Statistical Analysis of NASA POWER Meteorological Data for the Assessment of Climate Variability in Adamawa State

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This study addresses the critical need for reliable, long-term meteorological data to assess the impact of global warming on food security and human well-being. The research demonstrates the utility of satellite-based spatial databases, particularly NASA's POWER Data Viewer, in evaluating regional climate trends. We analysed six climatic parameters from 1992 to 2022 across three climatic sub-regions of Adamawa state, Nigeria, using data from fixed stations. Linear regression analysis of the thirty-year trends revealed increases in mean, maximum, and minimum temperatures, along with decreases in precipitation and relative humidity, suggesting regional warming. ANOVA tests validated the linear models for mean temperature in Ganye and Yola, maximum temperature and relative humidity in Ganye, and the all-sky insolation clearness index across all regions. The findings underscore the significance of satellite data in climate assessment and call for further studies to identify the most accurate predictive models for parameters where the linear hypothesis was rejected.

Keywords: Adamawa, NASA POWER Data Viewer, Global Warming, Satellite Data

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Introduction

Climate change is one of the most pressing challenges facing the global community today, with its effects already evident worldwide. In Africa, significant climate changes are unmistakable, and substantial evidence confirms the reality of climate change (Odjugo, 2011). These alterations are occurring on both regional and global scales, primarily driven by global warming (Kayano & Sansigolo, 2008). Predicted increases in atmospheric greenhouse gas concentrations are expected to lead to higher global temperatures, resulting in warmer conditions, increased evaporation and precipitation, earlier snowmelt in spring, and the melting of glaciers. These changes contribute to the expansion of ocean waters and rising sea levels (Mimura, 2013).

The United Nations Framework Convention on Climate Change (UNFCCC, 2007) has observed that both natural climate cycles and human activities have amplified the accumulation of heat-trapping greenhouse gases in the atmosphere, further exacerbating global warming. Although these temperature changes may seem minor, their impacts are significant. Current effects include the melting of glaciers, rising ocean levels, and shifts in plant growth cycles. Climate change poses a critical environmental threat to economic development and human sustainability across the globe (IPCC, 2014).

Climate change is triggering numerous regional transformations that are expected to intensify with further warming. These changes include shifts in precipitation patterns, wind dynamics, snow and ice behaviour, and the condition of coastal areas and oceans. The intensification of the water cycle is altering rainfall patterns, while rising sea levels increasingly threaten coastal regions throughout the 21st century. Furthermore, permafrost thawing, the loss of seasonal snow cover, and the melting of glaciers and ice sheets are becoming more widespread. Ocean warming, combined with flooding from heavy precipitation events, poses significant risks to coastal cities (IPCC, 2021).

The global concern over climate change predominantly stems from human activities, particularly the emission of carbon dioxide and other greenhouse gases. These emissions result from burning fossil fuels, deforestation, and other activities that significantly contribute to greenhouse gas accumulation. Evidence of climate variability and change in various countries includes rising surface air temperatures, increasing heatwaves that promote disease vectors and communicable diseases, sea-level rise and associated coastal erosion, flooding, saltwater intrusion, mangrove degradation, food security threats, freshwater pollution, and accelerated extinction of plant and animal species (Kaiho, 2022). Additionally, increased evaporation leads to the drying up of streams and rivers, loss of forest vegetation which fosters soil degradation and desertification, and changes in seasonal climatic patterns that reduce agricultural productivity (Willison, 2003).

In Nigeria, nearly all states are experiencing warmer conditions compared to 35 years ago, with evidence of rising minimum and maximum atmospheric temperatures (Amadi et al., 2014). Adamawa State, predominantly agrarian, relies heavily on agriculture, which engages about 80% of its population (FAO and ICRISAT, 2019). The state's climate and ecological conditions favor the cultivation of both food and cash crops and support large-scale livestock rearing.

However, approximately 90% of Adamawa's agricultural production is rain-fed, making it highly vulnerable to climate change impacts.

Recent reports indicate a decline in agricultural outputs, attributed to climate change and subsequent soil fertility reduction (FAO, 2019). Empirical evidence points to delayed rainfall onset, increased dry days during the rainy season, and higher maximum temperatures, all linked to climate change (Adebayo, 2010). In response, various policies and programs have been implemented to enhance the agricultural sector's resilience to climate change. These include the Agricultural Promotion Policy (APP) and the National Policy on Climate Change and Response Strategy (NPCCRS), aiming to set the state on a path of sustainable development amid changing climatic conditions (FAO, 2019).

Baseline data on climate variability is essential for successful policy formulation and program implementation. While meteorological stations provide detailed and continuous data on climate variability for specific locations, their limited availability and sparse distribution, especially in remote areas, result in spatial gaps in data coverage (Hussaini & Matazu, 2023; Umar & Salihu, 2017). Additionally, most meteorological stations in the north eastern part of the country are relatively new, with some experiencing operational disruptions due to various reasons.

