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GEOSPATIAL ASSESSMENT OF THE IMPACTS OF PRECIPITATION AND TEMPERATURE ON CROP YIELD AT FUTA RESEARCH FARM, ONDO STATE, NIGERIA

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ABSTRACT

Agricultural productivity is highly influenced by climatic factors such as temperature, and precipitation. This study geospatially evaluates the impact of climate variability on the Federal University of Technology Akure (FUTA) Research Farm over eleven planting seasons (2012–2022). Primary data, including crop yield measurements and GNSS observations for planting boundaries, were integrated with satellite imagery and climate records. Vegetative indices (NDVI and GCI) showed fluctuations, with an increase from 2014 to 2016, a decline from 2017 to 2019, and a subsequent rise in 2021–2022, indicating improved crop health. A weak negative correlation (-0.014) was found between temperature and crop yield, while precipitation exhibited a strong negative correlation (-0.821), suggesting excessive rainfall adversely impacts crop production. The correlation between GCI and yield (-0.001) was non-significant, emphasizing precipitation as a primary determinant of yield variations. These findings highlight the critical role of climate in agricultural productivity and the need for data-driven strategies to enhance farm resilience. This study provides valuable insights for sustainable farm management under changing climatic conditions. The study recommends the implementation of improved water management strategies to mitigate the adverse effects of climatic variability on crop yield at the FUTA Research Farm.

Keywords: Crop Yield, Green Chlorophyll Index (GCI), Normalised difference vegetation Index (NDVI), Precipitation, Temperature

1.0 Introduction

Agriculture plays a key role in economic development and food security, particularly in developing countries such as Nigeria. One of the primary objectives of agricultural production is to achieve maximum yield at minimal cost [7]. However, agricultural productivity is highly sensitive to climatic factors, including temperature, precipitation, humidity, solar radiation, and wind speed, all of which significantly influence crop growth, soil health, pest dynamics, and water availability [11]. The Federal University of Technology Akure (FUTA) Research Farm, a key agricultural facility for teaching, research, and practical training, is similarly affected by climatic variability and change.

The FUTA Research Farm supports a range of agricultural activities, including crop cultivation, livestock production, aquaculture, and agroforestry [5]. However, the farm's productivity and sustainability are increasingly threatened by climatic variability, including rising temperatures, irregular rainfall patterns, prolonged dry spells, and extreme weather events [8]. Climate change has introduced new challenges to agricultural production, impacting food security, supply stability, and economic planning [6]. Studies indicate that climatic fluctuations progressively affect crop yields, with global agricultural output growth slowing by approximately 21% due to climate change [4];[10]. Additionally, topographic features such as slope and aspect influence water drainage and soil moisture availability, further affecting crop development and yield potential [3]; [6]. Effective farm management strategies, including irrigation, fertilization, and pest control, are essential for mitigating the adverse effects of climatic variability on agricultural productivity.

Given the increasing challenges posed by climate variability, a comprehensive assessment of its impact on the FUTA Research Farm is essential. Geospatial technologies, such as Geographic Information Systems (GIS) and Remote Sensing, offer powerful tools for analyzing climatic influences on agricultural productivity. These technologies enable the integration of diverse datasets to examine the spatial and temporal distribution of climatic variables and their effects on crop performance. GIS-based spatial interpolation techniques, such as kriging and inverse distance weighting, facilitate the estimation of crop yields in unsampled locations, providing valuable insights into spatial variability within the farm [5]. This study aims to assess the impact of climatic factors on the FUTA Research Farm using geospatial techniques and the specific objectives are to evaluate the spatial and temporal variations of key climatic parameters (temperature, precipitation) over the FUTA Research Farm; assess the spatial and temporal variations of vegetation indices over the FUTA Research Farm; and analyze the correlation between climatic factors and farm performance indicators such as crop yield and vegetation indices. The findings will help farm managers develop adaptive strategies to address climate-related challenges and improve agricultural productivity. Ultimately, this research will contribute to enhancing farm sustainability, ensuring food security, and increasing overall agricultural resilience in response to changing climatic conditions.

