Journal of Geoscience and Environment Protection, 2024, 12, 54-69
https://www.scirp.org/journal/gep
ISSN Online: 2327-4344
ISSN Print: 2327-4336

Spatio-Temporal Variability of Rainfall and Temperature and Their Effects on Pasture Variability over East Africa: Implication on the Cattle Grazing Areas

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How to cite this paper: Peter, N., Wen, W., Matthews, N., Aina, R. S. N., & Donnata, A. (2024). Spatio-Temporal Variability of Rainfall and Temperature and Their Effects on Pasture Variability over East Africa: Implication on the Cattle Grazing Areas. *Journal of Geoscience and Environment Protection, 12,* 54-69.
https://doi.org/10.4236/gep.2024.123004

Received: January 19, 2024
Accepted: March 18, 2024
Published: March 21, 2024

Abstract

Understanding the spatiotemporal variability of climatic parameters and their effects on pasture variability is vital for pasture management interventions over East Africa. The present study aims to assess the spatial-temporal variability of rainfall, temperature and Normalized Difference Vegetation Index (NDVI) (which is being used to assess pasture quality and productivity) over the region, between the period of 1982 and 2019. This study used annual mean values for rainfall, temperature and NDVI which were calculated for the period mentioned above. NDVI was derived from National Oceanic and Atmospheric Administration (NOAA) Global Area Cover (GAC) (NOAA-07-GAC) data. The rainfall data was acquired from the Climate Hazards Group Infrared Precipitation with Station (CHIRPS) while temperature is ERA5 reanalysis data sourced from the European Centre for Medium-Range Weather Forecasts (ECMWF). The study utilized the empirical orthogonal function (EOF) to identify patterns and dominant relationships between the climate variables. The correlation was calculated between rainfall, temperature and NDVI to assess the relationship among them. A non-parametric Mann-Kendall trends test was used to determine whether annual precipitation, temperature and NDVI had statistically increasing or decreasing trend. Results revealed a positive correlation between rainfall and NDVI while a negative correlation between NDVI and temperature. Positive correlation between rainfall and NDVI indicates that pasture health (quality and productivity), will improve accordingly. A negative correlation between temperature and NDVI indicates that pasture health will decrease with increase in temperature while improving with decreasing temperature. Outcome from this study suggests that changes in climatic variables influence the distribution of pasture in East Africa's cattle grazing areas. The study hence recommends prioritisation of climatic (weather) information during pasture management over East Africa.

Keywords

NDVI, Climatic Parameters, EOF, Pasture, East Africa

1. Introduction

The response of vegetation to climatic conditions has become a hot topic in the East Africa and the globe at large (Afuye et al., 2021; Xu et al., 2023; Zhao et al., 2022). Vegetation, the main component of terrestrial ecosystems, plays an important role in the carbon cycle of terrestrial ecosystems (Tian et al., 2020; Whitlock & Bartlein, 1997). Dynamic monitoring of vegetation change allows us to assess ecosystem quality and reveal the effects of environmental change on the ecosystem (Payette et al., 1989). Therefore, a number of studies have monitored the spatio-temporal changes in vegetation at different spatial scales using long time series satellite remote sensing data (Tian et al., 2020; Wang et al., 2020). Due to the non-linearity and non-stationarity of vegetation change, more recent studies have investigated vegetation change from the perspective of different time series, focusing on monitoring long-term trends in vegetation change (Jiao et al., 2020). In this study, the vegetation being looked at is specifically pasture. Its variability mainly being influenced by rainfall and temperature is closely related to hydrothermal conditions, making it an ideal choice for considering the relationship between climate and pasture variability (Deaton, 2022; Walter et al., 2012).

The study aims at unravelling the microscopic relationships between climate variables and cattle grazing conditions (Reich, 2013). It critically has the potential to increase agricultural resilience, inform sustainable land management practices (FAO, 2003; Funk et al., 2015), and contribute to global efforts to address climate change impacts on ecosystem and livelihoods. In addition, the impact of climate change on herders is the loss of livestock, which results in reduction in the food supply to the ever increasing population, especially in Africa (Ayanlade & Ojebisi, 2019; Wang et al., 2020; Kumar et al., 2023; Zhong et al., 2019). Other studies have also shown that the reductions in the number of cattle are due to death caused by lack of green pasture during extreme drought events, disease and starvation, as herders do not have enough fund to buy processed food for the cattle (Kabonesa & Kindi, 2013; Ojima et al., 2017; Roever et al., 2016). Nonetheless, the response of herders to climate change varies greatly due to differences in their adaptive capacities (Grothmann & Patt, 2005; Martin et al., 2008).

Most of the studies in this region have done a very tremendous work as far as climate change is concerned, several others address the issue globally with little or no consideration given to the variability of rainfall and temperature and their effect on pasture variability in East Africa, especially its impacts on cattle grazing (Nimusiima et al., 2018; Zhang et al., 2022). Also, accounts of the effects of rainfall and temperature on green pasture which is food to the livestock for traditional pastoralists are missing.

