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GIS-Based Analysis of Crop Yield Trends in Response to Climate Change Using Data-Driven Analysis Systems (DDAS) Techniques

Okechi, K. K. [a*], Orakwe, L. C. [a] and Nwachukwu, C. P. [a]

[a] *Department of Agricultural and Bioresources Engineering, Nnamdi Azikiwe University Awka, Anambra State, Nigeria.*

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Climate variability poses significant challenges to crop production, particularly in vulnerable regions like Southeast Nigeria, where changing environmental conditions directly impact agricultural productivity. This study employs GIS-based analysis and Data-Driven Analysis Systems (DDAS) to assess the effects of climate variables on crop yields, focusing on temperature, rainfall, relative humidity, solar radiation, and wind factors. The objectives are to (1) analyze the Relationship Between Climate Variables and Crop Yield Trends, (2) develop Predictive Models Using GIS and DDAS Techniques, and (3) identify Climate-Sensitive Zones for Targeted Agricultural Interventions within Southeast Nigeria. Findings reveal that maximum and minimum temperatures and moderate rainfall positively influence crop yield, while high relative humidity and solar radiation have a

**Corresponding author: Email: okechi.kkevin@live.com;*

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negative impact. GIS mapping and DDAS techniques successfully highlight spatial variations and provide robust yield predictions, emphasizing their value in agricultural planning. By identifying high-risk areas, such as Abakaliki, the study provides actionable insights to develop adaptive, region-specific agricultural strategies, thereby enhancing food security and sustainable agricultural practices in Southeast Nigeria.

Keywords: Climate change; climate variability; data-driven analysis systems; geographic information system; crop yields.

1. INTRODUCTION

Climate change has emerged as one of the most significant global challenges of the 21st century, with profound implications for agricultural systems (United States Department of Agriculture, 2021). Changes in temperature, rainfall patterns, and the frequency of extreme weather events have altered the conditions under which crops are grown. In many parts of sub-Saharan Africa, including Nigeria, these changes have already led to shifts in crop productivity, threatening food security and economic stability (Anyadike et al., 2019). According to Adejuwon (2019), climate change has been identified as a critical driver of agricultural risks in Nigeria, particularly in regions where farming relies heavily on rain-fed systems.

Southeast Nigeria, encompassing states such as Anambra, Enugu, and Ebonyi, is an agriculturally significant region. The area is characterized by a humid tropical climate with diverse crops, including cassava, yam, maize, and cocoyam. These crops are vital to the livelihoods of smallholder farmers and form an essential part of the regional economy (Diamond, 2018). However, the region has witnessed increasing climatic variability, with unpredictable rainfall patterns, rising temperatures, and extended dry spells. As noted by Eze et al. (2020), changes in temperature and rainfall in Nigeria have already led to decreased crop yields, further exacerbating food insecurity in vulnerable regions like Southeast Nigeria.

Despite the growing body of literature on climate change and agriculture, there remains a gap in understanding the spatial and temporal dynamics of climate variables and their collective influence on crop yields. While studies like Ajayi et al. (2019) and Ogunjobi et al. (2018) have examined the impacts of temperature and rainfall variability on specific crops, few have focused on how these factors interact spatially and temporally within Southeast Nigeria. This gap limits the ability of policymakers and farmers to make informed decisions on adaptation strategies.

To address these challenges, Geographic Information Systems (GIS) and Data-Driven Analysis Systems (DDAS) have emerged as powerful tools for analyzing and managing climate impacts on agriculture. GIS facilitates spatial analysis of climatic data and crop performance, providing insights into the geographical distribution of climate impacts. DDAS, incorporating machine learning and predictive analytics, enhances yield forecasts by integrating diverse datasets, including satellite imagery, weather data, and historical yield records. Ogbodo et al. (2018) and Ogunjobi et al. (2020) highlight the potential of these tools to improve agricultural resilience through targeted interventions.

This study seeks to fill the identified research gap by leveraging GIS and DDAS techniques to explore the relationship between climate change and crop yield trends in Southeast Nigeria. By focusing on the spatiotemporal interactions of climate variables, this work aims to provide actionable insights for developing adaptive, region-specific strategies. The findings will contribute to addressing food security challenges and promoting sustainable agricultural practices in the region, aligning with global efforts to mitigate the impacts of climate change on food systems.