1.1 Study Area

The research focuses specifically on the FUTA farm, located in Akure, Nigeria. The study area encompasses the entire farm, including its diverse crop cultivation and experimental plots. The study area is located between 7º18′0″ N, 5º8′ 45″ E and 7º17′ 45″ N, 5º9′0″ E in Akure as shown in Figure 1. In terms of land cover, Akure is a rapidly growing city. Urban development in the city has converted agricultural and forestry land into built-up areas, such as residential, commercial, and industrial areas. The study area consists of 10 plots which cover an area of 45.895 hectares. The area of each of the 10 plots is 5.854 hectares, 9.499 hectares, 2.958 hectares, 3.539 hectares, 5.428 hectares, 5.134 hectares, 0.891 hectares, 6.479 hectares, 5.459 hectares and 0.654 hectares.

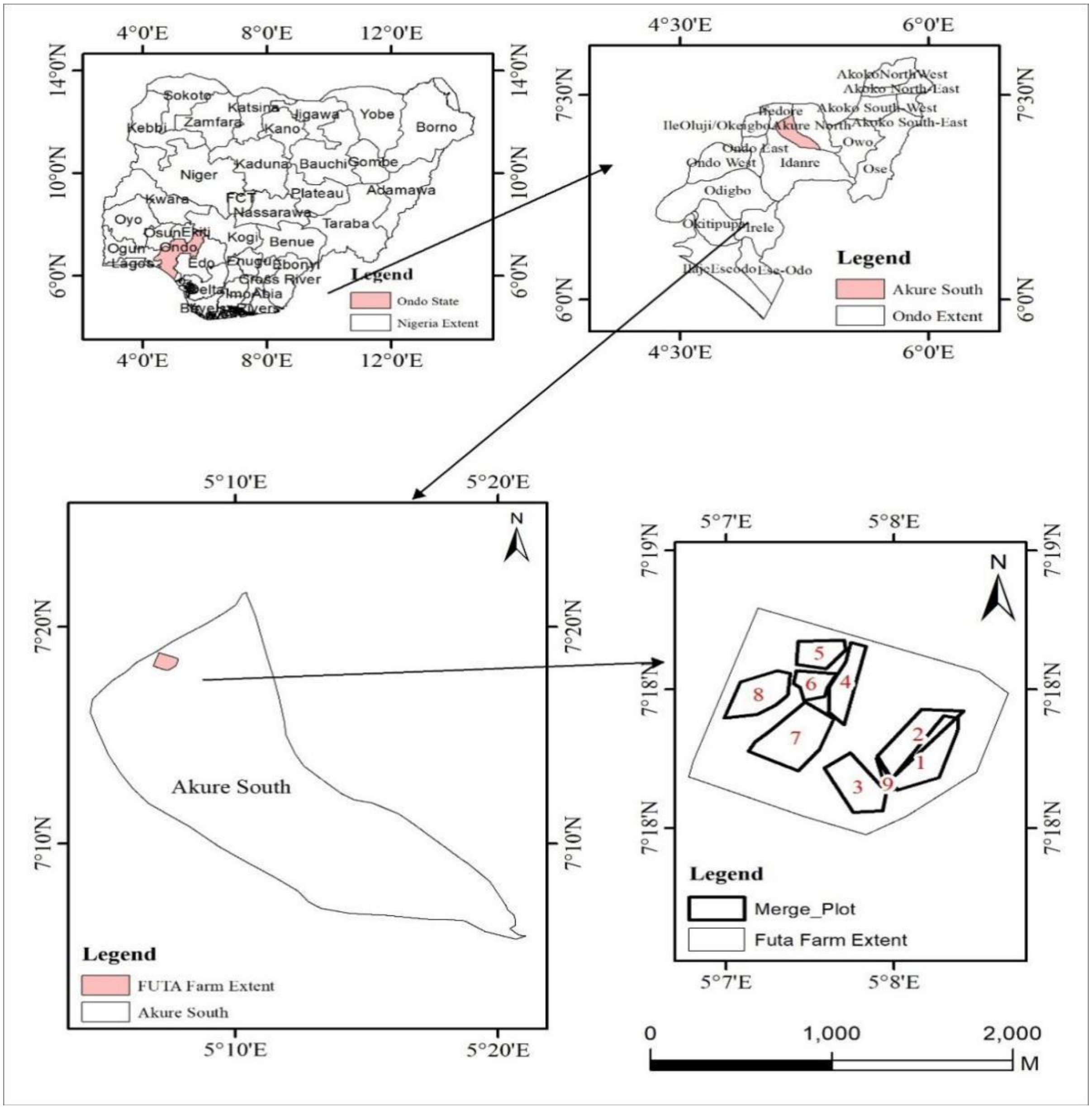

Figure 1: Map of the Study area

Source: Author's Work (2023)

