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Analyzing vegetation health dynamics across Across Western Kenya through Normalised Difference Vegetation Index (NDVI) and climatic variables

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Abstract

Climate change is one the most pressing challenges facing humanity in today's world. It is primarily observed through the long-term, interconnected shifts in temperature, precipitation patterns, and an increase in extreme weather events such as floods and droughts. Climate change impacts communities in diverse ways ranging from the degradation of vegetation health thus affecting the sustainability of livelihoods in many communities Bungoma and Busia County of Kenya is endowed with various vegetation cover ranging from grasslands, forests and bamboo, however, the relationship between climatic changes and vegetation health remains under-researched. This study assesses the relationships between vegetation dynamics and climatic variations in Bungoma and Busia Counties from 1993 to 2023. Employing high-resolution Landsat data for Normalized Difference Vegetation Index (NDVI) assessments, integrated with climate variables from CHIRPS and TERRACLIMATE datasets, our approach leverages Google Earth Engine (GEE) and ArcGIS PRO 3.2 for efficient processing. It combines statistical methodologies, including linear regression, Mann–Kendall trend tests, Sen's slope estimator and partial correlation analyses. The study established a mean positive Mann Kendall Tau value of 0.100 for temperatures, and 0.0457 for precipitation. This reflects an increase in both precipitation and temperature of the study area and the increase trend was statistically significant at P= 0.0000. The study established a mean positive PDSI Tau value of 0.15 and an NDVI Tau value of 0.200 an indication of overall increase on vegetation cover and overall wetness of the region. The results revealed a negative relationship (r=-0.158469, P=0.00029) between NDVI and LST, (r=0.132497, P=0.00249) between NDVI and Precipitation and a (r=0.132478, P=0.002494) between NDVI and Standardised Precipitation Index (SPI) of the study area, highlighting that precipitation as a primary driver of vegetation growth while increased temperatures drives vegetation degradation thus illustrating its crucial influence in Bungoma and Busia counties. Our investigation further revealed the complex association between vegetation health and climatic factors, which varies spatially across different parts of the county. There is need to mitigate rising temperatures while supporting increased precipitation in the region for enhanced vegetation health of the region.

Keywords

Climate Change, Normalised Difference Vegetation Index, Palmer Drought Severity Index

Introduction

Climate change is one the most pressing challenges facing humanity in today's world. Climate change drives instability in the ecology and human survival through phenomena such as droughts, floods and temperature rises [Jung, 2024], changes that are anticipated to increase in the future [Westley *et al.,* 2023]. Historically, climate change was driven by natural phenomena whereas current changes are associated with human activities [Kim et al., 2012]. East Africa's forests, have suffered severe encroachment and exploitation due to the long history of human settlement and population pressure [Riggio et al., 2019]. Mwangi et al. [2018] attribute forest degradation to agricultural expansion into forest lands for subsistence and commercial agriculture, unsustainable harvesting and trading of wood products. Kenya's forest cover decreased from 3.7 million to 3.4 million hectares between 1990 and 2010, a decline that impacted the climatic conditions of the region [FAO 2010].

Global and regional climate change often affects vegetation growth, which alters its structure and function [Mehmood et al 2024]. Similarly, vegetation can also positively affect the corresponding climatic conditions of a region [Vélez et al 2023]. Vegetation health and their responses to climate variation have become critical area of research in global change research [Andreevich et al. 2020]. Vegetation is vital in providing for essential ecosystem services ranging from preservation of climate equilibrium, sustaining the hydrological cycle and carbon equilibrium, and modifying land surface characteristics [Aslam et al 2022]. Akram et al. [2022] indicated that there is need for in depth research on the intricate connection between vegetation distribution, health and factors like climate change, human activities, elevation, and edaphic factors.

Various climatic such as precipitation and temperatures influence spatial temporal variations in vegetation distribution and health [Ren et al. 2023]. Temperature and precipitation changes can affect photosynthesis and respiration rates of vegetation. Increased precipitation and precipitation could lead to rapid vegetation growth rates in the tropical lowlands yet have a negative effect on vegetation at the mountain picks and in the polar regions. In contrast, inadequate precipitation could restrict vegetation growth and development in arid and semi arid regions. [Mehmood et al 2024]. Analysing spatial and temporal patterns in climatic variables could provide enhanced insight into how Earth's ecosystems adapt to global changes and the potential environmental or economic impacts.

In Kenya, widespread areas of the country have experienced significant temperature increase. Between 1985-2015 temperatures changed from 0.6^{o} to 1.0 ^{o} C [Vigren, 2017], coupled with declines in annual rainfall amounts at a rate of −0.93 mm/year [Mumo et al., 2019]. These changes in the climate have been exacerbated at the microclimate level by human-induced factors such as land use changes and deforestation driven by population increase [Muhati et al., 2018]. These alterations impact ecosystem goods and services which large human and animal populations are dependent on. The equatorial counties of Bungoma and Busia in western Kenya are agricultural zones that contribute to the country's breadbasket [Lupao, 2016] are particularly vulnerable to these climate change impacts. These counties are experiencing adverse effects of climate change on crop and livestock production [Nalianya, 2023; Sorre, 2017; Sorre et al., 2017].

Despite numerous studies addressing climate variabilities in Kenya, a detailed Spatio-temporal examination of vegetation dynamics and its relationship to with vegetation health of Bungoma and Busia Counties remains scarce. This information is very critical since these counties enjoy varying topography, vegetation types, and diverse human communities that influence and are influenced by climatic conditions of the region. Given that future climate warming, it is crucial to investigate the interrelationships between vegetation health and climatic variations. This understanding is essential for developing and implementing evidence-informed and sustainable landscape-scale practices that are effective at both the regional and global contexts. This study investigates the link between climatic changes and vegetation health in Bungoma and Busia Counties of western Kenya. Specifically, we addressed four research questions: (1) What are the variations and trends in precipitation, temperatures, Palmer Drought Severity Index and vegetation health in Bungoma and Busia County between 1993 and 2023 (2) What are the linkages between climatic variabilities and vegetation health in Bungoma and Busia County between 1993-2023.

