FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 6 No. 4, August, 2022, pp 160 - 173
DOI: https://doi.org/10.33003/fjs-2022-0604-1059

INFLUENCE OF CLIMATE INDICES ON VEGETATION DYNAMICS IN KAMUKU NATIONAL PARK, NIGERIA USING COUPLED MODEL INTERCOMPARISON PROJECT PHASE 6 (CMIP6)

Bashariya Mustapha Baba, *Zaharaddeen Isa, Auwal Faruq Abdussalam, Abu-Hanifa Babati

Department of Geography, Kaduna State University, Kaduna, Nigeria.

*Corresponding authors' email: isazaharaddeen@gmail.com

ABSTRACT

This study examined the influence of climate indices on vegetation dynamics in Kamuku national park, Nigeria. MODIS NDVI dataset was obtained from 2000 – 2021, while temperature and rainfall data were obtained from NiMet Kaduna international airport from 1980 - 2015. Downscale climate indices from Six-generation (Coupled Model Intercomparison Project Phase 6 (CMIP 6)) global climate model was obtained from Copernicus from 1850 - 2099. Coefficient of variability, Mann Kendall and correlation were used to examine the variability, trend and relationship. Subsequently, multiple linear regression was used to assess the influence of climate indices on vegetation dynamics. The result revealed that rainfall indices have moderate variability and temperature indices show a low variability, while the normalized vegetation index revealed a low variability of vegetation vigour in the study area. In addition, there is a weak positive relationship between the rainfall indices and vegetation and a negative relationship between temperature indices and the vegetation vigour. The climate indices were able to explain 47 % (R2 = 0.47) variance of the vegetation vigour in Kamuku national park. While the remaining 53% might be a result of other factors such as human activities and other environmental factors. In conclusion, the vegetation vigour regulates the distribution of the climate extreme indices and might likely be more influenced by the human activities.

Keywords: climate indices, vegetation, protected area, Kamuku national park, regression

INTRODUCTION

Vegetation has a significant impact on the terrestrial carbon and climate systems, consequently influencing the provision of ecosystem services. Human and natural factors have a tremendous impact on it. As a result, its components vary from season to season in a periodic and successional manner, implying distinct responses and feedbacks by various species and systems (Weiskopf et al., 2020). Depending on the perspective used, the climate in any location of the world can be described at either macroclimate or microclimate levels (De Frenne et al., 2021). Previous research has linked vegetation growth dynamics to climate variability, and chronic climate variability that continues over time and results in climate change (Adenle et al., 2020; Bastian, 2013). Climate change is one of humanity's most pressing issues, with negative effects on global food security and human health (Musa & Solomon, 2011). According to the IPCC, communities and resource managers need to understand the effects of climatic variability and change to adapt to and plan for larger swings as global climate change becomes more apparent (Isa & Danjuma, 2018; Ismail et al., 2019; Yunusa et al., 2017; Zaharaddeen et al., 2017). Vegetation has an impact on climate through biochemical and biophysical processes (Perugini et al., 2017). Plant albedo and emissivity effects, as well as energy distribution between sensible and latent heat over land by vegetation parameters, are examples of biophysical aspects. Biochemical processes involve the regulation of carbon exchange, with plants absorbing more than one-third of the CO concentration in the atmosphere during photosynthesis and returning a comparable amount of O_2 or water vapour during respiration (Nwilo et al., 2020). Climate variability in Nigeria, combined with population shifts, has been shown to alter the structure, distribution and variety of vegetation through variations in vegetation indices and the recruitment-mortality interactions of woody and herbaceous plants (Brandt et al., 2017).

Greenhouse gases warm the atmosphere significantly by storing long-wave reflected radiation from the earth's surface, causing the climate to change (Abdussalam & Zaharaddeen, 2017). This is related to humid atmospheric conditions, which are connected to a range of environmental processes that influence the uptake of long-wave reflected radiation from the earth's surface (Tan et al., 2015). Downpours received a large amount of its energy from water vapor because a lot of latent energy is discharged when the vapor accumulates or freezes (Oki & Pat, 2014). An examination of the global and yearly average radiative forcing since the pre-industrial period reveals a strong dominance of greenhouse-gas-related warming. Human-caused emission scenarios elements include greenhouse gas emissions and vegetation changes, although not all are responsible for the water vapor present in the atmosphere(Cassia et al., 2018). Furthermore, the current industrial period includes activities that emit significant amounts of greenhouse gases into the atmosphere, such as the use of fossil fuels and the clearance of croplands and forests (Appiah et al., 2015).

Changes in vegetation can be efficiently examined using remotely sensed data (Shobairi, 2018). This is because flora has different reflecting and absorptive qualities than other objects on the earth's surface(Bashariya et al., 2022; Yunusa et al., 2017). The reflective property of plants has been employed in the development of many vegetation indicators (He et al., 2015). The spectral vegetation indices are a mathematical combination of many spectral bands, most of which are in the visible and near-infrared sections of the solar electromagnetic spectrum (Koko et al., 2021). The Normalized Difference Vegetation Index (NDVI) is an indicator of vegetation greenness that has gained popularity due to its positive relationships with

biophysical and biochemical parameters such as vegetation covering, leaf area, chlorophyll density, green biomass and growth conditions (Wang et al., 2015). Given the foregoing, NDVI can be utilized not only to analyze spatiotemporal variability in vegetation but also to show vegetation feedback to climate change (Mansour et al., 2020). A gradual change over a time series of NDVI values that stalls or reverses, showing a significant change in slope is referred to as a breakpoint (Adenle et al., 2020). Break points on NDVI time series are very significant in revealing different effects caused by inter-annual variability due to artifacts of harmonized datasets from different sensors, meteorological distortions (clouds or snow cover) and environmental processes such as year-to-year variation in weather conditions on plant activity(Rousta et al., 2020).
Therefore, this research aims to assess the influence of climate indices on vegetation dynamics. The following objective was achieved; the variability and trend of climate indices and normalized difference vegetation index were assessed. Multiple regression was used to established the relationship and assess the influence of climate indices on vegetation. Subsequently, the predicted climate indices were compared with the historical and it was used to predict the future vegetation dynamics of Kamuku national park.

MATERIALS AND METHODS

MOD13Q1 products (vegetation indices 16-Day L3 Global 250 m version 5) were downloaded from the National Aeronautics and Space Administration (NASA) of the United States (US) Warehouse Inventory Search Tool (WIST). These data were distributed By the Land Processes Distributed Active Archive Center (LP DAAC), located at the US Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (https://lpdaac.usgs.gov). MOD13Q1 data were provided every 16 days at a spatial resolution of 250 m in the sinusoidal projection. The NDVI data were extracted for the study area.