This research aims to analyse climate parameter variability in Adamawa State, providing baseline data for assessing spatial and temporal patterns of long-term climate trends. The study involves examining the spatial and temporal trends of the mean, minimum and maximum temperatures, , relative humidity, precipitation and sky clearness. This analysis serves as an assessment tool for policymakers in developing response strategies, planning, adaptation, and mitigation mechanisms.

Study Area

The study area, Adamawa State, is located in north-eastern Nigeria. It spans an area of approximately 36,917 square kilometres and is predominantly agrarian, with agriculture serving as the primary economic activity for about 80% of its inhabitants (FAO and ICRISAT, 2019). The state's geographical coordinates are between latitudes 7° and 11°N and longitudes 11° and 14°E (Figure 1).

The landscape of the area is dominated by mountains and the valleys of major rivers, the Benue and the Gongola. This topography influences the state's vegetation zones of the area supporting agriculture and cattle rearing, the mainstays of the local economy.

The state’s diverse ecological conditions facilitate the cultivation of a variety of crops, including maize, sorghum, millet, rice, sweet potatoes, yams, cassava, and other cereals (Kadams et al., 2020). Additionally, Adamawa is well-known for large-scale livestock farming, with cattle, goats, sheep, pigs, and poultry being the primary animals reared. However, approximately 90% of agricultural activities in Adamawa are rain-fed, making them highly susceptible to the impacts of climate change.

Adamawa's climate is characterized by a tropical savanna climate, marked by a distinct wet season from May to October and a dry season from November to April. The region's average annual rainfall ranges from 700 mm in the northern parts to 1600 mm in the southern parts. The temperature varies considerably, with an average minimum of 18°C and a maximum of 40°C, particularly during the dry season. Humidity is generally low but rises significantly during the rainy season, influenced by maritime air masses. Rainfall is the most critical climate element, impacting agriculture and infrastructure. It arrives in April, starting with light showers that increase steadily throughout the wet season (May-September). Peak rainfall occurs in August and September, with the southern regions receiving more precipitation than the north (Adebayo & Zemba, 2020).

The vegetation formation of the state is roughly divided into three: Southern Guinea Savanna, in the southern part of the state, the Northern Guinea Savanna lying roughly at the centre and form the largest vegetation zone and the Sudan Savanna at the extreme norther part of the state (Akosim *et al*., 2020). The Southern Guinea Savanna zone received the largest mean annual rain fall within the state and last for about six to seven months. The Northern Guinea Savanna received intermediate rainfall within the state and last for four to five months while the Sudan Savanna zone received the least mean annual rain fall that last for three to four months (Akosim *et al*., 2020). It is observed however that within each of the formation, excessive agricultural land expansion, indiscriminate cutting down of trees for extraction of firewood have led to deforestation resulting into the extinctions of many indigenous wood plant species and changes in the weather pattern of the area (Mubi & Ba, 2020).

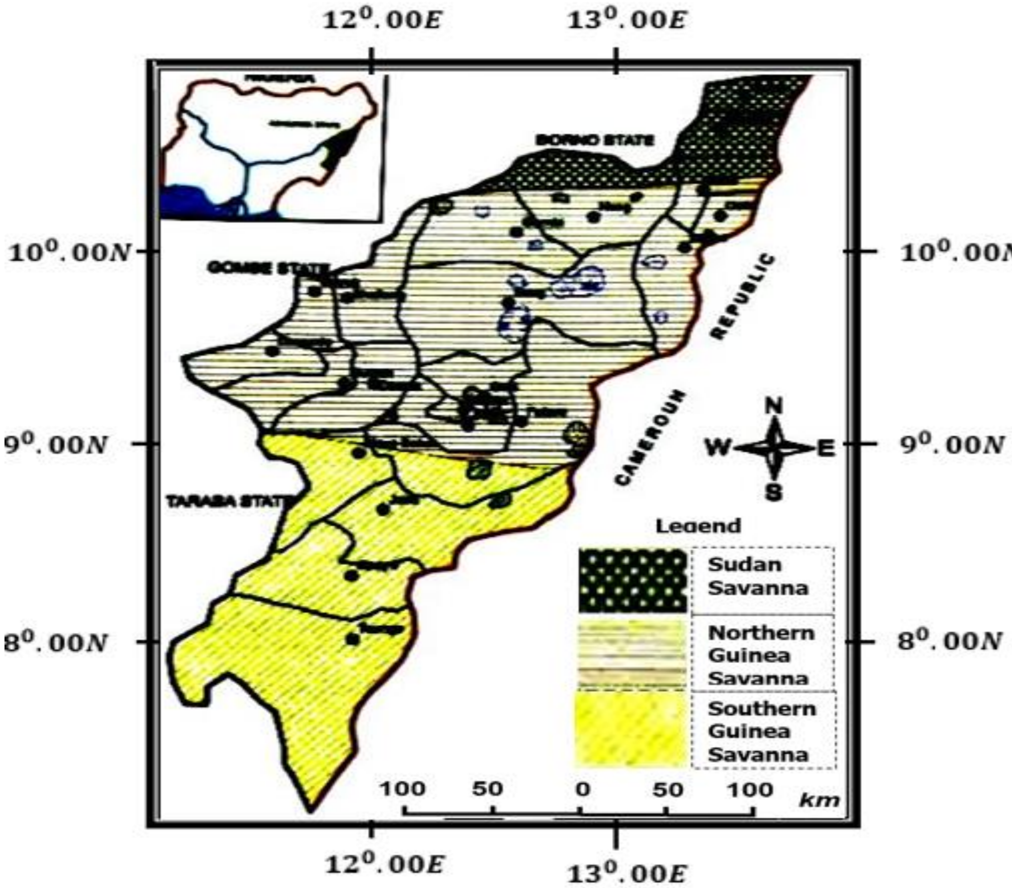

Figure 1: The three vegetation zones (Akosun & jatau, 2020)