2.0 Materials and Methods

2.1 Data Collection

The study involves the collection of both primary and secondary sources of data. The primary source of data includes GNSS data of each plot for designating the boundaries of the cultivated areas. The secondary data were gathered from existing datasets, such as satellite imagery and climate data. Landsat satellite imagery was acquired with appropriate spectral bands and temporal coverage to capture crop growth dynamics throughout the growing seasons. Climatic data was acquired for the study area from the World Weather online website. Also, data on crop yield samples were collected from the Department of Crop, Soil & Pest Management, Federal University of Technology, Akure. The process by which these data were collected is explained below in Table 1.

Table 1: Primary Data, Source, Mode of acquisition, Resolution, format and usefulness

S/N	Data	Source	Resolution	Period of Acquisition	Application
1	Crop Yield in tonnes	Crop, Soil and Pest Management (CSP), Department, FUTA	-	2012-2022	Ground truth data
2	Farmland Plots boundary data	Field Observation	-	2022	To understand the area used for plantation within the study area alongside their effects in determining the yield of crops within such area.
3	Landsat 7, 8, 9 Imagery OLI/TIRS	USGS through Earth Explorer	30	(2012 – 2021)	Vegetative indices (NDVI and GCI).
4	Temperature	NASA Power		(2012 – 2021)	To assess the impact of temperature on farm performance
5	Precipitation	NASA Power		(2012 – 2022)	To assess the impact of temperature on farm performance

Source: Author's compilation (2023)

2.2 Data Processing

2.2.1 Image Processing

The Landsat imageries 7, 8 and 9 with band combinations 4,3,2 and 5,4,3 were identified and combined to form a composite using the Geoprocessing tool of ArcMap 10.8. The research area's boundary was clipped out from the composite Landsat Image with the location shapefile. The maximum likelihood classifier, which is a method of supervised classification was used to classify land cover types of the study area. The area was classified into three (3) different land cover classes which are: built-up areas, Vegetated Areas, and Open Spaces. The field calculator button of ArcMap 10.8 was utilized to compute the area of each class depicted on the land use map, using Equation 1.

$$Area\ of\ each\ Class = \text{Total Number of Pixel per Class} \times \text{Total Resolution of imageries} \quad (1)$$

2.2.2 Remote Sensing Indices

Vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), Green Chlorophyll Vegetation Index (GCI) were calculated, using satellite imagery to quantify crop growth and vegetation vigour. The Normalized Difference Vegetation Index (NDVI) uses Red and Near-Infrared bands of Landsat images to determine the state of health of vegetative properties within the area. Hence, it is calculated in ArcGIS 10.8 environment using the expression shown in Equation 2

$$\text{NDVI}=\frac{NIR-R}{NIR+R} \quad (2)$$

Where:

NIR is the Near Infrared band of the Landsat series (Band 5 for Landsat 8 and Band 4 for Landsat 7)

R is the Red Band (Band 4 for Landsat 8 and Band 3 for Landsat 7)

The GCI's ability to determine the chlorophyll content of a particular vegetated area was used to determine the growth stage and health of crops in the study area. The formula in Equation 3 was used to derive the GCI of the study area for this study.

$$\text{GCI} = \frac{NIR}{GREEN} - 1 \quad (3)$$

Where:

Green is Band 3 in Landsat 8 and Band 2 for Landsat 7

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These indices are used as an indicator for crop yield in the study area and it was validated by crop yield values of each year collected from the Crop, Soil and Pest Management (CSP) department of FUTA.