Climate data

The daily precipitation amounts and daily maximum and daily minimum temperatures were obtained for the period 1980 to 2015. Although the data was obtained from the Nigerian Meteorological Agency (NiMet) Kaduna – a government organization in charge of all-weather stations across the country. A downscale of thirteen climate indices were downloaded from https://cds.climate.copernicus.eu. The climate indices were from the sixth generation CMIP6 of Global Climate Model from Canada laboratory (CanEMS) from 1850 - 2099 (Copernicus Climate Change Service, 2021). The thirteen climate indices were computed based on the ETCCDI recommended core indices (Folland et al., 2001; Peterson et al., 2002). Therefore, the indices of temperature and precipitation were selected to investigate extreme climate conditions for the study area between 1850 and 2099. The selected indices for this study are presented in Table 1.

Variability and trend analysis

To assess the variability of climate and vegetation, several techniques have been developed for the analysis of hydro-meteorology, which generally fall into variability and trend analysis categories. Variability analysis involves the use of Coefficient of Variation (CV) of inter-annual data of climate indices and vegetation. The coefficient of variation (CV) provides a measure of year-to-year variation in data series. The seasonal variability was compared using the analysis of variances (ANOVA). Furthermore, comparison was used to account for the direction in which the variation exists, this method uses a Student distribution whereby it corresponds to a t-test performed on the ranks. In addition, the modified Mann-Kendall (M-K) trend test was used to determine the direction, magnitude and significance of the trend in climate variables. The significance of the trend was tested at 5% levels and the test statistics are then computed as integer values.

Table 1: List of ETCCDI Indices investigated in the study

S/No	ID	Indicator Name	Definitions	Units
1.	TXx	Max Tmax	Monthly maximum value of daily maximum temp	ºC
2.	TNx	Max Tmin	Monthly maximum value of daily minimum temp	ºC
3.	TXn	Min Tmax	Monthly minimum value of daily maximum temp	ºC
4.	TNn	Min Tmin	Monthly minimum value of daily minimum temp	ºC
5.	DTR	Diurnal temperature range	Monthly mean difference between TX and TN	ºC
6.	Rx5day	Max 5-day precipitation amount	Monthly maximum consecutive 5-day precipitation	Mm
7.	SDII	Simple daily intensity index	Annual total precipitation divided by the number of wet days (defined as PRCP>=1.0mm) in the year	Mm/day
8.	R10	Number of heavy precipitation days	Annual count of days when PRCP>=10mm	Days
9.	R1	Number of days above 20 mm	Annual count of days when PRCP>=1 mm, 20 is user defined threshold	Days

10.	CDD	Consecutive dry days	Maximum number of consecutive days with RR<1mm	Days
11.	CWD	Consecutive wet days	Maximum number of consecutive days with RR>=1mm	Days
12.	PRCPTOT	Annual total wet-day precipitation	Annual total PRCP in wet days (RR>=1mm)	Mm

Multiple linear regression

Initially, a partial correlation was conducted to ascertain the relationship between the variables under study. Subsequently, the multiple linear regression was used to assess the influences of climate indices on vegetation vigour whereby the indices were the independent variables while the NDVI was the dependent variable. The following equation was used:

$$y = a + bx \pm e$$

The above equation was modified as;

$$NDVI = a + b_1CDD + b_2CDW + b_3DTR + b_4PRCPTOT + b_5R10MM + b_6R1MM + b_7SDII + b_8RX5DAY + b_9TNN + b_{10}TNX + b_{11}TXX + b_{12}TXN + b_{13}TR$$

A stepwise architecture was utilized whereby the combination of independent variables was retained and some were omitted to ascertain the best model to determine the influence of climate indices on vegetation dynamics. The computed climate indices from the observed climate data were used to train the model until a minimal mean square error and a high coefficient of the determinant were achieved. Subsequently, the climate indices from the global climate model were used to predict the nature of vegetation dynamics in the study area.

RESULTS AND DISCUSSION

The regional climate indices and vegetation vigour of Kamuku national park were subjected to the coefficient of variance, Mann Kendall, correlation, regression and post hoc test to determine the variability trend and extent to which the climate indices influence vegetation vigour in the study area.

Table 2: variability of climate indices and normalised vegetation index

Indices	Mean	STD	CV
CDD	141	19.06	13
CWD	48	21.96	46
DTR	11.00	0.45	4
PRCPTOT	1840.67	295.10	16
R10MM	43	8.25	19
R1MM	178	12.43	7
RX5DAY	197.05	36.04	18
SDII	10.30	1.31	13
TNN	10.57	0.79	7
TNX	28.20	0.87	3
TXN	24.07	1.36	6
TXX	44.36	1.26	3
TR	235.18	8.81	4
NDVI	0.48	0.02	4

Table 2 shows that majority of rainfall indices have moderate variability such as CDD, CWD, PRCPTOT, R10MM, RX5DAY, and SDII while R1MM has a low variability. In addition, the temperature indices show a low variability in Kamuku national park. In contrast, the normalized vegetation index revealed a low variability of vegetation vigour in the study area.