Research Methodology

Experience revealed that analyses of climate parameter variability in Adamawa state in particular, and the entire north-eastern region of Nigeria in general are constrained by inadequate and inconsistent data record, wide data gap and poor data management (Umar & Salihu, 2017). Although there are meteorological stations in all the selected regions of the study area, nearly half of the required data needed by agricultural planners for optimization of planting schedules are missing or incomplete (Umar & Salihu, 2017). In this work, we used satellite observation- based climate data source, the National Aeronautics and Space Administration (NASA) Prediction of Worldwide Energy Resource (POWER) Data Viewer (https://power.larc.nasa.gov/data-access-viewer/).

NASA Power data is freely available online whose sources have proved record of accuracy. It is a veritable online tool developed by NASA with the goal of providing access to worldwide meteorological data. The project is aimed at providing meteorological information for research and agriculture and renewable energy resource optimization (Jed *et al*., 2022).

The data viewer has a user friendly interface that contains repositories of variable meteorological parameters in the categories of temperatures and thermal fluxes, solar radiation fluxes, wind/pressure, humidity/precipitation etc. the primary source of the data include satellite observation, data reanalysis, which involves the integration of past observation into model of past weather and climate changes over time, predictive climate model based on current trends (Tan *et al*., 2023; Quansah *et al*., 2022; Liu *et al*., 2021). NASA POWER data is regularly validated by calibration with ground observation. It has the historical record of generating accurate climate data owing to its advanced modelling technique of reanalysis (Marzouk, 2021).

Three meteorological stations, each strategically within the climatological sub region of the stations were selected as a representation of the sub region. The selected points within the regions are centrally located to represent the region and play crucial and dynamic role in the agricultural sector due to their significant contributions to food production, agro industrial and economic development. The geographic coordinates of the selected stations are given in Table 1.

Table 1: Selected stations and their geographic locations

Vegetation Sub-region	Station	longitude	latitude
Southern Guinea Savanna	Ganye	8.46145^0	12.05367^0
Sudan Savanna	Mubi	10.27987^0	13.28962^0
Northern Guinea Savanna	Yola	9.25436^0	12.43193^0

Thirty-one year climate data was obtained with respect to the three point locations for the period between 1992 to 2022. The data downloaded and analysed include

- Monthly and annual mean air (dry bulb) temperature at 2m above the surface of the earth (T-2m).
- Monthly average of the daily maximum air (dry bulb) temperature at 2m above the surface of the earth (Tx-2m).
- Monthly average of the daily minimum air (dry bulb) temperature at 2m above the surface of the earth (Tm-2m).
- Monthly and annual Relative Humidity (RH), which is the ratio of the actual partial pressure of water vapour to the partial pressure at saturation, expressed in percent.
- Monthly and Annual All Sky Insolation Clearness Index (ASICI) ; which is a fraction of clearness of the atmosphere; the all sky insolation that is transmitted through the atmosphere to strike the surface of the earth divided by the average of top of the atmosphere total solar irradiance incident. All Sky Insolation Clearness Index (ASICI) is a weather-dependent insolation parameter, which unlike land surface temperature, is independent of the land surface cover type.
- Monthly & Annual Precipitation Corrected (PC): The bias corrected average of total precipitation at the surface of the earth in water mass (includes water content in snow).

In this work, we used simple descriptive statistics and linear regression analysis to estimate the changes in the climatic variables with time over the thirty-one year period. Statistical regression analysis was used to analysis and identify statistical significance of the trends of the above parameters spatially and temporally. The analysis describes the relationship between the observed variable Y_i for a given independent variable of year x_i as

$$Y_i = \alpha + \beta x_i + \epsilon_i$$

where the parameters α and β are the regression model that provide the best fitting to the data points while ϵ_i is an error term associated with ith measurement. Each of the observation was tested statistically on the basis of null hypotheses at 5% alpha level of significance.

Results

The accuracy of satellite observation data is demonstrably influenced by both spatial and temporal resolution. To enhance the temporal resolution of point data, a longer study period with shorter sampling intervals is preferable (Jed *et al*., 2022). In this study, daily records spanning thirty-one years were obtained for monthly data. Monthly averages were then combined to generate annual means for subsequent time-series analysis.