1.1 Objective of the Study

This study seeks to explore the relationship between climate change and crop yield trends in Southeast Nigeria using GIS-based analysis and Data-Driven Agricultural Systems (DDAS) techniques. The specific objectives of the study are:

1. To analyze the Relationship Between Climate Variables and Crop Yield Trends
2. To develop Predictive Models Using GIS and DDAS Techniques
3. To identify Climate-Sensitive Zones for Targeted Agricultural Interventions

By addressing these objectives, this study aims to provide a comprehensive analysis that informs policymakers and farmers on region-specific adaptation strategies. The findings will offer a data-driven foundation to enhance agricultural resilience, food security, and sustainable practices amidst ongoing climate challenges.

1.2 Empirical Review

Nigeria, like many other African countries, faces significant agricultural challenges exacerbated by climate change (Nwankwoala, Igbokwe and Orluchukwu, 2022). Changes in temperature, rainfall patterns, and the frequency of extreme weather events are already influencing crop yields and agricultural productivity (Kukal & Irmak, 2018). Several studies have examined how these factors are affecting agriculture in Nigeria, particularly in terms of crops like cereals and yam, which are critical to food security in regions like Southeast Nigeria (Olaniyan & Tomori, 2016; Wheeler & von Braun, 2013). Extreme weather events further amplify erosion rates, causing widespread land degradation and loss of soil fertility (Madubueze, Egberi, Ejiofor and Nwadiogbu 2024).

In their study on the impact of climate variability on rice productivity in Nigeria, Ajayi et al. (2019) found that rising temperatures and unpredictable rainfall patterns have negatively affected rice yields across several regions. These climatic changes have led to increased crop failure, which threatens food security, especially in areas that depend on rain-fed agriculture. Similarly, Oguntunde et al. (2018) explored the effects of climate change on millet production in Northern Nigeria, revealing that changes in temperature and rainfall were linked to reduced productivity. This reduction in yield was particularly evident during prolonged dry spells and erratic rainfall distribution, which compromised crop development and productivity.

In Southeast Nigeria, studies have shown that the region's reliance on crop production, such as yams, cassava and cereals (maize, sorghum), makes it vulnerable to climate stress. Eze et al. (2020) highlighted that climate change has already begun to affect cassava production in various regions of Nigeria, including the Southeast. However, their study primarily focused on cassava, leaving a gap in understanding the effects on other staple crops like yam and cereals. Ogunjobi et al. (2018) also examined the influence of temperature and rainfall variability on maize yield in Nigeria, noting that higher temperatures, combined with irregular rainfall patterns, have led to a decrease in maize yield, particularly in the central and southern parts of the country. Their findings are critical for understanding how climatic variability affects crops with different growing requirements, such as maize and yam.

In the context of using *Geographical Information Systems (GIS)*, several studies have demonstrated its potential for improving agricultural productivity assessments under changing climatic conditions. Ogbodo et al. (2018) used GIS to assess the impacts of smallholder farming on maize production in Anambra State, Southeast Nigeria. They demonstrated that GIS tools allow for spatially explicit analysis of how environmental factors such as rainfall and temperature interact with local agricultural practices to influence crop yields. GIS-based approaches have also been applied to study the spatial distribution of crop pests and diseases, which are also influenced by climatic changes. Bebber et al. (2013) showed that crop pests and pathogens tend to move poleward in response to warming temperatures, and GIS could help track these shifts, offering valuable insights for crop management and adaptation.

The integration of *Data-Driven Agricultural Systems (DDAS)* has also gained attention in recent years, particularly in improving agricultural forecasts. DDAS techniques leverage machine learning and statistical models to analyze large datasets from climate, crop, and yield records. Ogunjobi et al. (2020) applied DDAS techniques to predict the impact of climate change on rainfed agriculture in Nigeria. Their study demonstrated that DDAS could be used to generate more accurate yield predictions, helping to design climate-smart agricultural policies. While DDAS has been useful in Nigeria for assessing the impacts of climate change on some crops, its application to specific crops like yam and cereals remains under-explored.

