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TRENDS IN HEATWAVE CHARACTERISTICS OVER BURKINA FASO

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ABSTRACT

In West Africa, particularly in Burkina Faso, heatwave studies are limited. However, several international studies forecast that this region will be especially vulnerable to increased heatwave events due to climate change. The characteristics of heatwaves in Burkina Faso from 1991 to 2021 have been examined by analysing observed data and climate model simulations. The Bias-Correction Spatial Disaggregation (BCSD) method generated the NEX-GDDP-CMIP6 dataset. The algorithm compares the GCM outputs with corresponding climate observations over a standard period. The maximum and minimum temperatures for the models were subjected to root mean square error (RMSE), standard deviation (S.D.) and correlation coefficient (R2) to determine the best substitute for observed data. The Taylor diagram showed that MRI-ESM2-0, with the least RMSE and S.D. values and highest R2 values for both maximum and minimum temperature values, is the best-substituted model for the observed data. According to the heatwave index HWN (Heatwave Number, HWD) (Heatwave Duration), and HWA (Heatwave Amplitude), the trend-based maps of heatwave characteristics often display a consistent pattern of positive or negative changes. The trend for a specific heatwave index characteristic may be either positive or negative, depending on the location and model considered when compared to the observed. The trends in heatwave characteristics concerning minimum temperatures show higher (warmer) values than those relating to maximum temperatures, indicating a situation of unusually warm nights. This study emphasizes trends in heatwave characteristics based on minimum and maximum temperatures, and calls for attention to the associated risk of rising nighttime temperatures during heatwaves.

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1. Introduction

Global average temperatures rose by approximately 0.07°C per decade from 1901 to 2010 (Morice et al., 2012). Questions have emerged regarding the effects of changing climatic conditions onthe environment and humanity. This rise in temperature has been linked to the impact of greenhouse gases and has not been

evenly distributed across the globe. Tropical countries like Burkina Faso, a landlocked nation in West Africa, are particularly vulnerable in terms of both health and economics. These findings are substantiated by studies conducted in the West African sub-region (Boureima et al., 2017; –Guigma et al., 2020). The frequency of extreme heat is continuously rising, leading to heatwaves. A heatwave is a prolonged period of unusually high temperatures that surpass the typical average for a specific area and season, often lasting several days. These extreme temperature events can severely affect human health, agriculture, and infrastructure. Heatwaves occur due to certain atmospheric conditions, such as high-pressure systems that trap hot air and are frequently worsened by climate change.

A universally accepted definition of a heatwave does not exist; somewhat, the definition can differ depending on the specific area of focus. Severe heatwaves have a substantial impact on people's health and well-being. For instance, approximately thirty thousand people died during the heatwave in Europe in 2003 (Hajat et al., 2006). Heatwaves are the deadliest natural hazard in Australia (Coates et al., 2014)and the leading cause of mortality in urban areas across the United States (National Weather Service, 2018). Studies have shown that heatwaves can reduce workers' abilities and skills, resulting in decreased output and a slower economy (World Bank Blog, 2024). Oueslati et al. (2017) describe the Sahel as one of the world's hottest regions. Since 1980, the temperature in West Africa has risen by 0.5 to 1 °C, and this trend is currently speeding up –(Ruppel et al., 2014). According to climate model studies, heatwaves will become more common in West Africa's arid and semi-arid regions in the following years. Russo et al., (2014) found that intense heatwaves, which are currently infrequent, will become more regular by the end of the century. There has been very little research on heatwaves in Burkina Faso. Nonetheless, Burkina Faso is one of the countries where people are most vulnerable to the effects of the climate. The fact is, living circumstances are harsh (Kima *et al*., 2015). Poor working condition, poverty, unplanned outages of water and light, especially in the summer months which have been established to be warmer, can contribute to the heatwave vulnerability of the populace.To mitigate the impact of heatwaves, it is essential to forecast their onset and address associated issues. Recent studies have shown that the duration, frequency, and severity of heatwaves have all increased in recent decades (Fontaine *et al*., 2013; Moron *et al*., 2016; Ceccherini et al., 2017;– Barbier et al., 2017). Future projections also indicate an increasing risk of extreme heat in Africa (Nangombe *et al*., 2019; Rohat *et al*., 2019).

