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Research Article

Assessing the Long-Term Changes in Selected Meteorological Parameters over the North-Rift, Kenya: A Regional Climatology Perspective

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Abstract

Understanding long-term trends in climatic variables is essential for assessing climate change impacts on regional ecosystems and human livelihoods. A regional analysis of climatic variables over some domains is inevitable due to their geographical location and importance to the agricultural sector. Due to the aforementioned demands, the current study analyzes, trends in precipitation (from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)), and minimum and maximum temperatures (from TerraClimate) over the North-Rift region of Kenya for over thirty (30) years using satellite data. The seasonal decomposition analysis was performed for each variable to explore the trends and residual components. The findings by the current study indicate that most counties, have experienced enhance precipitation which corresponds to a declining diurnal temperature from 2019 onwards. The seasonality component reveals repeated patterns or variations occurring at steady intervals within each region's data, hence suggesting a distinct regional seasonal trend in the selected meteorological parameters over time. Basically, all counties have reported a relatively constant variability in both maximum and minimum temperatures during the study period except from 2017 onwards where significant variability in the two properties is recorded. In conclusion, the foregoing results that the selected climatic variables exhibit significant spatiotemporal and interannual variability.

Keywords

North Rift, Climate Change, Rainfall, Temperature, East Africa, Long Term Trends, Climatic Variables, CHIRPS and TerraClimate Datasets

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1. Introduction

Climate change is one of the most pressing global challenges of the 21st century, with far-reaching implications for ecosystems, economies, and the livelihoods of local communities while negatively impacting biodiversity in Kenya and globally [1]. Like many other regions around the world, the North Rift region of Kenya has experienced a loss of biodiversity and livelihood exposing the local communities to the negative effects of climate change. As a crucial element of terrestrial ecosystems and human survival, vegetation plays an indispensable role in influencing climate systems regulating carbon cycles, and energy exchange between the atmosphere and the land surface via the process of evapotranspiration, photosynthesis, and surface albedo [2-4] while entirely depending on a selected range of meteorological parameters among them rainfall and temperature ranges [5]. It is established that 20% of the Earth's surface is covered by vegetation, and vegetation growth is susceptible to changes in climatic variables [4, 6].

Understanding the long-term trends in rainfall, maximum, and minimum temperatures over a given region is crucial to unravel climate dynamics and their implications on the livelihoods of the local communities [7]. As mentioned earlier, these climatic variables play pivotal roles in both ecosystem health and biodiversity which significantly influence the local community's livelihoods. Long term studies in meteorological parameters have in the recent past underscored the significance of analyzing historical data with a view of identifying trends and potential shifts in these variables over extended periods. Such assessments not only inform scientific understanding but also support decision-making processes aimed at mitigating climate risks and enhancing resilience [8, 9] at community level. By examining the trends in maximum and minimum temperature and precipitation patterns, this study forms a basis for understanding the changing climate dynamics in the region and their potential implications for agriculture, water resources, and ecosystems all of which determine the livelihoods of the local communities. Therefore, fathoming climate variability is a key factor in an attempt to unravel the effect of climate change and its influence on the vegetation cover that directly influences the livelihoods of the local communities [10], particularly those in the North-Rift region of Kenya.

In recent years, advancements in remote sensing and climate modeling have facilitated the analysis of long-term trends in climatic variables at regional and global scales [11, 13]. Most recently, the IPCC Fifth Assessment Report documented that the mean global surface temperature exhibited an increase of 0.85 ℃ over the period 1880–2010 [14]. Additionally, the duration, severity, and frequency of precipitation have been affected majorly by increased extreme climate events [15]. The occurrence of these events has left most local communities mostly in the North Rift of Kenya susceptible to the negative effects of climate change, mostly loss of livelihood. This study aims to conduct a comprehensive analysis of long-term trends in selected climatic variables over the North-Rift region of Kenya using Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) for precipitation and TerraClimate for maximum and minimum temperature datasets. Utilizing these datasets, the current study will determine trends in key climatic variables i.e. maximum and minimum temperature and precipitation from 1990 to 2023 over the eight counties in the North rift region of Kenya.

Recent studies have highlighted the increasing frequency and severity of climate-related events in Kenya, including prolonged droughts, erratic rainfall patterns, and rising temperatures [16]. Additionally, challenges such as climate variability, soil degradation, and water scarcity have been consistent in the recent past, posing threats to food security and livelihoods [17] in the region where agriculture is a primary source of income for many communities [18]. Therefore, understanding the long-term trends in climatic variables is crucial for informing adaptive strategies and enhancing resilience to climate change impacts by local communities will vital. By conducting a systematic analysis of historical climate data, this study aims to contribute to the existing knowledge base on climate change in the North-Rift region of Kenya. The findings of this research provide valuable insights for policymakers, researchers, and local communities to develop informed strategies for climate change adaptation and mitigation in the region.

2. Materials and Methods

2.1. Study Area

The study covered the North Rift region of Kenya which is part of the Great Rift Valley which extends through several countries i.e. from Lebanon in Asia to Mozambique in Southeast Africa. The North Rift region covers a geographical scope of eight (8) counties that include Turkana, West Pokot, Elgeyo Marakwet, Baringo, Nandi, Uasin Gishu, Trans Nzoia, and Samburu with varying elevations above sea level [19]. This region experiences a largely variable tropical climate with two distinct rainy seasons: the long rains from March to May (MAM) and the short rains from October to December (OND) [20] while the dry seasons are from June to September (JJAS) and January to February (JF). The North Rift region is dominated by a climate that is semi-arid with an annual precipitation of approximately 700 mm yr^{-1} over the rift floor. Annual average temperatures are 23–25 ℃ with potential evaporation of 2500 mm, which greatly exceeds precipitation [21, 22]. Generally, the climate within the Kenyan Rift Valley is semi-arid with rainfall amounts ranging from >600 mm at Lake Naivasha to <300 mm over the Suguta Valley floor [22].

Table 1 shows the latitude and longitudes of the eight (8) counties that represent the North-rift region of Kenya.

Table 1. *The latitude and longitudes of the eight (8) counties that represent the North-rift region of Kenya.*

Name of the County	Latitude	Longitude	Population Source: [23]
Turkana	34º 30′ and 36º 40′ E	1º 30′ and 5º 30′ N	926,976
West Pokot	1 ºand 2 ºN	34º 47′ and 35º 49′ E	621,241
Elgeyo Marakwet	0º 20′ and 1º 30′ N	35º 0′ and 35º 45′ E	454,480
Baringo	0º 13′ S and 1º 40′ N	35º 36′ and 36º 30′ E	666,763
Nandi	0º 6′ 23.76″ N	35º 11′ 1.61″ E	885,711
Uasin Gishu	0º 3′ S and 0º 55′ N	34º 50′ E and 35º 37′ W	1,163,186
Trans Nzoia	1º 2′ 42″ N	34º 58′ 44″ E	990,341
Samburu	0º 30′ and 2º 45′ N	36º 15′ and 38º 10′ E	310,327

Kenya is the second most populous among the East African (EA) countries with a population totaling 47.6 million [23]

2.2. Satellite Data

This study established trends in precipitation, and temperature, using digital platforms. Precipitation data was acquired from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) daily data set while data on minimum and maximum temperature was acquired from the TerraClimate website [11].

2.2.1. Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS)

Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is a 35+ year quasi-global rainfall data set. Spanning 50°S-50°N (and all longitudes) and ranging from 1981 to near-present, CHIRPS incorporates the in-house climatology, CHPclim, 0.05° resolution satellite imagery, and in-situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring [11]. The process of creating the gridded rainfall datasets involves blending satellite-derived infrared Cold Cloud Duration (CCD) data with station measurements to enhance accuracy and spatial resolution. Additionally, the temporal resolution of daily, pentadal, and monthly data is particularly useful for identifying and analyzing both global and regional rainfall patterns and anomalies [11, 24, 25].

2.2.2. TerraClimate Dataset

TerraClimate is a comprehensive high-resolution monthly climate dataset from 1958 to the present and a spatial resolution of approximately 4 km (1/24th degree) which allows for both regional and global climate phenomena [12]. The primary datasets utilized in the present study are the monthly maximum and minimum temperatures over the entire region of the north rift. Validation of these datasets is normally based on station-based observation from several platforms worldwide including WorldClim datasets [26].

2.3. Data Analysis and Methods

To perform trend analysis in the desired climatic variables, pretreatment procedures were applied to the monthly-derived datasets from CHIRPS (precipitation) and TerraClimate (Minimum and Maximum Temperature) for over thirty years at five-year intervals from 1990 to 2022) over each of the eight (8) counties in the north rift region of Kenya. The datasets consist of precipitation, maximum, and minimum temperature data for the North Rift region, comprising nine (9) variables (i.e. date plus the eight (8) counties in the North Rift region under study) each and a total of 12053 observations. The datasets have undergone profiling analysis, revealing the following key insights: data integrity, variable description, dataset consistency, and profiling reports. Seasonal decomposition analysis was performed for each column separately to explore the observed, trend, seasonal, and residual components for each variable and dataset.