This current study is the first to investigate the relationship between rainfall, temperature and NDVI in the East African region. The study adds value by providing a comprehensive, data-driven analysis of the spatial and temporal patterns of climate variability and quality of pasture if one or more of the potential gaps are addressed. The contributions span a variety of areas, including scientific understanding, policy formulation, and potential methodological improvements in environmental research.

2. Data and Methodology

2.1. Study Area

The study area is East Africa, made up of Kenya, Tanzania, Uganda, Rwanda and Burundi mostly located over the eastern part of the African continent. It is known for its diverse cultures, stunning landscapes and lies alongside the equator. It is bounded by latitudes 6˚N and 13˚S and longitude 28˚E and 43˚E (**Figure 1**). It is bordered by South Sudan and Ethiopia in the North, Somalia in the North East, The Indian Ocean in the East, and Mozambique in the south, Malawi in the south West, Zambia and Democratic Republic of Congo on the western side.

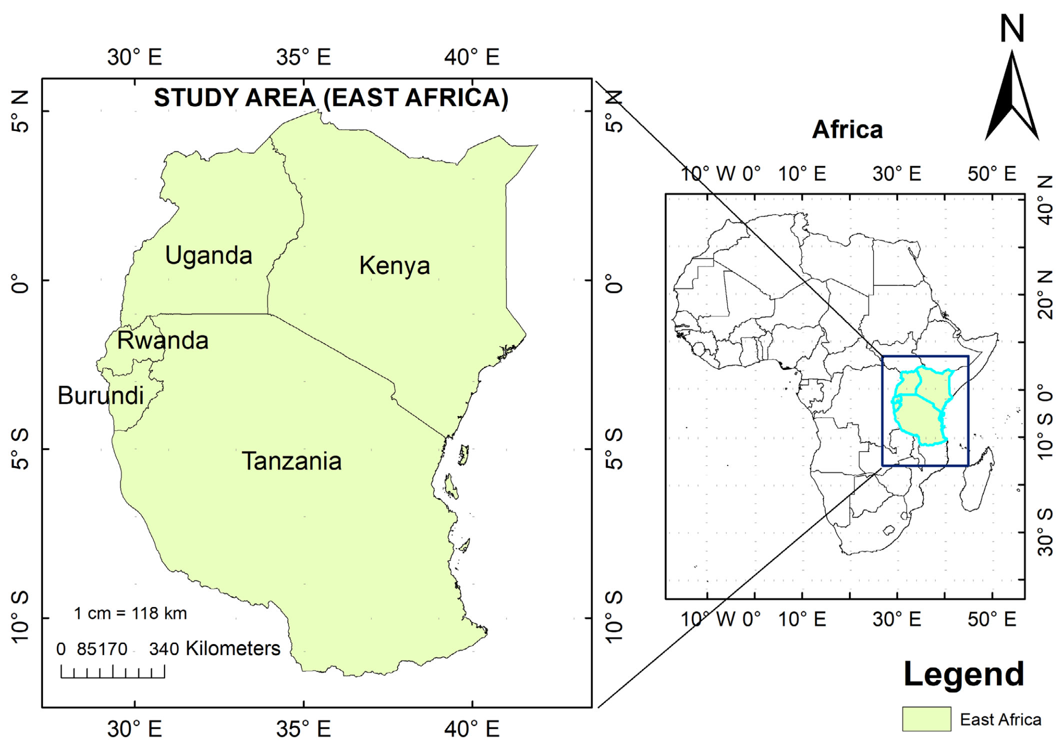
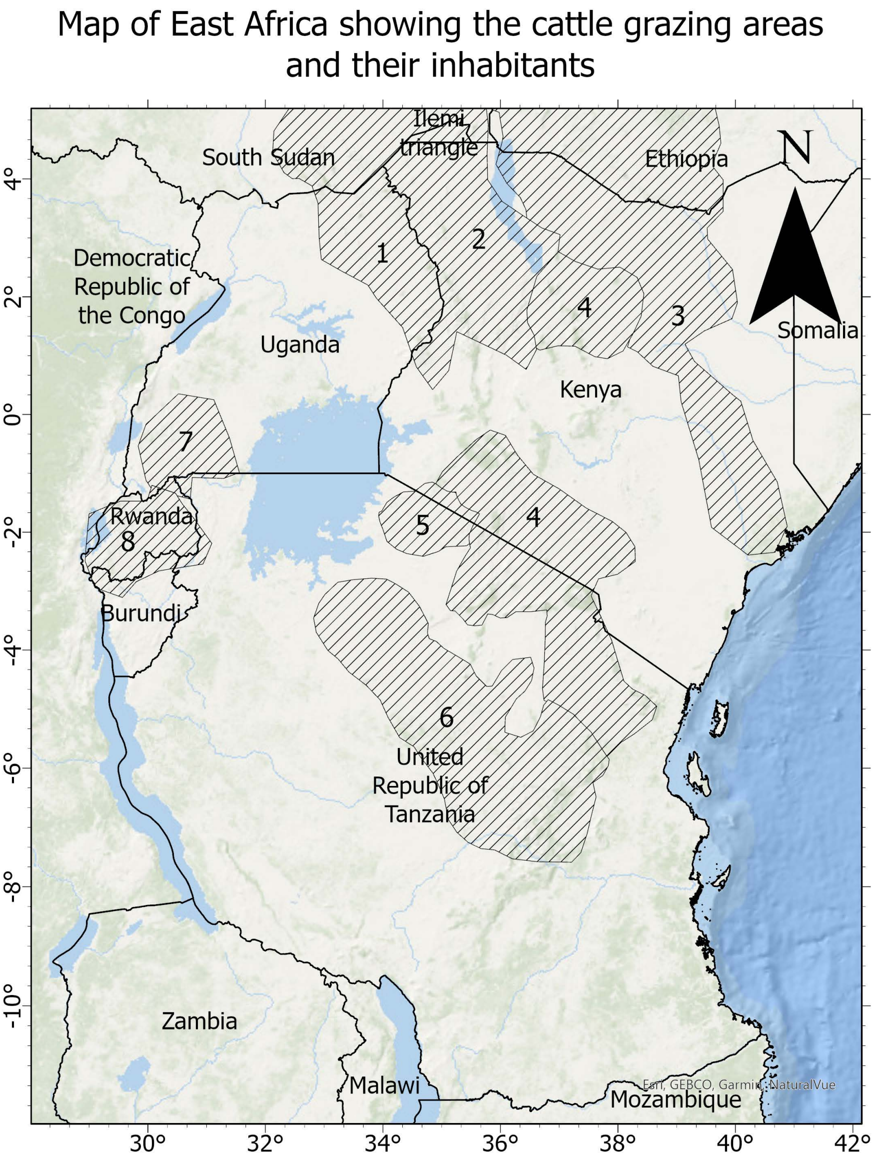