However, contrasting evidence shows unchanging frequency (Adeniyi and Oyekola, 2017), possibly due to the heatwave metric used. Heatwaves have a variety of characteristics, including intensity, frequency, duration, timing, and spatial extent. Furthermore, each characteristic can be defined in various ways, likely due to itsbroad impact. This undermines a thorough understanding of how heatwaves have evolved on regional and global scales. In addition to accurately assessing the occurrence and changes in heatwave impacts, an all-inclusive and consistent assessment is also necessary to

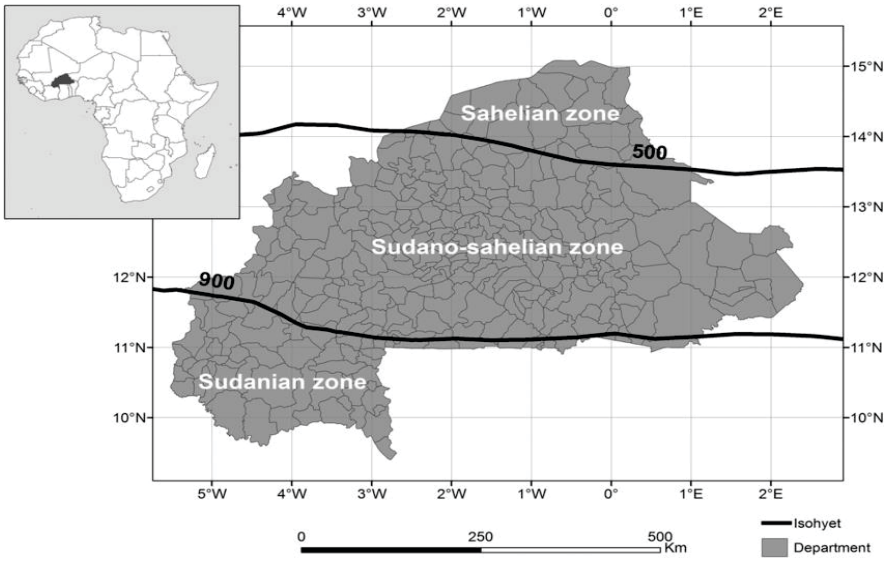


Figure 1: Map of Burkina Faso showing the three (3) ecological/climatic zones

establish confidence in the consensus suggested by prior disparate studies. This will help achieve the Sustainable Development Goals (SDG1), which are related to eradicating poverty, promoting human health and well-being (SDG3), and taking immediate action to address climate change and its impacts (SDG13). This study provides such an assessment by analysing the trend in heatwave characteristics in Burkina Faso from 1991 to 2021.

2. Research Methodology

2.1 Study Area

Burkina Faso is a landlocked country in West Africa, stretching from south to north between 9.25 and 15.01°N and from east to west between 2.22°E and 5.32°W. The national territory covers an area of 272,967 km2. Burkina Faso is located chiefly on a savannah plateau, the altitude varying between 250 m and 400 m. The country has two main climates: the north, covered by grasslands, is characterised by steppes and three to five months of precipitation, often erratic. The country has three (3) climatic zones: the Sahelian, Sudano-Sahelian, and Sudanian (Figure 1). From a thermal point of view, average temperatures differ slightly from one zone to another and increase from the South to the North. Figure 1 shows the map of Burkina Faso with the different climatic zones.

2.2 Data

Input daily maximum (TX) and minimum (TN) near-surface air temperature data were accessed for 11 climate models from the NEX-GDDP-CMIP6 dataset. The Bias-Correction Spatial Disaggregation (BCSD) method used to generate the NEX-GDDP-CMIP6 dataset is a statistical downscaling algorithm specifically developed to address these limitations of global GCM outputs (Wood et al., 2004; Thrasher et al., 2012; Shrestha et al., 2017). These models provide data at a spatial resolution of 0.25° × 0.25°. The dataset includes TX, TN, and precipitation (PR) data from 1981 to 2014, accessed at https://ds.nccs.nasa.gov/thredds/catalog/idd/bypass.html. Observed data were obtained from

ANAM (AgenceNationale de la Meteorologie du Burkina Faso) from ten synoptic stations across the country from 1991 to 2021. This observed data was spatially interpolated to generate a comprehensive meteorological dataset.