Materials and Methods

Study Area

The study covered the entirety of Bungoma and Busia counties of Kenya renowned for its wide-ranging landscapes and climates, leading to a vast array of vegetation types. Busia County is located in western Kenya between latitude 0º 00' and 0º 45'N and longitude 34º 25'E and covers about 1,695 km^2. It falls under the Lake Victoria Basin that supports over 25 million livelihoods

[Onyango and Opiyo, 2021]. The county's elevation varies from about 1,130 m above sea level on the shores of Lake Victoria to a maximum of about 1,500 m in the Samia and North Teso Hills [Busia County Government, 2023]. Administratively, Busia is divided into seven sub-counties, 35 wards, 60 locations and 181 sub-locations. Busia borders Siaya to the south-west, Bungoma to the north, Kakamega to the east, Lake Victoria to the south-east and Uganda to the west [Busia County Government, 2023]. As of 2019, the county had a population of 893,653 with 467,401 (52.30%) female and 426,252 (47.70%) males [KNBS, 2019]. The climate is warm with a mean annual temperature ranging from 21-27°C [Wanyama, 2018]. Rainfall patterns vary across the county with areas near Lake Victoria receiving the least rainfall of about 760-1,015 mm and regions near the highlands such as Butula and Nambale receive the highest rainfall of up to 2,000 mm. The rainfall pattern is bimodal with long rains occurring between March and May, and short rains between August and October [Atsiaya et al., 2022].

Bungoma County lies within the Lake Victoria Basin between latitude 00 28ºN and latitude 10 30ºN of the equator, and longitude 34º 20'E and 35º 15'E. The county covers an area of 3,024 km^2 at an altitude ranging from 1,200 to 4,321 m above sea level [Munyao *et al*., 2022]. The annual temperature ranges from 0°C and 32°C and a mean annual temperature of 20.3°C [Bungoma County Government, 2023]. The annual rainfall varies from 400mm to1,800 mm. The county experiences two rainy seasons, with long rains from March to July and short rains from August to October. Bungoma County hosts the trans-boundary Mt Elgon forest. The main economic activities in both counties are crop farming, livestock farming and fishing [Sorre, 2017; Chenge, 2015]. Figure 1 below shows map of the study area.

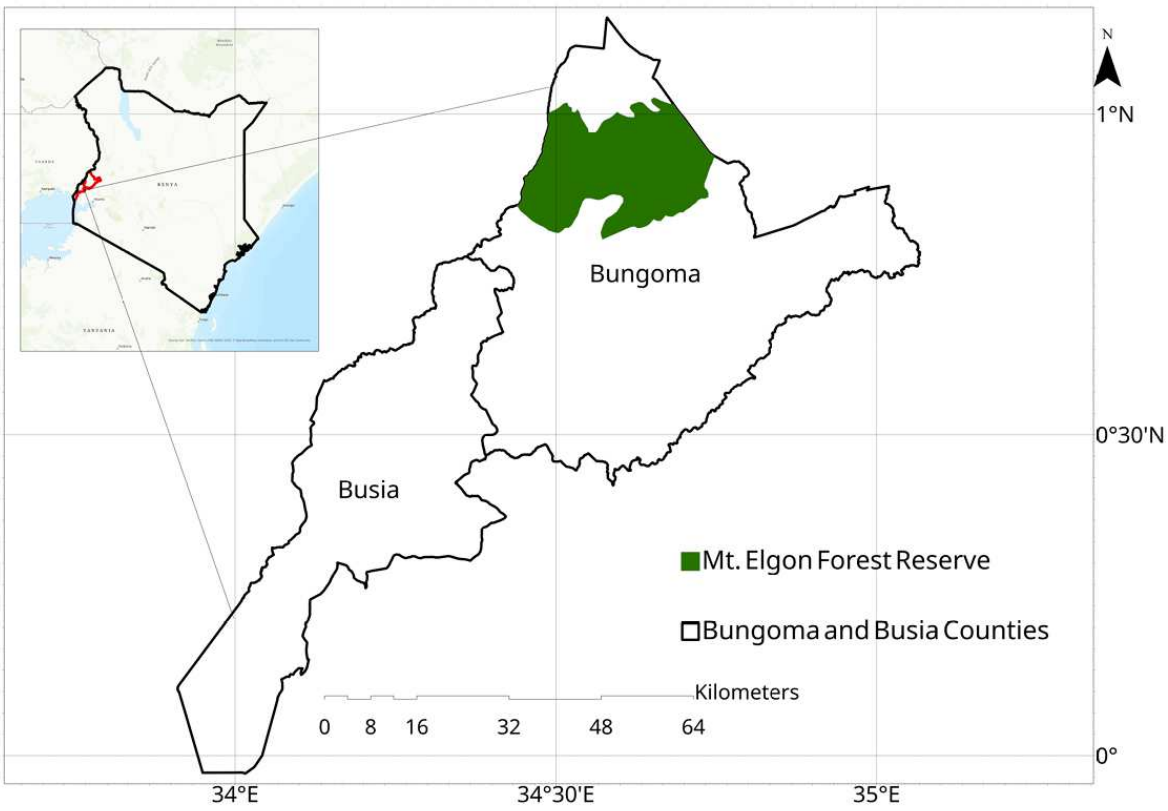


Figure 1: Map of the Study Area

Data Source

Precipitation data was collected from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) website. CHIRPS is a high-resolution pentadal precipitation dataset [Funk et al., 2015]. Temperature data and the Palmer Drought Severity Index (PDSI) was obtained from the TERRACLIMATE data portal. PDSI and Standardized Precipitation Index (SPI) was used to establish trends in the drought and moisture conditions of the study area. The data was analysed annually between 1993 and 2023. It was downloaded using Google Earth Engine (GEE) and analysed and visualised using ArcGIS Pro 3.2 and Microsoft Excel.

The formula for PDSI

Equation (1)

Recursive Formula: $X_i = 0.897 * X_{i-1} + Z_i/3$.