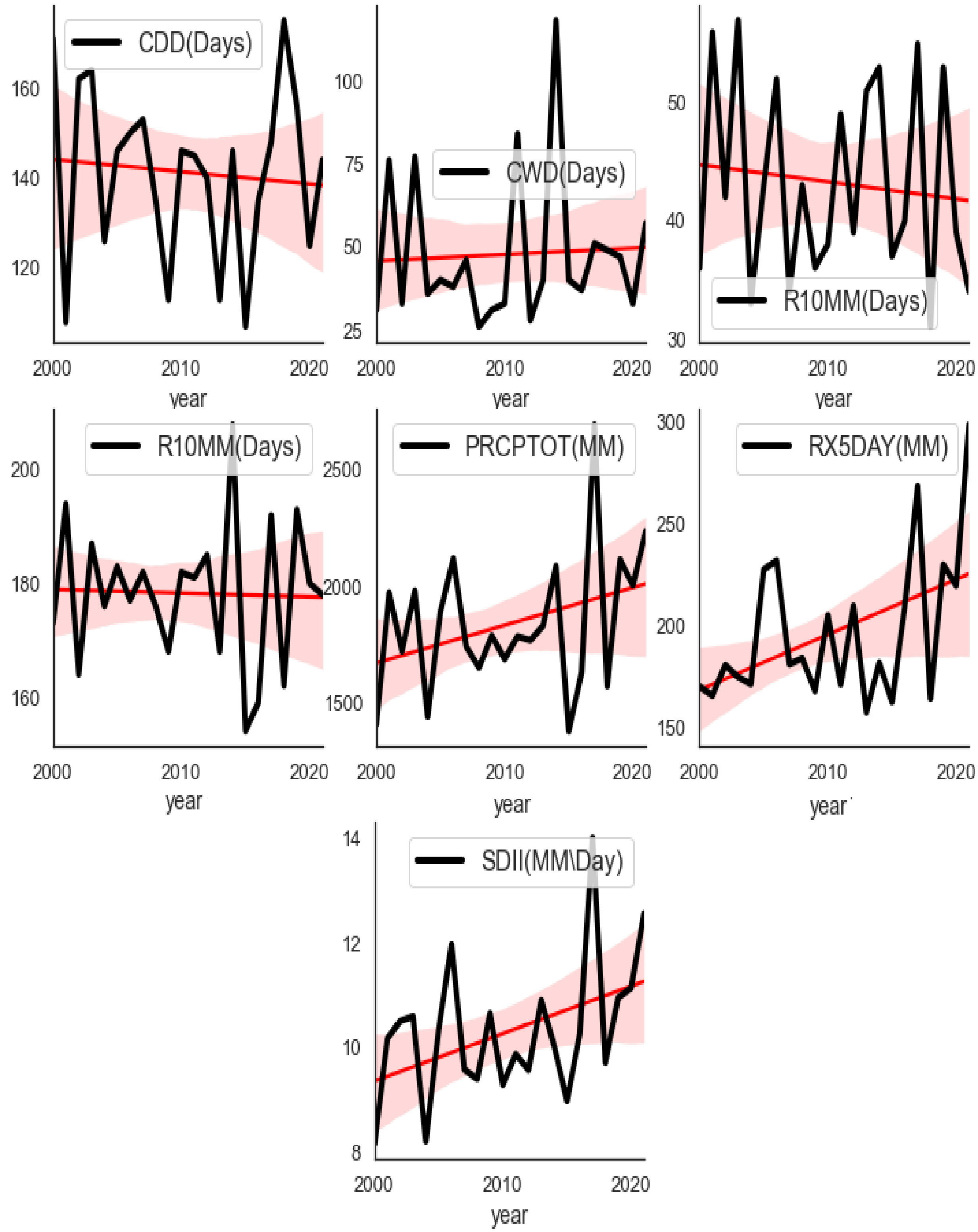

Figure 1: time series of rainfall indices in Kamuku national park.

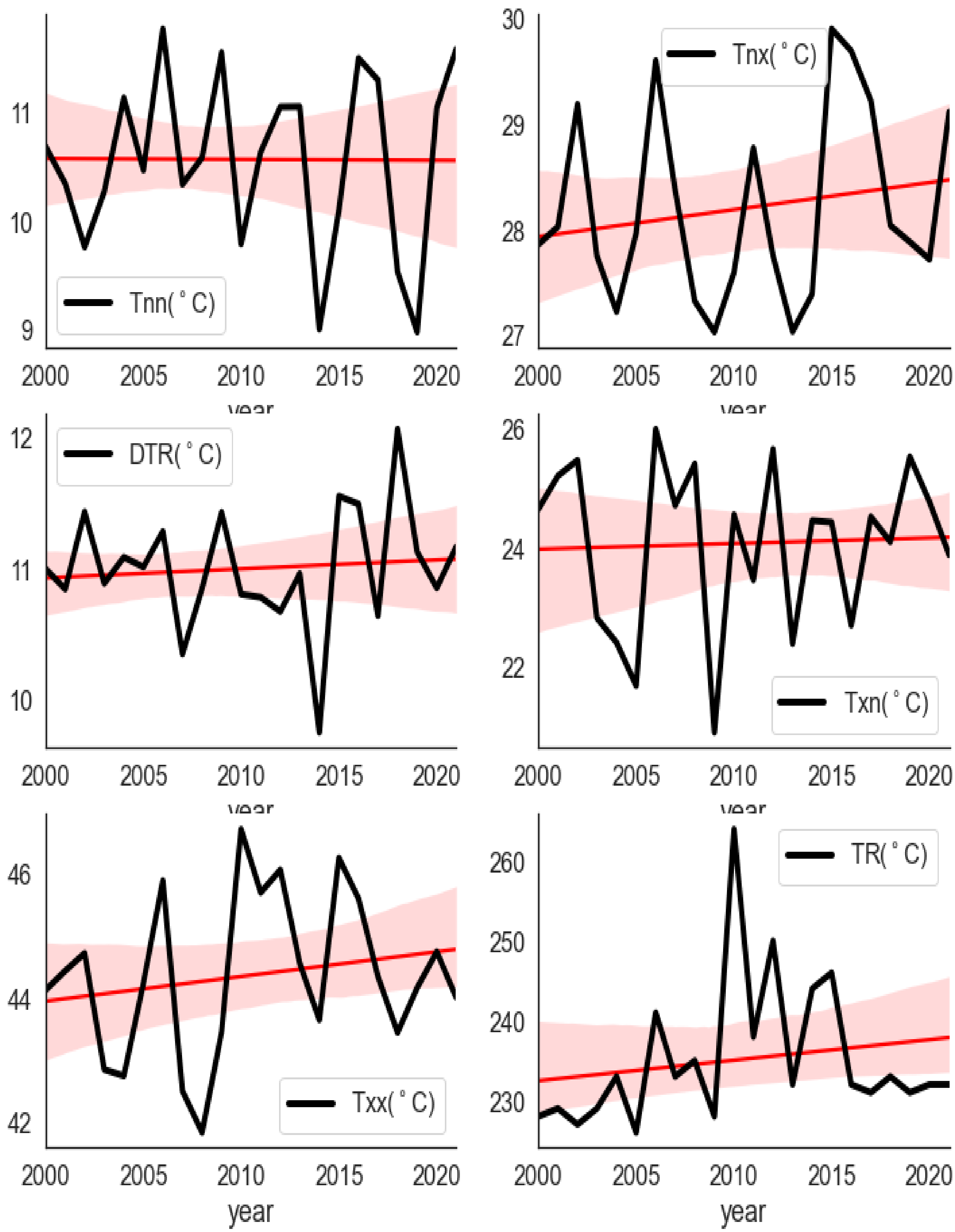

Figure 2: time series of temperature indices in Kamuku national park

The linear trend was computed for the climate indices in Kamuku national park. Figure 1 revealed that majority of the rainfall indices show a positive trend, for instance, CWD, PRCPTOT, RX5DAY and SDII, while CDD and R10MM show a negative trend. A similar result was obtained using Mann Kendall for the rainfall indices (table 3). In addition, most of the temperature indices revealed a positive trend except TNN, which shows no trend based on the linear approach Figure 2. A similar result was obtained using Mann Kendall which shows that temperature indices trend except TXN that shows a negative trend while TNN has a positive trend. Despite the trend and magnitude, observe it was an insignificant trend for all the climate indices. Furthermore, the NDVI trend shows an insignificant positive trend in Kamuku national park.