2.3 Method for analysing the trend in heatwave characteristics

The first step in answering our research objective is to define a heatwave day across our study area.

2.3.1 Heatwave definition

Pre-processing of the original model TX (maximum temperature) and TN (minimum temperature) datasets was performed using Climate Data Operators (CDO), ensuring compliance with ClimPACT2 instructions. The heatwave calculations used in ClimPACT2 are based on Perkins and Alexander, (2013). Two heatwave definitions are used based on the 90th percentile of TN-designated TN90 and the 90th percentile of TX-designated TX90. According to the two heatwave definitions (TN90 and TX90), a heatwave event is defined as any length of three or more days where one of the following conditions is met:

1. TN > 90th percentile of TN.
2. TX > 90th percentile of TX.

The percentiles for TN90 and TX90 are calculated from 1991 to 2021 and for each calendar day using a 15-day running window. For each definition, Heatwave Number (HWN), Heatwave Duration (HWD), and Heatwave Amplitude (HWA) are calculated. The HWN represents the total number of heatwave events in a year, the HWD is the length in days of the most prolonged heatwave defined by HWN, and the HWA is the peak daily value in the hottest HW.

2.3.2 Model Biases and Limitations

While valuable, the 11 climate models within NEX-GDDP-CMIP6 have limitations in simulating temperature and heatwave indices, particularly regarding extreme events and regional variations. These models can underestimate the severity of heatwaves and exhibit biases in temperature distributions, which can impact the accuracy of heatwave index projections. The bias correction and downscaling processes also introduce uncertainties, particularly at the local scale. Some studies suggest that NEX-GDDP-CMIP6 models, even after bias correction, may not fully capture the severity of extreme heat events, potentially underestimating the magnitude of the largest historically observed heatwaves. This can be a concern when evaluating the impacts of climate change on vulnerable populations and ecosystems.

The models may exhibit systematic biases in temperature distributions, particularly at certain locations or during specific seasons. This means that the models might consistently over- or underestimate temperature values compared to observations, leading to inaccurate projections of heatwave frequency and intensity. The limitations in simulating temperature and heatwave indices can affect the accuracy of projections for various heatwave indices, such as the number of heatwave days, maximum heatwave temperature, and heatwave duration. These indices are crucial for understanding the impacts of climate change on human health, agriculture, and other sectors.

2.3.3 Trend Analysis and Significance Testing

Mann-Kendall test (Mk) (Mann, 1945; Kendall,

1975; Wang *et al.*, 2005) was also used for the trend analysis. This method was utilised to identify discontinuities resulting from inhomogeneous time sequences. Its uniqueness lies in the absence of presumptions regarding data distribution, making it widely accepted for trend analysis. This characteristic has garnered widespread acceptance for trend analysis(Ajayi and Ilori, 2020; Arowolo and Oluleye, 2022). It is a non-parametric statistical method for identifying monotonic trends in time series data. It is advantageous because it does not require the time series to be distributed normally, accommodates time series with missing data, and is robust to the influence of extremes. Mk statistic can be described as:

$$K = \sum_{i=1}^{n} \sum_{j=1}^{i-1} sign\,(xi - xj) \qquad (3.6)$$

Where *xi* and *xj* are the values of the sequential generic data, *n* is the total length of data,
while sign (xi-xj) can be defined as;

$$\begin{bmatrix} 1, & if(xi - xj) & 0 \\ 0, & if(xi - xj) & 0 \\ -1 & if(xi - xj) \cdots & 0 \end{bmatrix} \qquad (3.7)$$

The variance Var (S) was calculated as follows when S statistic is approximately distributed with the E(S) mean:

$$E(S) = 0, \qquad (3.8)$$

$$\{n(n-1)(2n+5) - \sum_t t(t-1)(2t+5)\} \qquad (3.9)$$

where t is any given tie extent, ∑t represents the summation of all values of the tie number, while n denotes the series length. The Z-standardized statistics for the test can then be evaluated using the equation below:

$$\begin{pmatrix} -1, & if & K < 0 \\ 0, & if & K = 0 \\ \frac{S+1}{\sqrt{Var(S)}} & if & K > 0 \end{pmatrix} \qquad (3.10)$$

When a dataset of n variables is randomly distributed independently without trend and ordering is equally likely, the null (H0) hypothesis is accepted. The absolute value of Z (test statistic) is then compared with the value of Z(1-p/2) at p level of significance to reject or accept the H0 hypothesis.