3. Results and Discussion

Seasonal decomposition of precipitation and Temperature (Maximum and Minimum) over the eight counties in the North Rift region of Kenya has been determined. The data's seasonal decomposition generally involves breaking down the observed precipitation and maximum and Minimum Temperature values into different components to understand the underlying patterns and variations better. This typically includes decomposing the data into several components such as trend, seasonal, and residual components that are highlighted in the proceeding figures. To start with, the interpretation of seasonal decomposition in precipitation and Temperature (Maximum and Minimum) over the North Rift region involved breaking down the data into various components i.e. Observed data: the original data is plotted with a view of understanding the overall pattern and variability. Trend Component: this normally represents the long-term characteristics in the data, basically as the trend increases then it depicts an increase in the parameter of interest. Seasonality component: this component captures the seasonal fluctuations throughout the study. The residual component on the other hand represents variability in the data that cannot be explained by both trend and seasonal components. To start with, seasonal decomposition in Precipitation and Temperature (maximum and minimum) over the eight counties has been demonstrated through various graphs. From Figures 1 to 24, (a) represents a plot for the observed data, (b) represents the trend within the data, (c) represents the seasonality component within the data, and (d) represents the residual part. Overall, the seasonal decomposition of precipitation and temperature (maximum and minimum) provides valuable insights into the underlying patterns and variations in precipitation data, helping researchers and decision-makers better understand and plan for extreme weather events whose occurrence has increased in severity, and assess the impacts of climate change normally dictated by the said meteorological parameters of interest. To start with, the seasonal decomposition of precipitation (Figure 1), and temperature (maximum (Figure 2) and minimum (Figure 3) over TransNzoia County have been plotted as shown.

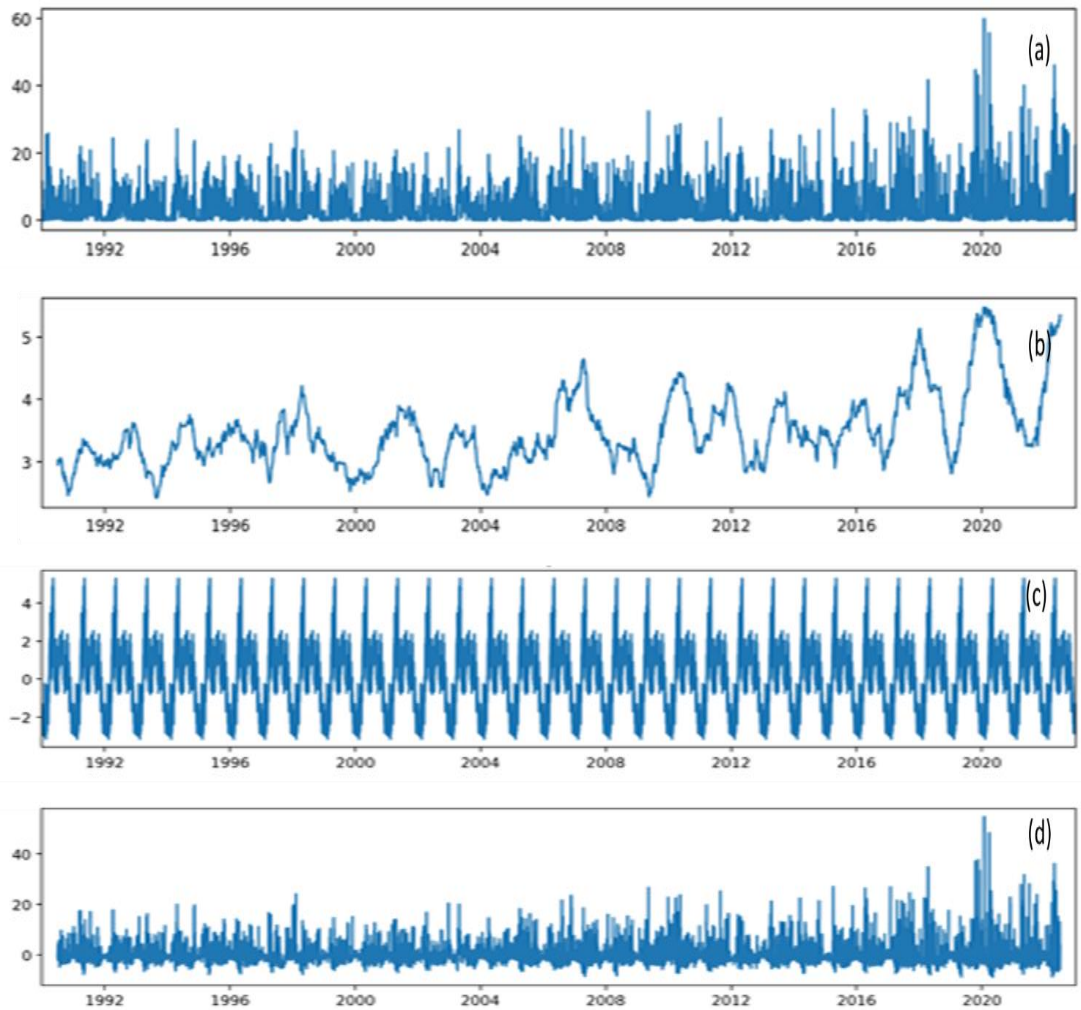

Figure 1. *Seasonal Decomposition of Precipitation i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over TransNzoia County.*

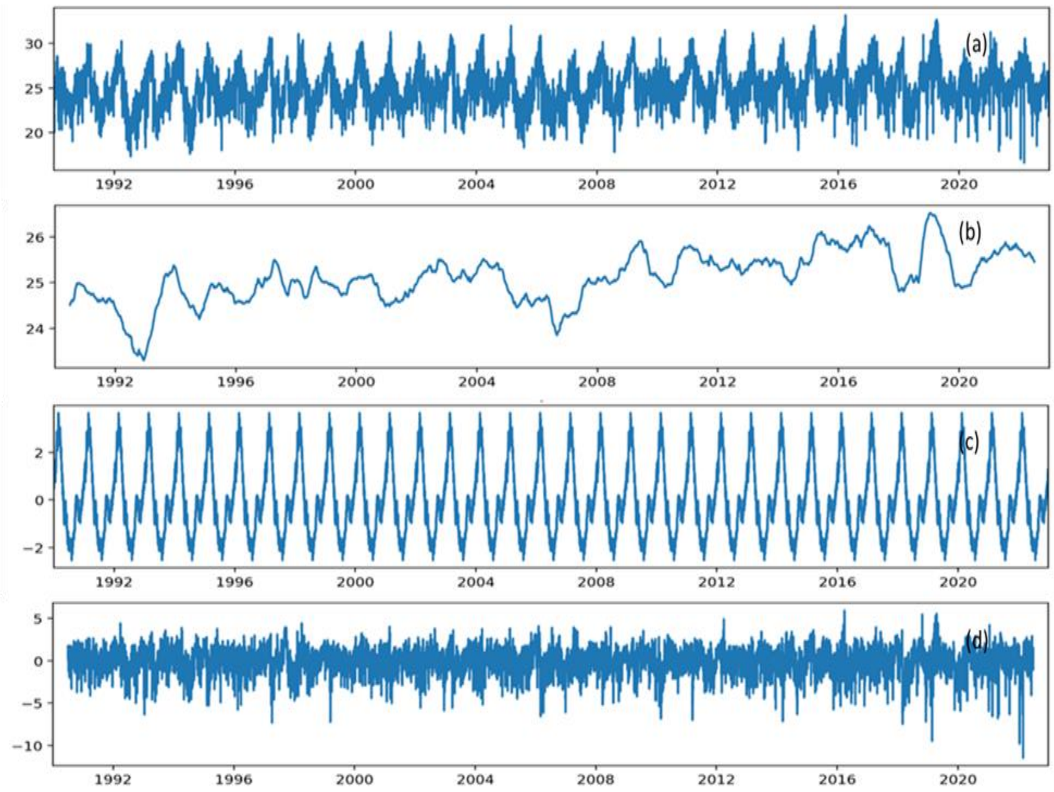

Figure 2. *Seasonal Decomposition of Maximum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over TransNzoia County.*

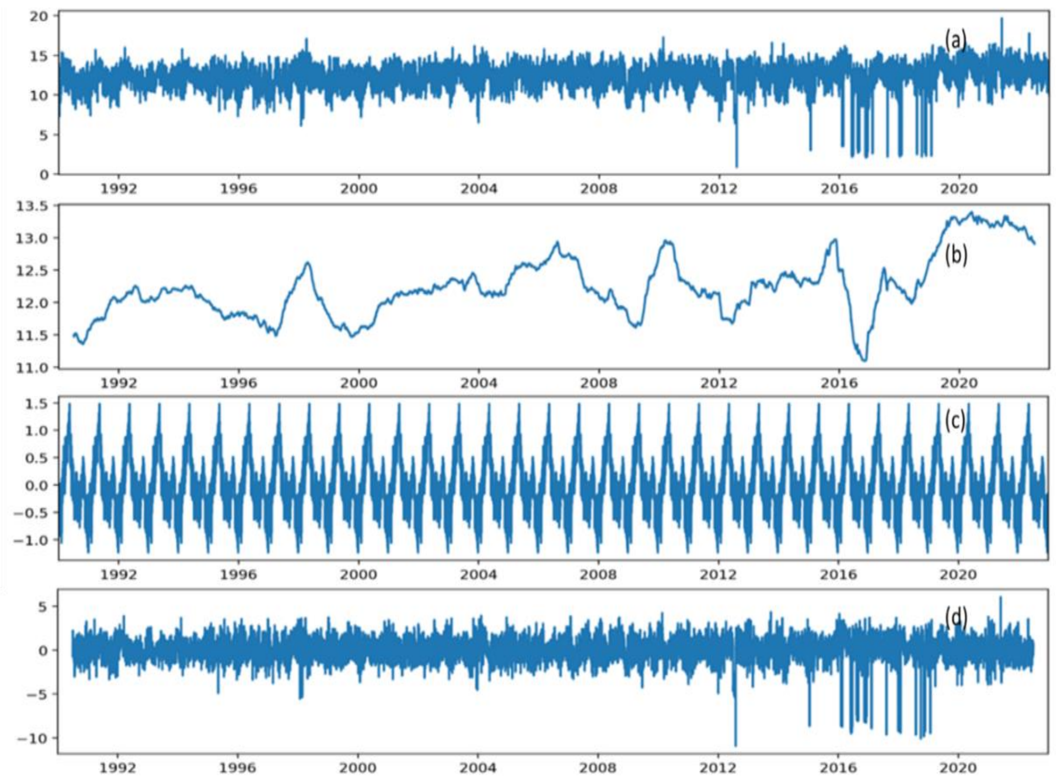

Figure 3. *Seasonal Decomposition of Minimum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over TransNzoia County.*