Table 3: trend of climate indices and normalised difference vegetation indices

INDICES	Z	S	P-value
CDD	-0.12	-28	0.45
CWD	0.17	38	0.30
DTR	0.04	9	0.82
PRCPTOT	0.19	45	0.21
R10MM	-0.04	-10	0.80
R1MM	-0.03	-8	0.84
RX5DAY	0.26	61	0.09
SDII	0.29	67	0.06
TNN	0.05	11	0.78
TNX	0.09	21	0.57
TXN	-0.05	-11	0.78
TXX	0.08	19	0.61
TR	0.19	43	0.23
NDVI	0.06	13	0.74

The correlation analysis was conducted between the climate indices and normalized differences in vegetation indices (Figure 3). It revealed that there is a weak positive relationship between the rainfall indices and the vegetation vigour while a weak negative relationship was observed between the temperature indices and vegetation vigour except for DTR, which show a weak positive relationship. Furthermore, a strong high positive relationship between the rainfall indices was the observed and a weak relationship with the temperature indices.

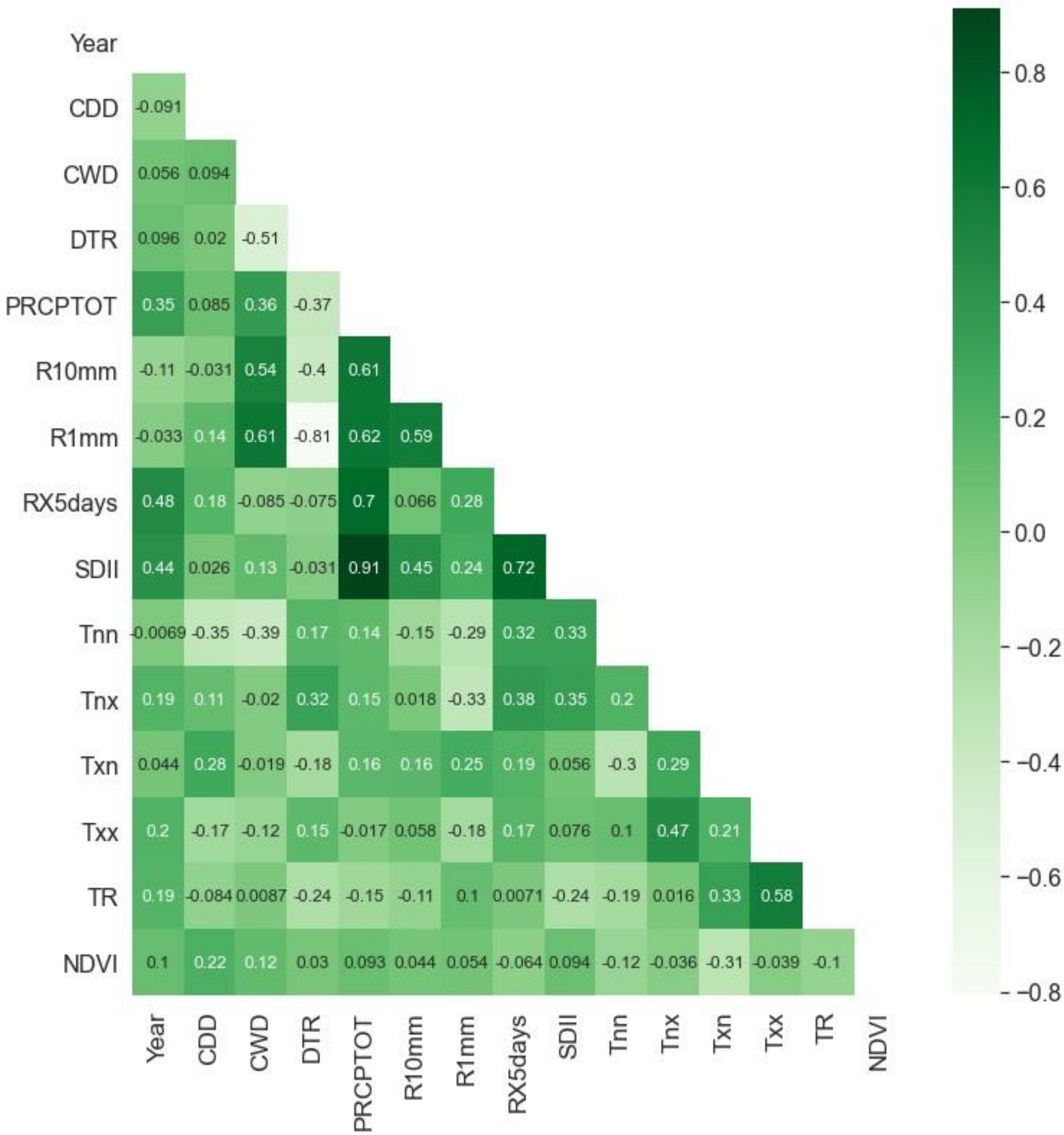

Figure 3: Correlation between the climate indices and normalized difference vegetation index in Kamuku national park.

Table 4: Modelling the influence of climate indices on vegetation vigour in Kamuku national park.

No. of variables	Variables	Variable IN-OUT	Status	MSE	R^2
13	CDD - CWD - DTR - PRCPTOT - R10MM - R1MM - RX5DAY - SDII - TNN - TNX - TXN - TXX – TR		IN	0.001	0.47
12	CDD - CWD - DTR - PRCPTOT - R10MM - R1MM - RX5DAY - SDII - TNN - TNX - TXN – TR	TXX	OUT	0.001	0.47
11	CDD - CWD - PRCPTOT - R10MM - R1MM - RX5DAY - SDII - TNN - TNX - TXN – TR	DTR	OUT	0.000	0.46
10	CDD - CWD - PRCPTOT - R10MM - R1MM - RX5DAY - SDII - TNN - TNX – TXN	TR	OUT	0.000	0.44
9	CDD - CWD - PRCPTOT - R1MM - RX5DAY - SDII - TNN - TNX – TXN	R10MM	OUT	0.000	0.39
8	CDD - CWD - PRCPTOT - R1MM - RX5DAY - SDII - TNX – TXN	TNN	OUT	0.000	0.34
7	CDD - CWD - R1MM - RX5DAY - SDII - TNX - TXN	PRCPTOT	OUT	0.000	0.31
6	CDD - R1MM - RX5DAY - SDII - TNX – TXN	CWD	OUT	0.000	0.27
5	CDD - R1MM - RX5DAY - SDII – TXN	TNX	OUT	0.000	0.26
4	CDD - RX5DAY - SDII – TXN	R1MM	OUT	0.000	0.24
3	CDD - SDII – TXN	RX5DAY	OUT	0.000	0.21
2	CDD – TXN	SDII	OUT	0.000	0.20
1	TXN	CDD	OUT	0.000	0.10

Note: MSE: Mean Squared Error, R^2: Coefficient of determinant.