3. Results and Discussion

The trend in three (3) heatwave-related characteristics was studied from 1991 to 2021 for TN and TX. The annual values of the number of events per year, the number of days participating in heatwaves, and the peak temperature during the hottest heatwave. The chosen level of significance is 0.05, and this was translated in the figures with dots. The dotted areas are regarded as regions of significance of the specific heatwave index characteristic, as derived from the in-built Mann-Kendall analysis in the model. Hence, areas devoid of the dots shows the insignificance of the heatwave trend in the region.

Figures 2a and b are Taylor diagrams that show the statistical analyses of observed data against the model data for the minimum and maximum temperature, respectively. The analyses from the figures were standard deviation (S.D.), correlation coefficient (R^2) and the root mean square error (RMSE). The black broken line is the observed data indicator, the red broken line is the line of root mean square error, the green arc is the line of standard deviation, while the green broken straight line is the line of correlation coefficient.

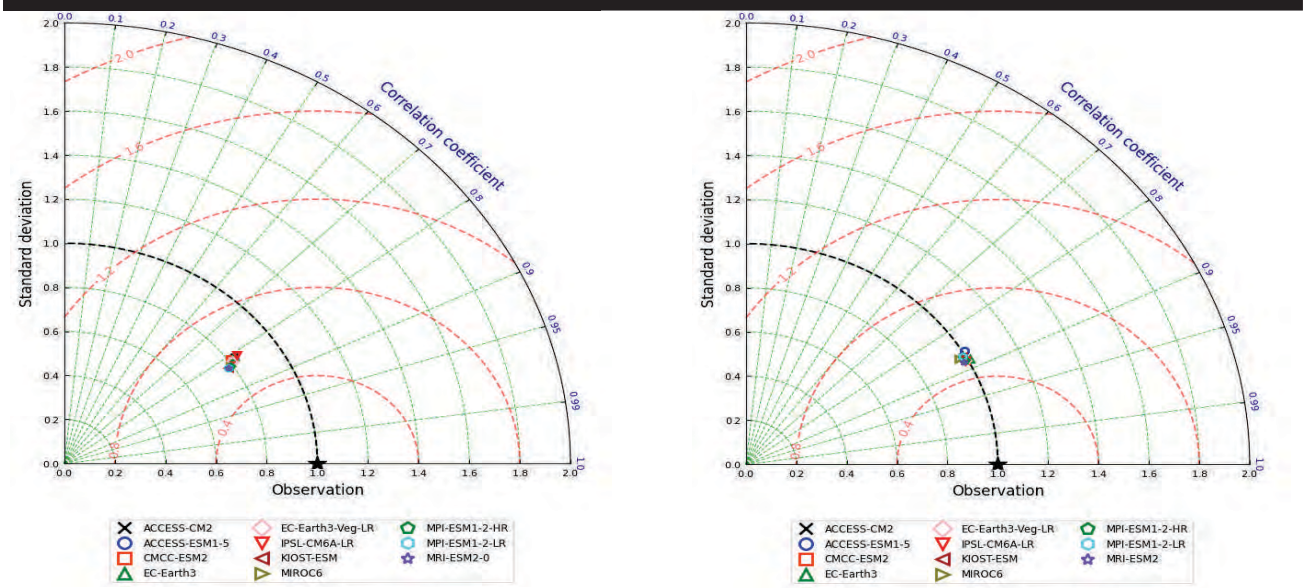


Figure 2: Taylor's diagram for (a) minimum and (b) maximum temperatures of observed data against other models

Figure 2a shows that most models overestimated by 0.6 with a standard deviation of 0.8 and a correlation coefficient of about 0.82. Figure 2b shows the models to have overestimated by 0.5 and a standard deviation of 1.0, with a correlation coefficient between 0.87 and 0.89. It can also be deduced from these figures that the closer the root mean square error and standard deviation are to zero, the better the performance of the models. The closer the correlation coefficient values of the models against the observed values are to 1, the better the models. The resultant outcome of these statistical analyses of the models against observed data from Figures 2a and b is summarised in Table 1.