It uses current moisture anomaly ((Z_i) and the previous month's PDSI (X_{i-1}) to track cumulative severity, where (Z_i is a product of climatic weighting and moisture deviation.

X_i (PDSI): Represents the severity of drought (\(<0\)) or wetness (\(>0\)).

X_{i-1} : Index from the previous month (representing persistence).

Z_i (Moisture Anomaly Index): The difference between actual precipitation and "Climatically Appropriate for Existing Conditions" (CAFEC) precipitation, adjusted for the region

Moisture Anomaly Z_i: = K_i*D_i, where D_i is the moisture departure from normal ((P - P^) and K_i is a weighting factor.

Water Balance Equation: P = ET + R + ΔS, where P is precipitation, ET is actual evapotranspiration, R is runoff, and ΔS is the change in soil moisture.

The formula for Standidised Precipitation Index

Equation (2)

SPI_i=(X_i-X)\ϵ_x

X_i: Current precipitation total for the period.

X: Long-term mean precipitation for the period.

ϵ_x : Standard deviation of precipitation for the period

SPI_i-Standardised Precipitation Index

To establish trends in vegetation health, NDVI was generated from satellite images acquired from the United States Geological Survey (USGS)website were analysed for each year from 1993 to 2023. For the years 1993-2000, Landsat 5 images were used and a median of one image derived for each year. For 2000-2013, Landsat 7 images were used while for 2014-2023, at 8 images were used. Using GEE and ArcGIS Pro, the images underwent preprocessing, which included, cloud removal, cloud masking, clipping and compositing based on the area of study. The images were then merged to generate images that give trends in NDVI FROM 1993-2023. To determine vegetation health, the Normalized Difference Vegetation Index (NDVI) was used. NDVI is a popular satellite-based index used for monitoring vegetation health over large areas [Kumar et al., 2022] and has been widely applied to investigate the effects of climate change on vegetation [Rojas *et al*., 2011]. The NDVI values range from −1 to +1, with water bodies having negative values, bare soil having a value around zero, and plants having a positive value [Lillesand et al., 2015].

The formular for NDVI

Equation (3)

NDVI= ({NIR}-{Red}/{NIR}{Red})

Where

NIR=(Near-Infrared): Strongly reflected by healthy vegetation.

Red= (Visible Red): Strongly absorbed by chlorophyll in healthy vegetation.

The Mann–Kendall test was used to analyze spatial trends in NDVI, precipitation, temperature, Palmer Draught Severity Index and standardised Precipitation Evaporation Index measurements within the study area. A negative Tau value indicates a downward trend while in contrast, a positive Tau value indicates an upward trend. A statistically significant 5% confidence level trend is signal led by a Z value beyond ± 1.96. The Mann Kendall test was used to assess whether there is a an increasing or decreasing trend in Climatic Variables and vegetation health in the study region. Correlation analysis was used on sampled points to determine relationships between climatic variables and NDVI using GEE and visualised using ArcGIS PRO.

Results

Trends in Climatic Variables

Variations were noted in the total amount of precipitation recorded between 1993 and 2023. The year 1993 recorded a total annual precipitation of 1382.34 mm followed by 2004, 2000 and 2009 with 1427.45 mm, 1434.20 mm and 1436.60 mm respectively. The year 2020 recorded the highest amount of precipitation with 2720.00 mm followed by 2010, 2007 and 2012 with 2025.20 mm, 1952.87 mm and 1947.46 mm respectively. Over the period 1993 to 2023, the mean precipitation was 1754.99 mm (Figure 2). Based on a linear equation, there was a 12.66mm per annum rise in precipitation in the study area which translated to a 24.03% rise in precipitation from 1993 to 2023.

The study established variation in mean minimum and mean maximum temperature between 1993 and 2023. The year 1993 saw a mean minimum annual temperature of 12.91°C while 2023 a mean minimum temperature of 14.31°C. Over this period, the lowest mean minimum temperature was recorded in 1994 at 12.57°C. The highest mean minimum temperature was recorded in 2002 at 14.51°C. Other years that recorded high minimum temperatures were 2019 and 2023 at 14.41°C and 14.31°C, respectively. Variations were also reported in mean maximum temperatures with the highest being recorded in 2019 (28.47°C). Variations were also reported in mean maximum temperatures with the highest being recorded in 2019 (28.47 ºC). Other years that reported high mean maximum temperatures were 2020 (28.40ºC) and 2009 (28.23ºC). The lowest mean maximum temperatures were reported in 2018 at 27.08ºC (Figure 2b). The linear trend lines revealed a 0.0214ºC annual increase in maximum temperature and a

0.0285°C increase in minimum temperature between 1993 and 2023. This translates to 0.723 ° C increase in maximum temperatures and 0.86 °C increase in minimum temperature over the thirty-year period.