The initial analysis involved constructing scatter plots depicting the monthly and annual means of the climatic parameters. Each year (x-axis) corresponded to the average value of the parameter across all days in that year (y-axis). Figures 3(a-f) presented the linear regression models for these parameters between 1992 and 2022. The solid lines represent the predicted model data, while the scattered points represent the observed data. An Analysis of Variance (ANOVA) test was conducted to assess the relationships between variables over time. This analysis evaluated the variance (residuals) in the data and its effect on the dependent variables.

Temperature analysis

Visual observations of Figure 2 revealed a generally positive trend in temperature parameters across all the study regions, albeit at varying rates. The model equations for mean air temperature (T-2m) in Table 2 displayed positive correlations with time for all three vegetation zones. The fitting coefficient R^2 values of 0.6, 0.2, and 0.3 were obtained for Ganye, Mubi, and Yola zones, respectively. These values suggest a fair linear fit between observed data and the model.

Statistically significant increases in mean atmospheric temperature were observed for Ganye and Yola zones over the past thirty years (p-values: 2.5E-05 and 0.017, respectively; $p < 0.05$). This indicates a linear dependence on time, with warming rates of 0.054°C/year and 0.041°C/year, respectively. Conversely, the p-value of 0.19 ($p > 0.05$) for the Mubi region suggests a non-significant linear increase in temperature. While evidence of warming exists, the relatively low and potentially unreliable constant increase of 0.0026°C/year warrants further investigation.

To further explore temperature variations, the mean minimum monthly air temperature was also modelled across the study period. Figure 3 displayed the scatter plots of observed and modelled data. Visual inspection suggests that local variations in minimum temperature were less pronounced compared to mean temperature for all three regions. The low R^2 values (0.026, 0.002, and 0.001) for Ganye, Mubi, and Yola (Tables 2, 3 and 4) respectively, indicate a weak linear fit to the regression lines. Despite positive incremental rates (0.03°C/year, 0.007°C/year, and 0.005°C/year for Ganye, Mubi, and Yola, respectively), the high p-values (> 0.05) suggest that the null hypothesis (no linear dependence) is statistically supported for all the regions.

The study then examined the dynamics of maximum temperature (T_m-2m) using monthly means. Figure 4 visually indicated an increase in Tm_2m over time for Ganye and Mubi zones, with R^2 values of 0.249 and 0.029, respectively. However, a negative slope was observed in the Yola zone (Table 4), suggesting a decrease in overall maximum air temperature. The p-value of 0.026 ($p < 0.05$) for Ganye (Table 2) indicated a likely reliable linear dependence of T_m-2m on time. In contrast, the higher p-values for Mubi (0.753) and Yola

(0.0757; both $p > 0.05$) (Tables 3 and 4) suggest that the observed trends are likely not statistically significant.

Relative humidity analysis

Relative humidity (RH) is a climate parameter influenced by both temperature and regional factors. As air temperature increases, it can hold more moisture, leading to higher evapotranspiration rates, especially near open water sources like oceans, lakes, and rivers. Conversely, drier regions prone to drought may experience excessive evapotranspiration exceeding their moisture retention capacity. Understanding RH dynamics is therefore crucial for predicting climate change patterns and their regional impacts on agriculture and public health.

Our analysis of the monthly average annual relative humidity across the three study regions over the thirty-year period revealed a negative trend in all regions (Fig. 5), indicating a decrease in RH. The rates of decrease were -0.226%/year, -0.0025%/year, and -0.116%/year for Ganye, Mubi, and Yola, respectively.

The goodness-of-fit values (R^2) for the linear models were 0.37, 0.42, and 0.09 for Ganye, Mubi, and Yola, respectively. The p-values associated with these models were 7.7E-5 (<0.05), 0.416 (>0.05), and 0.052 (>0.05). A statistically significant decrease in RH (p-value < 0.05) was observed only in the Ganye region (Table 2). This suggests a reliable linear relationship between decreasing RH and time in this region. The higher p-values in Mubi and Yola (Tables 3 and 4) indicate that the observed decreases in RH may not be statistically significant and could be due to random chance. The overall decrease in RH with time suggests an inverse relationship between relative humidity and temperature.

Precipitation analysis

The scatter plots for precipitation (Figure 6) revealed complex patterns, with both positive and negative slopes in the regression model lines. Precipitation refers to the condensation of water vapor from various atmospheric phases. In most tropical regions, precipitation is essentially synonymous with rainfall. The data used in this analysis is the monthly and annual bias-corrected average satellite-derived daily precipitation (in mm/day). This data has been statistically adjusted to match ground station observations.

The linear regression model for the Ganye zone has a negative slope of -0.065, suggesting a decrease in rainfall at a rate of -0.065 mm/day/year. The model has a good fit with an R^2 value of 0.455. Similarly, a negative slope was observed for the Yola zone, indicating a decrease of -0.029 mm/day/year with a lower R^2 of 0.002. The high p-value of 0.714 in Yola (Table 4) suggests that the observed decrease may not be statistically significant. In contrast, the Mubi zone exhibited a slightly positive slope in the model line, suggesting a potential increase in rainfall of 0.02 mm/day/year. However, the R^2 value of 0.087 and the high p-value of 0.135 (Table 3) indicate that this increase is likely not statistically significant.

