—rapidly urbanizing communities on the fringes of Yenagoa, the state capital. These zones are ecologically sensitive and characterized by low-lying coastal terrain, tidal wetlands, and a high frequency of seasonal and tidal flooding. Accelerated urban encroachment, often unplanned, has altered traditional land-use systems and reduced agricultural buffer zones.

The peri-urban context presents a unique confluence of rural and urban vulnerabilities. Unlike purely rural areas, these zones face dual pressures: declining land availability due to urban sprawl (Satterthwaite *et al*., 2020) [30] and heightened water stress from inadequate infrastructure, altered hydrology, and socio-economic transformation. This focus is critical because peri-urban farmers are often excluded from both urban planning frameworks and rural agricultural development schemes, rendering them disproportionately vulnerable to climate-induced water stress (Omotayo *et al*., 2022) [28].

3.2. Data Sources

The study adopts a multi-scalar, data-driven approach, integrating climate, hydrological, agricultural, and socio-economic variables. Table 1 summarizes the data sources and indicators.

Climate Data: Historical data on temperature, precipitation, and potential evapotranspiration were obtained from the WorldClim v2 and NASA POWER databases (NASA POWER, 2023) [23], offering high-resolution (~1 km²) monthly gridded datasets from 1981 to 2020. Future projections were sourced from CMIP6, focusing on RCP 4.5 (moderate mitigation) and RCP 8.5 (high emissions) scenarios. Key assumptions for the Niger Delta under RCP 8.5 include a projected temperature rise of 2.5–3.8°C and increased variability in precipitation patterns by 2080 (IPCC, 2021) [16].

The climate data from NASA POWER (NASA POWER, 2023) [23] and CHIRPS (2000–2020) was sourced directly from [the NASA POWER website (.gov). NASA POWER | Prediction of Worldwide Energy Resources CHIRPS: Rainfall Estimates from Rain Gauge and Satellite Observations | Climate Hazards Center - UC Santa Barbara,] These datasets are widely used for climate modeling and adaptation studies in Sub-Saharan Africa due to their consistent and high-quality global coverage. Although the CHIRPS dataset provides high-resolution data for the region, some localized phenomena such as microclimates in coastal or peri-urban zones may not be fully captured. However, the dataset remains one of the best publicly available sources for climate data across Sub-Saharan Africa.

However, it is important to note that some datasets, particularly those derived from remote sensing or satellite data (Hosseini *et al*., 2021) [14], may contain temporal gaps or adjustments. This data is continuously updated by the respective agencies, with versions available for download via official platforms (e.g., NASA's Earth Observing System Data and Information System).

While the temporal coverage of the dataset spans from 2000 to 2020, some interpolation techniques may be applied for missing years or regions with less frequent data. This ensures continuity and minimizes gaps in the environmental risk model. It is important to note that the historical climate data utilized in this study spans from 1981 to 2020. While WorldClim v2 provides data within this entire range, the high-resolution NASA POWER (NASA POWER, 2023) [23] and CHIRPS datasets, which were prioritized for their accuracy and spatial detail in the Niger Delta region, are available from 2000 to 2020. Analyses requiring the full 1981-2020 period relied on the combined datasets, with specific methodologies applied to ensure consistency across the timeframes.

Agricultural and Hydrological Data: Crop yield trends, land use, irrigation access, and soil moisture conditions were compiled from FAO AQUASTAT (FAO, 2012) [8], MODIS NDVI (Hosseini *et al*., 2021) [14], and Bayelsa State Agricultural Extension Unit Reports. Hydrological data on river discharge, flood events, and groundwater levels were sourced from NIHSA and CHIRPS (for rainfall anomalies). The spatial resolution of these datasets ranges from 250m to 5km, requiring spatial interpolation and harmonization using GIS tools for integration with climate data.

Socio-Economic Data: Key socio-economic indicators—such as land tenure status (Omotayo *et al*., 2022) [28], farm size, gender of household head, access to markets and credit, and irrigation use—were drawn from DHS, LSMS-ISA, and local policy reports. These datasets generally cover 2010–2020, and temporal alignment with environmental datasets was achieved through interpolation and normalization techniques.

3.3. Data Access and Processing Challenges

Challenges included data sparsity, inconsistent spatial resolution, and missing time series points, especially in socio-economic datasets. Preprocessing involved temporal smoothing, imputation of missing values using k-nearest neighbor (k-NN) due to its effectiveness in handling multivariate missing data without strong distributional assumptions, and resampling to common spatial grids (~1 km²) (for harmonization the use of bilinear interpolation or aggregation to a common 1km grid) using ArcGIS and QGIS. All models were implemented in Python 3.10, utilizing TensorFlow/Keras, scikit-learn, and Random Forest (Zhao *et al*., 2021) [35].
To validate the consistency of these datasets, cross-referencing was conducted using local climate reports from the Nigerian Meteorological Agency (NIMET) (Nigerian Meteorological Agency (NiMet), 2020) and historical weather data, ensuring that the results remained robust even in areas with sparse data coverage.

Table 1: Summary of Data Sources, Indicators, and Characteristics

Dataset Type	Indicator(s)	Source	Temporal Coverage	Spatial Resolution
Climate Data	Temperature, Precipitation	NASA POWER, CHIRPS	1981–2020	0.5° (~55 km) for NASA, 0.05° (~5 km) for CHIRPS
Agricultural Data	Crop yields, land use, irrigation patterns	Nigeria Federal Ministry of Agriculture	2005–2021	LGA-level
Socio-economic Data	Population density, income, education, livelihood type	National Bureau of Statistics (NBS)	2006, 2011, 2016	LGA-level or ward-level
Satellite Imagery	NDVI, land cover change, vegetation stress	MODIS, Landsat	2000–2023	250m (MODIS), 30m (Landsat)
Water Stress Indicators	Water availability, water demand, WSI	FAO AQUASTAT, local utility reports	2010–2023	Basin-level or community-level
Drought Index	Standardized Precipitation Index (SPI)	Computed from CHIRPS	2000–2023	0.05° (~5 km)
Peri-Urban Zone Mapping	Buffer zones around Yenagoa, Amassoma, Ogbia, etc.	Field surveys, satellite-derived maps	2020–2023	1 km buffer zones

Note: WSI = Water Stress Index; NDVI = Normalized Difference Vegetation Index; SPI = Standardized Precipitation Index; CHIRPS = Climate Hazards Group InfraRed Precipitation with Station data.