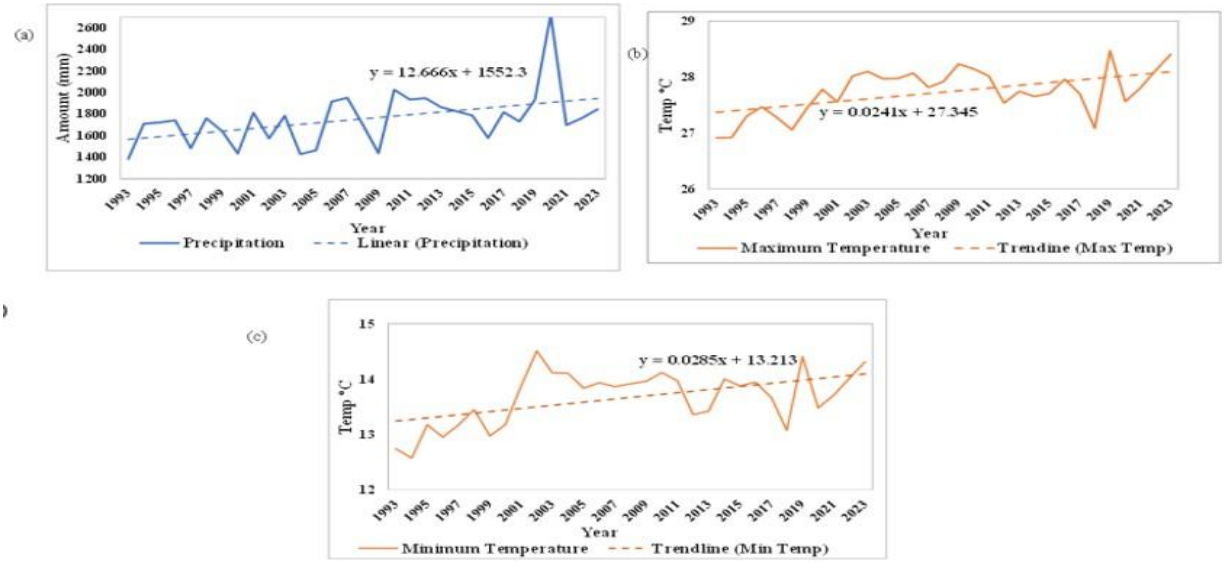


Figure 2: Trends in climatic variables between 1993-2023 with (a)Precipitation (b)Maximum Temperatures and (c)Minimum Temperatures.

The Mann Kendall test is a widely used method for detecting trends in time series data, particularly in climate variables. It assessed whether there was a significant monotonic trend, which could be either increasing or decreasing trend in climatic variables over the 30-year period from Bungoma and Busia counties of western Kenya. The study established a mean positive value of 0.100 in Mann Kendall's Tau values for temperatures and 0.0457 for precipitation (Figure 3 a&b). This reflects an increase in both precipitation and temperature of the study area and the increase trend was statistically significant as evidenced by a p-value of 0.000 which is below the 0.05 threshold [alpha value].

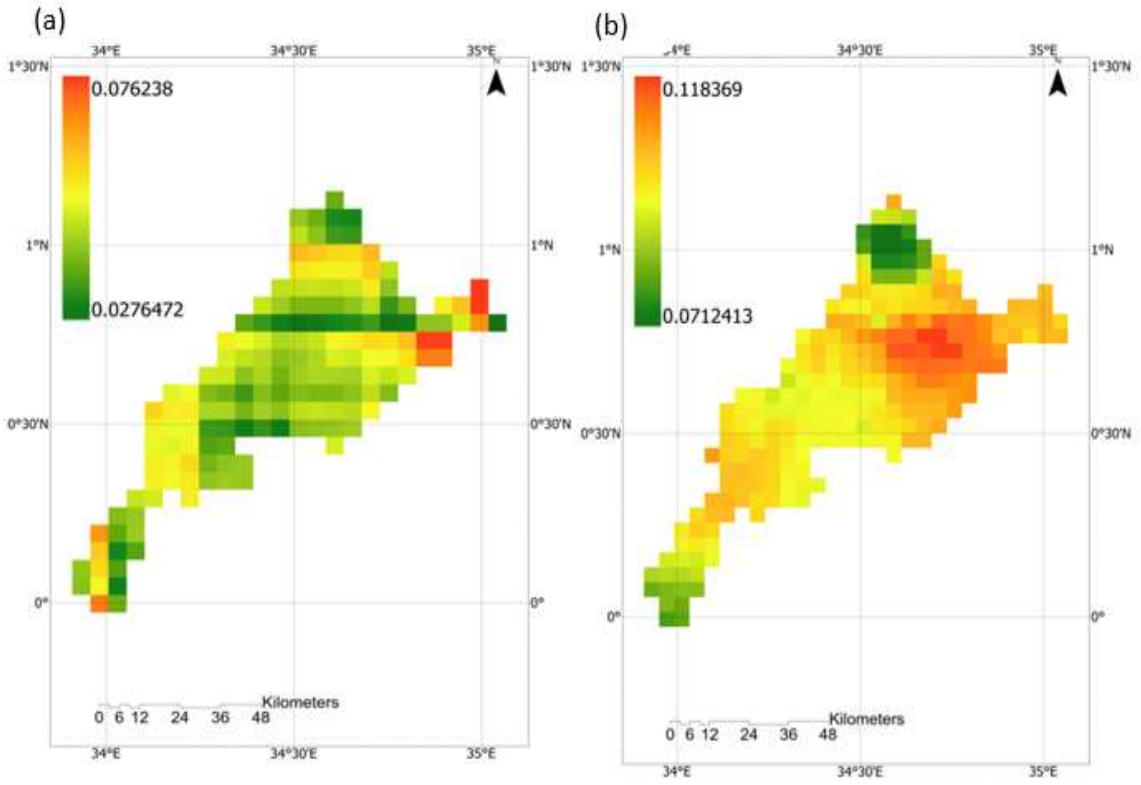


Figure 3. Trends in Mann Kendall Tau Values between 1993-2023 with [a]Precipitation [b] Temperatures.

The study established that the region had four seasons: December-January-February (DJF), March-April-May (MAM), June-July-August (JJA) and September-October-November (SON). The highest mean seasonal precipitation was reported during MAM at 616.78 mm for the period 1993-2023. Over the period MAM, the total precipitation amounts varied, with the lowest recorded at 462.45 mm for 2004 and the highest at 883.19 mm for 2018. The linear equation established that MAM saw a 3.26mm annual increase and an 17.15% increase in precipitation between 1993 and 2023. This was followed by SON with a seasonal mean precipitation of 502.67 mm. The season recorded the lowest precipitation in 1993 with a total of 286.16 mm and the highest precipitation in 2020 with a total of 836.93 mm. Based on the linear equation, SON recorded a 4.738mm annual increase in precipitation and 33.05% increase in precipitation between 1993 and 2023 (Figure 4a). The season JJA recorded a mean seasonal precipitation of 434.14 mm. The season received the highest amount of precipitation in 2020 with a total of 654.62 mm and the lowest in 2009 with a total of 296.43 mm. The linear equation revealed an annual increase of 3.21mm and a 25.05% increase in precipitation during the thirty-year JJA season (Figure 3b). DJF recorded a mean seasonal amount of 201.404 mm. The highest amount of precipitation was in 2010 with 451.46 mm; the lowest was in 1999 with 95.29 mm. Based on the linear equation, DJF saw an annual increase of 1.09mm and an 17.65%

increase in precipitation over the thirty-year period (Figure 4b). The highest increase in seasonal precipitation was recorded in SON while the lowest increase was in DJF.