Thirteen Multiple regression model was developed and compared between them to ascertain the best model for determining the influence of climate indices on vegetation vigour (Table 4). The result revealed that the first two models outperformed the other models. However, the only difference among the models is the number of variables and it appears that there is no significant difference in their performance. As such, the first model with all the climate indices was adopted as the independent variable. In addition, it revealed that the climate indices were able to explain 47% (R^2:0.47) variance of the vegetation vigour in Kamuku national park. While the remaining 53% might be because of other factors such as human activities and other environmental factors.

Table 5: level of influence of each climate indices on vegetation vigour

Source	Value	t	P-Value
CDD	0.311	0.979	0.356
CWD	-0.747	-1.31	0.227
DTR	0.225	0.426	0.681
PRCPTOT	-6.606	-0.92	0.385
r10mm	-0.45	-0.875	0.407
r1mm	4.233	1.223	0.256
rx5day	-1.149	-1.608	0.147
SDII	6.098	1.046	0.326
Tnn	-0.298	-0.751	0.474
Tnx	0.864	1.357	0.212
Txn	-0.837	-2.049	0.075
Txx	-0.019	-0.04	0.969
Tr	0.209	0.472	0.649

Table 5 revealed the level of influence of each climate indices on vegetation vigour. It revealed that the majority of the rainfall indices have a negative influence on the vegetation vigour except for CDD, R1MM and SDII, which have positive influence. It implies that as the climatic indices increases the vegetation vigour decreases and vice versa, while as CDD, R1MM and SDII increase the vegetation vigour increases. Furthermore, the temperature indices influences negatively o the vegetation vigour except for DTR and TR which were positive. This implies that as the temperature indices increases, the vegetation vigour decreases and vice versa.

The variation of climate indices between the historical and predicted the future scenario were presented using violin plot (Figure 4 and 5). Figure 4 revealed that the magnitude of historical CDD and CWD was almost equal to that of the far future but more than the near future. The total precipitation has less magnitude in the historical period while it increased in the far future. A similar pattern of the variation of R10mm, R1mm, RX5day and SDII indices was observed to that of total precipitation. Furthermore, most of the majority of temperature indices revealed a variation between the period under study whereby the far future had more magnitude followed by the near future and the historical period, which had less magnitude except for DTR, but historical and far future had almost equal magnitude.

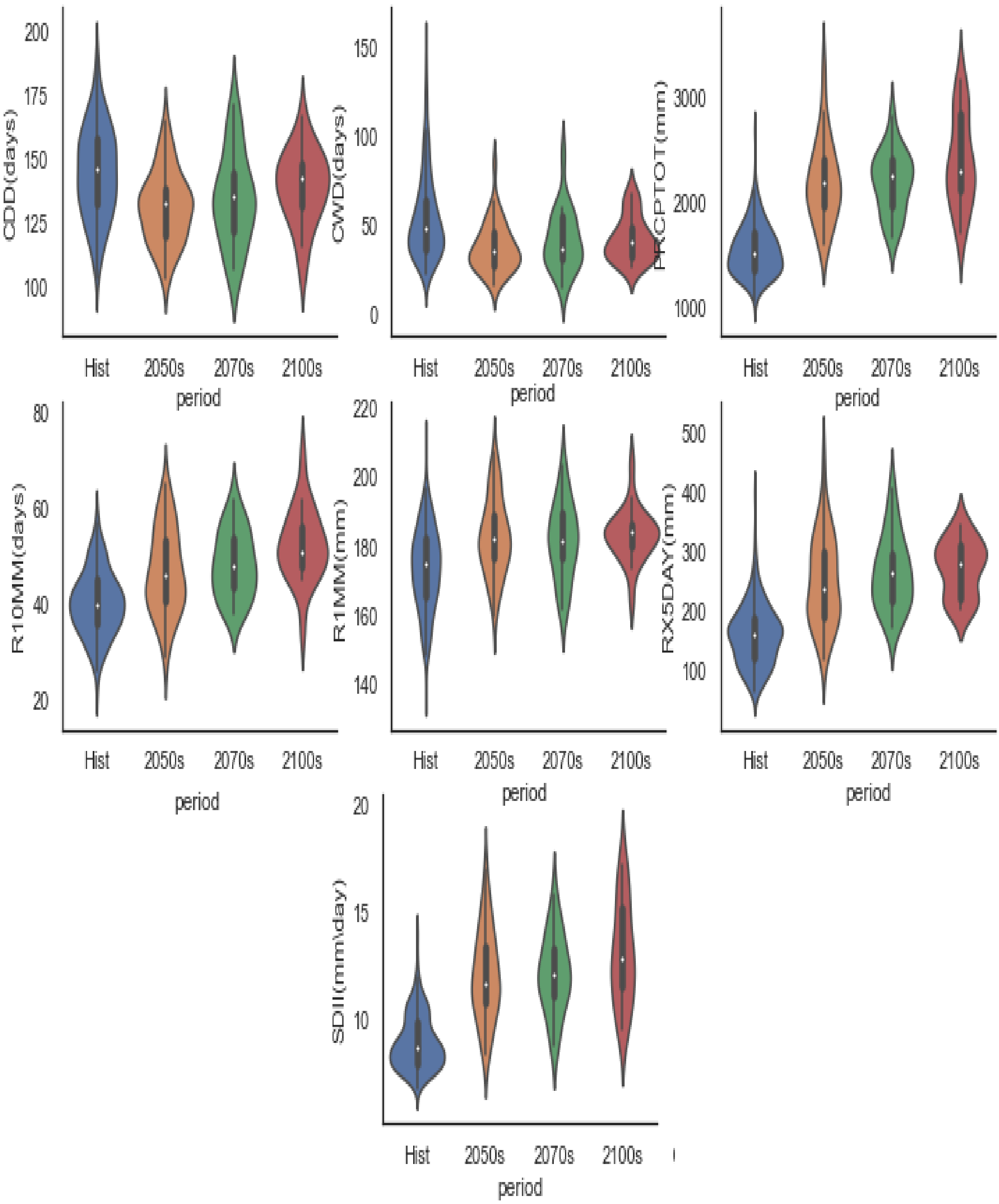

Figure 4: Comparison of the rainfall indices between the periods.