To understand the long-term changes in precipitation and temperature (maximum and minimum) were analyzed. The trends in precipitation (Figure 1b) and temperature (maximum (Figure 2b) and minimum (Figure 3b) depict long-term changes on a temporal scale. From Figure 1b, temporal trends in precipitation remain relatively stable from 1990 to 2003 and 2008 to 2016. Additionally, from 2004 to 2006, there is an observed increase in precipitation over TransNzoia County. TransNzoia County experienced significant variability in precipitation from 2017 onwards with the year 2020 being a year of extreme precipitation. So far, seasonal variability in precipitation, maximum temperature, and minimum temperature have exhibited a recurring pattern during the study period as shown in Figures 1(c), 2(c), and 3(c) respectively. Likewise, the observed and residual graphs exhibited unexpected variations in precipitation (Figure 1(a) and Figure 1(d)), maximum temperature (Figure 2(a) and Figure 2(d)), and minimum temperature (Figure 3(a) and Figure 3(d)) at varying years. Specifically, unusual variability is depicted in the observed data in maximum temperature (Figure 2(a)) and residual data in maximum temperature (Figure 2(d)) from 2020 onwards. Additionally, the observed data in minimum temperature (Figure 3(a)) and residual data (Figure 3(d)) exhibited unusual variability from 2016 to 2020 over Trans-Nzoia County.

Seasonal decomposition over Uasin Gishu County for precipitation (Figure 4), maximum temperature (Figure 5), and minimum temperature (Figure 6) are displayed below. It is observed that seasonal decomposition in precipitation is displayed in Figure 4. Similarly, observed (Figure 4a) and residual (Figure 4d) graphs exhibit unusual variability in precipitation from around 2020 onwards. The seasonality component in precipitation has remained relatively constant with no observable variability (see Figure 4c). The trends in precipitation (Figure 4b) depict long-term changes on a temporal scale particularly from 2017 onward over Uasin Gishu County.

Seasonal decomposition in maximum temperature over Uasin Gishu county (see Figure 5) demonstrated a non-variable pattern in the observed (Figure 5a), seasonality (Figure 5c), and residual (Figure 5d). The trend in maximum temperature (see Figure 5b) is indicative of high variability across the study period over the county. On the other hand, the trend in minimum temperature remained relatively constant from 1990 to 2015 after which there was an increase from around 2017 onwards (see Figure 6(b)).

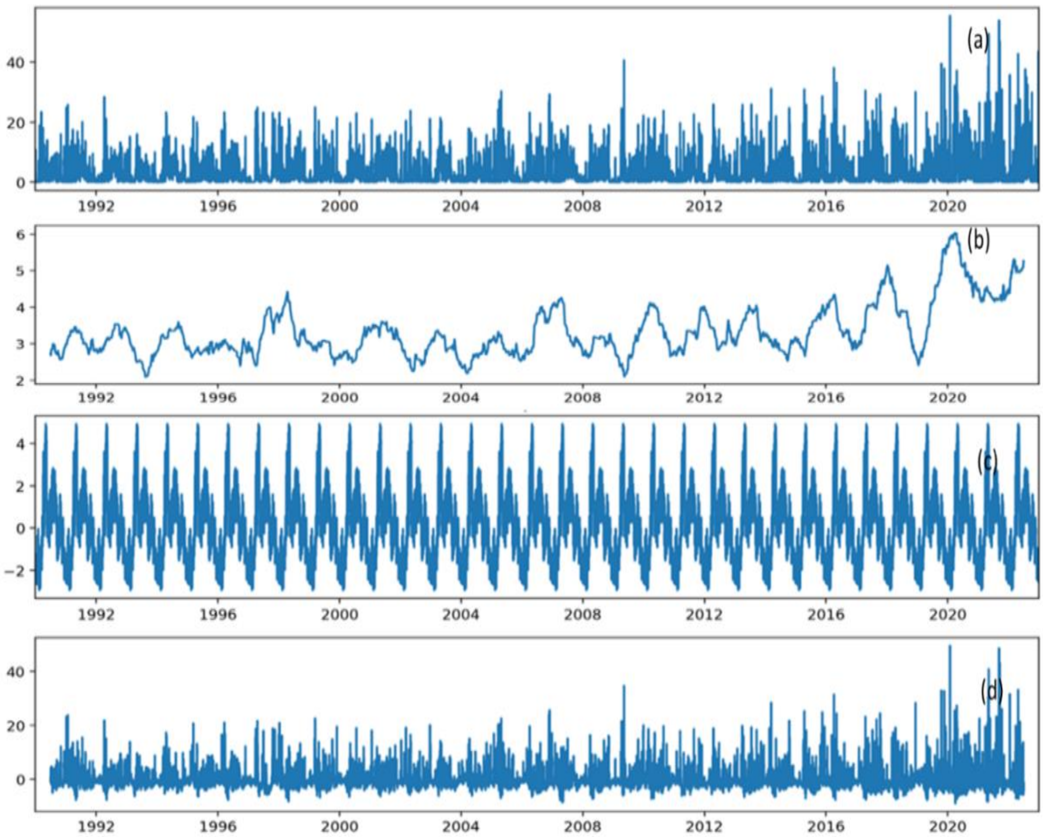

Figure 4. *Seasonal Decomposition of Precipitation i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Uasin Gishu County.*

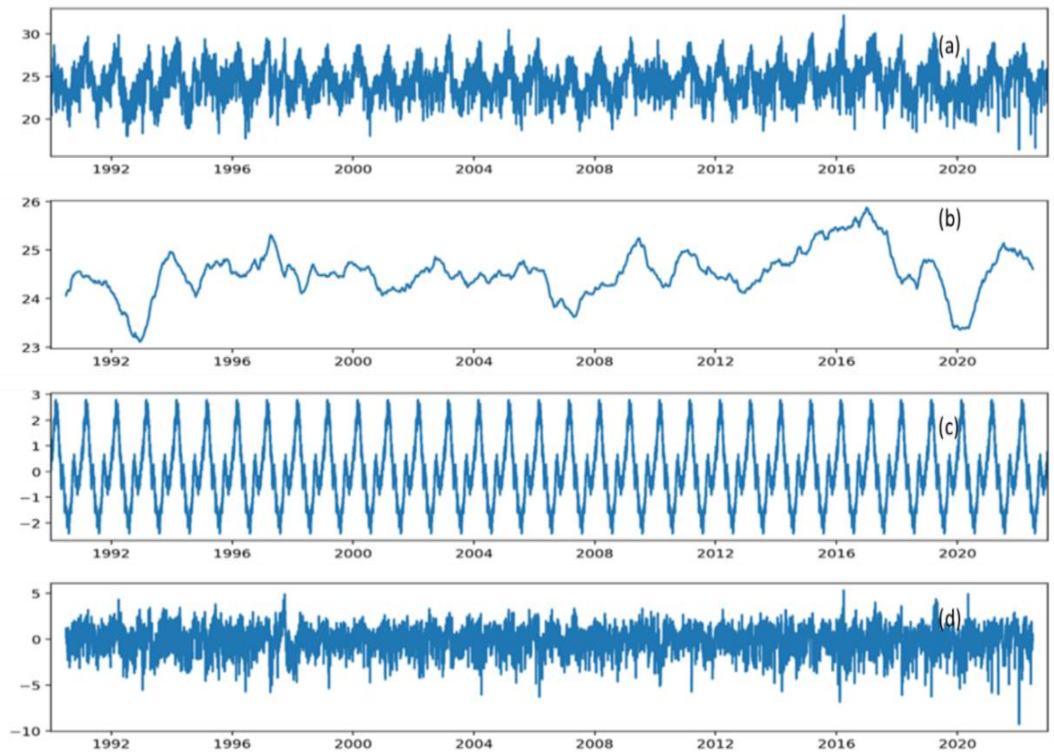

Figure 5. *Seasonal Decomposition of Maximum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Uasin Gishu County.*

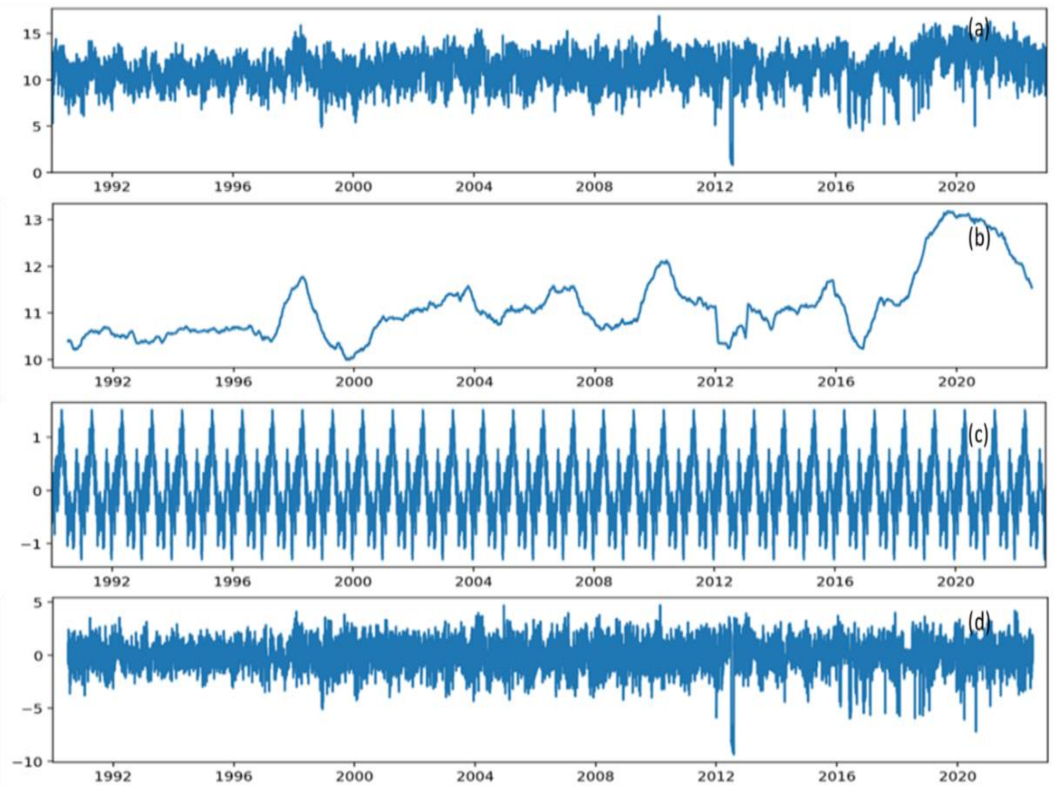

Figure 6. *Seasonal Decomposition of Minimum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Uasin Gishu County.*