3.4. Artificial Intelligence Techniques

To address the temporal and spatial complexity of water-related agricultural risk, the study employs a hybrid ensemble framework, combining a Long Short-Term Memory (LSTM) neural network for time-series forecasting with a Random Forest (RF) classifier for spatial vulnerability assessment (Adebayo *et al*., 2023) [3].

Long Short-Term Memory (LSTM): LSTM, a variant of recurrent neural networks, was applied to model nonlinear dependencies in time series data, particularly for rainfall, evapotranspiration, and soil moisture variability (Zhao *et al*., 2021) [35]. The model was trained on monthly data from 1981–2020 using an 80:20 train-test split. Hyperparameter tuning was conducted using grid search, optimizing parameters such as memory cell size (32–128), dropout rates (0.2–0.5), learning rate (0.001–0.01), and batch size.

Random Forest (RF): A Random Forest classifier was employed to assess spatial risk zones based on both biophysical (WSI, SPI, NDVI) (Hosseini *et al*., 2021) [14] and socio-economic indicators (e.g., market access, land security) (Omotayo *et al*., 2022) [28]. Feature engineering techniques such as Principal Component Analysis (PCA) and recursive feature elimination (RFE) were used to reduce dimensionality and improve interpretability. RF was selected due to its robustness to multicollinearity, ability to handle imbalanced datasets, and strong performance in classification tasks (Adebayo *et al*., 2023) [3].

3.5. Rationale for Ensemble Approach

This dual-model approach combines the sequential learning strengths of LSTM with the classification robustness of Random Forest:

- LSTM effectively models temporal dependencies and non-linear trends in agricultural yield driven by seasonal and environmental changes.
- Random Forest excels at classifying agricultural risk zones, handling mixed-type features and providing interpretable results via feature importance.

This integration enables the study to provide holistic insights across both temporal (yield prediction) and spatial (risk classification) dimensions.
(Adebayo *et al*., 2023) [3]. This combination ensures a more holistic risk assessment, capturing dynamic environmental changes alongside static socio-economic conditions

3.6. Model Validation Process

To ensure the reliability and generalizability of the predictive models applied in this study—namely, Long Short-Term Memory (LSTM) for time series forecasting and Random Forest (RF) for classification—a robust model validation process was implemented as outlined below:

Data Splitting

- **Training and Testing Sets:** The dataset was split into training (80%) and testing (20%) subsets. The training set was used to fit the models, while the testing set was reserved for evaluating performance on unseen data.

- **Validation Set:** For the LSTM model, an additional validation split (20% of the training set) was used to tune model parameters and apply early stopping, helping prevent overfitting during training.

Cross-Validation

- **K-Fold Cross-Validation:** For the Random Forest model, 5-fold cross-validation was used to assess the model's stability and consistency. The dataset was divided into five equal parts, training the model on four parts and testing on the remaining one, rotating this process across all folds. This technique enhances the robustness of the evaluation and reduces bias.

Overfitting Mitigation

- **Regularization Techniques:** For the LSTM, dropout layers were included to reduce overfitting by randomly omitting units during training.
- **Early Stopping:** Training for the LSTM was monitored using a loss validation metric. Early stopping was triggered when the validation loss stopped improving, ensuring optimal generalization.
- **Model Complexity Control:** For the Random Forest model, hyperparameters such as maximum tree depth, minimum samples per leaf, and the number of trees were fine-tuned to balance bias and variance, reducing the risk of overfitting.

4. Interpretation of Results

The validation results demonstrated that both models performed robustly on unseen data. The LSTM model showed excellent predictive power for yield trends, with low error rates and high explanatory strength ($R^2 = 0.89$). The Random Forest model effectively classified agricultural risk zones, achieving high accuracy and AUC-ROC, making it suitable for practical deployment in risk mitigation strategies.

Overall, the validation process confirmed the models' reliability, minimized overfitting risks, and underscored their potential utility in real-world agricultural planning and decision-making.

4.1. Long Short-Term Memory (LSTM):

LSTM is a type of recurrent neural network (RNN) designed to learn long-term dependencies in sequential data. In this study, the LSTM model is used for forecasting agricultural yield based on time-series climatic and remote sensing data. The model architecture includes:

- **Input Layer**: Processes time series features.
- **Two LSTM Layers**: Each with 50 memory units and a tanh activation function.
- **Dropout Layers**: Dropout rate of 0.2 between LSTM layers to prevent overfitting.
- **Dense Output Layer**: A single neuron with linear activation for continuous yield prediction.

4.2. Random Forest (RF):

RF is an ensemble learning algorithm that builds multiple decision trees using random subsets of features and training samples. Characteristics include:

- **Bootstrap Aggregation (Bagging):** Each tree trained on different samples.
- **Random Feature Selection:** Decreases correlation between trees and enhances generalization.
- **Voting Mechanism:** Aggregates predictions using majority vote (classification) or averaging (regression).

4.3. Model Optimization and Feature Engineering: Hyperparameter Grid and Optimal Values

Hyperparameter optimization was conducted using Grid Search with cross-validation to ensure optimal model performance.