Sky insolation clearness index analysis

The All Sky Insolation Clearness Index (ASICI) is a measure of the amount of solar radiation reaching the Earth's surface. ASICI is calculated as the ratio of global and diffused solar radiation reaching a horizontal surface to the maximum amount of solar radiation that could reach the top of the atmosphere in that area. An ASICI value of 1 indicates a perfectly clear sky, while a value of 0 indicates a completely overcast sky with dense clouds (Duffie & Beckman,2013). The parameter serves as an indicator of cloud cover within a region and is valuable for studying regional and seasonal variations in cloud cover. Interactions between greenhouse gases and solar radiation can lead to a decrease in ASICI. Therefore, understanding regional trends in ASICI can indirectly help assess atmospheric changes and their impact on global warming.

The linear regression model analysis of the monthly and annual ASICI data (Fig. 7) revealed negative slopes for Ganye and Yola (Tables 2 and 4), suggesting a decrease in sky clearness over the study period. The decrease was -0.00037/year for Ganye ($R^2 = 0.174$) and -0.0001/year for Yola ($R^2 = 0.0014$). Conversely, the Mubi zone displayed a positive slope of 7.5E-5 ($R^2 = 0.021$) (Table 3), suggesting a slight increase in sky clearness. The p-values for all three regions were statistically significant (p-value < 0.05), indicating that the linear regression models are reliable predictors of sky clearness trends in each region.

Analysis of the time trend of climatic data has so far shown a significant variability as evidenced by the magnitudes of the standard deviations shown in Tables 2, 3 and 4. The descriptive statistics shown in the tables indicates as expected, that Yola zone is generally experiencing warmer climatic condition than the remaining two regions. Both the relative humidity and the precipitation data consistently indicate that Ganye zone experiences significantly higher rainfall, followed by Mubi. Yola zone records the least rainfall within the study period. This is in line with the vegetation classification of the area and is fact the bases for the formation of the three vegetation zones. The increase in the minimum, maximum and mean temperatures at all the regions is in line with the findings of Adebayo *et al*. 2012) whose analysis of the trends of 36 years agro climatic data within the same area indicates a temporal trend of regional warming.

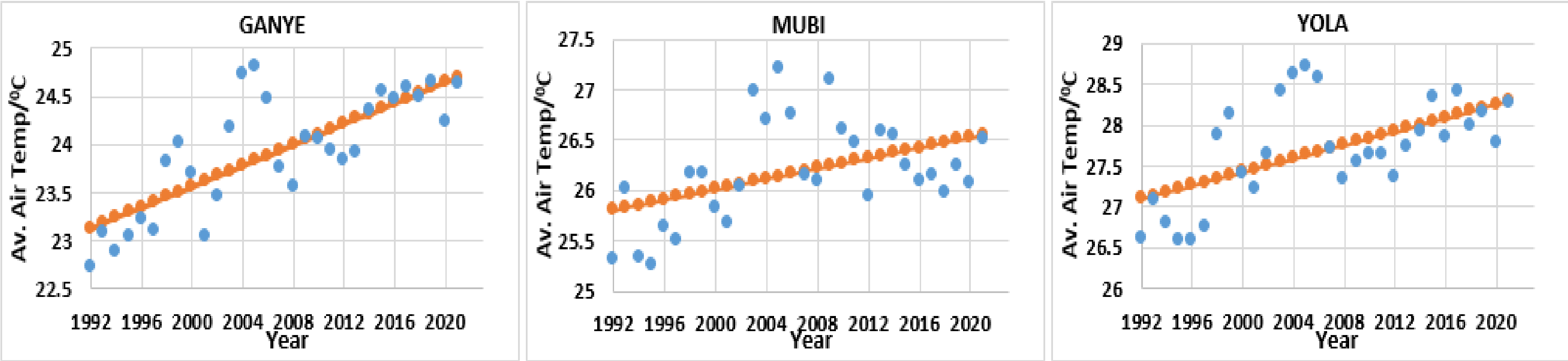

Figure 2: Trend of the monthly average air (dry bulb) temperature at 2 m above the earth surface

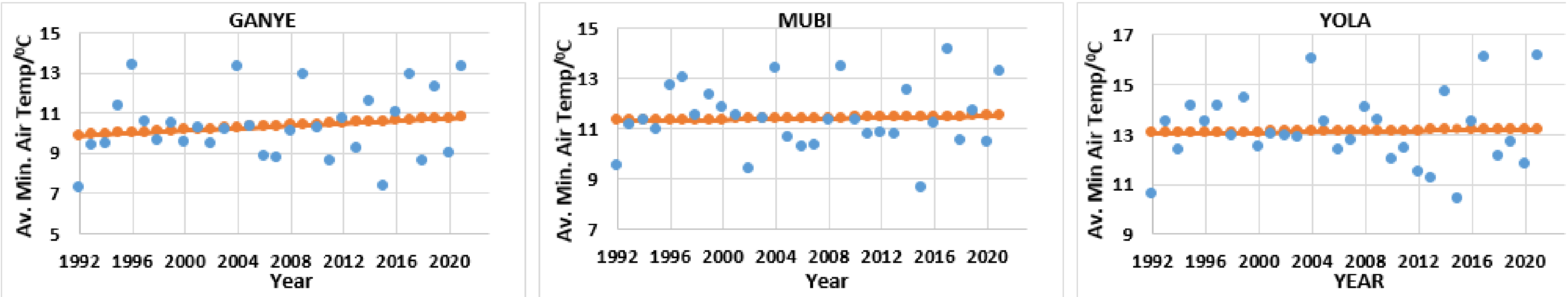

Figure 3: Trend of the monthly average minimum air (dry bulb) temperature at 2 m above the earth surface