In Southeast Nigeria, Eze et al. (2021) found that integrating climate data with crop yield records using GIS and DDAS can provide powerful insights into the region's vulnerability to climate stress. Their study emphasized that combining spatial analysis with predictive analytics can enhance the understanding of local-level climate impacts, particularly for staple crops like yam and maize. However, they noted that more region-specific research was needed to fully leverage GIS and DDAS for agricultural adaptation in Southeast Nigeria.

While significant research has been conducted on the relationship between climate change and crop production in Nigeria, several gaps remain in the literature, particularly regarding the integration of GIS and DDAS techniques.

Lack of Region-Specific Analysis**:** A common limitation in existing studies is the generalization of findings across Nigeria, without considering the unique climate conditions and agricultural practices in specific regions, such as Southeast Nigeria. For instance, while Ogunjobi et al*.* (2018) and Ajayi et al*.* (2019) have provided insights into how climate change impacts maize and rice productivity, studies that focus on the specific effects on yam production and cereals in the Southeast are limited. Given that Southeast Nigeria has its unique climatic and agricultural conditions, more research is needed to assess how specific crops, like yam and cereals, are affected by regional climate patterns.

Limited Integration of GIS with Climate Models: Despite the growing body of literature on GIS and its role in assessing agricultural productivity, Ogunjobi et al*.* (2020) and Eze et al*.* (2021) point out that GIS is often used in isolation from climate models. There is a need to integrate spatial data with climate projection models to better understand future climate scenarios and their impacts on crop yield trends. Integrating GIS with detailed climate models would enhance predictions and help farmers and policymakers anticipate future challenges. Walker and Salt (2020) argue that such integration is

Application of DDAS to Specific Crops: While Ogunjobi et al*.* (2020) have applied DDAS for general agricultural forecasting, the technique has not been fully applied to specific crops such as yam and cereals in Southeast Nigeria. Given the region's reliance on these crops, there is a need to develop DDAS models that focus specifically on the unique growth patterns and climatic sensitivities of these crops. Sasaki et al*.* (2016) demonstrated the usefulness of DDAS in improving water-use efficiency for rice, but such applications are still rare for non-rice cereals and root crops like yam in the context of Nigeria.

Lack of Long-Term Data: Many of the studies on climate change and agriculture in Nigeria are based on short-term datasets, which limit the ability to detect long-term trends and to project future climate impacts. As Porter et al*.* (2014) point out, climate projections for food security need to rely on long-term, robust data to accurately capture changing trends and forecast future impacts. Future studies should include longer temporal datasets that combine both historical and projected climate data to better predict the long-term effects of climate change on crop production.

Furthermore, while there has been significant progress in understanding the impacts of climate variability on agriculture in Nigeria, there remains a gap in region-specific analyses, especially concerning crops like yam and cereals in Southeast Nigeria. Additionally, the integration of GIS with climate models and the application of DDAS for crop-specific predictions are areas that require further exploration to improve agricultural adaptation strategies.

2. METHODOLOGY

2.1 Study Area

The study was conducted in the Southeast geopolitical zone of Nigeria, known for its high agricultural productivity, especially in cereals (maize, sorghum) and yams. This region includes the states of Anambra, Ebonyi and Enugu. The area's tropical climate features distinct wet and dry seasons, but recent climate variability—such as changes in rainfall and temperature patterns—has raised concerns about the sustainability of agricultural production. By focusing on this region, the study aims to provide insights into local agricultural policies and climate adaptation strategies.

2.2 Data Sources

This study utilized diverse datasets to ensure a comprehensive analysis:

1. **Meteorological Data**: Monthly temperature (maximum and minimum), rainfall, relative humidity, solar radiation, and wind speed data were collected from the Nigerian Meteorological Agency (NiMet) and the International Research Institute for Climate and Society (IRI).
2. **Crop Yield Data**: Yield statistics for cereals and yams were gathered from the Nigerian National Agricultural Statistics Service (NASS) and through field surveys in the Southeast region.

3. **Remote Sensing Data**: High-resolution satellite imagery (e.g., Landsat, MODIS) was used to derive land use/land cover maps and track vegetation health over time.