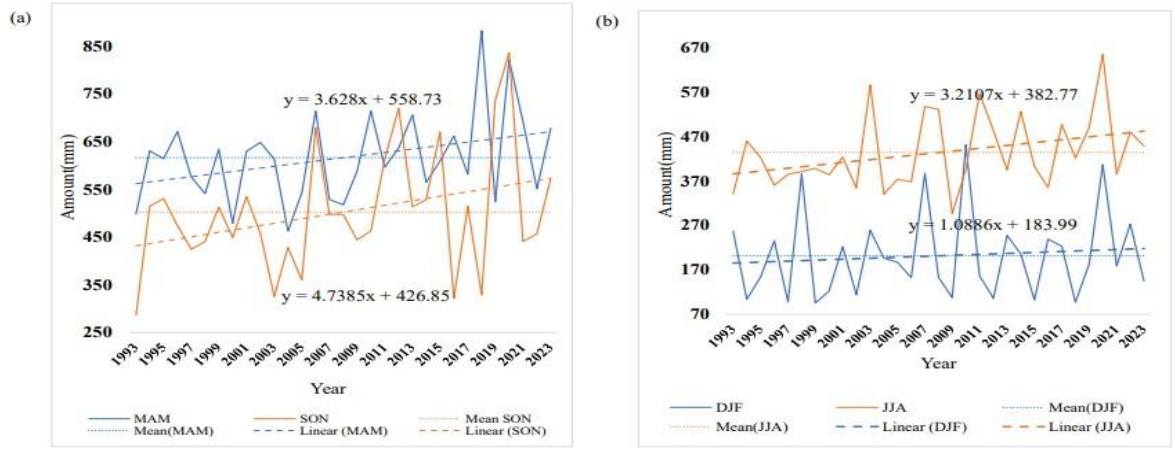


Figure 4: Seasonal variation in precipitation with (a) MAM and SON and (b)JJA and DJF

Seasonal variations in mean maximum temperatures were observed. DJF saw a mean maximum temperature of 29.03°C for the 30-year period. MAM recorded 28.07°C and SON 27.44°C, while JJA reported the lowest mean temperatures, 26.38°C, for the season. The study revealed increases in mean annual maximum temperatures with MAM recording a 0.57°C increase, SON a 0.69°C increase, DJF a 0.82°C increase and JJA a 0.82 °C increase. The mean minimum temperatures also varied based on the seasons. MAM recorded the highest mean annual minimum temperatures for the 30-year period at 14.23°C, followed by DJF at 13.66°C. SON recorded a mean annual minimum temperature of 13.49°C, while JJA recorded 13.29°C. The highest mean minimum seasonal temperature increase was recorded in DJF at 0.95°C. This was followed by MAM (0.83°C) SON (0.83 °C) and JJA (0.80 °C).

Trends in Palmer Drought Severity Index

The mean PDSI for the study area for the 30-year period was 0.012 which can be classified as normal condition. The highest PDSI was recorded in 2013 with a PDSI value of 6.3 which is very wet. High PDSI were also recorded in the year 2020 [6.19] and 2018 with PDSI of 3.93. The linear trend line revealed that the PDSI of the region has been increasing at a rate of 0.095 per annum for the last 30 years an indication that the region has become wet over time (Figure 5a). The study established a mean positive PDSI value of 0.15 in Mann Kendall's Tau values for the 30-year period. This signified a significant monotonic increasing trend in PDSI over the 30- year period indicates a shift towards positive conditions in the region. The trend was

statistically significant as evidenced by a P-value of 0.000 which is below the 0.05 threshold (alpha value). Areas around Bungoma town recorded high increasing trend in PDSI as compared to the area around the eastern part of Mt. Elgon and areas adjacent to Lake Victoria (Figure 5a & b).

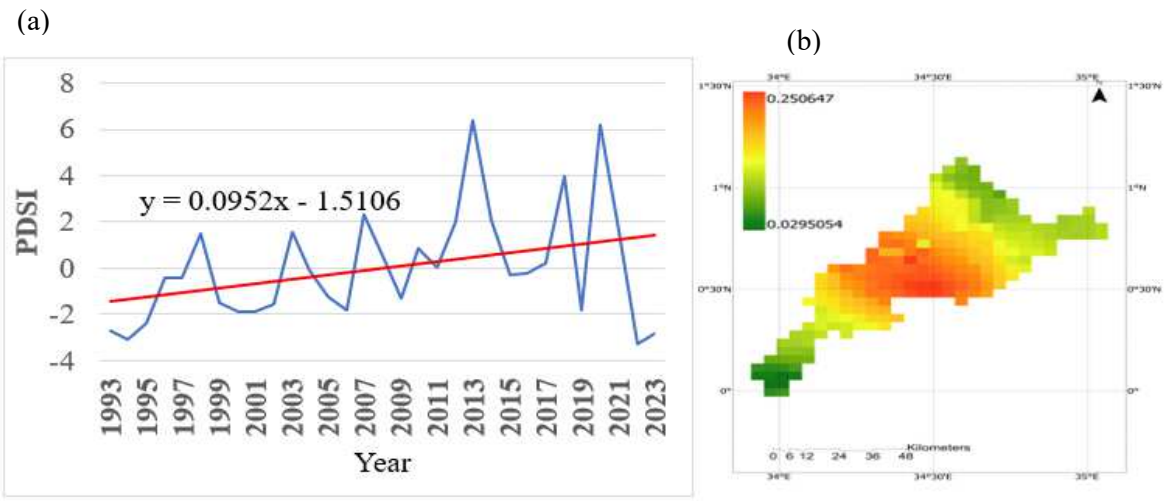


Figure 5: Trends in PDSI (1993-2023) with (a)linear trend and (b)PDSI Tau values

Trends in NDVI

The study area recorded a mean NDVI value of 0.53 for the 30-year period. The highest NDVI was recorded in the year 2013 with a mean NDVI value of 0.6. Other year that recorded high NDVI were 2009 with (0.58) and 2020 with (0.58). The lowest NDVI was recorded in the year 2019 and 2006 with 0.45 and 2009 with 0.46.