Figure 1. Extracted map of East Africa showing the study area and its location on the African map.

Of the cultures of some of the East African inhabitants is pastoralism, which is better researched with a number of scholars focusing on some of the main pastoral groups, including the Maasai, the Turkana, the Borana and Rendille, Karamajong, among others (Fratkin, 2001; Lind et al., 2020). **Figure 2**, indicates where some of these cattle grazing people can be located in East Africa. There are estimated to be 30 million pastoralists and agro-pastoralists in the Greater Horn of Africa (Somalia, Ethiopia, Kenya, South Sudan, Eritrea, Djibouti, Sudan, Tanzania, and Uganda) (Bollig & Göbel, 1997; Moritz, 2013).



Legend

Cattle Grazing Areas

Number	Ethnicity Name	Number	Ethnicity Name
1	Karimojong	5	Kuria
2	Turkana	6	Sukuma
3	Oromo	7	Hima
4	Masai	8	Tusi

Figure 2. East African Map showing the cattle grazing areas and their inhabitants.

2.2. Data Sources

This study used daily NDVI dataset sourced from NOAA-07 GAC at spatial resolution of 0.05˚ by 0.05˚ (Pettorelli et al., 2011; Garai et al., 2022). For rainfall, this study acquired CHIRPS-v2 data set which is generated from satellite ground observations to build high resolution (0.05˚) gridded precipitation climatology (Harrison et al., 2022) while Temperature data was retrieved from ECMWF, which is ERA5 monthly averaged data on single levels (reference). All the meteorological datasets span from 1982 to 2019, same period as NDVI.

2.3. Methodology

2.3.1. The Empirical Orthogonal Function (EOF)

The present study utilized the empirical orthogonal function (EOF) (**Figures 6-8**) to identify patterns and dominant relationships between climate variables (Ame et al., 2021; Islam & Xing, 2021) and NDVI, which was used to obtain a better understanding of influencing factors on to pasture variability (Hackney et al., 2015) in East Africa's cattle grazing areas. And the mean observed variables (rainfall, temperature and NDVI) of our study region (**Figure 1**) was based on 1982 to 2019 climatology. EOF analysis is frequently applied to derive patterns and indices used to identify climate models as expressed in state variables on the (Roundy, 2015). The approach identifies patterns in space known as EOF modes in one or multiple variables from eigenvectors of the covariance matrix (Hannachi et al., 2007; Kaihatu et al., 1998) for the gridded data sets. Then the original centred data are projected onto the spatial patterns to obtain time series indices (i.e., the principal components). Therefore, in this study the second EOF spatial mode of the mean JJA observed variables was taken as the dominant mode and further explained patterns and dominant relationships among climate variables (Islam & Xing, 2021) and NDVI. To quantify the relationship between rainfall, temperature and NDVI over the study domain (**Figure 1**), we used spatial correlation analysis (**Figure 4**). Spatial correlation helps to understand how geographic distribution of climate variables corresponds to the variability NDVI. Having realized that the special, and temporal (maps and principal component time series) provides the strength of EOF pattern over time, we assign the JJA second mode of EOF to represent rainfall, temperature and NDVI relationship (Kaihatu et al., 1998).