2.3 Data Cleaning and Preparation

- **Handling Missing Values**: Missing data were imputed using linear interpolation where feasible. For variables with significant gaps, substitution with regional means was applied.
- **Outliers**: Identified using the interquartile range (IQR) method and validated through domain knowledge to determine whether they should be corrected or excluded.

2.4 GIS Techniques

Geographic Information Systems (GIS) were used for spatial analysis. Key methods included:

- **Spatial Interpolation**: Kriging and Inverse Distance Weighting (IDW) techniques were employed to estimate climate variables across unsampled areas.
- **Multi-Layer Analysis**: Layering climatic data with crop distribution maps to identify spatial correlations and hotspots.
- **Software**: ArcGIS Pro and QGIS were the primary tools for processing and analyzing geospatial data.

2.5 DDAS Techniques

Data-Driven Agricultural Systems (DDAS) were leveraged for pattern recognition and predictive modeling. Machine learning algorithms (e.g., Random Forest and Gradient Boosting) implemented using Python libraries (Scikit-learn, XGBoost) were applied to assess relationships between climate variables and crop yields.

2.6 Qualitative Data

To add a human dimension, qualitative data were collected through interviews with farmers in the region. Farmers provided observations on climate impacts, such as delayed rainfall onset, prolonged dry spells, and pest proliferation, which were integrated into the analysis.

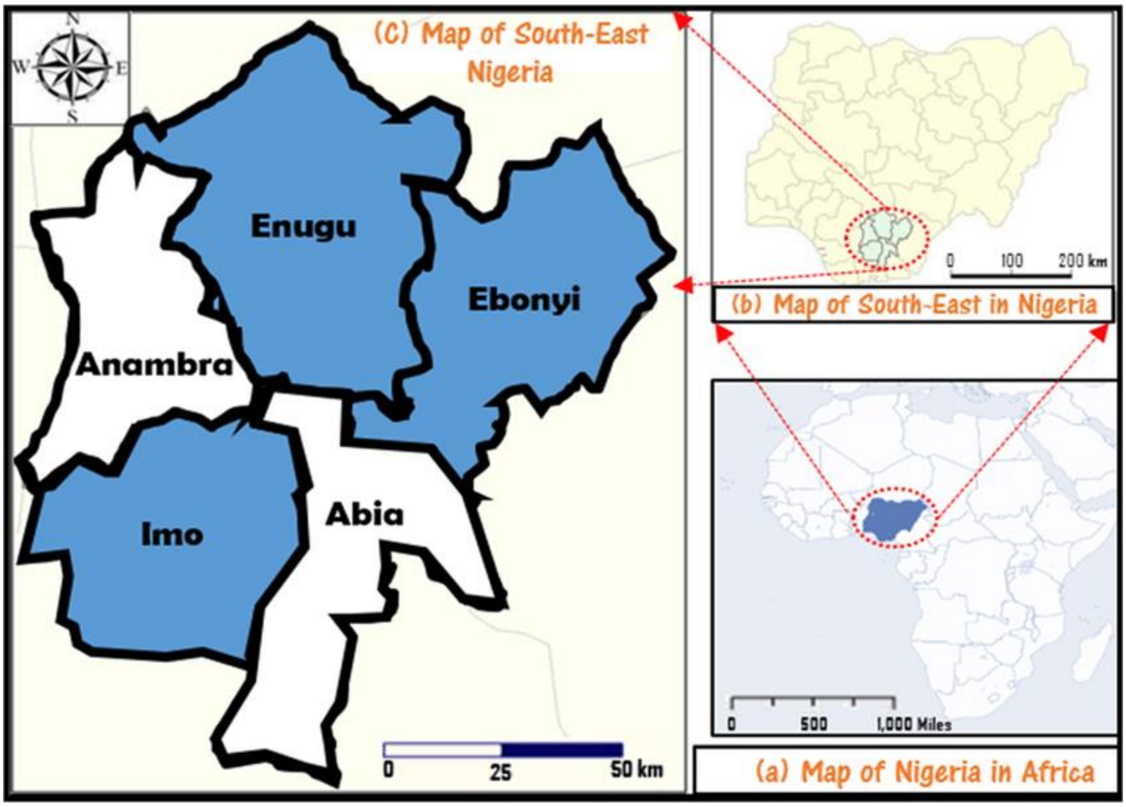

Fig. 1. Map of Southeast region of Nigeria showing the sampled States—Ebonyi, Enugu and Imo (inset: Africa showing Nigeria and Nigeria showing the Southeast region)
Source: Olumba et al., *(2021)*