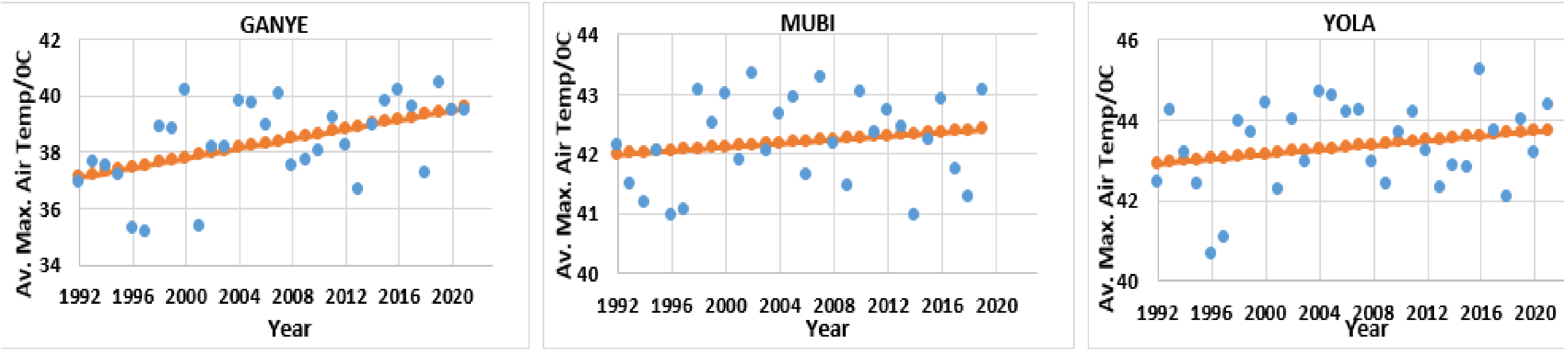

Figure 4: Trend of the monthly average maximum air (dry bulb) temperature at 2 m above the earth surface

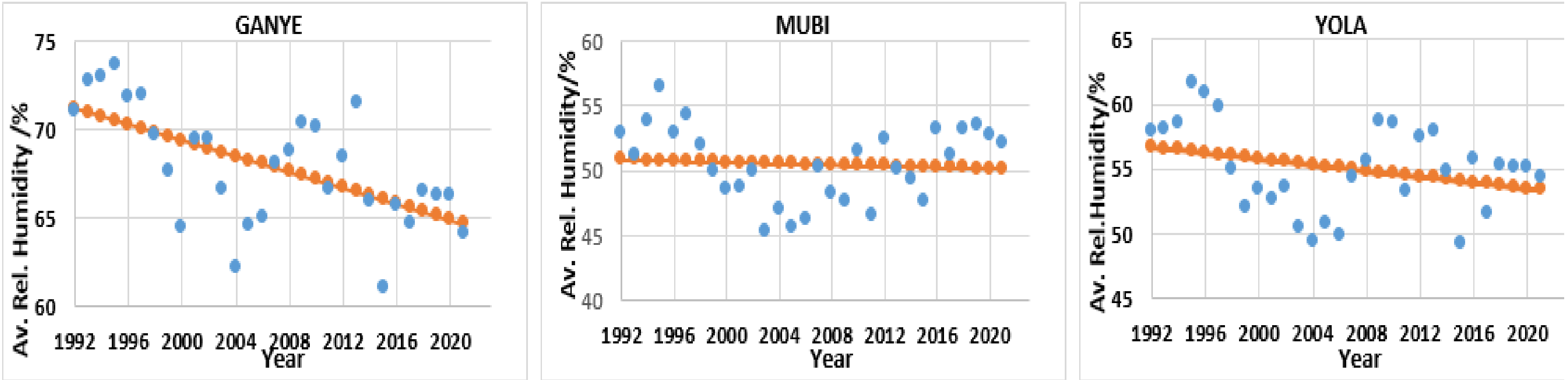

Figure 5: Trend of the monthly average relative humidity at 2 m above the earth surface