2.3.2. The Mann-Kendall Trend Test

This study used the Mann-Kendall, non-parametric trends test to determine whether annual precipitation, temperature and NDVI (**Figure 5**) have been undergoing a statistically significant upward or downward trend. The Mann-Kendall trends test is particularly advantageous in such a way that it is not dependent on normally distributed data and tests whether data show an upward trend as well as a downward trend through a sequential dataset e.g., over a period of years (Helsel & Hirsch, 2002; Esterby, 1996), hence suitable for the analysis in the present study.

The non-parametric Mann-Kendall (MK) statistical test (Abdi, 2007; Mann, 1945), has been applied in many studies to identify whether monotonic trends exist in hydro-meteorological data such as temperature, rainfall and stream flow. This test is often used because of its property that no assumptions are needed about the data that need to be tested. In the trend test, the null hypothesis Ho is that there is no trend in the population from which the dataset is drawn and the sample of data $\{x_j, j = 1, 2, \ldots, n\}$ is independent and identically distributed. The alternative hypothesis H1 is that the trend exists in the dataset.

Kendall's S, is defined as follows: (Suhaila et al., 2010)

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sign\left(x_j - x_k\right) \tag{1}$$

where x_j and x_k are the sequential data values, n is the length of the dataset, and

$$Sign(x) = \begin{cases} 1 \text{ if } x > 0 \\ 0 \text{ if } x = 0 \\ -1 \text{ if } x < 0 \end{cases} \tag{2}$$

Under the null hypothesis, the statistic S is normally distributed when $n \geq 8$ with zero mean and the variance is given as follows:

$$\mathrm{Var}(S) = \frac{n(n-1)(2n+5) - \sum_t^n t(t-1)(2t+5)}{18}, \tag{3}$$

where t is the extent of any given tie and denotes the summation over all ties. The standardized test statistic Z is computed by;

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{Var(S)}} \text{ for } S > 0 \\ 0 \text{ for } S = 0 \\ \dfrac{S+1}{\sqrt{Var(S)}} \text{ for } S < 0 \end{cases} \tag{4}$$

In a two-sided test for trend, Ho should be accepted if $|Z| \leq 1.645$ at the 0.01 level of significance. A positive Z value indicates an upward trend, whereas negative indicates a downward trend.

3. Results and Discussion

3.1. Distribution of Rainfall, NDVI and Temperature

The annual mean values for rainfall, Temperature and NDVI were calculated for the period 1982-2019. The results (**Table 1**) show that the highest annual mean rainfall was received in 1997 (96.885 mm) and 2019 (96.424 mm) while 2005 recorded the lowest mean rainfall (64.796 mm). The highest annual mean temperature was received in 2016 and 2019 (24.57˚C) and the lowest was in 1985 (23.2˚C). Furthermore, the NDVI had the highest mean annual values in 1998 (0.45631), whereas the lowest values were in 1988 (0.37658).

The spatial distribution of rainfall anomalies (**Figure 3(b)**) shows that parts of Northern Uganda and south western areas of Kenya had an increase of rainfall. The findings from this study are consistent with those of (Sagero et al., 2018) who observed that Spatial rainfall pattern and variability highlighted prevalence of wetter areas are in the western region bordering Lake Victoria. whereas most parts of the study area had a decreasing trend of rainfall. On the other hand, temperature (**Figure 3(c)**) depicted an increasing pattern throughout the Northern parts of Kenya. This can be compared to other studies such as (Ayugi and Tan, 2019) who also observed rising temperature on annual and seasonal basis over the Northern parts of Kenya while a decreasing pattern in scattered parts of south western Kenya near Lake Victoria and few areas of south western Tanzania near Lake Malawi. Just as (Ndayisaba et al., 2016)'s study, which revealed that the vegetation cover was characterized by an increasing trend of a maximum annual change. NDVI revealed increasing values in the northern and Western parts of Uganda and some parts of south-western Kenya. Furthermore, an increasing of NDVI was observed along the coastal regions and in Southern Tanzania (**Figure 3(a)**).

Table 1. Table showing the years of highest and lowest values used variables.

Parameter	Year	Highest	Year	Lowest
Rainfall	1997	96.885 mm	2005	64.796 mm
Temperature	2016 and 2019	24.57˚C	1985	23.2˚C
NDVI	1998	0.45631	1988	0.37658