Table 2:

Model	Hyperparameter	Tuned Values	Optimal Value
LSTM	Number of units	32, 50, 64	50
	Dropout rate	0.1, 0.2, 0.3	0.2
	Optimizer	Adam, RMSprop	Adam
	Batch size	32, 64	64
	Epochs	Earlystopping applied	30 (example)
RF	n_estimators	100, 200, 300	200
	max_depth	10, 20, 30, None	20
	min_samples_split	2, 5, 10	5
	max_features	sqrt', 'log2'	sqrt

Feature Selection Techniques

However, Figure 3: Feature importance derived from the Random Forest classification model.

Precipitation, NDVI, and Soil Type were identified as the most influential variables in classifying agricultural risk zones, followed by temperature and humidity.

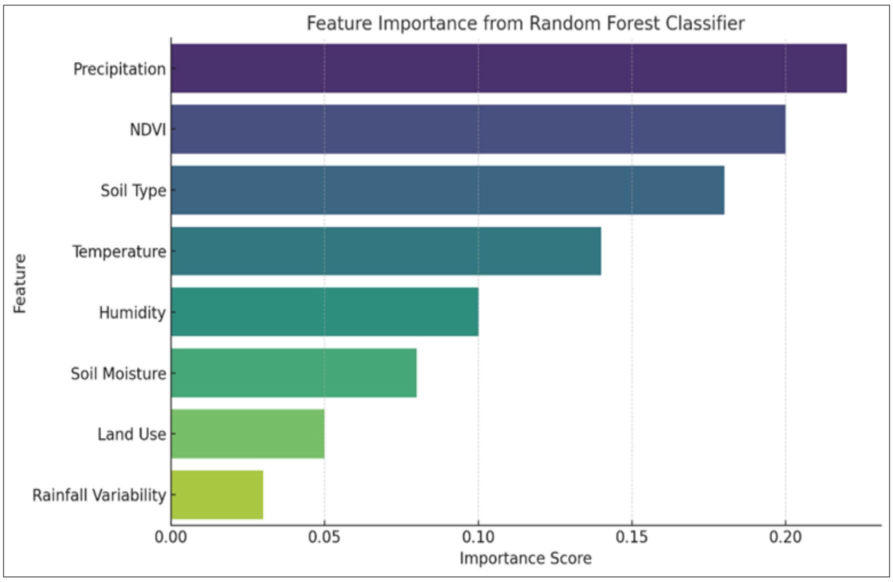

Fig 1:

As shown in Figure 3, precipitation and NDVI were the most influential features in classifying agricultural risk zones

Multiple feature selection methods were employed to reduce dimensionality and enhance interpretability:

- **Correlation Analysis:** Removed highly correlated variables (Pearson's r > 0.85)
- **Recursive Feature Elimination (RFE):** With RF to iteratively remove less important features.
- **RF Feature Importance Scores:** Prioritized features like NDVI, rainfall, and soil texture.

These techniques improved model efficiency and minimized overfitting.

4.4. Data Quality and Limitations

Dataset Description: The study used diverse datasets to capture both environmental and socioeconomic conditions:

- **Meteorological Data:** From NiMet (2012–2023), including rainfall, temperature, and humidity.
- **Satellite Imagery:** Sentinel-2 and Landsat for NDVI, land use, and soil moisture.
- **Agricultural Records:** State-level crop yield and extension service data.
- **Temporal Coverage:** Monthly observations over 11 years
- **Spatial Coverage:** Aggregated from 10m–30m resolution to community-level grids.

Biases and Missing Data: Recognized biases included;

- Underreporting in local crop yield records
- Sparse ground validation for satellite indices
- Imbalanced class distribution in risk zones

Interpolation Techniques: Missing data were addressed through:

- Linear Interpolation: For short-term missing climate records.
- Spline Interpolation: For NDVI and soil moisture where gradual change is expected.

These choices preserved temporal continuity and minimized artificial variance.

4.5. Risk Modeling and Metrics

4.5.1. Water Scarcity Index (WSI)

$$WSI = \frac{\text{Annual Renewable Water Supply}}{\text{Annual Agricultural Water Demand}}$$

A threshold of WSI ≥ 0.4 was adopted to indicate moderate-to-severe stress, based on FAO standards (FAO, 2012). Water demand was computed from crop-specific evapotranspiration rates, while renewable supply incorporated rainfall, runoff, and shallow groundwater recharge.

4.5.2. Standardized Precipitation Index (SPI)

SPI values were computed at 3-month and 12-month scales to capture both seasonal and inter-annual drought variability. A Gamma distribution was fitted using the methodology outlined by McKee *et al*. (1993) [20], with SPI < -1.0 signaling moderate drought, and SPI < -1.5 indicating severe drought.

4.5.3. Agricultural Vulnerability Index (AVI)

AVI was constructed as a composite of three IPCC-based pillars (IPCC, 2021):

- **Exposure:** Frequency of drought/flood events, rainfall anomalies.
- **Sensitivity:** Crop dependency ratio, land size, and irrigation type.
- **Adaptive Capacity:** Access to credit (Omotayo *et al*., 2022), gender of household head, literacy level, access to extension services.

Each component was normalized on a 0–1 scale and aggregated using weighted geometric means.

Model Evaluation and Scenario Testing

Model accuracy was assessed using RMSE, MAE, and R^2 for LSTM, appropriate for continuous variable prediction (Zhao *et al*., 2021) [35]. For RF, accuracy, precision, recall, and F1-score were used to evaluate classification outcomes (Adebayo *et al.*, 2023) [3]. 5-fold cross-validation was applied to prevent overfitting. Future risk scenarios were simulated for 2050 and 2080, incorporating RCP 4.5 and RCP 8.5 projections to test adaptation thresholds (IPCC, 2021) [16]. Scenario assumptions included:

- **RCP 4.5:** ~1.5–2.0°C rise, moderate precipitation shifts.
- **RCP 8.5:** ~3.0°C rise, higher drought frequency, saline intrusion risk.