Similarly, these occurrences are associated with the extreme events experienced over Uasin Gishu County during the stated period of study. There was no observable variability in the seasonal decomposition of minimum temperature over Uasin Gishu County in the observed (see Figure 6(a)), seasonality (see Figure 6(c)), and residual (see Figure 6(d)) graphs until 2020 onwards except for seasonality.

Seasonal decomposition in precipitation over Nandi County is displayed in Figure 7 with its corresponding components. The observed (see Figure 7a) and residual (see Figure 7d) precipitation graphs demonstrate a relatively stable pattern up to 2019 where unexpected events related to unusual weather patterns are evident from 2020 onward. On the other hand, the trend analysis precipitation graph (see Figure 7b) demonstrates a relatively stable variability in precipitation up to 2020 where enhanced variability in precipitation are noted. Lastly, seasonal variability in rainfall has remained relatively constant over Nandi County during the study period (see Figure 7c).

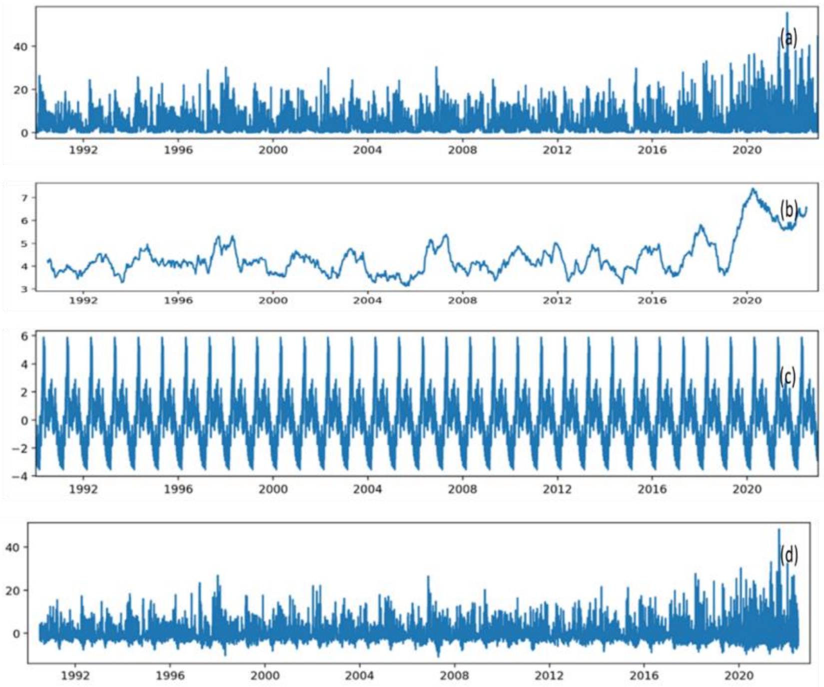

Figure 7. *Seasonal Decomposition of Precipitation i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Nandi County.*

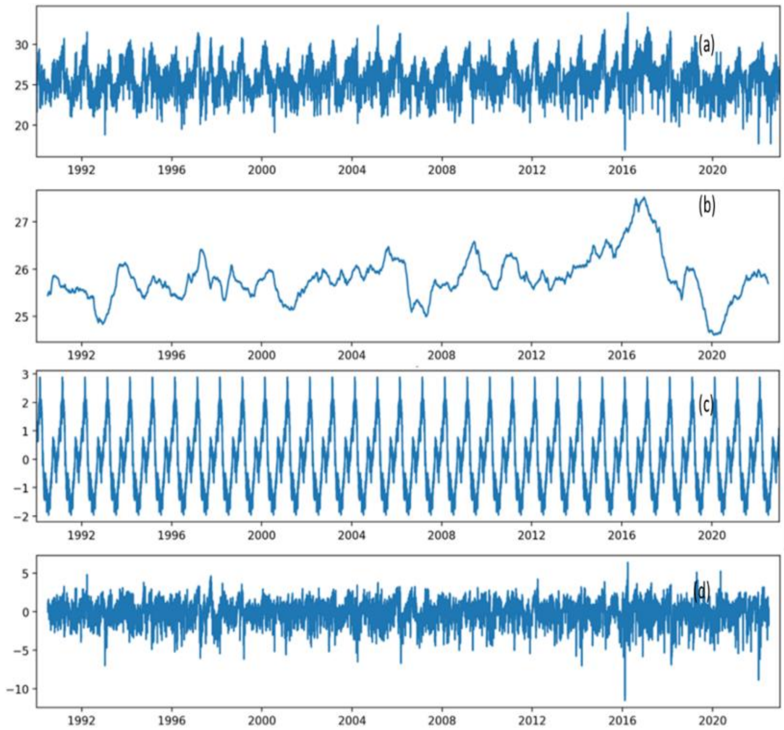

Figure 8. *Seasonal Decomposition of Maximum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Nandi County.*

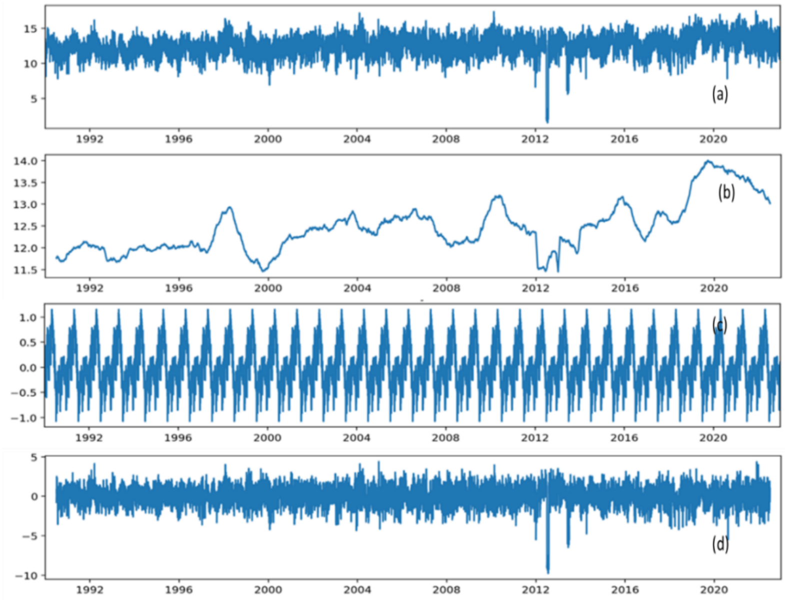

Figure 9. *Seasonal Decomposition of Minimum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Nandi County.*

The seasonal decomposition of maximum and minimum temperatures follows a very consistent pattern throughout the study period. The observed, seasonal, and residual graphs in both maximum (see Figure 8(a), Figure 8(c) and Figure 8(d)) and minimum (Figure 9(a), Figure 9(c) and Figure 9(d)) respectively remain relatively constant during the study period over Nandi County. Figure 8(b) a relatively constant variability in maximum temperature over Nandi County with a sudden increase around 2017 followed by a drop up to 2020 where the county experienced the lowest maximum temperature during the study period. The sudden drop in maximum temperature is associated with a corresponding increase in precipitation (see Figure 7b) over Nandi County during the study period. Similarly, the minimum temperature over Nandi County remained relatively stable until 2020 when it increased suddenly (see Figure 9(b)). The evidence of diminished diurnal temperature range i.e. difference between maximum and minimum temperature may explain the enhanced precipitation in 2020 over Nandi County [27].

The study [28] correctly predicted that precipitation variability increases in a warmer climate. This is observed over Turkana County which is characterized by elevated temperature (see Figures 11 and 12) with significant variability in maximum (see Figure 11(b)) and minimum (see Figure 12(b)) temperatures during the study period. Figure 10(a) and Figure 10(d) exhibit high variability in precipitation even though their seasonality remains fairly constant (see Figure 10(c)).