The results of this study further revealed a 0.2 in Mann Kendall NDVI Tau values an indication of overall improvement in vegetation health over the 30-year period. The Sen's Slope revealed that several areas of the study area revealed trends of degradation with areas on the base of Mt Elgon and in urban areas such as Bungoma town being the most affected by the degradation (Figure 6 a, b & c). Large area within the Mt. Elgon Forest ecosystem is revealing some slight greening. The southern parts of Busia County and some western parts of Bungoma county are experiencing significant vegetation greening. The increase in Nature based Solutions, particularly afforestation within the Mt. Elgon Forest and Samia hills in Busia County could explain the increased greening of vegetation health in the region

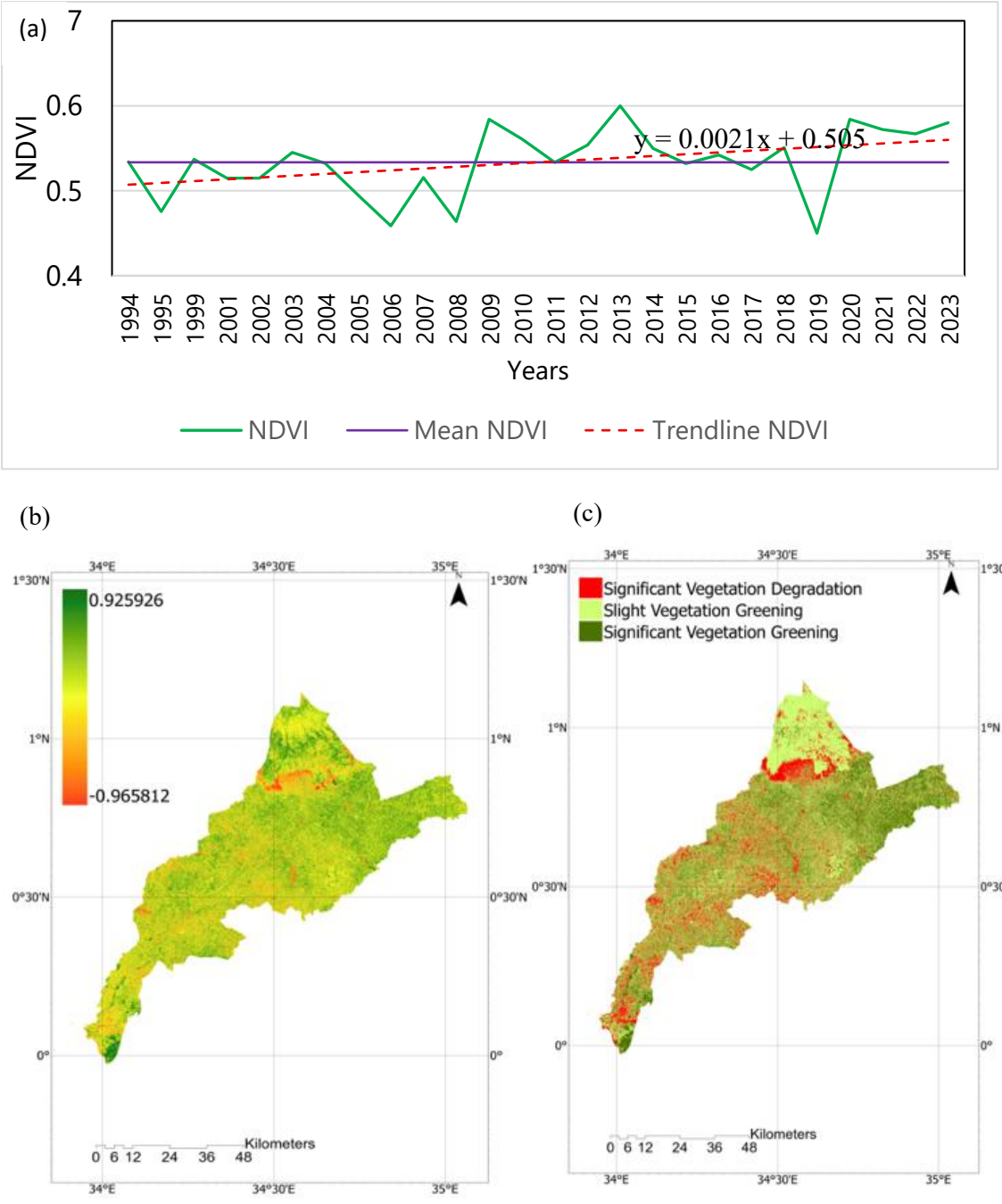


Figure 6: Trends in NDVI with (a) linear trends (1993-2023) (b)NDVI Tau values and (c) Sen's Slope

Relationship between Climatic Variables and Vegetation Health

a) Land Surface Temperature and Vegetation Health

The correlation between temperature and NDVI concentrations over the 30 years from 1993 to 2023 was analyzed by using Pearson correlation coefficients between temperature and NDVI. Correlation measures the strength and direction of a linear relationship between two variables. In the context of Land Surface Temperatures and NDVI. The results revealed a negative relationship (r=-0.158469, P=0.00029) between NDVI and LST in the study area an indication that increase in LST was related to decline in vegetation health (NDVI) (Figure 7). The relationship was significant.