2.2.3 Temperature and Precipitation

The temperature and rainfall data give the temperature distribution in degrees Celsius of the area while the rainfall gives the precipitation distribution of the study area. The downloaded data acquired from the NASA Power website was imported into Microsoft Excel for proper cleaning and preprocessing. The preprocessing process involves data cleaning to remove missing values and outliers. This was done to ensure proper distribution and understanding of the rainfall and temperature within the study area. After successfully preprocessing the data, the average values of the rainfall and the temperature for 2012 to 2022 were calculated using the average function present within Microsoft Excel.

2.3 Method of Data Analysis

After the data had been processed, it was subjected to some analysis which are discussed in this section.

2.3.1 Correlation Analysis

To understand the relationship between the vegetative indices and the factors influencing crop yield considered in this study, a Pearson correlation analysis was carried out using the SPSS software. The average temperature and rainfall were exported into the SPSS interface for the proper correlation analysis to gain a more in-depth understanding of the trend and its effects on the crop yield of the study area. The result is between -1 and +1, showing the relationship as either positive or negative with their level of significance.

3.0 Result and Discussion

3.1 Normalized Difference Vegetative Index (NDVI) changes

The study examines the health of crops in the study area during different years of planting. In 2012, the NDVI map shown in Figure 2a revealed that the crop had moderate health, with high values

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observed in most planting plots, except for plot 8. In 2013, all plots shown in Figure 2b had low NDVI values, indicating the crops are not very healthy. In 2014, the NDVI map shown in Figure 2c revealed that the crop are not very healthy, with values ranging from 0.09 to 0.309. In 2016, the NDVI values ranged between 0.065 and 0.385 as shown in Figure 2e indicating that the crop are not very healthy.

The NDVI map for 2017 and 2018 as shown in Figures 2f and 2g respectively shows that crops in the study area not healthy due to their value and growth stage. Plot 2 crops are healthier, while most crops in Plots 3, 5, and 8 have values between 0.153 and 0.21. Plots 3, 5, 6, and a part of Plot 2 have values between 0.153 and 0.21 as shown in figure 7. In 2019, Plot 1, 3, and 4 crops are healthier, while most in Plots 2 and 6 have values between 0.080 and 0.165 as shown in Figure 2h. In 2020, the NDVI change ranges between 0.06 and 0.389, indicating poor crop health. The NDVI map in Figure 2i suggests that most crops in the chosen plots have poor health, and it is unlikely that they were not planted during the time the image was captured.

The NDVI map of the study area for 2021 and 2022 as shown in Figure 2j and Figure 2k respectively reveals poor crop health due to the value and growth stage of the crops. The NDVI maps in Figures 2j and 2k show most crops in the chosen plots have poor health, suggesting that they were planted during the captured time. The NDVI values range from 0.06 to 0.389, indicating that the crops were not healthy during the time the image was captured.