Figures 3 to 7 show the spatial distribution of the calculated trends. The sidebar shows the range of

Table 1: Standard Deviation, Correlation Coefficient and Root Mean Square Error of Minimum and Maximum Temperatures from Taylor's Diagram.

S/N	Model	Minimum Temperature			Maximum Temperature		
		S.D.	R^2	RMSE	S.D.	R^2	RMSE
1.	ACCESS-CM2	0.82	0.81	0.54	0.99	0.87	0.51
2.	ACCESS-ESM1-5	0.82	0.82	0.55	1.01	0.86	0.55
3.	CMCC-ESM2	0.81	0.82	0.63	0.99	0.88	0.49
4.	EC-Earth3	0.83	0.81	0.59	1.01	0.88	0.53
5.	EC-Earth3-Veg-LR	0.81	0.82	0.58	0.99	0.88	0.51
6.	IPSL-CM6A-LR	0.84	0.83	0.64	0.99	0.88	0.48
7.	KIOST-ESM	0.78	0.83	0.64	0.99	0.87	0.52
8.	MIROC6	0.79	0.83	0.58	0.97	0.87	0.51
9.	MPI-ESM1-2-HR	0.79	0.83	0.56	0.99	0.88	0.5
10.	MPI-ESM1-2-LR	0.78	0.83	0.55	0.99	0.87	0.53
11.	MRI-ESM2-0	0.78	0.83	0.54	0.98	0.88	0.48

high and low values of temperature indices, while the dots show areas of the index significance over the study area. Based on the index, the trend of heatwave characteristics-based maps often displays an unmixed pattern of positive or negative changes. A statistically significant positive trend was observed over the western, southwestern, and northeastern parts of the country for HWN_TN90 (Figure 3). A similar result was found with models such as MPI-ESM1-2-HR and MPI-ESM1-2LR, while models ACCESS-CM2, ACCESS-ESM1-5, EC-Earth3, EC-Earth3-Veg-LR, IPSL-CM6A-LR, and KIOST-ESM overestimated the results and models CMCC-ESM2, MIROC6, and MRI-ESM2-0 underestimated the results.

The HWN_TX90 (Figure 4) showed a low, positive, significant trend over the northern and the northwestern part of Burkina Faso and the southern part. All the models overestimated the results by showing an increased trend across the country, except for model CMCC-ESM2, which showed an increasing trend only in the western part, and model EC-Earth3, with a rising trend in the northern part and a decreasing trend in the southern part. The trend in HWN is positive for minimum and maximum temperatures. The number of heatwave events is more pronounced at nighttime than at daytime, causing more impact on human health. –De Longueville et al. (2016) found that minimum temperatures are rising faster than maximum temperatures. This can impact human health because individuals will find it difficult to evacuate the heat stress accumulated throughout the day. Due to the predicted rise in HWN, excessive heat may become an almost regular occurrence in the area, making it harder for

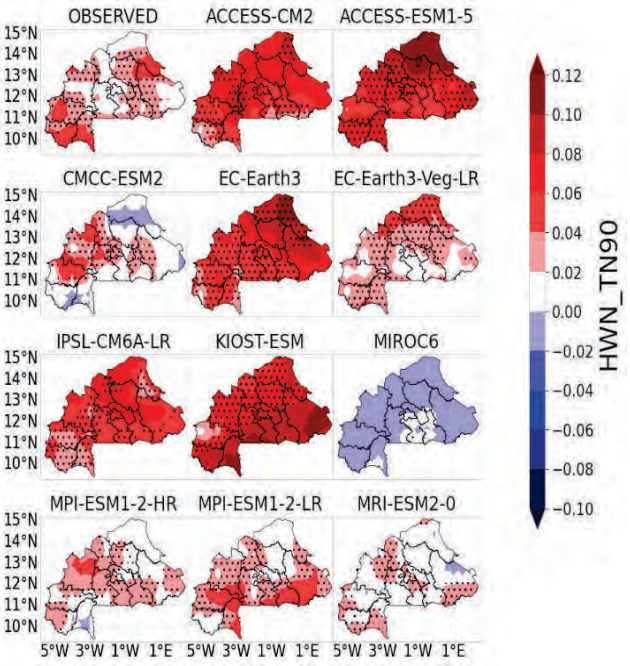


Figure 3: Trend analysis of heatwaves in Burkina Faso for HWN (Heat Wave Number) for TN90th percentile from 1991 - 2021.