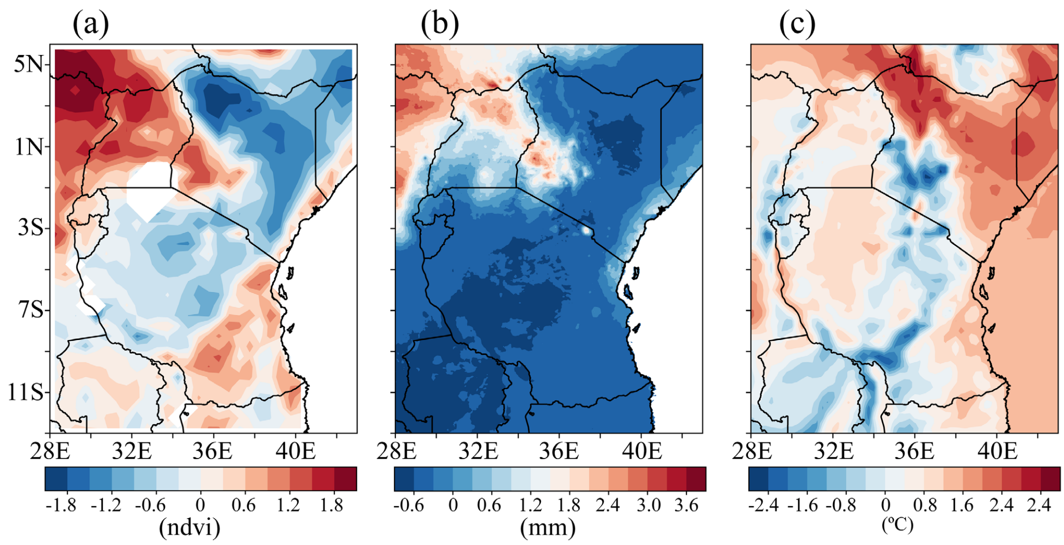


Figure 3. (a) Map showing the annual NDVI distribution (1982-2019) of East Africa. The NDVI value was distributed throughout the region by approximately ± 2.0. Map demonstrates that the high NDVI value indicates green and healthy vegetation. (b) Map showing the annual rainfall distribution (1982-2019) of East Africa. The highest maximum rainfall occurred in 1997 (96.885 mm) and the lowest or minimum rainfall occurred in 2005 (64.796 mm). (c) Map showing the annual Temperature distribution (1982-2019) of East Africa.

3.2. Correlation Analysis for NDVI and Meteorological Parameters

Correlation results between NDVI and precipitation (**Figure 4(a)**) revealed a positive correlation over East Africa. This indicates that variations in correspond to variations in rainfall amounts in the region. This pattern will hence affect the quality of pasture in the grazing areas as shown in **Figure 2** by improving its quality as well as quantity. This relationship is found across much of East Africa, showing a consistent pattern where more rainfall is associated with increased NDVI, as reflected in **Figure 4(a)**. A significant positive correlation ranging from 0.6 to 0.8 was observed between NDVI and rainfall in specific regions such as northern Uganda and western Tanzania. Changes in rainfall in these regions can have an outstanding impact on NDVI. We further compared with other previous studies such as those of (Pan et al., 2019) which revealed that NDVI has a higher correlation with precipitation in grassland and desert grassland areas. This suggests that the findings from this study are consistent with previous studies.

On the other hand, correlation between NDVI and temperature was generally negative in most parts of East Africa **Figure 4(b)**. This is not different from the study by (Garai et al., 2022), which also demonstrated inverse correlation between NDVI and land surface temperature. This negative correlation may indicate that NDVI is sensitive to changes in temperature, with higher temperatures potentially causing stress and reduced vigour in plants. This will hence affect pasture by reducing its quality and quantity. Correlation was observed to be significant in areas such as northern Uganda and north-western Tanzania.

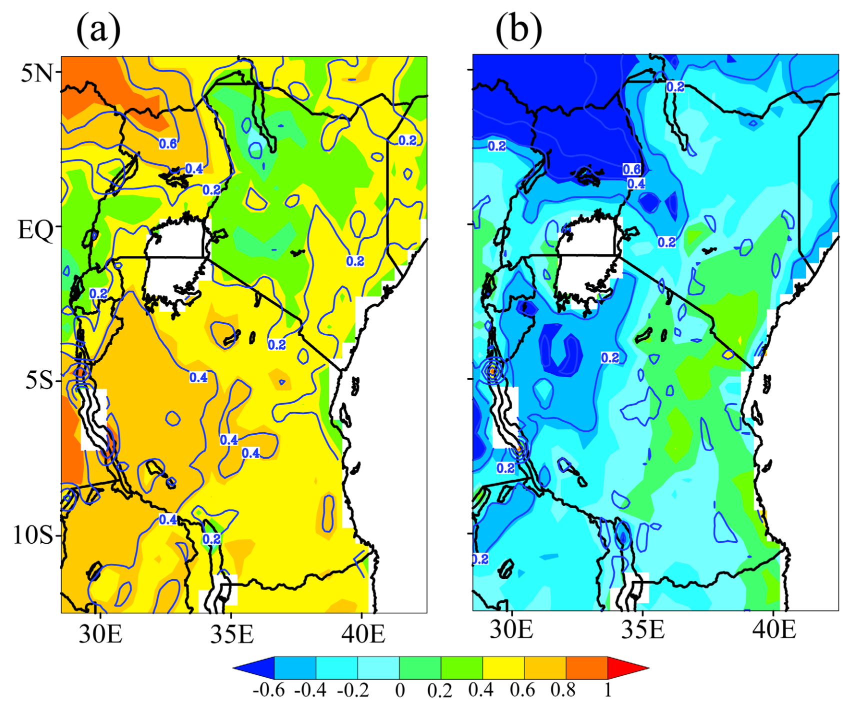


Figure 4. (a) Spatial correlation between rainfall and NDVI, (b) Spatial correlation between temperature and NDVI from the year (1982-2019).