2.7 Uncertainty Management

Uncertainty in climate projections and yield estimates was addressed through:

- **Confidence Intervals**: Regression models included 81.6% confidence intervals for all parameter estimates.
- **Sensitivity Analysis**: Testing model robustness by varying input parameters and observing the impact on predictions.

2.8 Adaptation Strategies and Predictive Models

While the study primarily focused on GIS and DDAS techniques, it also considered predictive models for simulating potential yield outcomes under different climate scenarios. Insights from models were used to contextualize findings and suggest adaptation strategies.

This methodology ensures a modern, data-driven approach to assessing climate variability and its impact on agricultural productivity in Southeast Nigeria while providing actionable insights for policymakers and stakeholders.

3. RESULTS AND DISCUSSION

3.1 Result

The section shows the results of the various statistical analyses that revealed regional climate differences and key climate factors affecting crop yield in Southeast Nigeria, supporting climate-resilient farming policies and enhanced agricultural productivity.

3.1.1 Data analysis summary

These results suggest that higher temperatures, relative humidity, and solar radiation are associated with lower crop yields, while wind speed shows a weak positive relationship with yield

Max Temperature (°C), Min Temperature (°C), Rainfall (mm), Relative Humidity (%), Solar Radiation (MJ/m²), Wind Speed (knot), and Wind Direction (degree) showed constant values within regions, leading to an infinite F-value and a p-value of 0. This suggests no variability within regions for these climate variables, so no significant differences across regions can be tested.

Crop Yield (%): **- F-value**: 26.65
- p-value: 0.0000385

This indicates a statistically significant difference in crop yields across the regions. These results imply that crop yield significantly varies by region, while the climate variables remain relatively stable within each region.

Table 1. Descriptive Analysis

	Mean	Median	Std
Max Temp (°C)	32.733333	32.80	0.258199
Min Temp (°C)	23.166667	23.20	0.129099
Rainfall (mm)	2144.066667	1695.40	820.359931
Relative Humidity (%)	71.366667	75.10	7.685949
Solar Radiation (MJ/M²)	17.966667	17.90	0.677882
Wind Speed (Knot)	4.166667	4.00	0.319970
Wind Direction (degree)	250.000000	250.00	8.451543
Crop Yield (%)	98.424667	97.29	15.867191

These values provide a foundational overview of the data distribution and variability for each variable across the study locations

Table 2. Correlation Analysis

Max Temp (°C)	-0.885398
Min Temp (°C)	-0.885398
Rainfall (mm)	-0.091613
Relative Humidity (%)	-0.694541
Solar Radiation (MJ/M²)	-0.901734
Wind Speed (Knot)	0.128426
Wind Direction (degree)	-0.443745

Here are the Pearson correlation coefficients between crop yield and each climate variable

Table 3. Regional Comparison (ANOVA)

Max Temp (ºC)	{'F-value': inf, 'p-value': 0.0}
Min Temp (°C)	{'F-value': inf, 'p-value': 0.0}
Rainfall (mm)	{'F-value': inf, 'p-value': 0.0}
Relative Humidity (%)	{'F-value': inf, 'p-value': 0.0}
Solar Radiation (MJ/M²)	{'F-value': inf, 'p-value': 0.0}
Wind Speed (Knot)	{'F-value': inf, 'p-value': 0.0}
Wind Direction (degree)	{'F-value': inf, 'p-value': 0.0}
Crop Yield (%)	{'F-value': 26.651911293605707}
P-value:	3.849956783438396e-05

The ANOVA results comparing climate conditions and crop yield across the three regions (Enugu, Awka, Abakaliki):