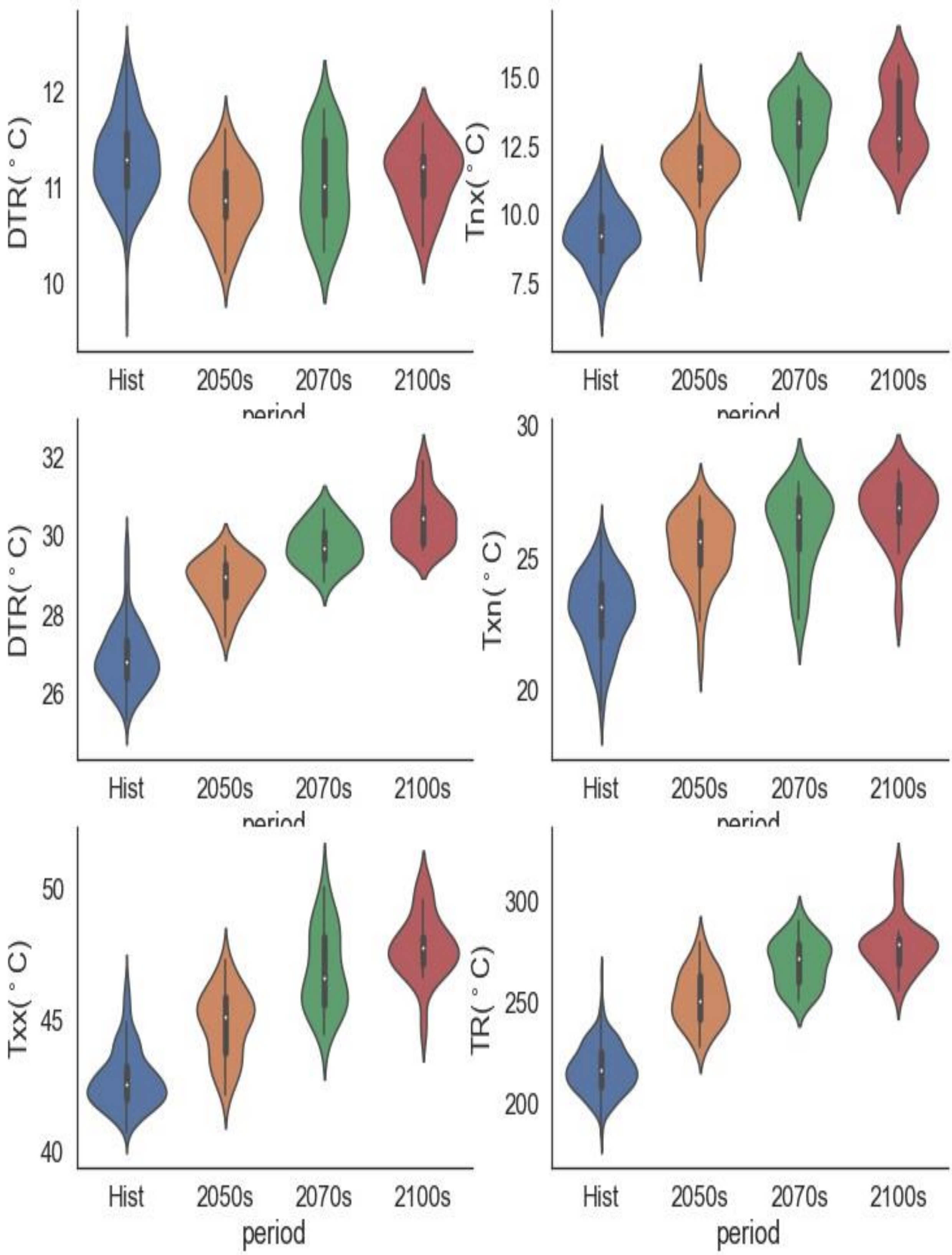

Figure 5: Comparison of the temperature indices between the historical and future scenarios

Table 6: Post hoc test between the history and future of climate indices in Kamuku national park

Indices	Hist vs 2050s	Hist vs 2070s	Hist vs 2100s	2100s vs 2050s	2100s vs 2070s	2070s vs 2050s
CDD	**13.5**	10.1	5.7	7.9	4.5	3.4
CWD	**17.1**	13.1	12.6	4.5	0.5	4.1
DTR	**0.4**	0.2	0.2	0.3	0.1	0.2
PRCPTOT	**838.1**	194.7	184.7	**653.4**	10.0	**643.4**
R10MM	**12.0**	**5.5**	4.0	**8.0**	1.5	**6.5**
R1MM	**9.7**	1.7	0.5	**9.1**	1.2	**8.0**
RX5	**111.2**	21.1	7.7	**103.5**	13.4	**90.1**
SDII	**4.1**	1.0	0.9	**3.2**	0.1	**3.1**
TNN	**4.1**	**1.7**	0.2	**4.0**	**1.5**	**2.5**
TNX	**3.5**	**1.6**	**0.6**	**2.9**	**1.0**	**1.9**
TXN	**3.8**	**1.5**	0.8	**3.0**	0.7	**2.3**
TXX	**5.0**	**2.9**	0.9	**4.1**	**2.0**	**2.1**
TR	**61.4**	**26.1**	8.6	**52.8**	**17.5**	**35.3**

Despite the variation between the climate indices observed in Figure 4 and 5 post hoc test was conducted to ascertain the significant of the variation (Table 6). It revealed that there is significant differences between historical and near future (2050s) for all the climate indices. The majority of rainfall indices show insignificant differences between historical and middle future (2070s) except R10MM, which showed significant differences. A similar result obtained for temperature indices showed that there is significant differences between historical and middle future except for DTR. While the differences between the historical and future show the only significant difference for the TNX. Furthermore, the differences between the far futures (2100s), the middle future (2070s) to the near future (2050s) revealed a significant difference of most of the climate indices except CDD, CWD, and DTR. However, the magnitude of the differences was high between the far future and near future compared with the middle future compared to the near future. In addition, most of the climate indices showed insignificant differences between far and middle future except for TNN, TNX, TXX and TR, which showed significance differences.