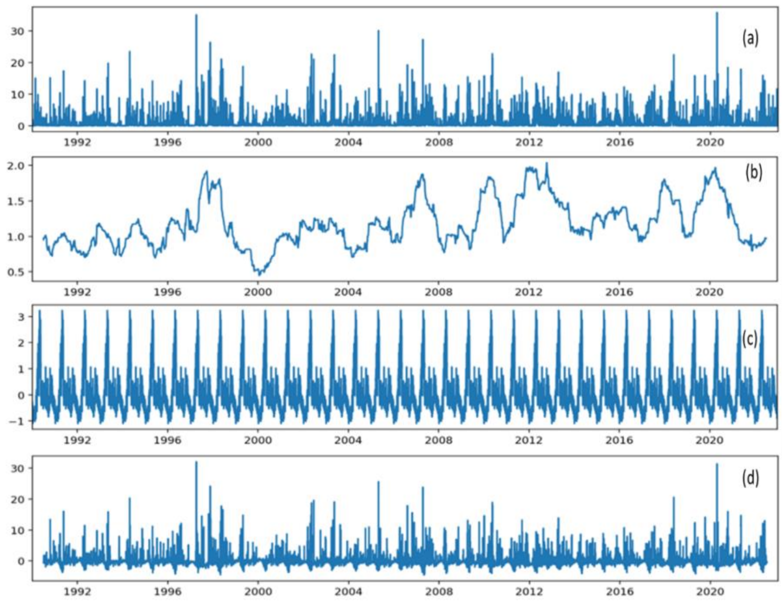

Figure 10. *Seasonal Decomposition of Precipitation i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Turkana County.*

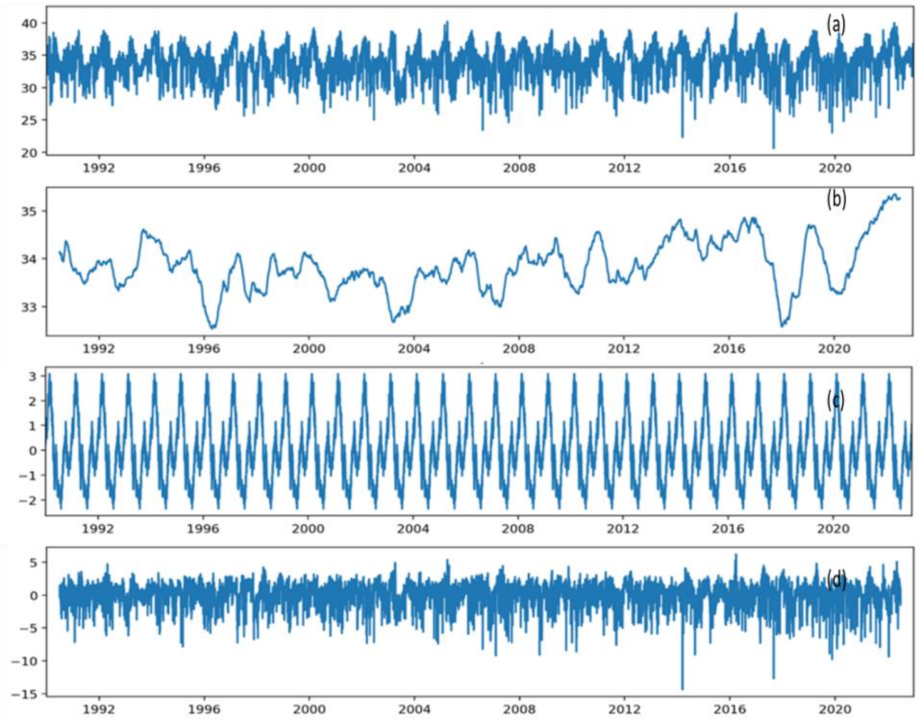

Figure 11. Seasonal Decomposition of Maximum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Turkana County.

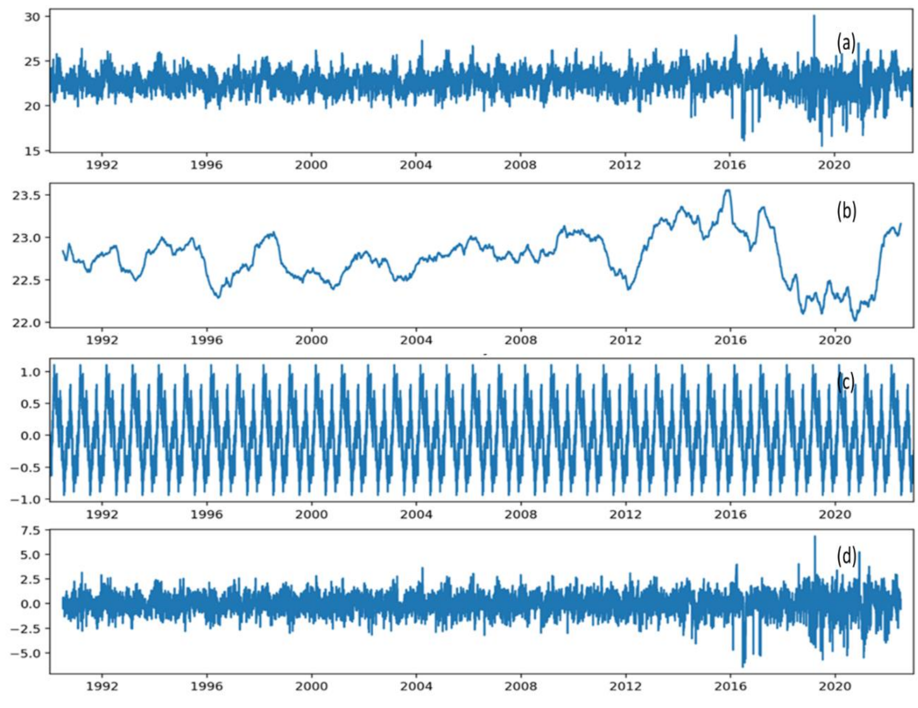

Figure 12. Seasonal Decomposition of Minimum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Turkana County.

Similarly, observed, seasonal, and residual graphs in both maximum (see Figure 11(a), Figure 11(c) and Figure 11(d)) and minimum (Figure 12(a), Figure 12(c) and Figure 12(d)) respectively remain constant up to 2020 when significant variability is noted over Turkana County.

Seasonal decomposition in precipitation over Baringo County is shown in Figure 13 with its corresponding components. The observed (see Figure 13(a)) and residual (see Figure 13(d)) precipitation graphs demonstrate an enhanced variability in precipitation from 1990 with the highest variability detected in 2020 onwards where unexpected events related to unusual weather patterns are evident. From the precipitation trend analysis graph (see Figure 13(b) a relatively unstable variability in precipitation up to 2020 where enhanced variability are exhibited. Similarly, the seasonality graph in precipitation virtually remains constant (see Figure 13(c)) over Baringo County. Temporal evolution in maximum temperature (see Figure 14) has been examined. The Observed (see Figure 14(a)), seasonality (see Figure 14(c)), and residual (see Figure 14(d)) maximum temperature graphs over Baringo County. The three graphs exhibit a uniform pattern in maximum temperature over the County unlike the trend graph (see Figure 14b) remains relatively stable from 1990 to 2017 where a sharp drop in maximum temperature is realized over the county (the lowest value in maximum temperature is observed in 2020 then a steep rise afterward.

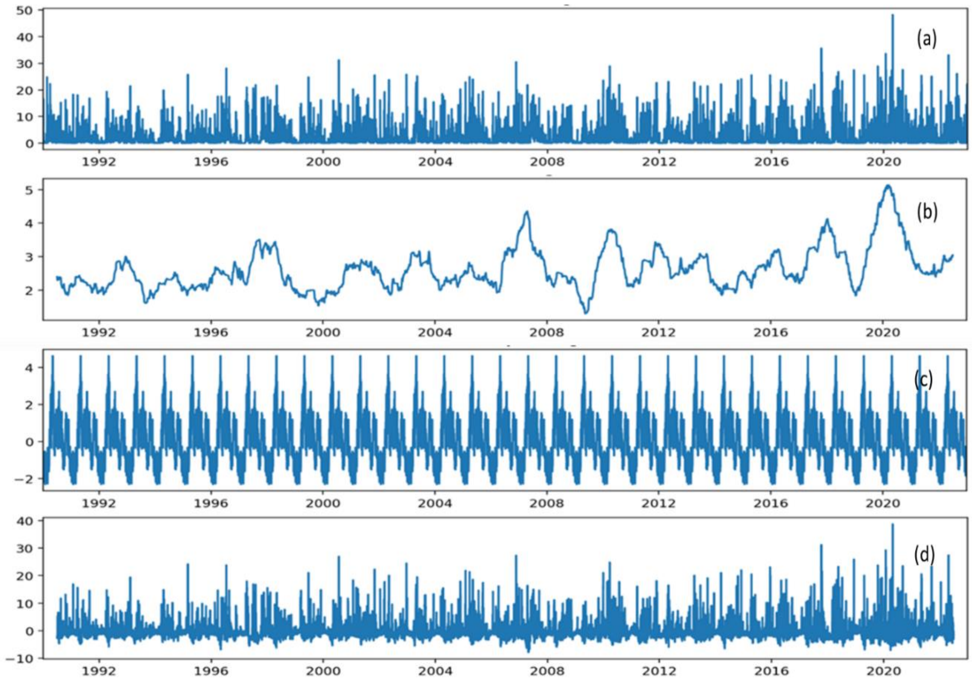

Figure 13. *Seasonal Decomposition of Precipitation i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Baringo County.*