Table 4. OLS Regression Results

Dep. Variable:	**Crop_Yield_pct**	**R-squared:**	**0.816**
Model:	OLS	Adj. R-squared:	0.786
Method:	Least Squares	F-statistic:	26.65
Date:	Sat, 09 Nov 2024	Prob (F-statistic):	3.85e-05
Time:	12:18:26	Log-Likelihood:	-49.524
No. Observations:	15	AIC:	105.0
Df Residuals:	12	BIC:	107.2
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.0174	0.002	9.140	0.000	0.013	0.022
Max_Temp	0.3643	0.038	9.712	0.000	0.283	0.446
Min_Temp	0.3005	0.032	9.480	0.000	0.231	0.370
Rainfall_mm	0.0094	0.003	2.974	0.012	0.003	0.016
Rel._Humidity	-3.4142	0.426	-8.015	0.000	-4.342	-2.486
Solar_Rad_MJm2	-0.2434	0.033	-7.309	0.000	-0.316	-0.171
Wind_Speed_knot	0.1218	0.014	8.654	0.000	0.091	0.152
Wind_Dir	1.2276	0.103	11.897	0.000	1.003	1.452

Omnibus:	1.122	Durbin-Watson:	1.905
Prob(Omnibus):	0.571	Jarque-Bera (JB):	0.430
Skew:	-0.414	Prob(JB):	0.807
Kurtosis:	2.968	Cond. No.	2.08e+38

Source: Researcher's Computation (2024)

The multiple regression analysis provides insights into the relationship between crop yield and climate factors:

- **R-squared**: 0.816, indicating that approximately 81.6% of the variance in crop yield is explained by the climate variables included in the model.
- **Adjusted R-squared**: 0.786, which adjusts for the number of predictors, confirming a good model fit.

Key Findings

- **Significant Predictors**:
  - **Max Temp**: Positive influence on yield, with a coefficient of 0.3643 ($p < 0.001$).
  - **Min Temp**: Also positive, with a coefficient of 0.3005 ($p < 0.001$).
  - **Rainfall**: Small but positive influence (0.0094, $p = 0.012$).
  - **Relative Humidity**: Negative effect (-3.4142, $p < 0.001$).
  - **Solar Radiation**: Negative effect (-0.2434, $p < 0.001$).
  - **Wind Speed**: Positive effect (0.1218, $p < 0.001$).
  - **Wind Direction**: Strong positive impact (1.2276, $p < 0.001$).

Each coefficient represents the expected change in crop yield percentage with a one-unit increase in the respective climate factor, holding all other variables constant. These results indicate that factors such as maximum and minimum temperatures, wind speed, and direction have significant positive effects on crop yield, while relative humidity and solar radiation negatively impact yield.