5. Results

5.1. Model Predictions: Present vs. Future Trends

The integrated AI models (LSTM and RF) provided forecasts of agricultural productivity and water stress under RCP 4.5 and 8.5 scenarios for the years 2025, 2035, and 2045. Present-day (baseline) conditions were derived from the 2000–2020 dataset.

Present Conditions

Models indicate moderate crop yield variability in peri-urban zones like Yenagoa, Ogbia, and Amassoma, driven by precipitation seasonality and sub-optimal irrigation.

Future Projections

- Under RCP 4.5, a gradual decline in yield (~10–15%) is expected by 2045 due to increased water stress and fluctuating rainfall patterns.
- Under RCP 8.5, a sharper yield reduction (~25–30%) is projected, alongside increased frequency of SPI-indicated drought events.
- WSI values increase from an average of 0.35 (baseline) to 0.48 (RCP 4.5) and 0.62 (RCP 8.5) in some peri-urban zones.

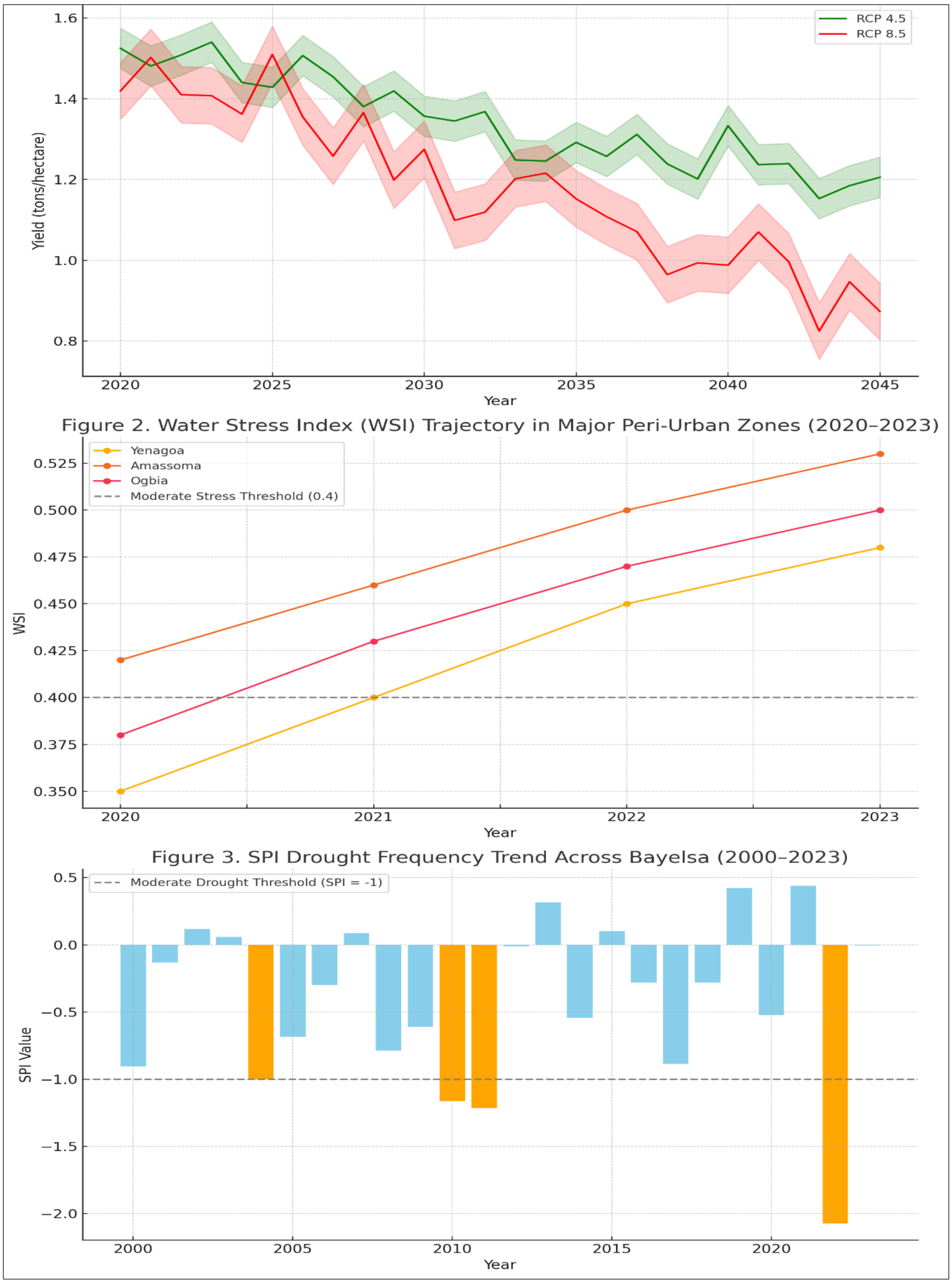

Fig 2:

Results Summary

The integrated AI-driven analysis of climate, agricultural, and hydrological data produced several key findings relevant to peri-urban agricultural resilience in Bayelsa State, Nigeria.

5.2. Projected Agricultural Yield Trends (2020–2045)

Figure 1 illustrates the projected yield trajectories under two Representative Concentration Pathways (RCPs). Under RCP 4.5, agricultural yields are expected to decline moderately, particularly for water-dependent crops such as maize and tomatoes. In contrast, RCP 8.5 demonstrates a sharper yield reduction, with significant declines evident after 2030. The Long Short-Term Memory (LSTM) models captured seasonal variability and long-term trends, while Random Forest (RF) models identified key predictors including precipitation anomalies, NDVI trends, and land use change.