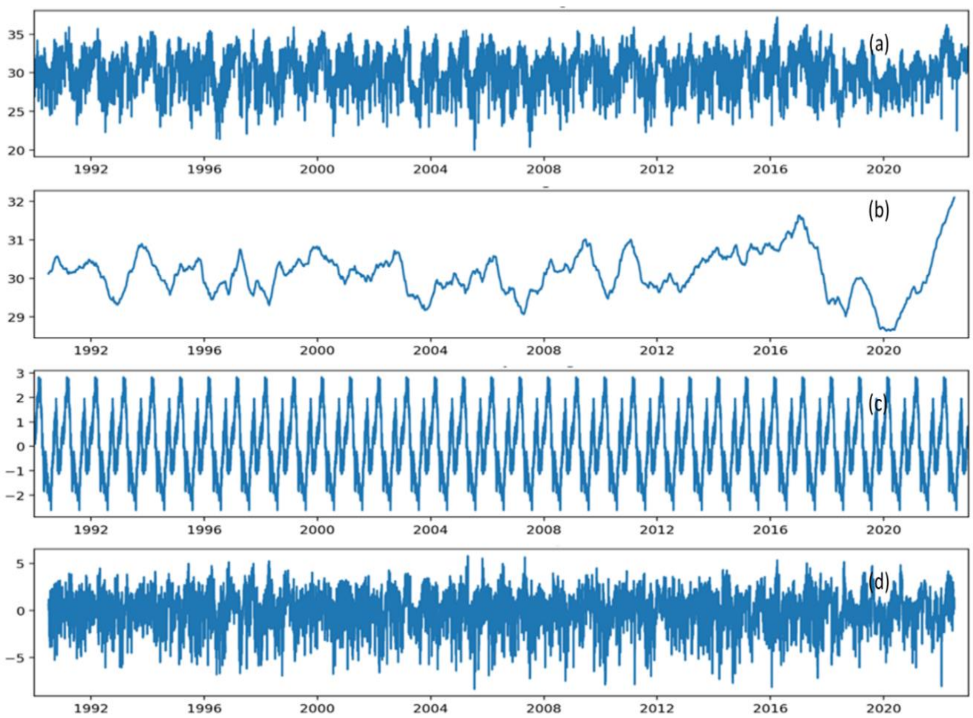

Figure 14. *Seasonal Decomposition of Maximum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Baringo County.*

Likewise, the minimum temperature (see Figure 15) has been noted to exhibit almost similar trends to the maximum temperature discussed above. The Observed (see Figure 15(a)), seasonality (see Figure 15(c)), and residual (see Figure 15(d)) minimum temperature graphs over Baringo County. These graphs exhibit a uniform pattern in minimum temperature over the County from 1990 to 2018 where a sharp drop in 2018 is realized. The trend in minimum temperature (see Figure 15(b)) remains relatively stable from 1990 to 2018 where a sharp drop in minimum temperature is realized around 2019 over the county. A point to note over the county is that there is a shrink in diurnal temperature over the county from around 2019 onwards which may explain the observed increase in precipitation over the county during the same period [27].

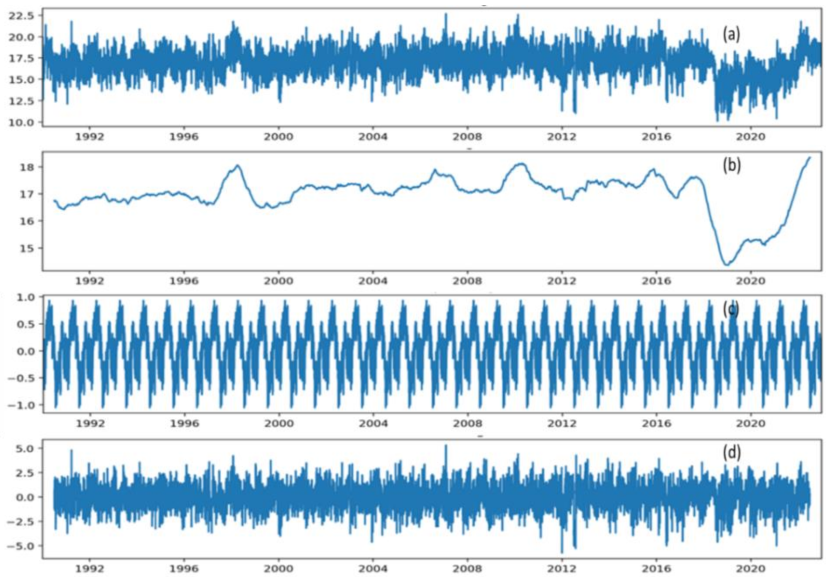

Figure 15. *Seasonal Decomposition of Minimum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Baringo County.*

Observed (see Figure 16(a)) and residual (see Figure 16(d)) graphs exhibit random variability in precipitation over West Pokot County. The county has been experiencing sporadic variability in precipitation during the study period. This is confirmed by the trend in precipitation (see Figure 16(b) from which it is observed that the county has been experiencing non-uniform variability in precipitation with significant variability realized between 2009 to 2011 and 2017 onwards. The seasonal decomposition of precipitation over West Pokot County follows a consistent pattern throughout the study period (see Figure 16(c)).

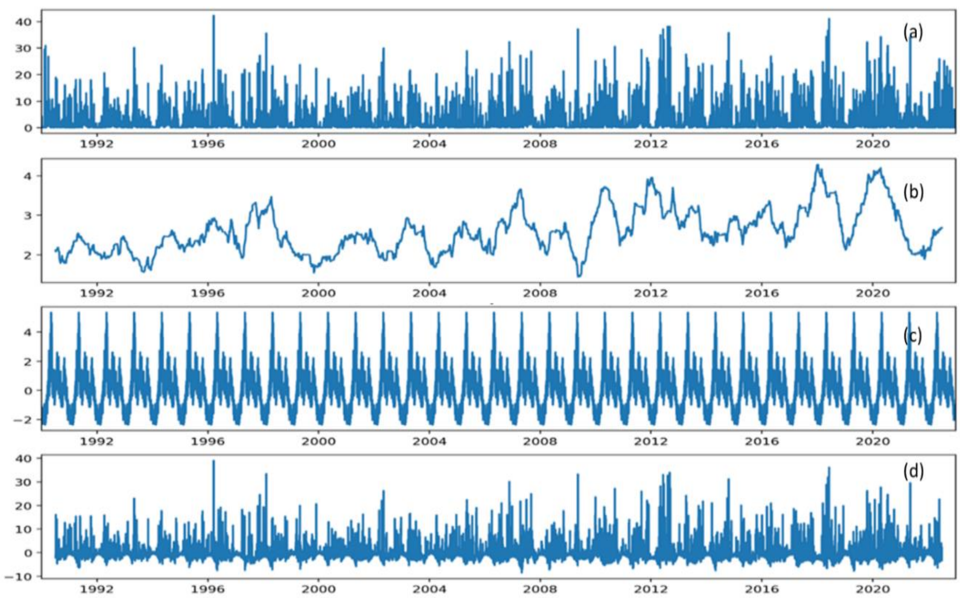

Figure 16. *Seasonal Decomposition of Precipitation i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over West Pokot County.*

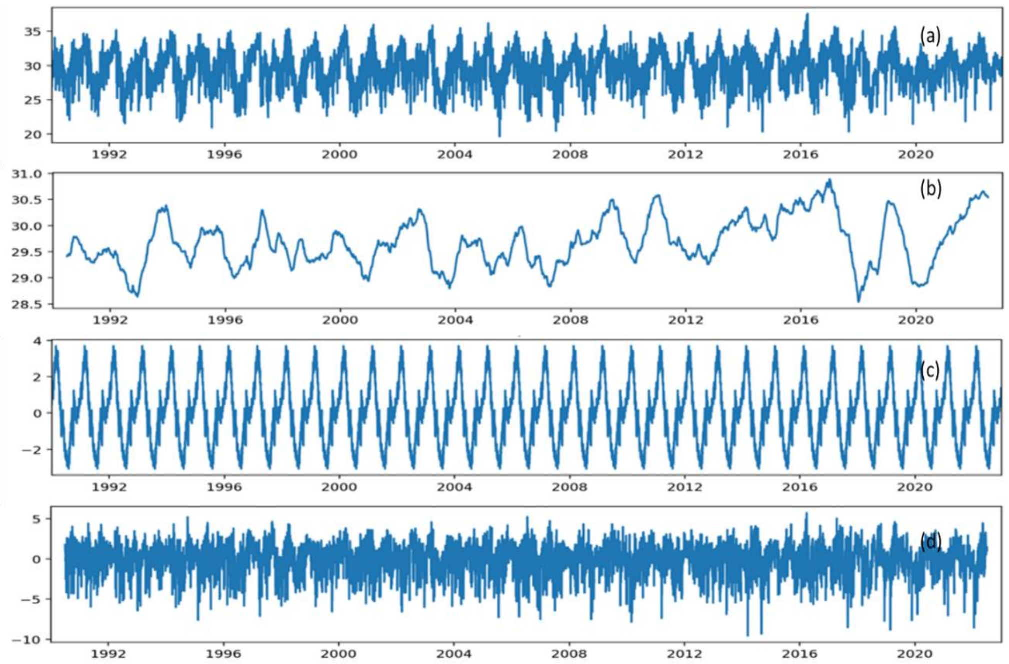

Figure 17. *Seasonal Decomposition of Maximum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over West Pokot County.*

Like precipitation, both maximum (see Figure 17) and minimum (see Figure 18) temperatures exhibit random variability over West Pokot County. The observed and residual graphs of maximum temperature (see Figure 17(a) and residual (see Figure 17(d)) exhibit random variability over West Pokot County. Likewise, the observed and residual graphs of minimum temperature (see Figure 18(a) and residual (see Figure 18(d)) exhibit random variability over the County. The trends in maximum (see Figure 17(b)) and minimum (see Figure 18(b)) temperatures demonstrate a high variability while seasonality in both maximum (see Figure 17(c)) and minimum (see Figure 18(c) remains invariant.

