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Dew Point Characteristics at Synoptic Stations in Northern Benin

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Authors' contributions

This work was carried out in collaboration among all authors. Authors HK and MWO designed the study, performed the statistical analysis, and wrote the first draft of the manuscript. All authors read and approved the final manuscript.

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ABSTRACT

The dew point temperature is a very important parameter for hydro and agro-climatological research. This work studied the temporal variability of dew point temperature in Northern Benin. The dew point data comes from three synoptic stations in Northern Benin and covers the period from January 1980 to February 2019. After, correction and homogenization of the data, statistical methods are employed to analyze its structure, distribution, and temporal variability. The average of the dataset is 16.607°C with a standard deviation of 6.871 and a coefficient of variation of 0.414. The distribution is negatively skewed without extreme values, with an interquartile range of 10.284. The analysis by days of month indicates an irregular change in values at the beginning of month. The days of week show a minimum at the beginning and a maximum at the end of week. The analysis of dew point temperature data by months of the year shows a bell-shaped distribution with a plateau covering the months from May to September. The average dew point temperature has

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been increasing over the years. The data also describe a non-stationary periodic series approved by statistical tests. The absence of an inflection point in the data and in the trend means that the distribution is evolving and cyclical but not regular.

Keywords: Dew point variability; climate change; temperature; Benin; dew point statistics.

1. INTRODUCTION

Dew point temperature is a measure that corresponds to the temperature at which air must be cooled to reach saturation (100% relative humidity), [1]. The dew point temperature is a weather condition that occurs when the air is fully saturated with water vapor and the number of water molecules evaporating from any surface is balanced by the number of molecules condensing, [2–6]. Thus, it is a quantity related to humidity. Humidity has atypical characteristics. It is difficult to measure accurately because it is directly affected by temperature and pressure, [7–12]. Humidity in processes is often a contaminant that can severely damage processes and equipment and reduce product quality, [13–15]. Humidity can penetrate almost all surfaces, render test results useless, lead to poor product quality, cause corrosion of tubes, lead to ice formation at low temperatures, cause premature wear and equipment failure, react with other chemicals and gases. Humidity has adverse effects on many finished products, [16–23]. In metallurgy, the level of humidity in a furnace must be carefully controlled to avoid brittle products, while in pharmaceutical production, powders must remain dry to prevent clumping, [24, 25]. Low humidity is necessary in refineries to avoid undesirable chemical reactions. Additionally, humidity is involved in cloud formation in general and thunderstorm clouds in particular. Its modeling from dew point temperature is relevant, [1, 26–34]. Accurate estimation of dew point temperature is very important for various applications in hydro and agro-climatic research, [2, 21]. Several studies have analyzed or modeled dew point temperature, [35–39, 2, 40–56].

The dew point is an interesting weather indicator for farmers. It can help improve agricultural practices, optimize irrigation practices, allowing farmers to better manage water based on ambient humidity. The north of Benin is an area where food crops and industrial crops are grown. Off-season crops are sometimes necessary, and the region would benefit from in-depth knowledge of meteorological parameters. Studies involving in-depth analyses of these parameters are almost non-existent.

This work aims to analyze the characteristics of the dew point in northern Benin. It seeks to understand the temporal distribution of dew point temperature data. Thus, the variability in the data by days of month, days of week, months of year, and years has been observed. Time series analysis has also been addressed. This study can serve as a basis for correlational or predictive analyses.

2. MATERIALS AND METHODS

2.1 Physical Framework

The Republic of Benin is located in West Africa. Its neighbours are Nigeria to the east, Niger and Burkina Faso to the north and Togo to the west.

The study area includes three synoptic stations: Kandi’s station in Alibori department, Parakou’s station in Borgou department, and Natitingou’s station in Atacora department.

2.2 Data

The dew point data comes from the three synoptic stations in Northern region of Republic of Benin. This data covers the period from January 1980 to February 2019, and the geographical area is indicated by the green line in Fig. 1. It consists of three-hour interval recordings of dew point at each station.

2.3 Methods

Data homogenization from the three nearby stations is necessary before performing statistical treatments such as trend analysis, [57, 58]. The methods adopted for this study are variants used by authors such as: [59–64].