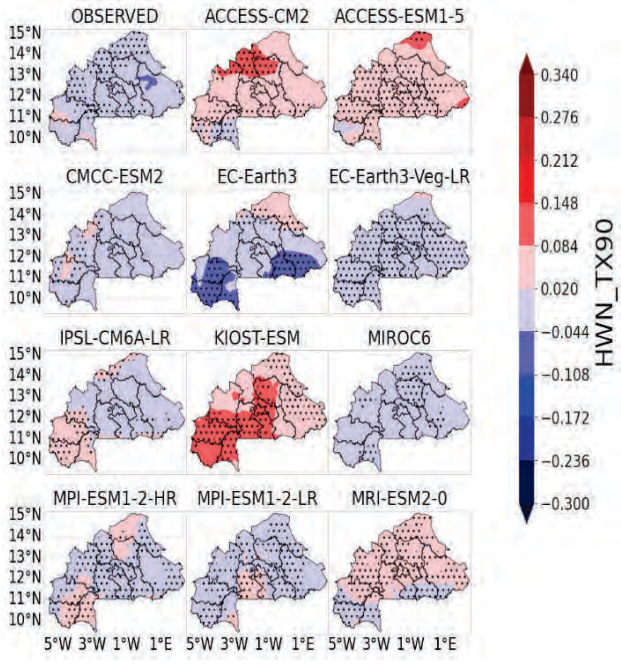


Figure 4: Trend analysis of heatwaves in Burkina Faso for HWN (Heat Wave Number) for TX90th percentile from 1991 - 2021.

vulnerable communities to remain resilient. This rise in heatwave occurrences increases the probability of overlapping or consecutive incidents, as noted by —Odoulami et al. (2017). The study noted that prolonged exposure to heat could affect animals, disturb agriculture, and weaken crop resilience, all of which would increase health issues in communities without access to cooling supplies.

Concerning HWD_TN90 (Figure 5), the decreasing trend is significant from the north to the northeast and the west of the country. The trend is decreasing in the other parts of the study area, but it is insignificant. The results obtained with the 11 models also show a decreasing trend in HWD but with different distributions of significance across the country. Models such as ACCESS-ESM1-5, EC-Earth3-Veg-LR, MIROC6, and MPI-ESM1-2-HR showed positive and negative trends.

The decrease is significant over the entire country for maximum temperature (Figure 6), with greater intensity from the central to the central southern part. The simulation models showed a mixture of positive and negative trends.

When analysing the trend observed under the HWD, the outputs from minimum temperature showed scattered decreasing trends across some locations of the study area, except the MPI-ESM1-2-LR, which shows about 90% of the study area being influenced by the trend. The maximum temperature showed a statistically decreasing trend across Burkina Faso. While the observed recorded an almost complete negative trend over the study area, the other models exhibited positive and statistically significant trends over Burkina Faso. This result again emphasises that Burkina

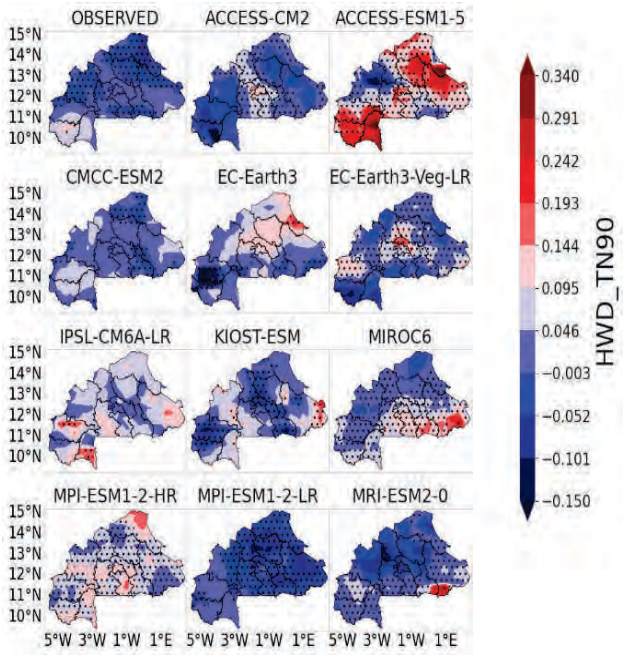


Figure 5: Trend analysis of heatwaves in Burkina Faso for HWD (Heat Wave Duration) Days for TN90th percentile from 1991 - 2021.