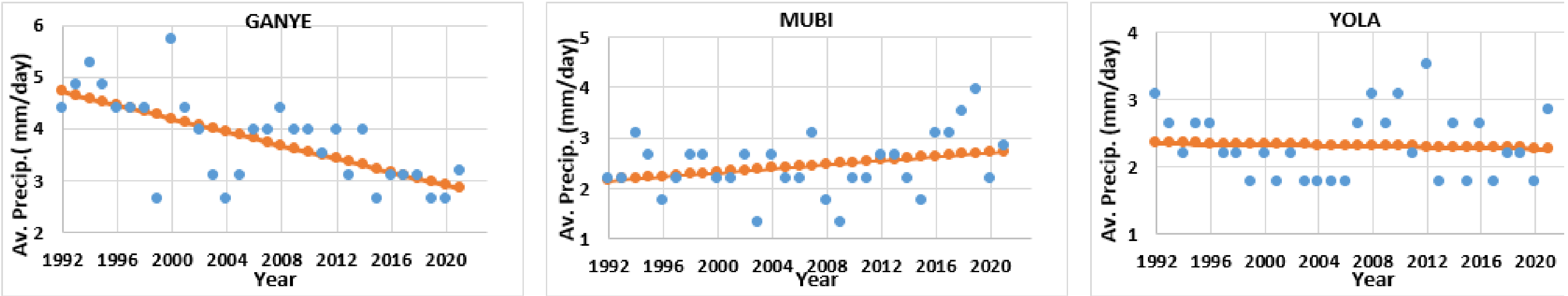

Figure 6: Trend of the monthly average precipitation corrected

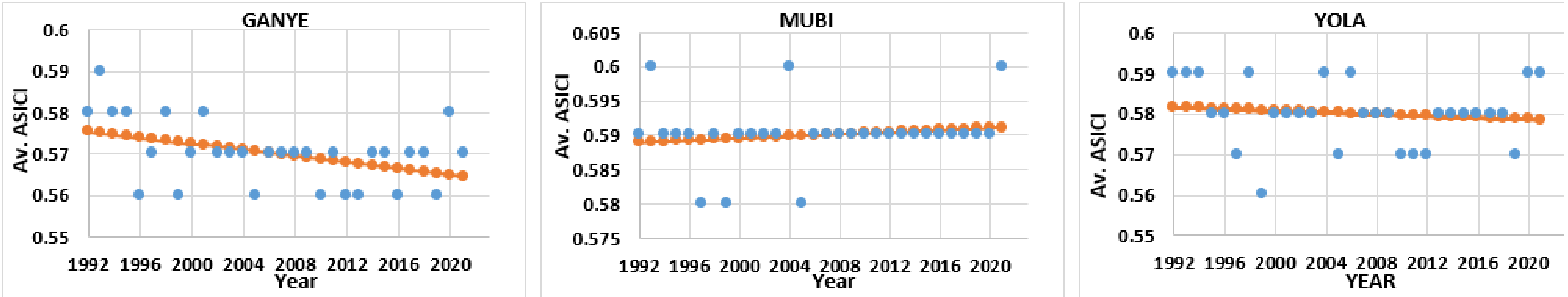

Figure 7: Trend of the monthly average All Sky Insolation Clearness Index

Table 2: ANOVA test of the linear regression model for Ganye zone

Parameter	Min	Max	Mean	SD	SE	R^2	p	Equation
Mean Air Temp.	22.72	24.42	23.914	0.615	0.112	0.598	2.56E-05	$Y = 0.054x - 84.513$
Min Air Temp	7.26	13.33	10.316	1.685	0.308	0.026	0.476	$Y = 0.031x - 51.758$
Max Air Temp.	35.13	40.47	38.333	1.503	0.274	0.249	0.0255	$Y = 0.085x - 132.48$
Relative Humidity	61.06	73.62	67.889	3.287	0.599	0.366	7.73E-05	$Y = -0.226x + 520.63$
Precipitation	2.64	5.71	3.767	0.843	0.154	0.455	3E-05	$Y = -0.065x + 133.40$
Sky Clearness index	0.56	0.59	0.57	0.0079	0.0014	0.174	0.000197	$Y = -0.00037x + 1.32$

Table 3: ANOVA test of the linear regression model for Mubi zone

Parameter	*Min*	*Max*	*Mean*	*SD*	*SE*	R^2	*p*	*Equation*
Mean Air Temp	25.26	27.21	26.176	0.506	0.092	0.201	0.199	$Y = 0.026x - 25.62$
Min. Air Temp	8.62	14.13	11.388	1.278	0.233	0.0023	0.963	$Y = 0.007x - 2.548$
Max. Air Temp	40.96	43.35	42.194	0.745	0.141	0.029	0.753	$Y = 0.015x + 11.151$
Relative Humidity	45.25	56.44	50.477	2.857	0.522	0.006	0.416	$Y = -0.025x + 101.33$
Precipitation	1.32	4.0	2.437	0.589	0.108	0.087	0.135	$Y = 0.02x - 37.257$
Sky Clearness Index	0.58	0.60	0.59	0.005	0.0008	0.021	0.0317	$Y = 7.56E^{-5}\ x + 0.438$