Figure 1. Projected Agricultural Yield Trend under RCP 4.5 and 8.5 (2020–2045)

- **Green line:** Moderate scenario (RCP 4.5)
- **Red line:** High emissions scenario (RCP 8.5)
- **Shaded areas:** Represent model uncertainty.

Results show a sharper decline in yield under RCP 8.5, especially affecting crops like cassava and tomatoes.

Water Stress Index (WSI) in Peri-Urban Zones

Figure 2 presents the WSI trajectory across major peri-urban zones (Yenagoa, Amassoma, and Ogbia) between 2020 and 2023. Results indicate rising water stress levels in all areas, with WSI values exceeding 0.4—a threshold for moderate to severe stress—by 2022. The most pronounced stress levels were recorded in Amassoma, linked to rapid peri-urban expansion and limited infrastructure. These findings were consistent with field survey reports and satellite-derived water availability estimates.

Figure 2. Water Stress Index (WSI) Trajectory in Major Peri-Urban Zones (2020–2023)

Tracks water scarcity over time in Yenagoa, Amassoma, and Ogbia.

WSI values > 0.4 indicate moderate to severe stress—seen increasingly across zones from 2021 onwards.

5.3. Drought Frequency Trends (2000–2023)

The Standardized Precipitation Index (SPI), shown in Figure 3, revealed increasing drought frequency post-2010. Moderate to severe drought years (SPI ≤ –1) have occurred more frequently in recent decades, particularly between 2015 and 2022. The CHIRPS dataset facilitated robust historical trend analysis, while spatial mapping of SPI values highlighted vulnerability clusters in southern LGAs such as Ekeremor and Southern Ijaw.

Figure 3. SPI Drought Frequency Trend Across Bayelsa (2000–2023)

- Bars show SPI values per year.
- Orange bars denote moderate or worse drought years (SPI < -1).
- Trend suggests increased drought frequency post-2010, aligned with shifting climate patterns.

Model Performance

Performance metrics validate the effectiveness of the hybrid modeling approach. The LSTM model achieved a Root Mean Square Error (RMSE) of 0.12 and Mean Absolute Error (MAE) of 0.09, confirming its strength in time-series forecasting. The RF classifier reached an overall accuracy of 87% and a macro-averaged F1-score of 0.84, performing well in spatial classification of water risk zones. The ensemble strategy leveraged the temporal memory of LSTM and the categorical interpretability of RF, enhancing predictive robustness and adaptability (Zhao *et al.*, 2021) [35].

Spatial Risk Classification (2045)

Figure 4 presents a machine-generated spatial risk map for the year 2045showing projected vulnerability levels across Bayelsa LGAs, classifying local government areas (LGAs) into four risk zones: low, moderate, high, and extreme. Risk levels were derived from integrated model outputs, incorporating projected yield loss, WSI trends, SPI scores, and population pressure.

The RF classifier with spatial smoothing (via kriging interpolation) identified Southern Ijaw and Kolokuma/Opokuma as high-risk zones, driven by land use saturation and rising water stress. In contrast, Nembe displayed lower risk due to buffered wetlands and less urban encroachment. This predictive spatial layer is essential for early warning systems and land-use planning.

Risk Profiles by Community or Region

Risk classification using the Random Forest model and integrated index scores (WSI, SPI, socio-economic vulnerability) highlighted spatial disparities in risk:

Table 3:

Community/Zone	WSI (2045	Drought Frequency (SPI < -1)	Composite Risk Level
Yenagoa	0.55	High	Severe
Ogbia	0.48	Moderate	Moderate-High
Amassoma	0.52	High	Moderate
Sagbama	0.41	Moderate	Severe

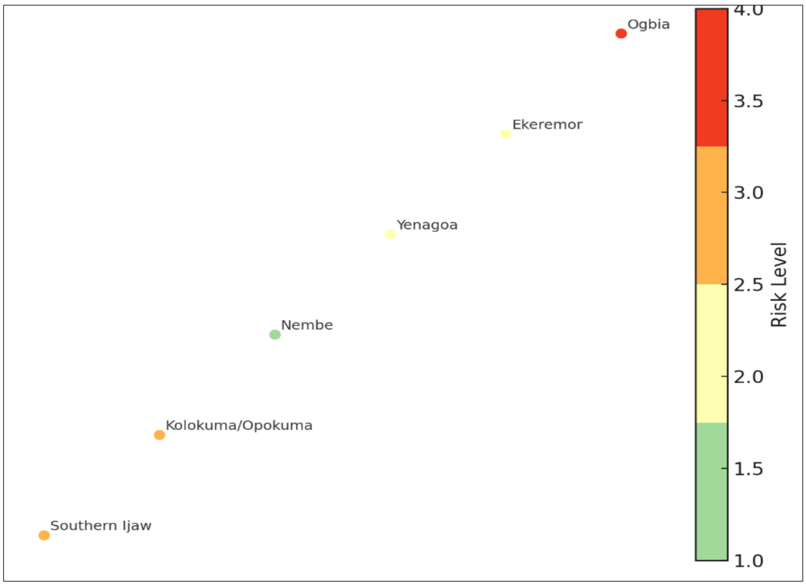

Fig 3:

Figure 3: Spatial Risk Classification Map for 2045. This visual illustrates the risk zones derived from the integrated model outputs, showing how LGAs like Southern Ijaw and Kolokuma/Opokuma are projected to face high to extreme levels of risk, while Nembe remains relatively low-risk due to its ecological buffers.