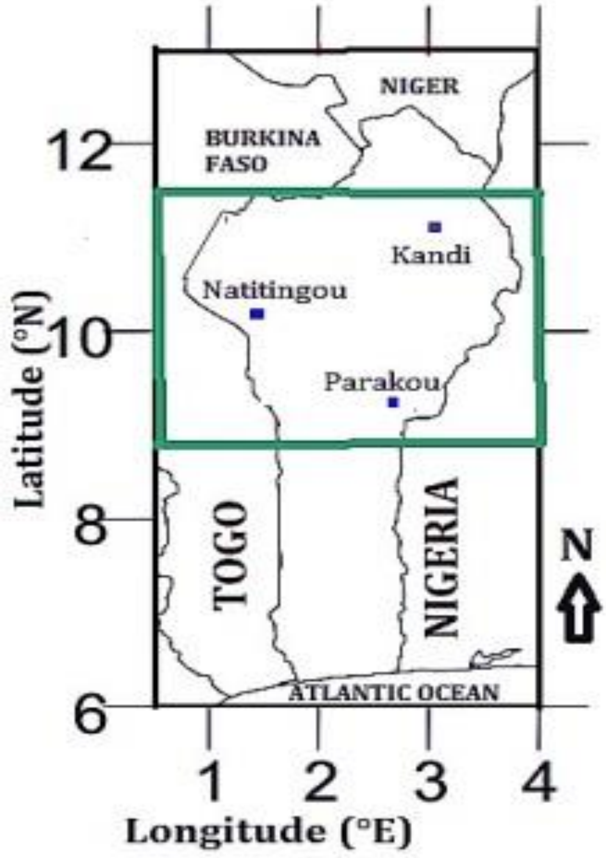


Fig. 1. Distribution of synoptic weather stations indicated by blue dots

The green line indicates the data coverage area

The data analysis began with a flat sorting, which allowed for the delineation of sample. It revealed the presence of missing values, leading to the calculation of gap rate. This preliminary work helped reduce potential biases that could be induced by missing data in the results. The gap rate at each station is less than 5%. Thus, the average of values surrounding the gap is used for imputation. After this correction, statistical methods are employed to analyze the structure, distribution, and temporal variability of the data.

3. RESULTS AND DISCUSSION

The dew point temperature is one of variables that can explain the formation of thunderstorm clouds. The average dew point temperature in the dataset is 16.607°C, with a standard deviation of 6.871 and a coefficient of variation of 0.414. The data are not clustered around the mean (see Fig. 2). The center of the distribution is very high (median at 20.664). The distribution is negatively skewed, as the lower part of box and lower whisker are longer than the upper. The distribution has no outliers, with an interquartile range of 10.284 (see Fig. 2a). It appears to have multiple modes (see Fig. 2b), suggesting that groups can be deduced. Its fitting is acceptable and highlights three groups.

The analysis by days of month indicates an irregular change in values at the beginning of month (Fig. 3a). A significant variability is observed between the 12th and 20th of month, with boxes displaying different distributions, but which are predominantly negatively skewed (Fig. 3b). Outliers are identifiable on the 15th of month. No conclusions can be drawn regarding the trend or cycle. However, there is a noticeable increase in values towards the end of month.

The days of week show a minimum at the beginning of week and a maximum at the end of week (Fig. 4a). The values are tightly clustered and do not support a hypothesis of seasonality throughout the week. Outliers are noted on the first day of week (Fig. 4b). All distributions are negatively skewed, with higher variability on the fourth and seventh days.

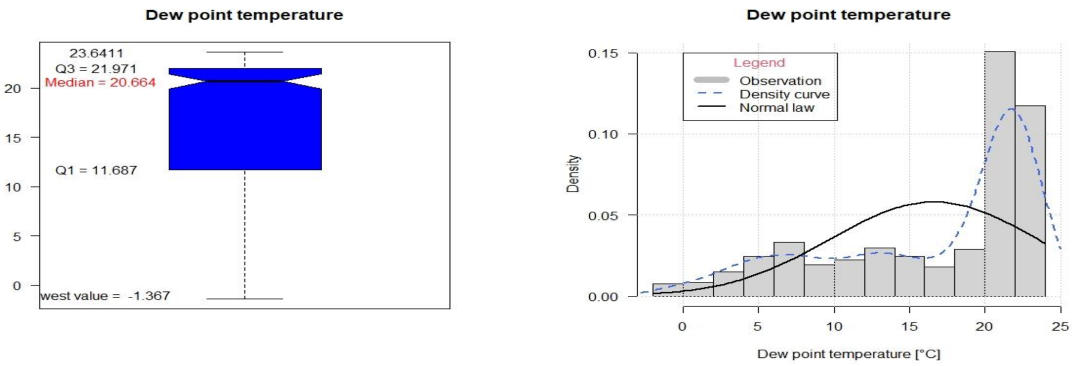
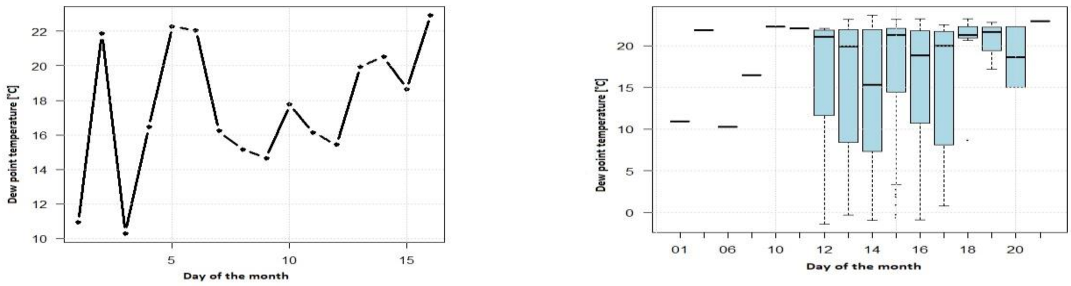