Table 4: ANOVA test of the linear regression model for Yola zone

	Min	*Max*	*Mean*	*SD*	*SE*	R^2	*p*	*Equation*
Mean Air Temp	26.59	28.71	27.67	0.625	0.116	0.340	0.017	$Y = 0.041x - 55.193$
Min. Air Temp	10.40	16.12	13.122	1.447	0.264	0.001	0.972	$Y = 0.005x + 2.186$
Max Air Temp	40.66	45.26	43.34	1.067	0.197	0.0547	0.757	$Y = -0.029x - 14.132$
Relative Humidity	49.25	61.69	55.008	3.430	0.626	0.088	0.052	$Y = -0.116x + 286.901$
Precipitation	1.758	3.515	2.305	0.505	0.092	0.002	0.714	$Y = -0.029x + 8.034$
Sky Clearness index	0.56	0.59	0.58	0.008	0.001	0.0014	0.026	$Y = -0.0001x + 0.794$

The decadent trends analysis also revealed that a decrease in relative humidity (RH) was observed in all regions, indicating an inverse relationship with temperature. These findings suggest a general warming trend in the region, accompanied by a decrease in relative humidity and rainfall, and a decrease in sky clearness. The Mubi region exhibited less significant trends, indicating more variability in its climate parameters.

Discussion

The results of this work highlight notable spatial and temporal trends in the climate parameters across the three studied regions over the past 31 years. These observations provide a valuable perspective on the variation in the climatic conditions across different vegetation regions and express complex dynamics of local climate systems.

The increase in mean air temperature across the study regions, particularly in the Ganye and Yola zones is in conformity with global warming trends reported in similar studies (Adebayo et al., 2012). The statistically significant warming rates recorded for Ganye (0.054°C/year) and Yola (0.041°C/year) suggest a strong, linear temporal dependence on temperature, which is in line with the global trends. The non-significant increase in Mubi, however suggest a need for further investigation of the potential moderating factors unique to this zone. These may include the factors such as topographic, localized weather patterns etc.

The recorded decrease in relative humidity with time, particularly in Ganye, corresponds to the rising temperature trends. This is an indication of the inverse relationship between temperature and RH and is based on the fact that temperature rise enhances the increase in the moisture retention capacity of air, which consequently leads to higher evaporation rates and thus decreased RH levels. The trend is statistically significant in Ganye ($p < 0.05$), is in line the known relationship RH and temperature. Despite slight decrease in RH, Mubi and Yola exhibited non-significant trends, suggesting that factors other than temperature alone may influence RH in these zones. For instance, the slight decrease in RH over Mubi zone ($p > 0.05$) is a reflection of the zone's the zone's relatively drier conditions, whereas that of Yola suggests random variability rather than a clear temporal trend.

The trends of precipitation over Ganye and Yola showed negative slope whereas that of Mubi indicates a slightly positive trend. These complex patterns are indication of the fact that unlike temperature or RH, precipitation is greatly influenced by localized atmospheric conditions and inter annual variability. The significantly negative precipitation trend over Ganye is an indication of drying pattern with time, might have impact on the water availability for agriculture and vegetation. On the other hand, the trends relative to Yola and Mubi suggest that precipitation changes in these zones are less predictable and likely influenced by short-term climatic oscillations, rather than a steady temporal trend.

The ASICI analysis showed that Ganye and Yola zones experienced a decrease in sky clearness, while Mubi exhibited a slight increase. These results imply a likely increase in cloud cover in Ganye and Yola, which can be associated with increased atmospheric moisture due to higher temperatures and regional weather systems. The statistically significant p-values across all three zones support the reliability of the observed ASICI trends, indicating that changes in solar radiation patterns are indeed occurring. This finding has implications for regional energy balance, as decreased solar insolation may reduce ground-level solar radiation, affecting local agriculture and renewable energy potential.

Conclusion

In this study, a variety of statistical tools were adopted (descriptive, linear regression, ANOVA) to analyse the trends in climatic parameters over a thirty-one period, with the aim of observing the significance of local climate variation in Adamawa state. The work utilized data provided by the National Aeronautics and Space Administration (NASA) database, specifically the NASA POWER Data Viewer, due to its consistency, validity, and availability of long-term records. A 31-year single-point record was used to represent each of the three identified vegetation sub-regions of the study area. Evidence of regional warming was generally detected, with monthly mean temperature exhibiting a linear increase over time. Non-linear relationships were observed with respect to monthly minimum and maximum temperatures. A general decrease in relative humidity over the study period was noted, with a linear model found to be valid in two of the three regions. Decreases in precipitation were recorded in two of the three regions, with non-linear fitting observed in both cases. The sky clearness index, however, virtually exhibited a slight decrease in two of the three regions, with a reliable linear model.

The thirty-one-year trends of climate variation across different sub-climatic regions, as observed using satellite-based data, offer advantages of consistency and comprehensiveness over traditional meteorological stations. Farmers and policymakers can therefore make optimal use of this data and advanced technology to improve the accuracy of weather forecasting, implement precision agriculture, and mitigate environmental risks such as drought. Additionally, these results provide a powerful tool for developing informed climate policies related to disaster risk management and supporting sustainable agricultural practices. We therefore suggest further studies to determine the most fitting predictive model for the parameters, focusing on the non-linear models.

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