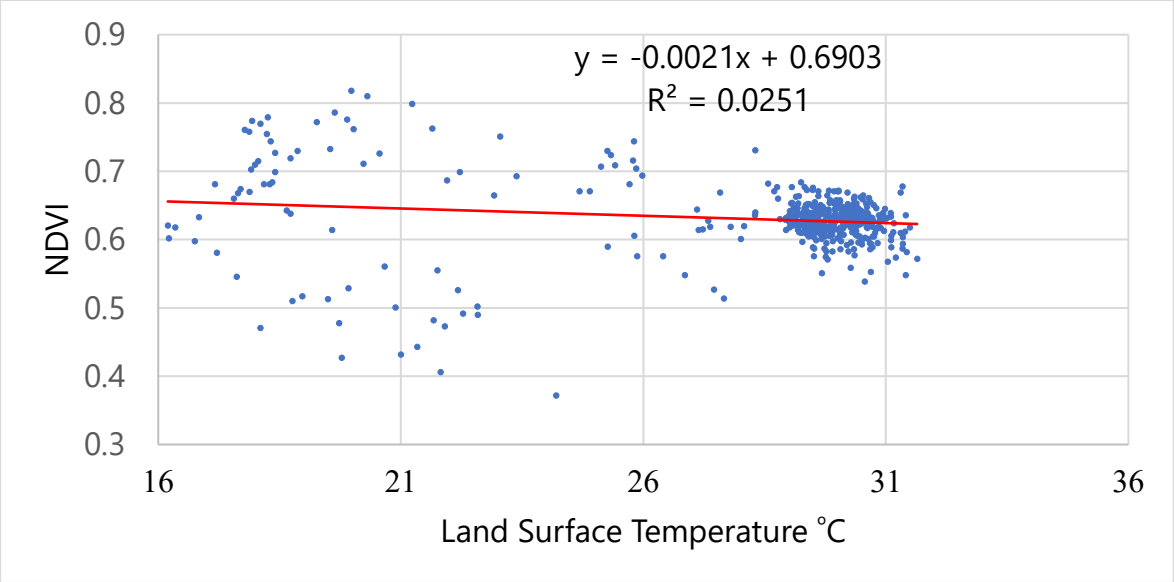


Figure 7: Relationship between Land Surface Temperature and NDVI

Precipitation and Vegetation Health

Similarly, correlation analysis was carried out to establish relationship between Precipitation and NDVI. The results revealed a significant positive relationship (r=0.132497, P=0.00249) between NDVI and Precipitation in the study area an indication that increase in precipitation was related to increase in vegetation health (NDVI) . Similar correlation analysis was carried out to establish relationship between Standardised Precipitation Index (SPI) and NDVI. The results revealed a positive relationship (r=0.132478, P=0.002494) between NDVI and SPI in the study area an indication that increase in SPI was related to increase in vegetation health (NDVI). The study further established that there was no significant relationship between NDVI and PDSI (Figure 8a, b & c)