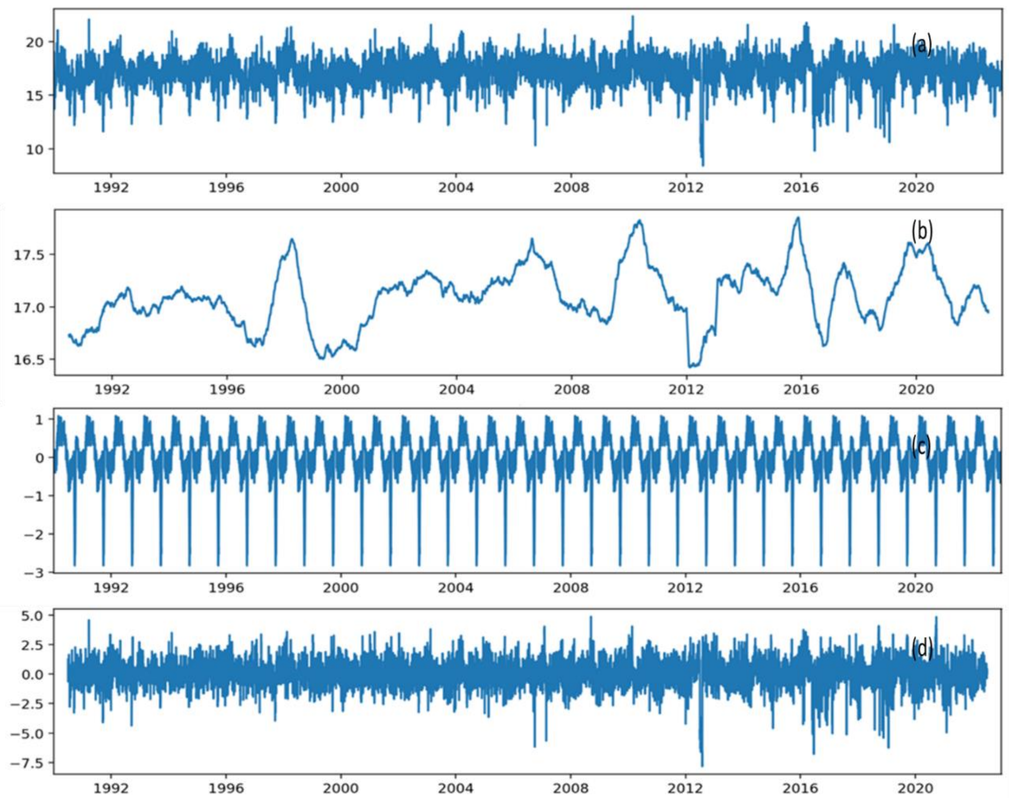

Figure 18. *Seasonal Decomposition of Minimum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over West Pokot County.*

Based on the observed (see Figure 19(a)) and residual (see Figure 19(d)) graphs, Samburu County had the most precipitation variability during the study period. Significant variability was noticeable from 1997 to 2000 and 2020 onwards (see Figure 19(b)). It is noted that though the amount of precipitation received has remained relatively constant, the variability for rainfall received was high. Furthermore, From Figure 19(c), seasonality in rainfall over Samburu County maintained a uniform pattern across the study period. Likewise, maximum temperature seasonal decomposition was also analyzed as follows. The observed (see Figure 20(a)), trend (see Figure 20(b)), and residual (see Figure 20(d)) graphs relatively stable pattern in maximum temperature from 1990 to 2017 with a sharp drop from 2018 to 2020 after which an observable increase is noted. The seasonality in maximum temperature over Samburu County maintained a uniform pattern across the study period (see Figure 20(c)). The observed (see Figure 21(a)), trend (see Figure 21(b)), and residual (see Figure 21(d)) graphs for the minimum temperature over Samburu County was noted to exhibit a sharp increase from 1998 to 2000. The minimum temperature is observed to exhibit a slight increase in minimum temperature up to 2017.

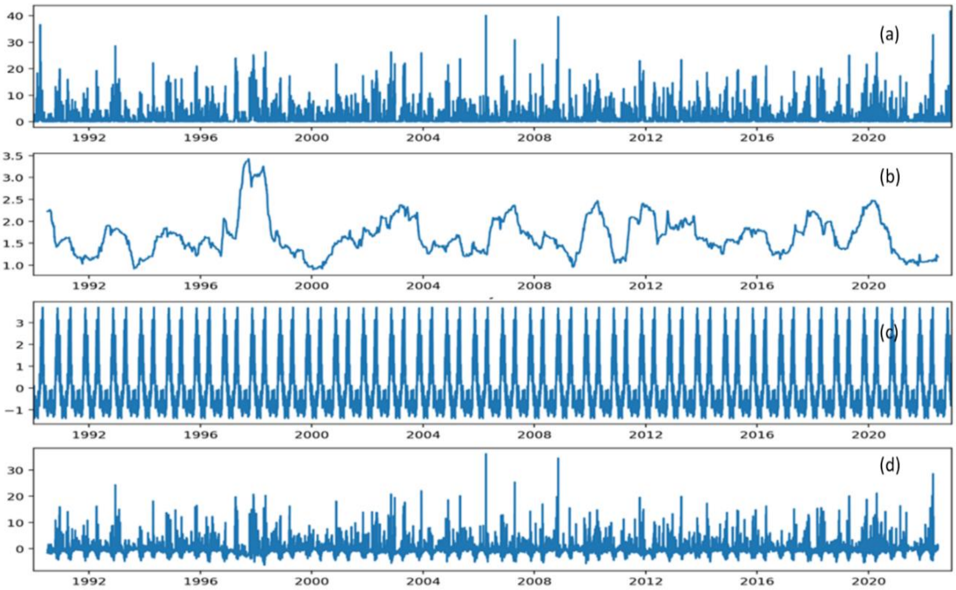

Figure 19. *Seasonal Decomposition of Precipitation i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Samburu County.*

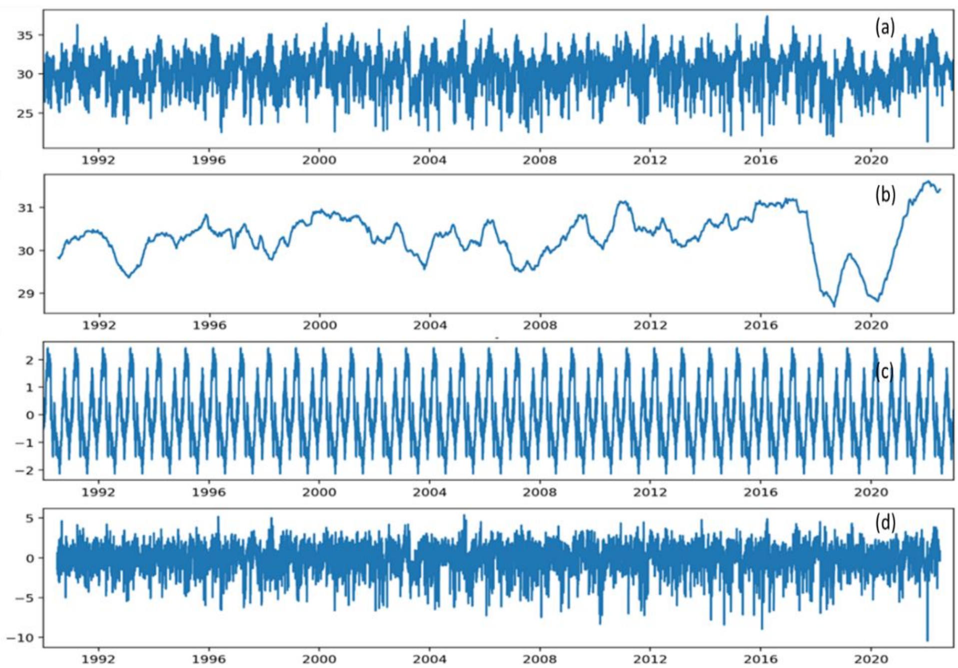

Figure 20. *Seasonal Decomposition of Maximum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Samburu County.*

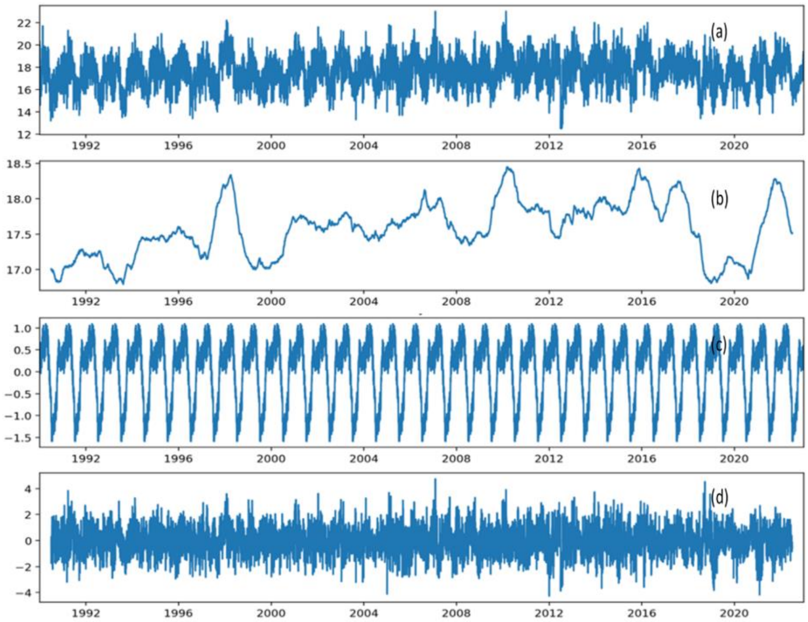

Figure 21. Seasonal Decomposition of Minimum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Samburu County.

A sharp decline is realized between 2018 and 2020. From Figure 21(c) a uniform seasonality pattern in minimum temperature is noted over Samburu County during the study period. A shrink in diurnal temperature over the county from around 2019 onwards also explains the observed increase in precipitation over the county [27].