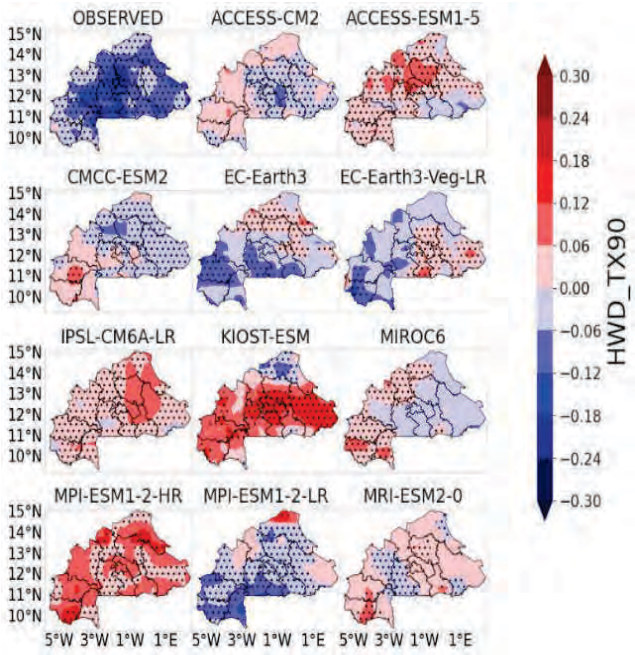


Figure 6: Trend analysis of heatwaves in Burkina Faso for HWD (Heat Wave Duration) Days for TX90th percentile from 1991 - 2021.

Faso experienced a longer duration of nighttime heat than daytime heat. Over the past several decades, excessively warm midnight minimum temperatures have been linked to higher mortality and adverse health effects, even though high daytime maximum temperatures are known to influence human life and health (Nissan et al., 2017). Thus, the increasing trend of temperature extremes based on minimum temperatures are alarming and necessitate more adaptation and mitigation measures to reduce nighttime temperatures.

The HWA_TN90 (Figure 7) showed a statistically significant downward trend from the eastern to the central and southwestern parts of the country. Similarly, a decreasing trend was observed with models like EC-Earth3 and ACCESS-CM2. Models like ACCESS-ESM1-5, EC-Earth-Veg-LR, IPSL-CM6A-LR, and MPI-ESM1-2-LR showed statistically significant upward trends, while the other models showed a mixed positive and negative trend.

The HWA_TX90 (Figure 8) depicted a negative statistically significant trend across the country, except for the extreme north and the southeastern part, where the trend is insignificant. On the other hand, the simulation models only showed a positive trend, with the location of statistical significance depending on the model considered. The trend in HWA is generally negative for the two heatwave definitions.

When comparing the trend of these two metrics, it is clear that the trend of HWA based on minimum temperatures is more coherent than that based on maximum temperatures. Also, changes in trends based on minimum temperatures are minimal (negligible on an individual scale) compared to

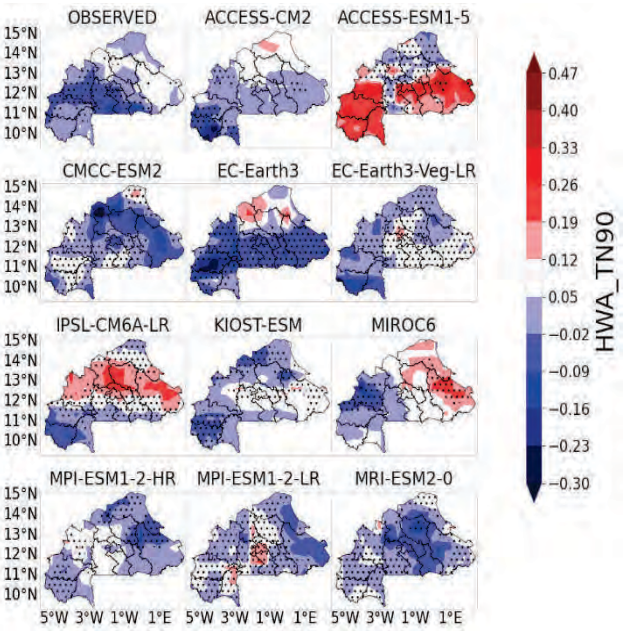


Figure 7: Trend analysis of heatwaves in Burkina Faso for HWA (Heat Wave Amplitude) °C for TN90th percentile from 1991 - 2021.