The developed model from the established relationship between the climate indices and vegetation vigour using a multiple linear regression model (Table 6) the long-term climate indices were used to predict and reconstruct the vegetation vigour (Figure 6A and 6B). It revealed a variability with an upward trend of the future vegetation vigour. In addition, the variation between the historical and future vegetation vigour in Kamuku national park revealed that far future has a slightly higher magnitude than the near future and historical period. According to (Adepoju et al., 2019) the NDVI was negatively correlated with temperature in savanna and concluded that vegetation vigour will continue to decline under rainfall and increasing temperature conditions, especially in dryer regions. This study is in accordance with (Zaharaddeen et al., 2016) that there is a negative relationship between temperature and vegetation. A similar result on the influence of climate on vegetation was found by (Adenle et al., 2020) that rainfall was able to explain 60% variance of the vegetation in Nigeria. Rousta et al., (2020) found that lower temperature can enhance the vegetation growth with a slight increase in rainfall, additionally, the study revealed that rainfall was able to explain 51% variance of the vegetation in Afghanistan. Similarly (Zhou et al., 2019) found an inversed changes between vegetation dynamics and extreme climate events in the Northeast Plain of North-south Transect of Eastern China.

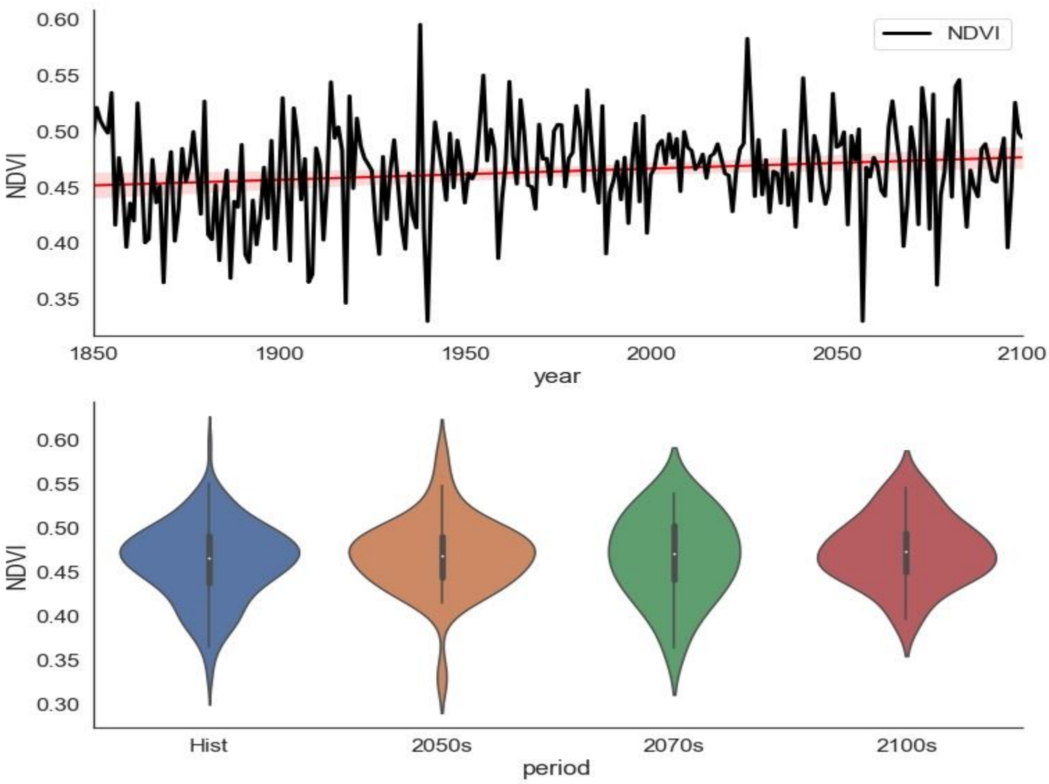

Figure 6: Predicted vegetation vigour in Kamuku national park (a) time series (b) comparison between time stamp.

CONCLUSION

From the results, the rainfall indices have moderate variability and the temperature indices showed a low variability. In contrast, the normalized vegetation index revealed a low variability of vegetation vigour in the study area. The correlation analysis was conducted between the climate indices and normalized differences vegetation indices which revealed that there is a weak positive relationship between the rainfall indices and the vegetation vigour while a weak negative relationship was observed between the temperature indices and vegetation vigour. In addition, it revealed that the climate indices were able to explain 47% variance of the vegetation vigour in Kamuku national park. While the remaining 53% might be a result of other factors such as human activities and other environmental factors. In conclusion, the vegetation vigour regulates the distribution of the climate extreme indices.

REFERENCES

Abdussalam, A. F., & Zaharaddeen, I. (2017). Temporal Variation of Reference Evapotranspiration in Lower River Kaduna Catchment Area , Nigeria. *Archives of Current Research International*, *8*(1), 1–11. https://doi.org/10.9734/ACRI/2017/32984

Adenle, A. A., Eckert, S., Adedeji, O. I., Ellison, D., & Speranza, C. I. (2020). Human-induced land degradation dominance in the Nigerian Guinea Savannah between 2003 – 2018. *Remote Sensing Applications: Society and Environment*, *19*. https://doi.org/10.1016/j.rsase.2020.100360

Adepoju, K., Adelabu, S., & Fashae, O. (2019). Vegetation Response to Recent Trends in Climate and Landuse Dynamics in a Typical Humid and Dry Tropical Region under Global Change. *Advances in Meteorology*, *2019*. https://doi.org/10.1155/2019/4946127

Appiah, D. O., Schröder, D., Forkuo, E. K., & Bugri, J. T. (2015). Application of geo-information techniques in land use and land cover change analysis in a peri-urban district of Ghana. *ISPRS International Journal of Geo-Information*, *4*(3), 1265–1289. https://doi.org/10.3390/ijgi4031265

Bashariya, M. B., Zaharaddeen, I., Auwal, F. A., & Abu-Hanifa, B. (2022). MODELLING THE SIGNATURE OF HUMAN INFLUENCE ON VEGETATION DYNAMIC IN KAMUKU NATIONAL PARK, NIGERIA. *Science World Journal*, *17*(2).