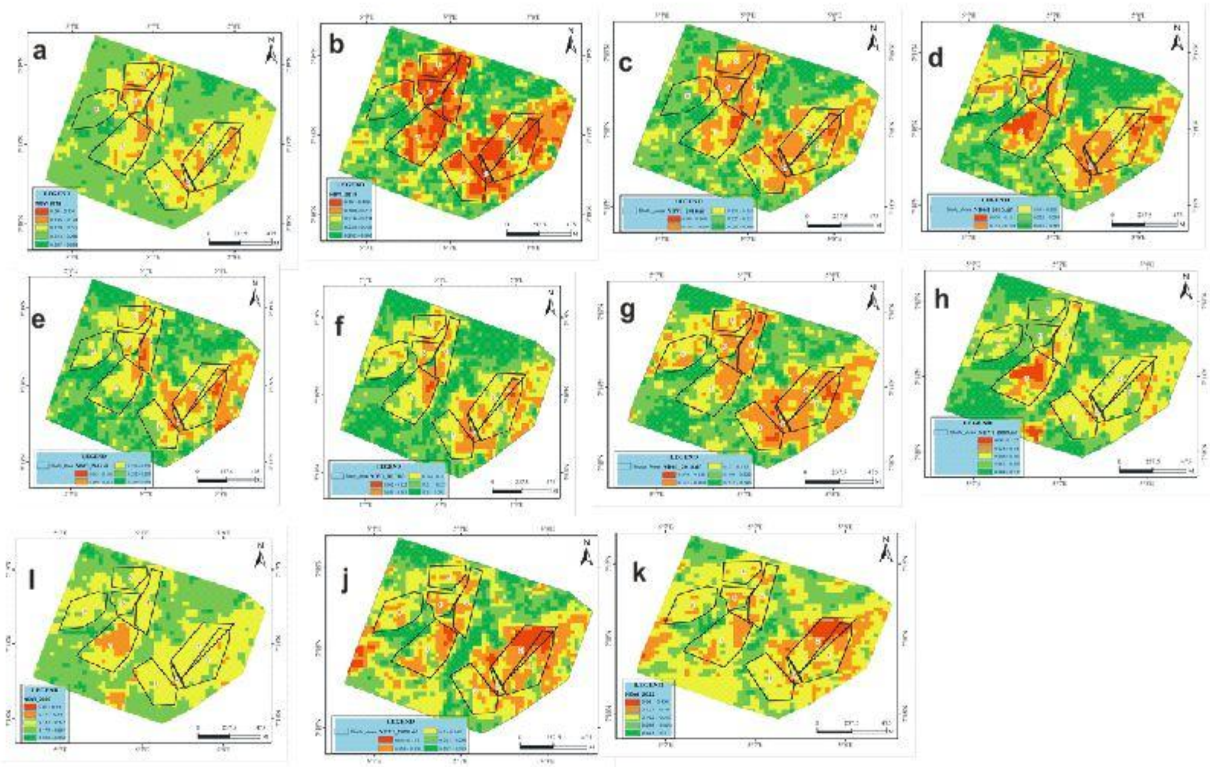

Figure 2: Map of the study area indicating the NDVI for the years (a) 2012 (b) 2013 (c) 2014 (d) 2015 (e) 2016 (f) 2017 (g) 2018 (h) 2019 (i) 2020 (j) 2021 (k) 2022

3.2 Green Chlorophyll Vegetation Index (GCI) Changes

The study examines the chlorophyll content of crops planted in the study area during different periods. In 2012, the crops were found to be moderately healthy, with values ranging from 0.203 to 0.549 as shown in Figure 3a. GCI map of the study area for 2013 shown in Figure 3b showed that the whole farmland was moderately healthy within the period of this study. In 2014, the crops were found to be healthy, with values ranging from 0.211 to 0.749 as shown in Figure 3c. However, plot 8 was expected to yield better due to its high GCI value. In 2015, the crops were healthy, with values ranging from 0.134 to 0.883 as shown in Figure 3d. Most plots had moderate chlorophyll content, except for plot 7 which had low content. In 2016, the crops were very healthy, with values ranging from 0.194 to 1.060 as shown in Figure 3e. However, some plots had low chlorophyll content, possibly due to early crop growth.

In 2017, the crops were healthy, with values ranging from 0.227 to 0.715 as shown in figure 3f. However, some plots had low chlorophyll content, suggesting stress or lack of plantation. Figure 3g showed that in 2018, the crops were healthy, but most had low chlorophyll levels, suggesting stress. Figure 3h shows that in 2019, the crops were fairly healthy, with values ranging from 0.197 to 0.546. However, only plot two had very low chlorophyll content, suggesting a built-up area.

Figure 3i shows that in 2020, the crops were found to be very healthy and experiencing little to no stress. However, only plot two had low chlorophyll content, possibly due to an increase after the COVID-19 break. Figure 3j showed that in 2021, the crops were very healthy and experiencing little stress, with values ranging from 0.072 to 1.072. However, only plot two had low chlorophyll content, possibly due to increased chlorophyll content after the COVID-19 pandemic.