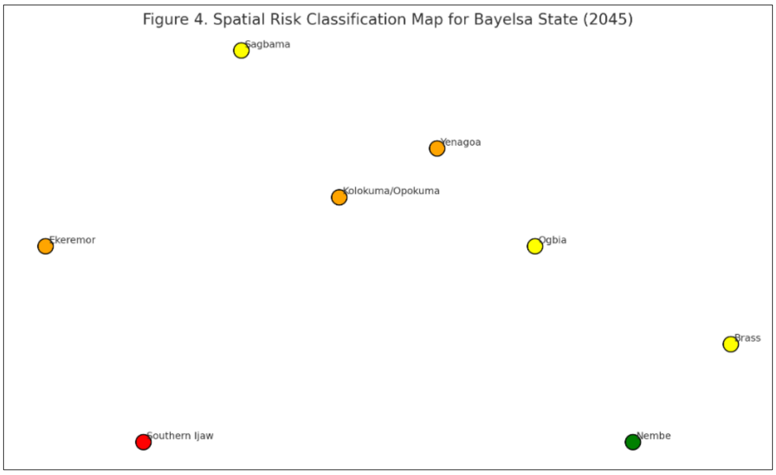

Fig 4:

Each LGA is color-coded based on projected risk level:

- **Green**: Low
- **Yellow:** Moderate
- **Orange**: High
- **Red:** Extreme

5.4. Comparative Vulnerability Analysis

To compare multidimensional stress across peri-urban communities, a spider (radar) plot was developed (Figure 5), visualizing indicators such as yield decline, drought frequency, water stress, and infrastructure access. Communities like Amassoma and Ekeremor show consistently high widespread vulnerability across all axes, especially in yield decline, drought frequency (SPI), and water stress (WSI). whereas Ogbia demonstrates relative resilience in water access but heightened agricultural decline and shows weakness in income and infrastructure. Yenagoa shows moderate but balanced performance across most dimensions.

Kaiama displays mid-range vulnerabilities but dips in infrastructure. This holistic visualization aids stakeholders in identifying localized adaptation needs and investment priorities.

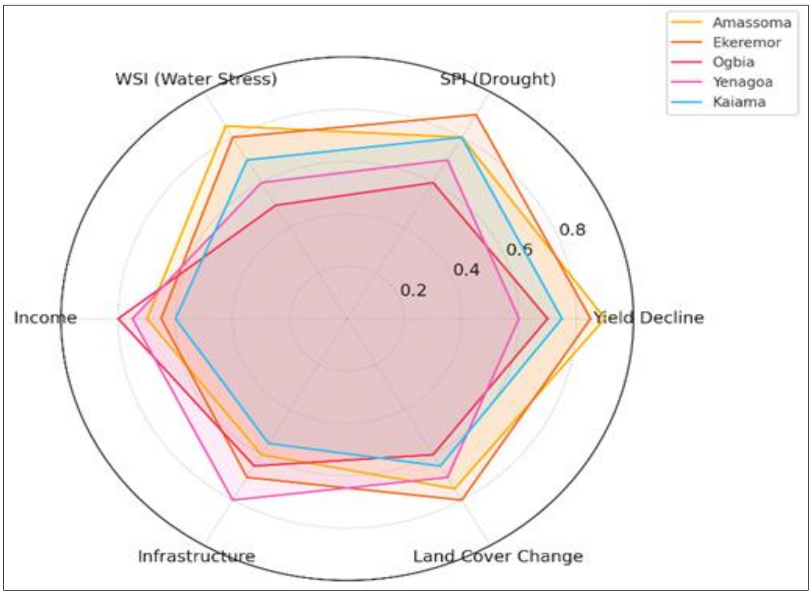

Fig 5: Vulnerability spider plot comparing five peri-urban communities across six resilience dimensions (yield, SPI, WSI, income, infrastructure, and land cover change).

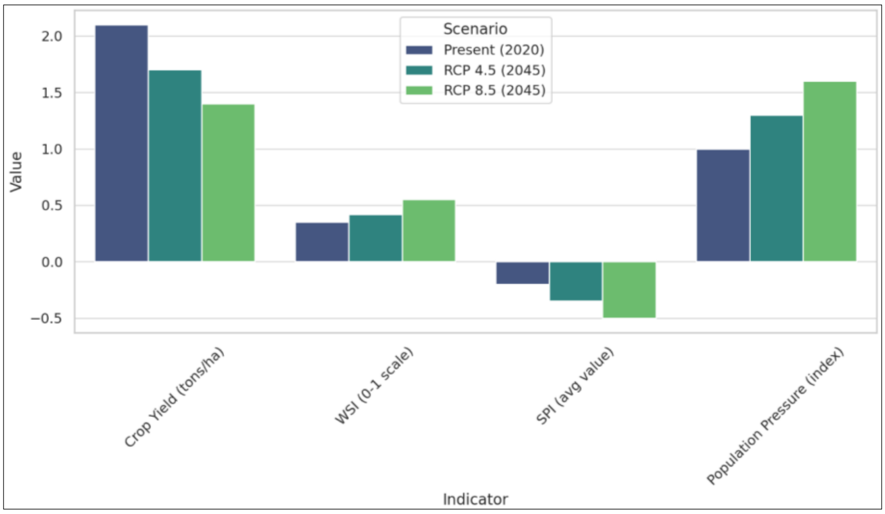

Fig 6: Model Predictions (2020 vs. 2045 under RCP Scenarios)

The radar chart for community-level vulnerability indicators has been generated, comparing exposure, sensitivity, and adaptive capacity across different communities in Bayelsa