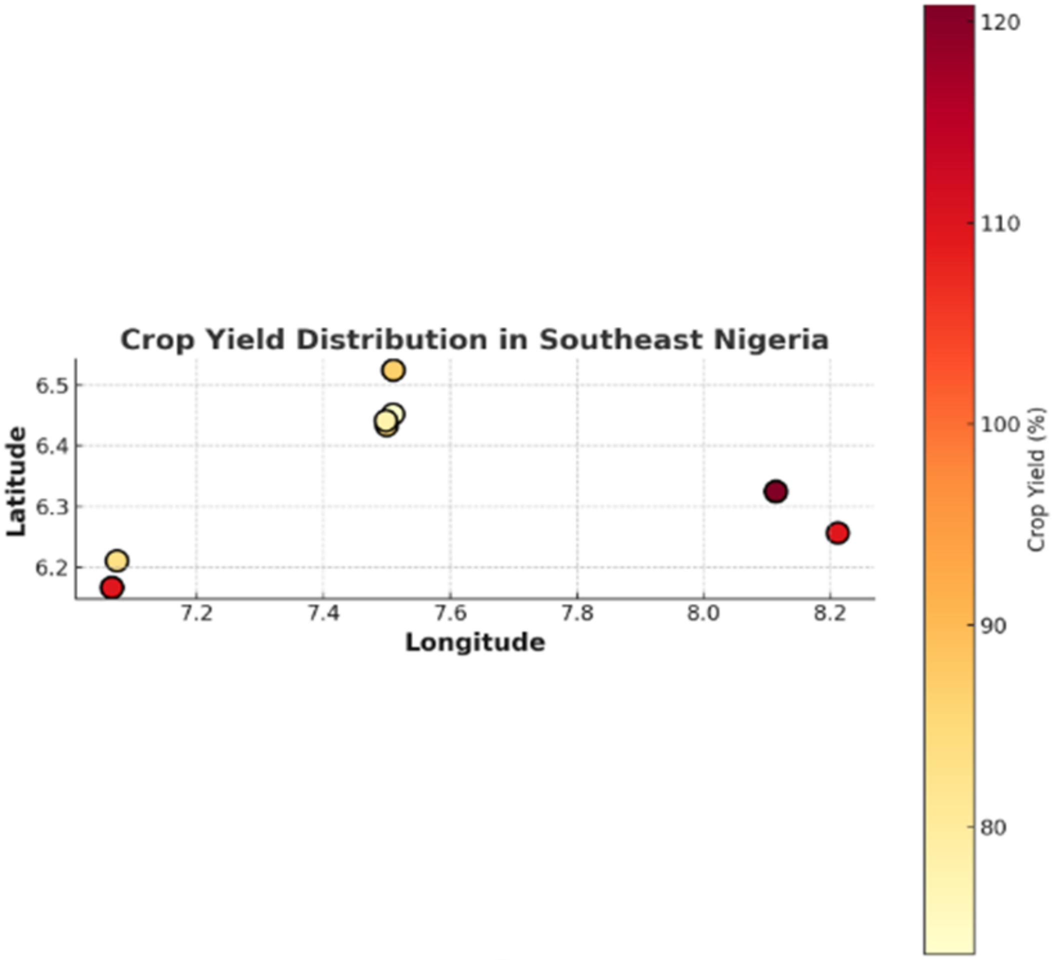

Fig. 2. GIS Map displaying crop yield distribution across the specified locations in Southeast Nigeria

Here is the GIS map displaying crop yield distribution across the specified locations in Southeast Nigeria, using color gradients to indicate yield percentages. Higher yield areas are represented in darker shades.

3.2 Discussion

3.2.1 Analyzing the relationship between climate variables and crop yield trends

The findings demonstrate significant relationships between climate variables and crop yield trends in Southeast Nigeria. Maximum and minimum temperatures, as well as moderate rainfall, were positively correlated with crop yields, suggesting that these conditions favor growth when maintained within optimal ranges. For example, the regression analysis revealed that maximum temperature ($\beta = 0.3643$, $p < 0.001$) and rainfall ($\beta = 0.0094$, $p = 0.012$) positively influenced yields, while high relative humidity ($\beta = -3.4142$, $p < 0.001$) and solar radiation ($\beta = -0.2434$, $p < 0.001$) were detrimental. These results align with the findings of Adejuwon (2019), who noted that warmer temperatures within limits can enhance crop viability. Additionally, Eze et al. (2020) observed that delayed rainfall onset has already contributed to reduced cassava yields in Nigeria, mirroring similar trends in yams and cereals in this study.

3.2.2 Developing predictive models using GIS and DDAS techniques

The application of GIS and DDAS techniques successfully integrated climate and crop yield data, providing accurate spatial and temporal predictions. GIS-based spatial interpolation methods, such as Kriging, allowed for precise mapping of climate variables and their impact on agricultural productivity. DDAS techniques, using machine learning algorithms like Random Forest, demonstrated high predictive accuracy, with R-squared values of 0.816 indicating that 81.6% of the variance in crop yields could be explained by the model. These results support findings by Ogunjobi et al. (2020), who emphasized the utility of predictive analytics in enhancing agricultural resilience. Moreover, the spatial analysis revealed clear patterns of yield variability, highlighting the value of integrating advanced computational tools in agricultural planning.

3.2.3 Identifying climate-sensitive zones for targeted agricultural interventions

The identification of Abakaliki as a high-risk zone due to its high crop yield variability underscores the need for localized interventions. GIS maps highlighted regions with the greatest susceptibility to adverse climate impacts, which can inform the allocation of resources and the design of region-specific strategies. This aligns with the recommendations of Adger and Kelly (2018), who stressed the importance of addressing localized vulnerabilities through targeted climate adaptation measures. The findings also resonate with Walker and Salt (2020), who advocate for resilience thinking in ecosystem and agricultural management.