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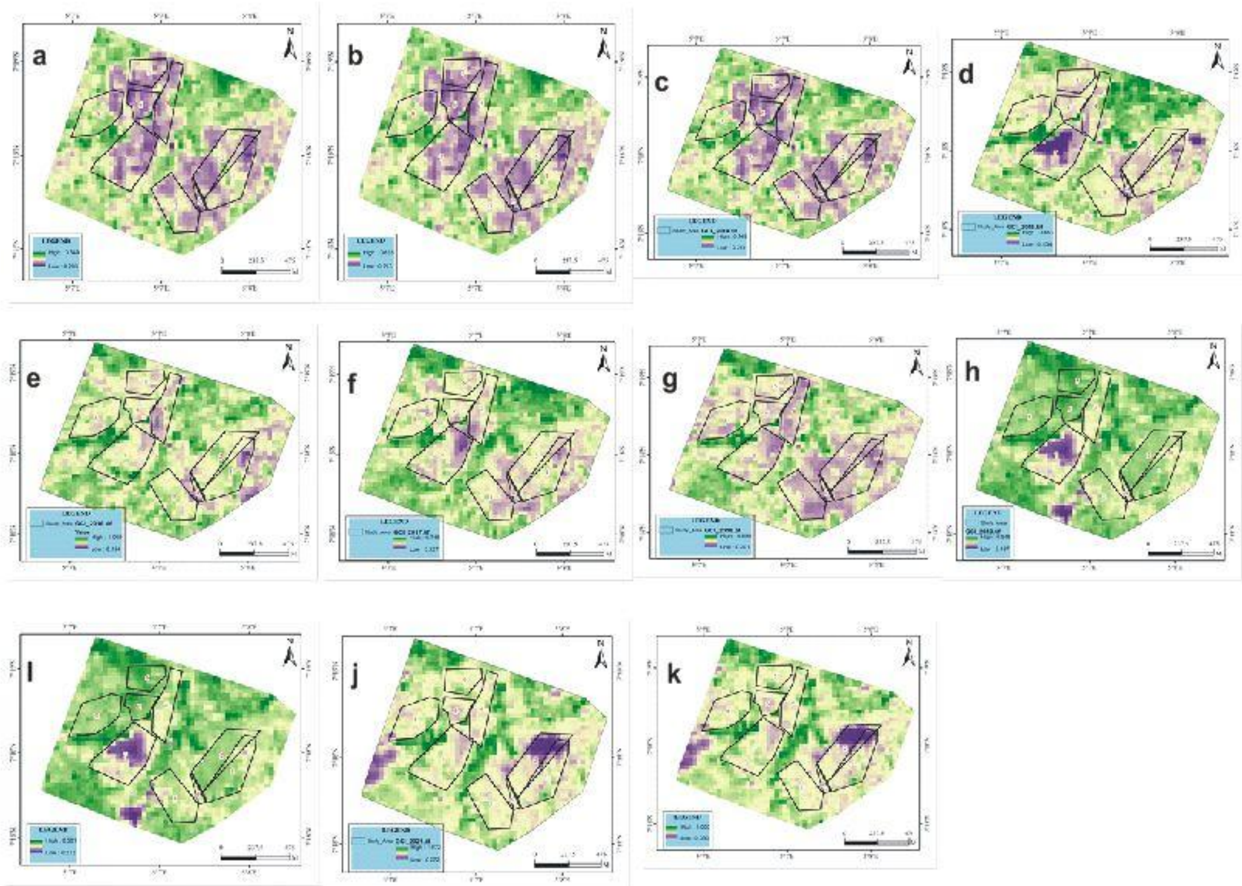

Figure 3: Map of the study area indicating the GCI for the years (a) 2012 (b) 2013 (c) 2014 (d) 2015 (e) 2016 (f) 2017 (g) 2018 (h) 2019 (i) 2020 (j) 2021 (k) 2022

Table 2 presents the Average GCI and NDVI values of the study area between 2012 and 2022. The highest average GCI value of 0.63 was recorded in 2016 while the lowest average GCI value of 0.32 was also recorded in 2020. Also, the highest average NDVI value of 0.50 was recorded in 2022 while the lowest average NDVI value of 0.13 was recorded in 2020.

Table 2: Average GCI and NDVI value of the study area

Year	GCI	NDVI
2012	0.49	0.20
2013	0.50	0.21
2014	0.48	0.20
2015	0.51	0.21
2016	0.63	0.23
2017	0.47	0.19
2018	0.45	0.18
2019	0.37	0.16
2020	0.32	0.13