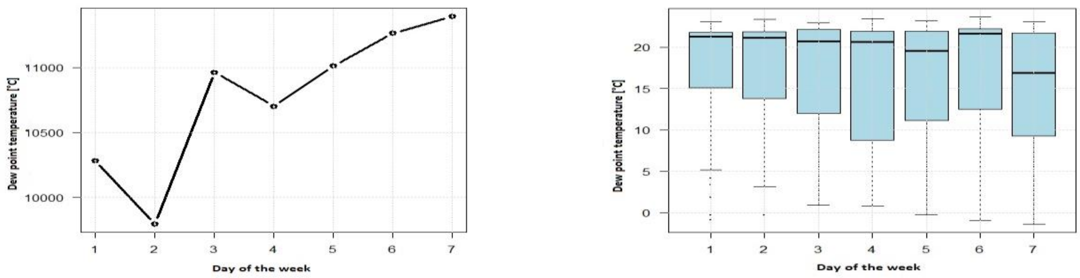
Fig. 2. Analysis of distribution of dew point temperature data



(a) Daily values

(b) Box plots

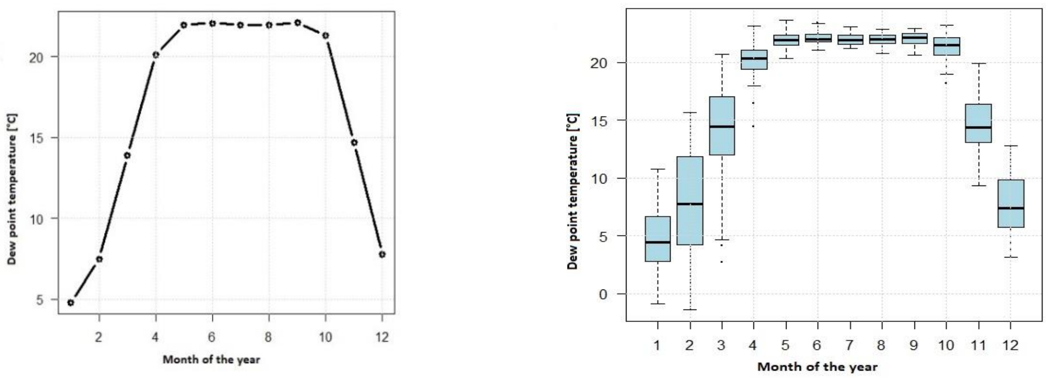
Fig. 3. Analysis of distribution of dew point data by days of the month



(a) Daily values

(b) Box plots

Fig. 4. Analysis of distribution of dew point data based on the days of week



(a) Values by month

(b) Box plots

Fig. 5. Analysis of distribution of dew point data by month of year

The analysis of dew point temperature data across the months of year reveals a bell-shaped distribution with a plateau covering May to September (Fig. 5a). The box plots show similar distributions for the first three and the last two months of year. At the plateau, the distribution is almost identical for the five months (Fig. 5b). Additionally, the distribution is nearly symmetrical for all months, with outliers in the third and fourth months. It is noteworthy that the values are less dispersed between April (4) and October (10) (Fig. 5b).