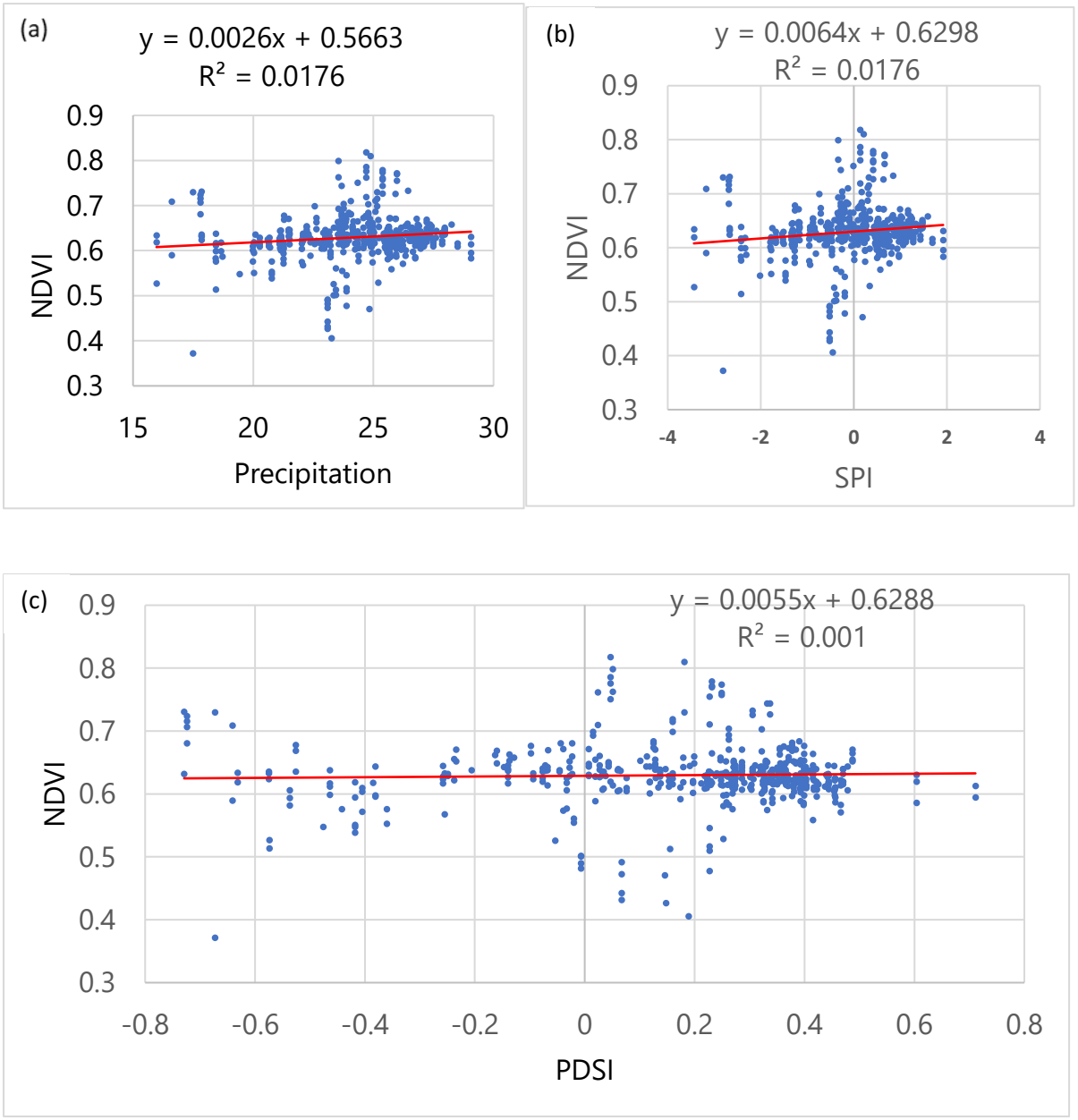


Figure 8. Relationship between NDVI and (a)Precipitation, (b) SPI and (c)PDSI

1.4 DISCUSSION

1.4.1 The Relationship between Climatic Variables and Vegetation Health

The results of the changes in vegetation health over the 30-year period show that there was an overall improvement in vegetation health across the region. However significant vegetation degradation was noted in areas around Mt Elgon forest ecosystems and in Urban areas such as Bungoma town. Significant gains were noted in the lower parts of Busia County especially in areas adjacent to Lake Victoria and Samia hills. Anthropogenic activities particularly agriculture expansion and human settlement on the base of Mt Elgon Forest could explain this deterioration of vegetation health on the buffer of Mt. Elgon Forest. The Kenya forest Act of

2005 introduced participatory forest management on the buffer of Mt Elgon forest as a mechanism to conserve the forest ecosystem. This study however establishes the minimal contribution of this approach to the conservation of the forest ecosystem. The limited spatial extent of the PELIS agroforestry project within forest areas [covering on 0.22% of the study area] suggests its minimal direct impact and concentration within the forest region. Akotsi et al. [2009] also reported no significant changes in forest cover within Mt Elgon region between 2005 and 2007, despite the presence of a legislative framework for participatory forest management.

Over the same period of time, the study established an increase in temperatures, precipitation and PDSI. The study further demonstrated a positive correlation between precipitation and NDVI and a negative correlation between precipitation and Land surface temperatures indicating that increase in precipitation and PDSI withing the region could have contributed to improved vegetation health. The study further reported slight improvement in vegetation health especially within the Mt Elgon forest The study attributed the rise in precipitation to afforestation and agroforestry programmes undertaken by many of the Nature based Solutions (NbS) within the study area. The variety of Nature based Solutions such as afforestation, agro-forestry within the regions and increased precipitation could partly explain the improved vegetation health in this region. The increased precipitation was further linked to improved vegetation health. Githui et al. [2009] reported an increase in precipitation from 2.4% to 23.2% between the 1970s and 2008 in Western Kenya. Niang *et al*. [2014] agree that temperatures are rising in Africa with the Intergovernmental Panel on Climate Change [IPCC] predicting higher temperature increases in the Africa than the global mean rise. In Pakistan, temperature and precipitation were reported to influence changes in vegetation[Anees et al. 2022]. Similarly, Mehmood et al. [2024] observed that precipitation and temperature are critical in vegetation's growth and decline.

Garai et al. [2022] demonstrated similar results by reporting a direct relationship between rainfall and NDVI in Eastern India, and an inverse relationship between NDVI and land surface temperature. Rainfall directly affects plant growth and water stress, thus influencing the NDVI values [Garai et al., 2022]. Meneses-Tovar [2011] further supports these findings noting that the highest NDVI values are typically associated with high-and medium-altitude rainforests and mountain forests, and they can be linked to the evergreen nature of the ecosystem.

Raymond and Spoehr [2013] agree that climatic variables significantly influence vegetation cover and overall ecosystem health.

This study established a s positive correlation between vegetation health and SPI values. The results agree with Shakirudeen *et al.* [2021] who indicate that African vegetation remains highly vulnerable to drought impacts and that the changing climate heightens this. In China, Wang et al. [2016] established a positive relationship between NDVI and SPEI, suggesting that vegetation in arid and semiarid area was significantly affected by droughts.

1.5 Conclusion

Bungoma and Busia Counties have reported an increase in precipitation, temperature, PDSI and SPI within the 30-year period. Increase in precipitation is partly associated with the increase in forest cover in the region facilitated by the government of Kenya and other organisations that support the adoption of Nature based Solutions. There an increase in temperature and precipitation especially within urban centers an indication that human activities such as urbanization could be partly contributing to increased temperatures in the study area. The study observed a period of forest health decline especially on the base of Mt Elgon. The decline was associated with the introduction of agricultural activities especially the Nyayo Tea plantations. The study further revealed that a significant positive correlation between precipitation, SPI, PDSI and NDVI and a negative correlation between temperatures and NDVI. These findings suggest that for an enhanced vegetation health in the region there is need for increased precipitation, SPI and PDSI. Mitigate rising temperatures while supporting increased precipitation in the region can be partly achieved if Nature based Solutions such as afforestation are adopted in the region.

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CrediT authorship contribution statement

Nelly Masayi: Writing – review & editing, Writing – original draft, Visualisation, Methodology, Investigation, Formal analysis, Data curation, Conceptualisation.

Daniel O. Olago: Writing – review & editing, Supervision, Funding acquisition.

Declaration of Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Dr. Nelly Nambande Masayi reports financial support was provided by DAAD Global Centers – African Climate and Environment Center – Future African Savannas.

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Legend

Figure 1: Map of the Study Area

Figure 2: Trends in climatic variables between 1993-2023 with [a]Precipitation [b]Maximum Temperatures and [c] Minimum Temperatures.

Figure 3. Trends in Mann Kendall Tau Values between 1993-2023 with [a]Precipitation [b] Temperatures.

Figure 4: Seasonal variation in precipitation with [a] MAM and SON and [b]JJA and DJF

Figure 5: Trends in PDSI [1993-2023] with [a]linear trend and [b]PDSI Tau values

Figure 6: Trends in NDVI [1993-2023] with [a]linear trend and [b]NDVI Tau values

Figure 7a: Relationship between Land Surface Temperature and NDVI

Figure 7b: Relationship between Precipitation and NDVI

Figure 7c: Relationship between Standardized Precipitation index and NDVI

Figure 7d: Relationship between PDSI and NDVI