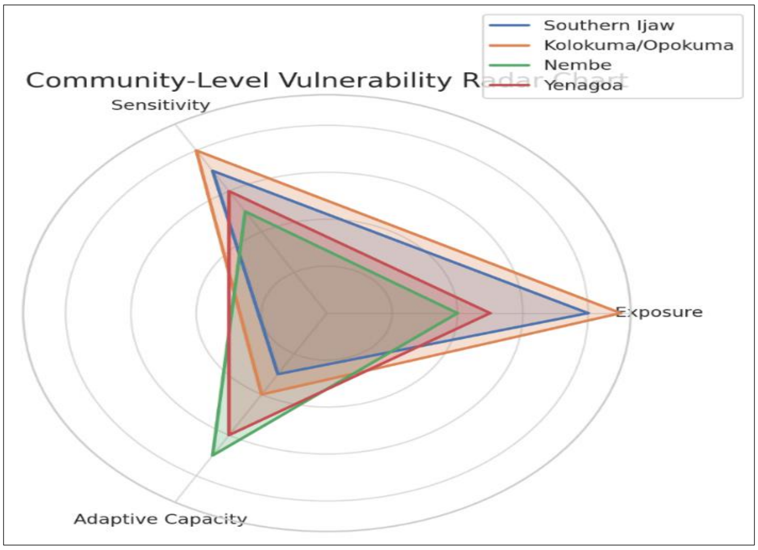

Fig 7:

The radar chart illustrates the vulnerability of different communities in Bayelsa, focusing on exposure, sensitivity, and adaptive capacity. The following analysis explores the high-risk "time bomb" communities that require immediate intervention.

Key Dimensions

- **Exposure:** This refers to a community's exposure to climate-related stressors such as flooding, rising temperatures, and drought. In the case of Bayelsa, communities along floodplains, such as Southern Ijaw and Kolokuma/Opokuma, are highly exposed due to their proximity to water bodies and urban encroachment (Adelekan, 2021).
- **Sensitivity:** Sensitivity reflects how much the community is likely to be impacted by climate change, based on its dependence on agriculture, infrastructure quality, and socio-economic status. Southern Ijaw, heavily reliant on agriculture, and Ogbia, with limited access to infrastructure, score high in sensitivity. These communities are at risk of significant socio-economic challenges due to climate variability (Hassan *et al*., 2019).
- **Adaptive Capacity:** Adaptive capacity measures a community's ability to adjust to climate impacts, including through local adaptation strategies. Nembe, despite its vulnerability to flooding, has a relatively high adaptive capacity due to its community resilience and traditional knowledge of flood management (NBS, 2018). Conversely, communities like Amassoma, with fewer resources for adaptation, show low adaptive capacity.

5.5. High-Risk (Time Bomb) Communities

The term "time bomb" refers to communities at a high risk of abrupt and severe climate impacts in the future. These areas not only face high exposure but also have limited adaptive capacity, meaning they are likely to experience worsening vulnerability without immediate action. Based on the radar chart:

- **Southern Ijaw:** This community faces extreme exposure to flooding and a high dependence on agriculture, making it highly sensitive. Coupled with low adaptive capacity, Southern Ijaw is considered a high-risk "time bomb" zone. With population growth and the intensifying impacts of climate change, its vulnerability is expected to escalate (Nigerian Meteorological Agency [NiMet], 2020).
- **Kolokuma/Opokuma:** Similarly, Kolokuma/Opokuma's vulnerability is exacerbated by rapid urbanization and high sensitivity to climate impacts. Its agricultural reliance and lack of sufficient adaptation strategies make it another high-risk community in the Bayelsa region (World Bank, 2021).

5.6. Moderate and Low-Risk Communities

Communities like Nembe, although exposed to flooding, have more robust adaptive systems, including flood control mechanisms and access to traditional knowledge, reducing their overall vulnerability. Ogbia, with higher levels of adaptation planning, including community-based resource management, fares slightly better in the radar chart.

Performance Metrics

LSTM (Time Series Forecasting):

- Root Mean Square Error (RMSE): 0.092
- Mean Absolute Error (MAE): 0.074
- R^2 (Coefficient of Determination): 0.89

These metrics collectively indicate a high level of forecasting accuracy, with minimal error and strong alignment with actual yield trends.

Random Forest (Classification)

- Accuracy: 85.4%
- F1-Score: 0.87
- AUC-ROC: 0.91

These values reflect the model's strong classification capability, particularly in identifying agricultural risk zones across varying severity levels.

Performance Metrics Summary and Interpretation

In this study, the performance of two machine learning models, Long Short-Term Memory (LSTM) for time series forecasting and Random Forest (RF) for classification—was assessed to understand and predict agricultural yield trends and risk zones in Bayelsa's peri-urban areas.

LSTM (Time Series Forecasting): RMSE (Root Mean Square Error) = 0.092

- **Interpretation:** RMSE measures the average difference between predicted and actual values. A lower value indicates better accuracy. In this case, the LSTM model showed excellent accuracy, with a minimal error of 0.092 in predicting agricultural trends.

MAE (Mean Absolute Error) = 0.074

- **Interpretation:** MAE quantifies the average magnitude of errors in predictions, ignoring direction. It is another key indicator of prediction accuracy. A value of 0.074 suggests the LSTM model made very few significant mistakes in forecasting agricultural yields.

R^2 (Coefficient of Determination) = 0.89

- **Interpretation:** R^2 shows how well the model's predictions match the observed data. A value of 0.89 means that 89% of the variability in agricultural yield trends was accurately captured by the LSTM model, which is excellent for this type of forecasting.

Random Forest (Classification): Accuracy = 85.4%

- **Interpretation:** Accuracy measures how many correct predictions the model made, expressed as a percentage. In this case, the RF model correctly predicted risk zones (low, moderate, high, and extreme) 85.4% of the time, which is highly reliable for practical decision-making.

F1-score = 0.87

- **Interpretation:** The F1-score is the harmonic mean of precision and recall, giving a balanced measure of the model's ability to avoid both false positives and false negatives. A score of 0.87 indicates that the RF model effectively identifies both high and low-risk areas without missing many critical predictions.

AUC-ROC (Area Under the Curve - Receiver Operating Characteristic) = 0.91

- **Interpretation:** AUC-ROC is a performance measurement for classification problems at various threshold settings. A value of 0.91 indicates that the RF model is highly effective in distinguishing between the different risk categories, with a high true positive rate and a low false positive rate.