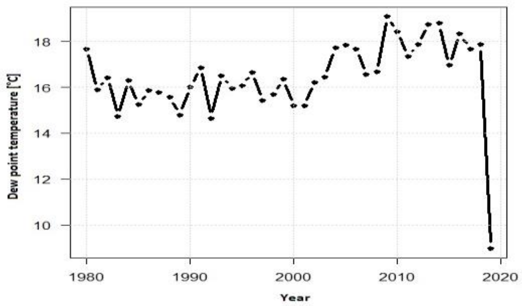
The analysis of distribution over the years shows a trend towards the end of series. The average temperature at the dew point increases over the years (Fig. 6a). The dispersion is similar for each year. All the boxes display a negatively skewed distribution (Fig. 6b).

The analysis reveals a significant peak at lag 1, followed by an alternating pattern of positive and negative correlations, indicating a periodic nature of data (Fig. 7a). The autocorrelation reaches a minimum at a half-period lag, suggesting the presence of higher-order autoregressive term.

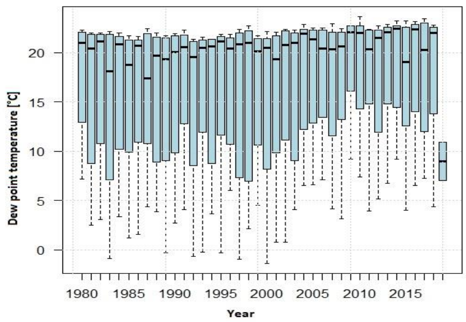
The results of correlation tests show a low Pearson coefficient (0.287), but significant at 5% level (p = 2.6e-10), with a confidence interval of 0.201 to 0.368, excluding zero. This proves a link between time and the data.

The results of Dickey-Fuller test (p = 0.02245), Box-Pierce (p < 2.2e-16), Box-Ljung (p < 2.2e-16), and Kwiatkowski-Phillips-Schmidt-Shin (p = 0.01822) confirm that the series is non-stationary, indicating the need for differencing for analysis.

No inflection point was found in the series of dew point temperature data distribution (Fig. 8a) or in the trend (Fig. 8b). Therefore, the distribution is evolutionary and cyclical with an irregular cycle.