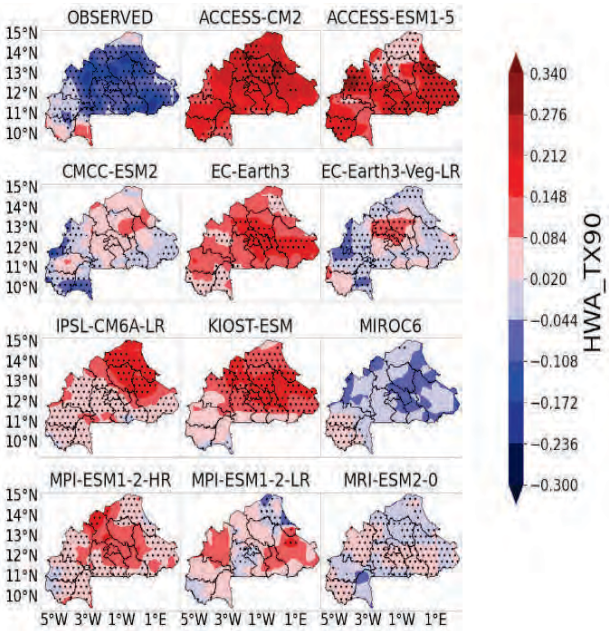


Figure 8: Trend analysis of heatwaves in Burkina Faso for HWA (Heat Wave Amplitude) °C for TX90th percentile from 1991 - 2021.

those based on maximum temperatures. While elevated daytime temperatures are well-documented for their influence on human well-being, persistently high nighttime minimum temperatures have been associated with increased mortality and detrimental health effects during extreme heatwaves worldwide over the past few decades (Nissan et al., 2017). Consequently, the rising tendency of temperature extremes based on minimum temperatures is concerning and calls for additional mitigation and adaptation actions to lower evening temperatures.

It can be concluded that the relationship between time and temperature is evident, although the strength of the relationship is weak. The results corroborated the findings of similar analyses conducted by Sanogo et al. (2015) on the spatio-temporal characteristics of temperatures in the Sudanian region, highlighting the need for continuous monitoring and an in-depth understanding of local climate change. Burkina Faso is characterised by a semi-arid to arid climate with a short rainy season. Temperatures can be sensitive to climatic variations, mainly due to monsoon variations. Previous studies by –Hulme (2001) highlight the region's sensitivity to climate variations, which could amplify the impacts of observed warming.

In summary, these results indicated a statistically significant trend towards an increase in temperature over the years, although the relationship is very weak in magnitude. These outputs could motivate adaptation actions to deal with climate change, such as developing resilient agricultural practices, improving energy efficiency, and raising awareness of climate challenges. Previous research (Ouedraogo and Stroosnijder, 2006), highlights the importance of developing resilient farming practices and adaptation strategies to mitigate the impacts of climate change in the region.

4. Conclusion

This study investigated the spatial trend of heatwave characteristics (HWN, HWD, HWA) over Burkina Faso based on two heatwave definitions. These measures offer a comprehensive framework for analysing heatwaves. The results showed a statistically significant trend indicating an increase in temperature over the years, although the relationship is very weak in magnitude. In comparing heatwave trends, it is evident that heatwave characteristics based on minimum temperatures showed greater spatial coherence than those based on maximum temperatures. Additionally, trends associated with minimum temperatures are notably more positive than those related to maximum temperatures. The trend for a given characteristic was positive or negative, depending on the location and model considered. The findings expand our understanding of heatwave variability over Burkina Faso. A comprehensive approach is crucial for creating effective strategies to adapt to and build resilience against climate impacts, where heatwaves severely affect communities and ecosystems.

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