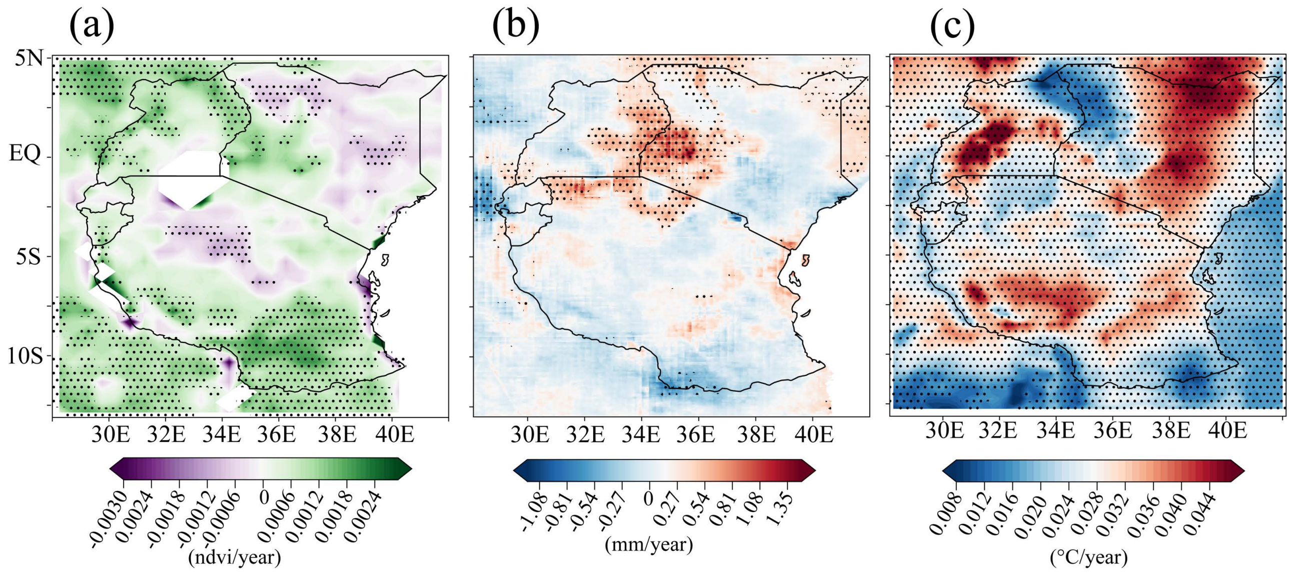


Figure 5. (a) East African mean annual spatial trends of NDVI, (b) Rainfall and (c) Temperature from the year (1982-2019).

3.3. Annual Trends of Rainfall, Temperature, and NDVI

In this study, analysis using MK trend test **Figure 5(a)**, revealed an increase of NDVI over Karamoja, Northern parts of Masai, Hima and Tusi areas (**Figure 2**) including North western Uganda and Southern parts of Tanzania. The increasing trend of NDVI signifies high quality and quantity of pasture in these locations. A decreasing trend of NDVI was detected over Oromo and Sukuma (**Figure 2**). Such a decrease will reduce the quality and quantity of the pasture.

Rainfall trends **Figure 5(b)** revealed an upward (positive) trend in the regions where NDVI showed positive trend while negative trend where NDVI also showed negative trend. This suggests that the decreasing pattern of rainfall inhibited the development of vegetation hence low NDVI values. This will therefore affect the quality and quantity of the pasture such as in grazing areas. This will therefore affect the quality and quantity of the pasture such as in grazing areas. This is in good agreement with (Garai et al., 2022; Kalisa et al., 2019), where results indicated that high values of NDVI corresponds to spatial distribution of precipitation than temperature. **Figure 5(c)** clearly showed temperature had positive trends in areas where NDVI had negative trends while negative in areas where NDVI showed positive trends. This suggested that increase in temperature hampered the development of vegetation whereas low temperature enhanced the development of vegetation hence affecting the quality and quantity of pasture in the grazing areas.