The observed (see Figure 22(a)) and residual (see Figure 22(d)) graphs, Elgeyo Marakwet County experienced precipitation variability during the study period. Significant variability was realized between 1997 to 1998, 2006 to 2008, and 2017 to 2020 onwards (see Figure 22(b)). Increasing precipitation over the county in 2020 (see Figure 22(b) corresponds to a decline (increase) in maximum temperature (see Figure 23(b)) (minimum temperature (see Figure 24(b))). This scenario necessitates a declining diurnal temperature, which fosters enhanced precipitation over the county [27]. The pattern in the seasonal decomposition in precipitation, maximum, and minimum temperature remained relatively constant across the study period (see Figures 22(c), 23(c), and 24(c)) respectively over Elgeyo Marakwet County. The maximum temperature (minimum temperature) over the county has exhibited a relatively unstable pattern during the study period (see Figure 23(a), and residual (see Figure 8(d) graphs) ((see Figure 24(a), and residual (see Figure 24(d) graphs)).

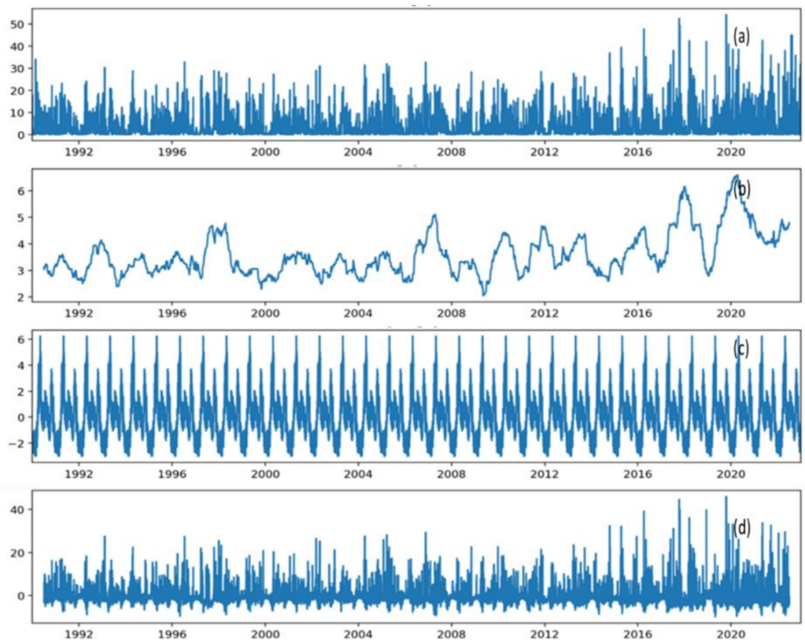

Figure 22. Seasonal Decomposition of Precipitation i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Elgeyo Marakwet County.

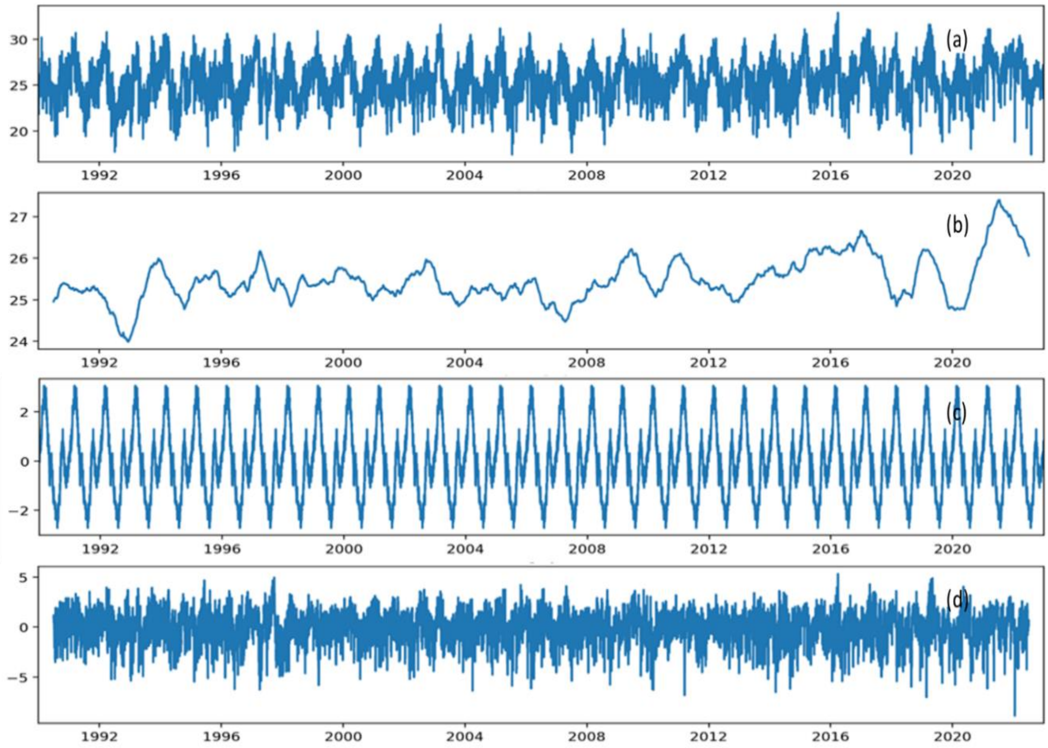

Figure 23. *Seasonal Decomposition of Maximum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Elgeyo Marakwet County.*

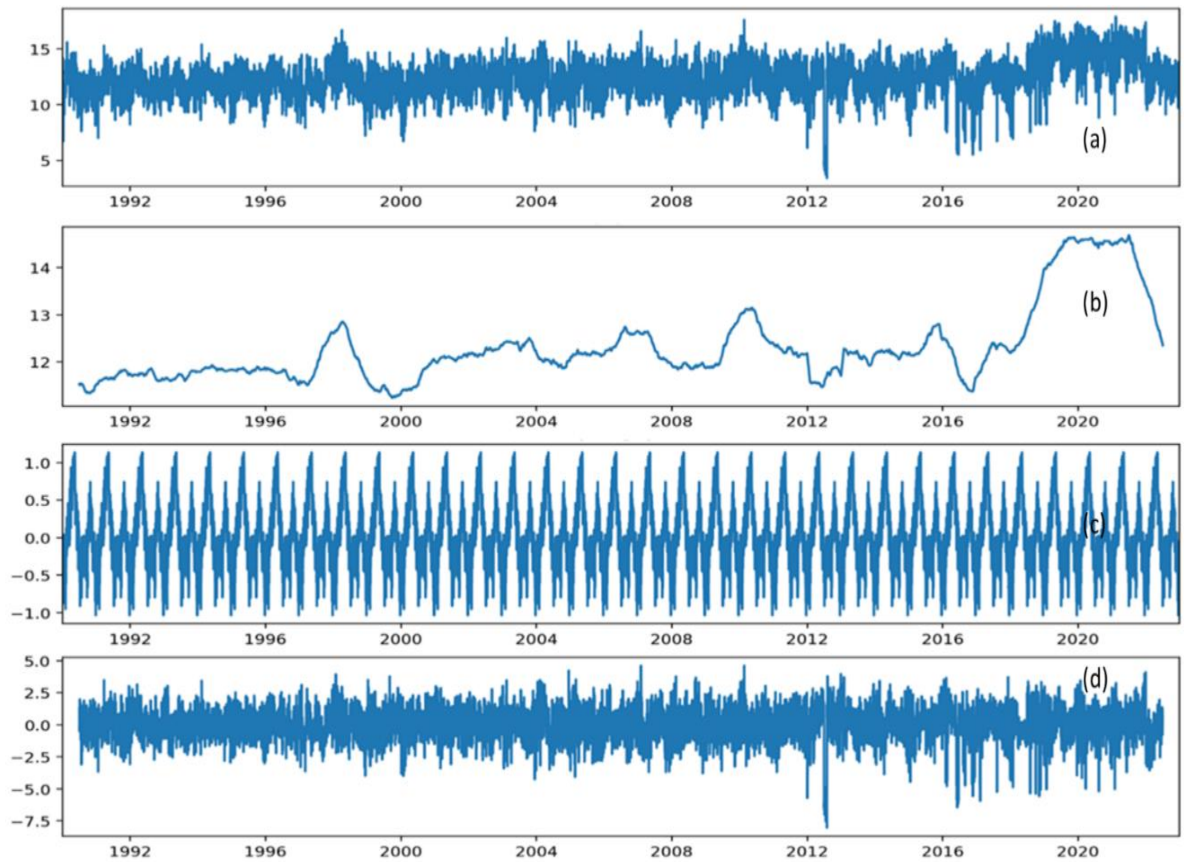

Figure 24. *Seasonal Decomposition of Minimum Temperature i.e. (a) Observed (b) Trend (c) Seasonality (d) Residual over Elgeyo Marakwet County.*

4. Conclusion

In the present study, assessing the long-term changes in selected meteorological parameters have been investigated over the North-Rift, Kenya. The conclusions drawn from the present study are listed as follows:

1. From the results above it is evident that the north rift region of Kenya is exhibiting significant spatiotemporal and Interannual variability in the selected climatic variables whose frequency, intensity, and duration have increased in the recent past. The results established Changes in Precipitation both in temporal and Spatial Scales. Decrease in precipitation between 1990-2000 with Turkana and Samburu being the most affected counties. Increases in precipitation were reported between 2006-2011 with the greatest beneficiaries being Uasin Gishu, Nandi, and Elgeyo Marakwet. The year 2020 was a year of extreme precipitation over the entire North rift region.
2. A slight variation in the distribution of minimum temperatures was noted with a major increase in temperature in 2005, 2012, and 2015. A decline in both maximum and minimum temperature between 2019 and 2020 was noted in Samburu. A decline in diurnal temperature exacerbated an increase in precipitation in selected counties. The seasonality component captures recurring patterns or fluctuations that occur at regular intervals within each region's data. These patterns suggest that in each region follows a distinct seasonal trend, exhibiting periodic variations over time.

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Conflicts of Interest

The authors declare no conflicts of interest.

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