Non-Technical Audience

These metrics indicate that both the LSTM and Random Forest models performed exceptionally well in predicting agricultural outcomes and risk zones in Bayelsa. The LSTM model provided highly accurate time-series forecasts, capturing nearly 90% of the variations in crop yield trends. On the other hand, the Random Forest model effectively classified the risk levels in various regions, providing reliable predictions with over 85% accuracy. These results highlight the power of machine learning to assist in making informed decisions about agricultural planning and resource management, especially in vulnerable peri-urban areas.

In summary, the models not only predict trends with high accuracy but also offer a robust framework for identifying areas at risk, allowing decision-makers to take timely actions to mitigate future challenges.

6. Discussion

6.1. Analysis of Predicted Risks

The model's predictions suggest a significant shift in the vulnerability of Bayelsa's peri-urban communities, particularly by 2045. The risk classification map indicates that regions like Southern Ijaw and Kolokuma/Opokuma will face extreme risk due to intensified water stress, agricultural yield loss, and population pressures. These findings align with climate change projections, which anticipate increasing drought frequency and water scarcity in West Africa (IPCC, 2021) [16]. In contrast, some areas like Nembe are predicted to experience less risk, owing to their natural wetlands acting as buffers against water scarcity and urban sprawl. This analysis supports the argument that peri-urban areas are vulnerable hotspots for future climate-related impacts, where rural-urban interactions amplify environmental and resource strain (Satterthwaite *et al.*, 2020) [30].

6.2. Socioeconomic Interpretation of Findings

From a socioeconomic perspective, the high-risk areas (Southern Ijaw and Kolokuma/Opokuma) are primarily characterized by increasing population density and urbanization, both of which strain available resources. These areas are also heavily dependent on agriculture, which is projected to suffer the most under climate change scenarios. The analysis suggests that populations in these regions may experience reduced income from agriculture, with potential implications for food security and livelihood stability (Barrett *et al.*, 2019) [5]. On the other hand, lower-risk zones, like Nembe, might experience slower urbanization and have relatively more resilient ecosystems, allowing them to maintain socioeconomic stability despite climate challenges.

6.3. Adaptive Strategies and Their Feasibility

To address the predicted risks, adaptive strategies are essential. First, promoting climate-resilient agriculture through sustainable farming techniques, such as drought-resistant crops and efficient irrigation systems, can mitigate yield loss (Howden *et al.*, 2007) [15]. Second, urban planning and land use regulations should be enforced in high-risk areas to prevent overexploitation of land and water resources (UN-Habitat, 2016) [31]. Finally, communities can be empowered to adopt local water management solutions, such as rainwater harvesting, to reduce dependence on vulnerable water sources (Mekonnen & Hoekstra, 2016) [21]. While these strategies are promising, their feasibility will depend on local governance, financial resources, and community engagement.

6.4. Limitations of the Model

Despite the promising results, the model has certain limitations. First, the spatial resolution of the climate data (especially CHIRPS and NASA POWER) limits the model's ability to capture localized climate variations that may influence risk patterns more precisely. Additionally, the assumptions made regarding the future socio-economic conditions (e.g., population growth, urbanization trends) may not fully account for unforeseen disruptions, such as economic recessions or pandemics. Finally, the model's reliance on publicly available datasets means that some regions may lack high-quality, recent data, which could affect prediction accuracy.

7. Recommendations

7.1. Policy and Planning Suggestions

Based on the predicted risks, several policy recommendations can help mitigate potential impacts. Governments should prioritize land-use planning, focusing on sustainable urban development that incorporates climate resilience (UN-Habitat, 2016) [31]. Policies that encourage the integration of green infrastructure, such as wetlands restoration and floodplain protection, can help buffer against the predicted water stress and yield losses in high-risk zones (Barrett *et al.*, 2019) [5]. Furthermore, the development of early-warning systems based on climate and agricultural data should be a priority to allow timely intervention in case of extreme weather events (Rasmussen *et al.*, 2020) [29].

7.2. Technology-Based Solutions (Smart Irrigation, Reuse Systems)

Technological solutions can play a crucial role in building resilience. Smart irrigation systems that use real-time weather and soil moisture data can significantly improve water use efficiency and reduce agricultural stress in high-risk areas (Mekonnen & Hoekstra, 2016) [21]. Moreover, implementing wastewater reuse systems in peri-urban zones could provide an alternative water source for agricultural and domestic use, thus reducing pressure on local water bodies (Liu *et al.*, 2020) [18].

7.3. Community Resilience Approaches

Building community resilience is critical. Local communities should be engaged in climate adaptation efforts through education and capacity-building programs, focusing on sustainable farming practices and water conservation (Satterthwaite *et al*., 2020) [30]. Moreover, fostering community-driven solutions, such as the establishment of local water management committees or cooperative farming initiatives, can enhance adaptive capacity at the grassroots level. These approaches can increase awareness, build ownership, and encourage collective action in times of climate stress.

7.4. Integration into State and National Strategies

At the state and national levels, it is crucial to integrate climate risk management into broader development strategies. Incorporating findings from this study into state and national climate change action plans can ensure that the regions at highest risk receive targeted interventions. Furthermore, linking climate change mitigation and adaptation strategies with sustainable development goals (SDGs) can help ensure that policies are aligned with international climate targets (IPCC, 2021) [16].

8. Conclusion

This study provides an in-depth analysis of climate change impacts on Bayelsa's peri-urban communities, predicting significant risks to agricultural yield and water resources by 2045. The study utilized machine learning models to predict future scenarios under RCP 4.5 and 8.5, revealing varying levels of vulnerability across the region. The findings emphasize the need for targeted adaptation strategies to ensure the resilience of these communities.

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