2021	0.57	0.22
2022	0.56	0.50

3.3 Average Annual Temperature and Precipitation

Table 3 presents the Average Annual Temperature of the study area between year 2012 and 2022. The highest average temperature of 25.13°C occurred in 2016 while the lowest average Annual temperature of 24.08 °C occurred in 2022. Overall, the temperatures appear relatively consistent, with most values clustering around the mid 24°C range. There are no extreme outliers or drastic fluctuations, suggesting a degree of stability in the recorded temperatures over the years. Table 3 also presents the Average Annual Precipitation of the study area between the year 2012 and 2022. The highest average Precipitation of 7.56mm occurred in 2021 while the lowest average Precipitation of 3.07mm occurred in 2013 and 2015. Figure 25 indicates annual fluctuations in precipitation, with some years experiencing higher or lower precipitation compared to the adjacent years. The year 2021 stands out with significantly higher precipitation compared to the other years, suggesting a potential anomaly or specific weather event during that year. Overall, there seems to be an increasing trend in precipitation from 2012 to 2022, with a noticeable rise in the latter years, particularly in 2019, 2021, and 2022. While there is variability in precipitation, the data doesn't exhibit extreme outliers or drastic fluctuations, indicating a degree of consistency in the recorded precipitation over the years.

Table 3: Average Annual Precipitation of the study area

Year	Average Annual Precipitation (mm)	Average Annual Temperature (°C)
2012	3.95	24.26
2013	3.07	24.35
2014	3.51	24.72
2015	3.07	24.74
2016	3.95	25.13
2017	3.96	24.80
2018	4.83	24.48
2019	5.27	24.64
2020	4.39	24.44
2021	7.56	24.67
2022	5.78	24.08

Source: NASA Power (2023)

3.4 Correlation Between NDVI and Average Annual Temperature

Table 4 presents the Pearson correlation analysis between NDVI and the average temperature is (r= -0.445, p = 0.170). The result shows a weak negative correlation between NDVI and average temperature, with a moderate tendency for green vegetation to decrease as temperature increases. This suggests that higher temperatures may negatively impact vegetation health, potentially affecting crop growth and productivity, and potentially causing stress on crops.

Table 4: Correlation analysis between NDVI and Average Annual Temperature

Correlation		**NDVI**
Temperature	Pearson Correlation	-0.445
	Sig. (2-tailed)	.170
	N	11

3.5 Correlation Between NDVI and Average Annual Precipitation

The positive correlation coefficient of 0.299 presented in Table 5 indicates a positive relationship between NDVI values and average precipitation, suggesting higher precipitation leads to healthier vegetation and improved crop yield. However, excessive precipitation can negatively impact crops during specific growth stages.

Table 5: Correlation analysis between NDVI and Average Precipitation

Correlation		**NDVI**
Precipitation	Pearson Correlation	0.299
	Sig. (2-tailed)	0.372
	N	11

3.6 Correlation Between GCI and Average Annual Temperature

The positive correlation coefficient of 0.256 presented in Table 6 suggests a positive relationship between GCI values and average temperature. Higher temperatures are linked to higher chlorophyll content in vegetation, indicating enhanced plant health and improved crop yield. However, it's crucial to consider potential temperature stress and the optimal temperature range for chlorophyll production.

Table 6: Correlation analysis between GCI and Average Temperature

Correlation		GCI
Temperature	Pearson Correlation	0.256
	Sig. (2-tailed)	0.448
	N	11

3.7 Crop Yield and Vegetative Indices

The understanding of the crop yield result and the vegetative indices used within this study was accessed to understand better the activities and effectiveness of using vegetative indices to determine crop health within the study area. Table 7 presents the crop yield value of FUTA farms for 2012 to 2022. A decline in crop yield from 2017 to 2018, attributed to herdsmen destroying crops. However, a high crop yield in 2016 was due to a large number of students planting maize during the 2015/2016 academic session. In 2020 and 2021, farming activities were disrupted by the COVID-19 pandemic and the university union industrial action, affecting student availability.