3.4. EOF Analysis

The results of EOF presented in **Figure 6**, and **Figure 7** showed positive pattern of NDVI over northeast of the study domain, which cover grazing areas of Turkana, Oromo, Masai and Sukuma (**Figure 2**). On the other hand, negative patterns were detected in western locations and Southeast of Tanzania. The positive

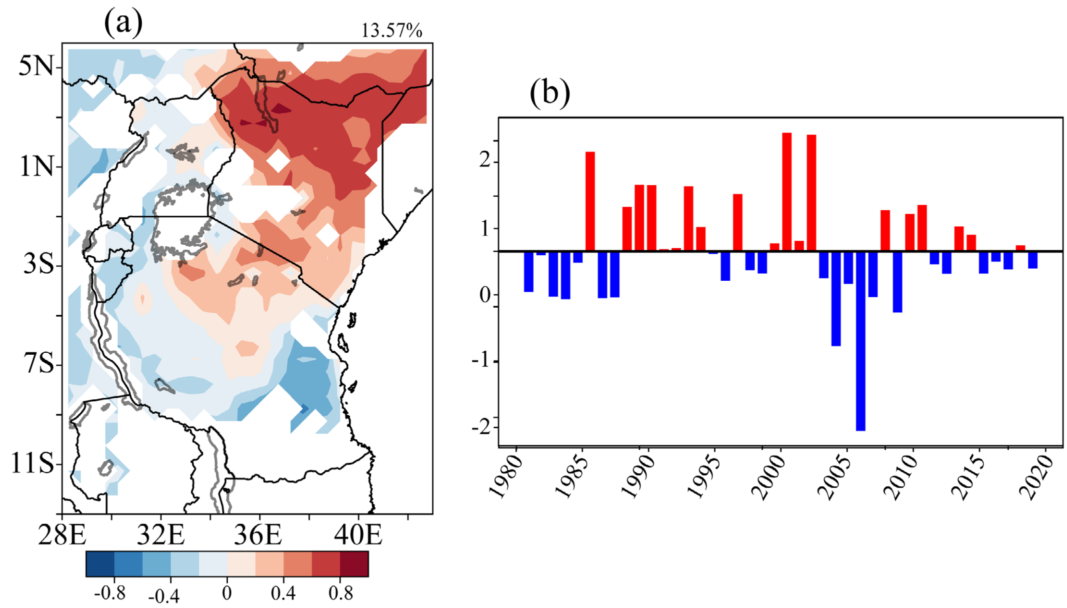


Figure 6. (a) Extracted map showing the spatial pattern of the second EOF mode (EOF2) of the mean NDVI during JJA season, (b) The corresponding principal component 2 (PC2) time series of the mean NDVI during JJA season based on 1982-2019 period.

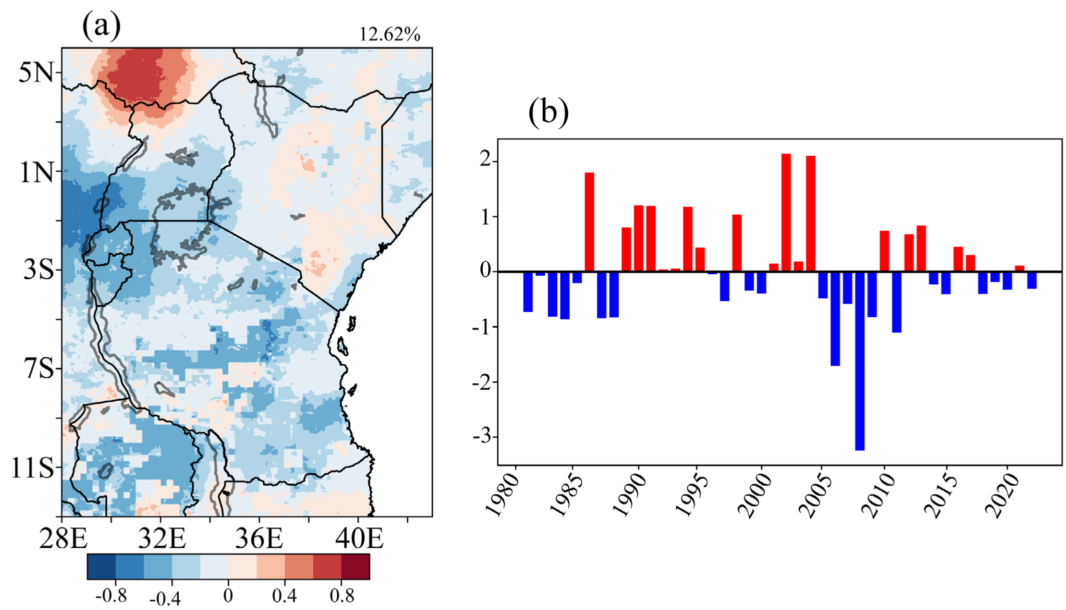


Figure 7. (a) Extracted map showing the spatial pattern of the second EOF mode (EOF2) and (b) Its corresponding principal component 2 (PC2) time series in of the mean rainfall during JJA season based on 1982-2019 climatology.