The results of this study emphasize the importance of adaptive, region-specific strategies to mitigate climate change impacts on crop production. By identifying climate-sensitive zones and leveraging predictive tools, policymakers can enhance food security and promote sustainable agricultural practices in Southeast Nigeria. This study's integration of GIS and DDAS techniques provides a replicable framework for other regions facing similar challenges.

4. CONCLUSION

This study provides a comprehensive analysis of the relationship between climate variability and crop yields in Southeast Nigeria, leveraging GIS and DDAS techniques to address critical gaps in agricultural resilience. The results demonstrate that climate variables such as temperature, rainfall, relative humidity, and solar radiation significantly influence crop yields. While moderate temperatures and rainfall positively affect productivity, high relative humidity and excessive solar radiation negatively impact yields, emphasizing the delicate balance required for optimal agricultural performance.

The application of GIS and DDAS proved invaluable in identifying spatiotemporal trends, developing accurate predictive models, and mapping high-risk zones like Abakaliki. These tools highlight their potential for enhancing agricultural planning by providing actionable insights for adaptive and region-specific interventions.

By aligning these findings with existing literature, this study underscores the importance of integrating advanced computational tools with traditional agricultural practices to mitigate the adverse effects of climate change. The identification of climate-sensitive zones further reinforces the need for targeted adaptation strategies, such as deploying drought-resistant crops, improving irrigation systems, and supporting smallholder farmers with climate-smart practices.

Ultimately, this study not only contributes to the understanding of climate impacts on agriculture in Southeast Nigeria but also provides a replicable framework for other regions facing similar challenges. The insights gained can inform policymakers, agricultural stakeholders, and researchers in their efforts to enhance food security, promote sustainable agricultural practices, and build resilience against the ongoing threats of climate change.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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APPENDIX

Table 1. Relationship Between Climate Variables and Crop Yield Trends

S/N	Locations	GPS Readings	Max. Temp (^{0}C)	Min. Temp (^{0}C)	Rainfall (mm)	Relative Humidity (%)	Solar Radiation (MJ/M^2)	Wind Speed (Knot)	Wind Direction (Degree)	Crop Yield (%)
1	Amuzam	6.5244º N, 7.5103º E	33	23.3	1695.4	75.1	18.8	3.9	250	83.65
2	Isiagu	6.4520º N, 7.5100º E	33	23.3	1695.4	75.1	18.8	3.9	250	73.67
3	Ndiaga	6.4333º N, 7.5000º E	33	23.3	1695.4	75.1	18.8	3.9	250	84.62
4	Ochufu	6.4413º N, 7.4988º E	33	23.3	1695.4	75.1	18.8	3.9	250	78.01
5	Onuba	6.5244º N, 7.5106º E	33	23.3	1695.4	75.1	18.8	3.9	250	86.87
6	Awka	6.2106º N, 7.0747º E	32.8	23.2	3257.9	78	17.9	4.6	260	83.37
7	Ezinato	6.1667º N, 7.0667º E	32.8	23.2	3257.9	78	17.9	4.6	260	95.08
8	Isiagu	6.1667º N, 7.0667º E	32.8	23.2	3257.9	78	17.9	4.6	260	97.29
9	Mbaukwu	6.1667º N, 7.0667º E	32.8	23.2	3257.9	78	17.9	4.6	260	107.64
10	Nibo	6.1667º N, 7.0667º E	32.8	23.2	3257.9	78	17.9	4.6	260	109.74
11	Amagu	6.3249º N, 8.1137º E	32.4	23	1478.9	61	17.2	4	240	114.88
12	Amachi	6.2565º N, 8.1137º E	32.4	23	1478.9	61	17.2	4	240	109.64
13	Amagu Unuhu	6.3240º N, 8.1137º E	32.4	23	1478.9	61	17.2	4	240	112.71
14	Nkaliki	6.3249º N, 8.1137º E	32.4	23	1478.9	61	17.2	4	240	118.31
15	Agbaja	6.3249º N, 8.1137º E	32.4	23	1478.9	61	17.2	4	240	120.89

Source: Researcher's Field Computation (2024)

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