Table 7: Crop Yield for the year 2012 to 2022

Year	GCI	NDVI	Crop Yield (Tonnes)
2012	0.49	0.20	14.90
2013	0.50	0.21	24.00
2014	0.48	0.20	18.70
2015	0.51	0.21	13.80
2016	0.63	0.23	24.70
2017	0.47	0.19	7.00
2018	0.45	0.18	5.00
2019	0.37	0.16	14.80
2022	0.57	0.22	14.40

Source: Crop, Soil and Pest Department, Federal University of Technology, Akure (FUTA) (2023)

A correlation analysis was conducted to understand the effects of precipitation, temperature, and vegetative indices on crop yield. Table 8 results showed a weak and negative correlation coefficient of -0.014 between temperature and crop yield, suggesting minimal influence of temperature on crop yield. A robust and statistically significant negative correlation coefficient of -0.821 was found between precipitation and crop yield, suggesting higher precipitation is associated with lower yields. Excessive rainfall or waterlogging could negatively affect crop production. The

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correlation coefficient of -0.001 between GCI and crop yield was not significant, suggesting no meaningful predictor of variations in yield. The correlation coefficient of 0.031 between NDVI and crop yield was non-significant, suggesting a minimal positive relationship. In practical terms, precipitation appears to be a more critical factor influencing crop yield, with higher precipitation associated with lower yields.

Table 8: Correlation Between Crop Yield and Vegetative Indices

Correlation		**Temperature**	**Precipitation**	**GCI**	**NDVI**
Crop_Yield	Pearson Correlation	-0.014	-0.821**	-0.001	0.031
	Sig. (2-tailed)	.968	.002	.998	.928
	N	11	11	11	11

Discussion of Results

The findings of this study showcase the impact of climatic variables, particularly precipitation and temperature on crop health and yield at the FUTA Research Farm. The observed fluctuations in vegetation indices (NDVI and GCI) over the study period align with previous research indicating that climate variability directly impacts agricultural productivity [10]; [5]. The correlation analysis revealed a strong negative relationship (-0.821) between precipitation and crop yield, suggesting that excessive rainfall adversely affects productivity, likely due to waterlogging and soil nutrient leaching, as similarly reported by [4]. In contrast, temperature exhibited a weak negative correlation (-0.014) with crop yield, indicating a less direct but still relevant influence, consistent with studies by [6] and [12], which found that temperature fluctuations impact crop phenology rather than yield alone.

The temporal variations in NDVI and GCI values between 2012 and 2022 suggest that crop health has been influenced by both climatic factors and agronomic management practices. The observed decline in vegetation indices from 2017 to 2019 coincides with disruptions in farming activities due to external factors such as herdsmen invasions and institutional challenges, reflecting similar findings by [1] on the impact of socio-environmental stressors on agricultural productivity. The increase in NDVI and GCI values in 2021 and 2022 suggests a recovery phase, potentially linked to improved farm management post-pandemic, in line with findings from [9] on the role of adaptive farming practices in mitigating climate impacts.

The study indicated the role of precipitation as a major determinant of crop yield in humid tropical environments, while also emphasizing the value of geospatial techniques for continuous monitoring and climate-smart decision-making in agricultural management. These results support the growing body of literature advocating for integrated climate adaptation strategies in farming systems vulnerable to climate change.

4.0 Conclusion and Recommendations

This study employed geospatial techniques to assess the impact of climate variability on crop health and productivity at the FUTA Research Farm over eleven years (2012–2022). Analysis of vegetation indices (NDVI and GCI) revealed fluctuations in crop health, with notable increases between 2014 and 2016 and a decline from 2017 to 2019, followed by an improvement in 2021 and 2022. Correlation analysis indicated that precipitation had a strong negative influence on crop yield (-0.821), suggesting that excessive rainfall adversely affects agricultural productivity. Temperature, however, exhibited a weak negative correlation (-0.014), indicating minimal direct influence on yield variations. The findings highlight the critical role of precipitation in determining crop performance, emphasizing the need for effective water management strategies. This study underscores the importance of geospatial technologies in monitoring climatic influences on agriculture, providing valuable insights for sustainable farm management.

To mitigate the adverse effects of climatic variability on crop yield at the FUTA Research Farm, it is essential to implement improved water management strategies, including the development of efficient drainage systems to prevent waterlogging and optimize soil moisture levels. Additionally, the integration of geospatial technologies for continuous monitoring of vegetation indices and climatic parameters should be prioritized, enabling data-driven decision-making for sustainable farm management. Finally, further studies should be conducted to explore additional environmental factors influencing crop yield, such as soil fertility, pest dynamics, and topographic variations, to develop more comprehensive climate adaptation strategies.

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