Bastian, O. (2013). The role of biodiversity in supporting ecosystem services in Natura 2000 sites. *Ecological Indicators*, *24*, 12–22. https://doi.org/10.1016/j.ecolind.2012.05.016

Brandt, M., Rasmussen, K., Peñuelas, J., Tian, F., Schurgers, G., Verger, A., Mertz, O., Palmer, J. R. B., & Fensholt, R. (2017). Human population growth offsets climate-driven increase in woody vegetation in sub-Saharan Africa. *Nature Ecology and Evolution*, *1*(4), 4–9. https://doi.org/10.1038/s41559-017-0081

Cassia, R., Nocioni, M., Correa-aragunde, N., & Lamattina, L. (2018). *Climate Change and the Impact of Greenhouse Gasses : CO 2 and NO , Friends and Foes of Plant Oxidative Stress*. *9*(March), 1–11. https://doi.org/10.3389/fpls.2018.00273

Copernicus Climate Change Service. (2021). *ERA5 hourly data on single levels from 1979 to present*. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). https://doi.org/10.24381/cds.adbb2d47

De Frenne, P., Lenoir, J., Luoto, M., Scheffers, B. R., Zellweger, F., Aalto, J., Ashcroft, M. B., Christiansen, D. M., Decocq, G., De Pauw, K., Govaert, S., Greiser, C., Gril, E., Hampe, A., Jucker, T., Klinges, D. H., Koelemeijer, I. A., Lembrechts, J. J., Marrec, R., … Hylander, K. (2021). Forest microclimates and climate change: Importance, drivers and future research agenda. *Global Change Biology*, *27*(11), 2279–2297. https://doi.org/10.1111/gcb.15569

He, C., Tian, J., Gao, B., & Zhao, Y. (2015). Differentiating climate- and human-induced drivers of grassland degradation in the Liao River Basin, China. *Environmental Monitoring and Assessment*, *187*(1). https://doi.org/10.1007/s10661-014-4199-2

Isa, Z., & Danjuma, B. (2018). Regressive vegetation cover status in river Kaduna catchment area Kaduna, Nigeria. *Environmental and Earth Sciences Research Journal*, *5*(3), 58–65. https://doi.org/10.18280/eesrj.050302

Ismail, M., Abdussalam, A. F., & Isa, Z. (2019). SPATIAL AND TEMPORAL VARIABILITY OF 40 YEARS TEMPERATURE AND PRECIPITATION IN THE. *FUDMA Journal of Science*, *3*(3), 1–11.

Koko, A. F., Wu, Y., Abubakar, G. A., Alabsi, A. A., Hamed, R., & Bello, M. (2021). Thirty Years of Land Use/Land Cover Changes and Their Impact on Urban Climate: A Study of Kano Metropolis, Nigeria. In *Land* (Vol. 10, Issue 11). https://doi.org/10.3390/land10111106

Mansour, S., Al-Belushi, M., & Al-Awadhi, T. (2020). Monitoring land use and land cover changes in the mountainous cities of Oman using GIS and CA-Markov modelling techniques. *Land Use Policy*, *91*, 104414. https://doi.org/https://doi.org/10.1016/j.landusepol.2019.104414

Musa, H. D., & Solomon, N. J. (2011). An Assessment of Mining Activities Impact on Vegetation in Bukuru Jos Plateau State Nigeria Using Normalized Differential Vegetation Index (NDVI). *Journal of Sustainable Development*, *4*(6). https://doi.org/10.5539/jsd.v4n6p150

Nwilo, P. C., Olayinka, D. N., Okolie, C. J., Emmanuel, E. I., Orji, M. J., & Daramola, O. E. (2020). Impacts of land cover changes on desertification in northern Nigeria and implications on the Lake Chad Basin. *Journal of Arid Environments*, *181*, 104190. https://doi.org/https://doi.org/10.1016/j.jaridenv.2020.104190

Oki, T., & Pat, J.-F. Y. (2014). *Encyclopedia of Remote Sensing* (E. G. Njoku (ed.)). Springer New York. https://doi.org/10.1007/978-0-387-36699-9

Perugini, L., Caporaso, L., Marconi, S., Cescatti, A., Quesada, B., De Noblet-Ducoudré, N., House, J. I., & Arneth, A. (2017). Biophysical effects on temperature and precipitation due to land cover change. *Environmental Research Letters*, *12*(5). https://doi.org/10.1088/1748-9326/aa6b3f

Rousta, I., Olafsson, H., Moniruzzaman, M., Zhang, H., Liou, Y. A., Mushore, T. D., & Gupta, A. (2020). Impacts of drought on vegetation assessed by vegetation indices and meteorological factors in Afghanistan. *Remote Sensing*, *12*(15). https://doi.org/10.3390/RS12152433

Shobairi, S. O. R. (2018). *Remotely Sensed Data And Vegetation Coverage Change Detection*. *March*.
Tan, Z., Tao, H., Jiang, J., & Zhang, Q. (2015). *Influences of Climate Extremes on NDVI (Normalized Difference Vegetation Index) in the Poyang Lake Basin ,*. *19*. https://doi.org/10.1007/s13157-015-0692-9

Wang, J., Wang, K., Zhang, M., & Zhang, C. (2015). Impacts of climate change and human activities on vegetation cover in hilly southern China. *Ecological Engineering*, *81*, 451–461. https://doi.org/10.1016/j.ecoleng.2015.04.022

Weiskopf, S. R., Rubenstein, M. A., Crozier, L. G., Gaichas, S., Griffis, R., Halofsky, J. E., Hyde, K. J. W., Morelli, T. L., Morisette, J. T., Muñoz, R. C., Pershing, A. J., Peterson, D. L., Poudel, R., Staudinger, M. D., Sutton-Grier, A. E., Thompson, L., Vose, J., Weltzin, J. F., & Whyte, K. P. (2020). Climate change effects on biodiversity, ecosystems, ecosystem services, and natural resource management in the United States. *Science of the Total Environment*, *733*. https://doi.org/10.1016/j.scitotenv.2020.137782

Yunusa, B. K., Yusuf, S., Zaharaddeen, I., & Abdussalam, A. F. (2017). Characteristics of Rainfall Variations in Kaduna State , Nigeria Characteristics of Rainfall Variations in Kaduna State , Nigeria. *Asian Journal of Advances in Agricultural Research*, *4*(3), 1–11. https://doi.org/10.9734/AJAAR/2017/36936

Zaharaddeen, I., Ibrahim, I. B., & Zachariah, A. (2016). ESTIMATION OF LAND SURFACE TEMPERATURE OF KADUNA METROPOLIS, NIGERIA USING LANDSAT IMAGES. *Science World Journal*, *11*(3), 36–41.

Zaharaddeen, I., Muhammad, S. O., Abdussalam, A. F., Richard, A. G., & Kagarko, I. I. (2017). Estimation of Biophysical Properties in Lower River Kaduna Catchment Area Kaduna , Nigeria. *Asian Journal of Environment & Ecology*, *4*(1), 1–13. https://doi.org/10.9734/AJEE/2017/32960

Zhou, Y., Pei, F., Xia, Y., Wu, C., Zhong, R., Wang, K., Wang, H., & Cao, Y. (2019). Assessing the impacts of extreme climate events on vegetation activity in the North South Transect of Eastern China (NSTEC). *Water (Switzerland)*, *11*(11), 1–18. https://doi.org/10.3390/w11112291