patterns indicated increasing NDVI while negative decreasing of NDVI. This study further investigated interannual changes of NDVI by using the corresponding PCs time series of EOF presented in Figure 6(b). The results demonstrated a low NDVI between the years of 1982 and 1988 and also between 2002 and 2008 while high during the other years such as between 1989 and 1995, including 1998 and 2001. The EOF pattern of rainfall was similar to that of NDVI as shown in Figure 7(a) and Figure 7(b). On the other hand, Temperature Figure 8(a) and Figure 8(b) revealed an opposite pattern where a positive index was notable over the northern areas of Uganda and north western areas of Kenya specifically, Karamoja and Turkana grazing areas. This result was consistent with those in a study by (Guo et al., 2020) in which NDVI interannual variability was significantly related to that of the corresponding temperature and precipitation for each biome. The rest of the areas were dominated by negative and insignificant changes of EOF values. The pattern observed above clearly suggested a possible influence of rainfall and temperature on NDVI. Furthermore, rainfall might have enhanced the development of vegetation in areas where both rainfall and NDVI showed positive EOF values whereas opposite in areas with negative EOF values. In contrary, temperature increase could have prohibited development of vegetation as it mostly showed positive EOF values in areas where NDVI had negative EOF values while opposite in areas where NDVI had positive values. The pattern discussed above is consistent with those of previous sections such as trends where increase and decrease of NDVI was highly associated with increase and decrease of rainfall and temperature respectively.

4. Conclusion

This study used seasonal and annual rainfall, temperature and NDVI data for the period 1982-2019 to examine the spatial temporal variability of rainfall and temperature on the variability of pasture on the cattle grazing areas of East Africa.

The study demonstrated a positive correlation between NDVI and rainfall while an inverse correlation between NDVI and temperature. The study showed that variability in both amounts of precipitation and temperature, affect pasture.

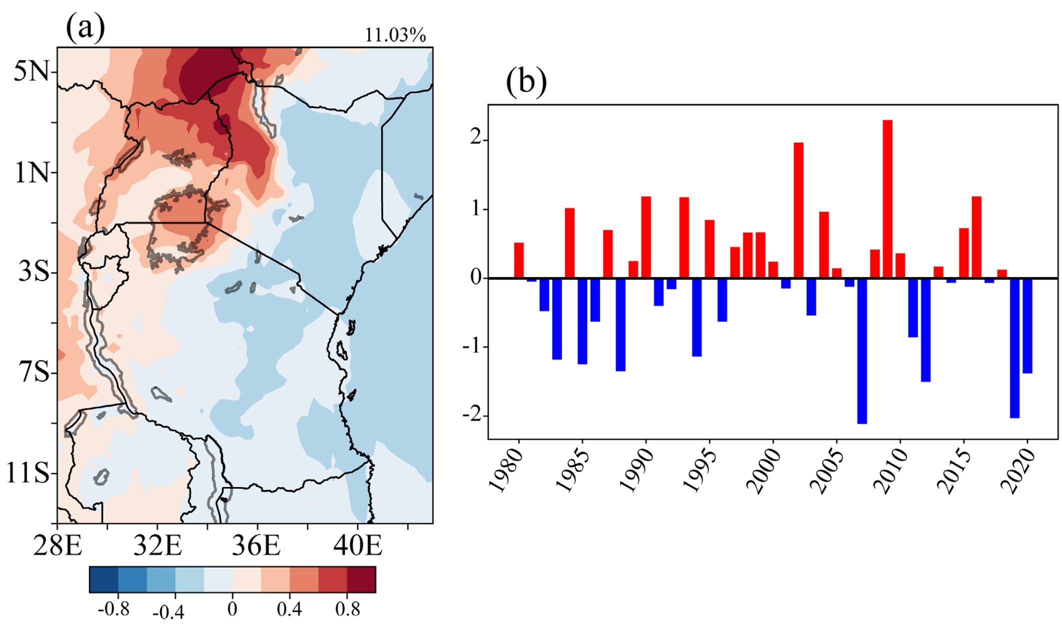


Figure 8. (a) The spatial pattern of the second EOF mode (EOF2) and its corresponding PC time series in (b), of the mean Temperature during JJA season based on 1982-2019 climatology.

This study contributes to the understanding of spatial and temporal response of pasture to varying climatic conditions. The major implication of the present study is to give guidance in decision making of pasture management in East African cattle grazing areas under changing climatic conditions. Based on the findings from this study, we propose further studies to be carried out on interpretation of meteorological information such as monthly or seasonal weather bulletins to the local pastoralists through agricultural specialists since they are directly venerable to the changes of weather patterns.

Acknowledgements

The first author would like to acknowledge the resources and services provided by the https://cds.climate.copernicus.eu/cdsapp#!/, CHIRPS and Temperature Data Portal, https://doi.org/10.7289/V5ZG6QH9, NDVI - NOAA-07 GAC data portal, Uganda National Meteorological Authority (UNMA) and the Ministry of Commerce of China (MOFCOM) for giving me the opportunity to study. Honour and thanks to Prof. Wang Wen for supervising and guiding me on this research.

Authors' Contributions

Conceptualization, Methodology, Data Analysis, Original draft preparation were performed by Natiko Peter. Data download was performed by Raharivelo Sitraka Ny Aina and Alupot Donnata, Image processing was performed by Nyasulu Matthews, and Emmanuel Yeboah. Manuscript review was performed by Nyasulu Matthews, manuscript editing, final drafting and supervision were performed by Prof. Wang Wen.

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Data Availability

The data that support the findings of the study are available on the request from the corresponding author.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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