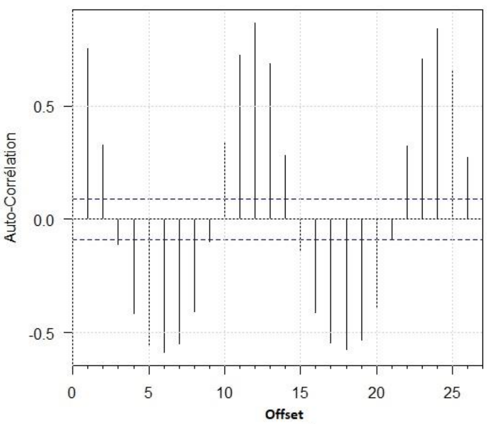


(a) Year Values

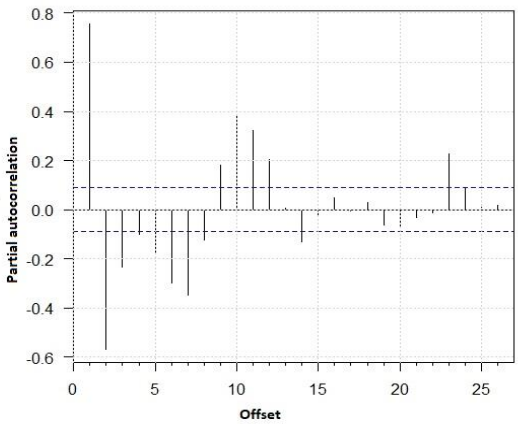


(b) Box plots

Fig. 6. Analysis of distribution of dew point temperature data over the years

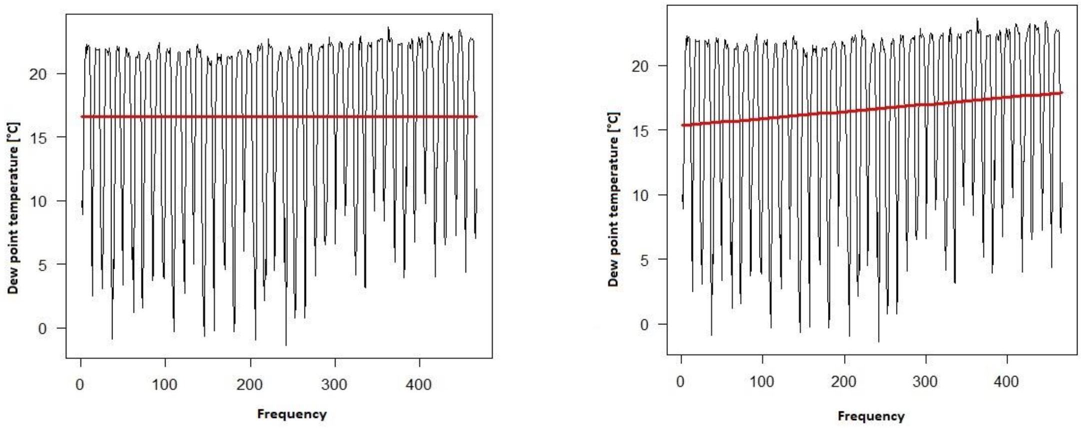


(a) Autocorrelation



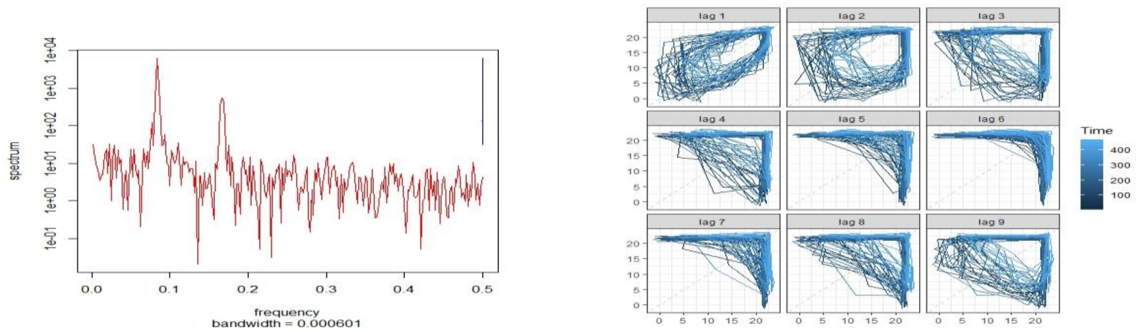
(b) Partial autocorrelation

Fig. 7. Estimation of autocorrelation function for distribution of dew point data



(a) Inflection Points **(b) Inflection Points in the Trend**

Fig. 8. Identification of inflection points in the distribution of dew point temperature data



(a) Spectrum of distribution **(b) Lag analysis**

Fig. 9. Spectrum and lag plots of dew point temperature data distribution

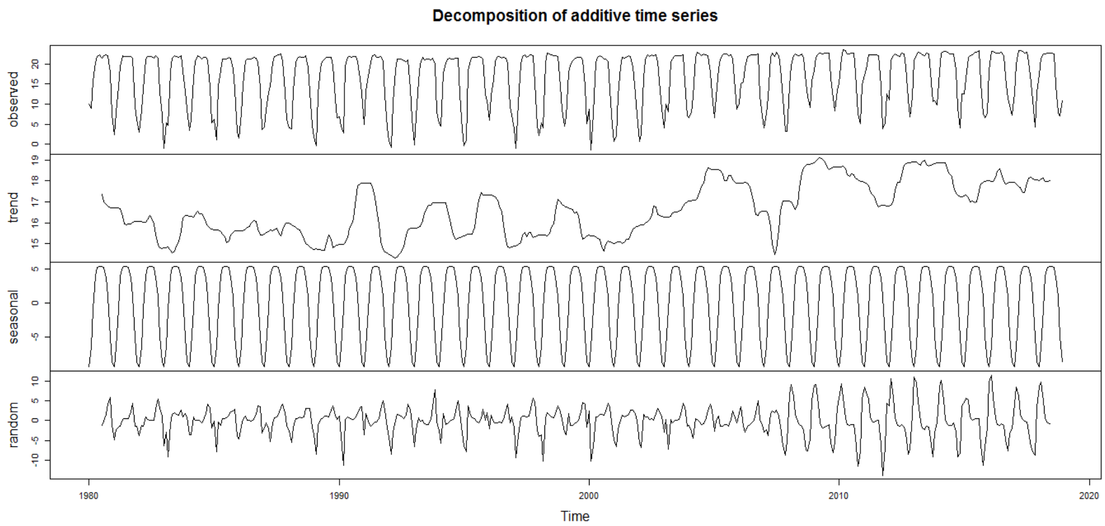


Fig. 10. Dew Point Structure: from top to bottom, it displays the observation, the trend, the seasonal component, and the residual component

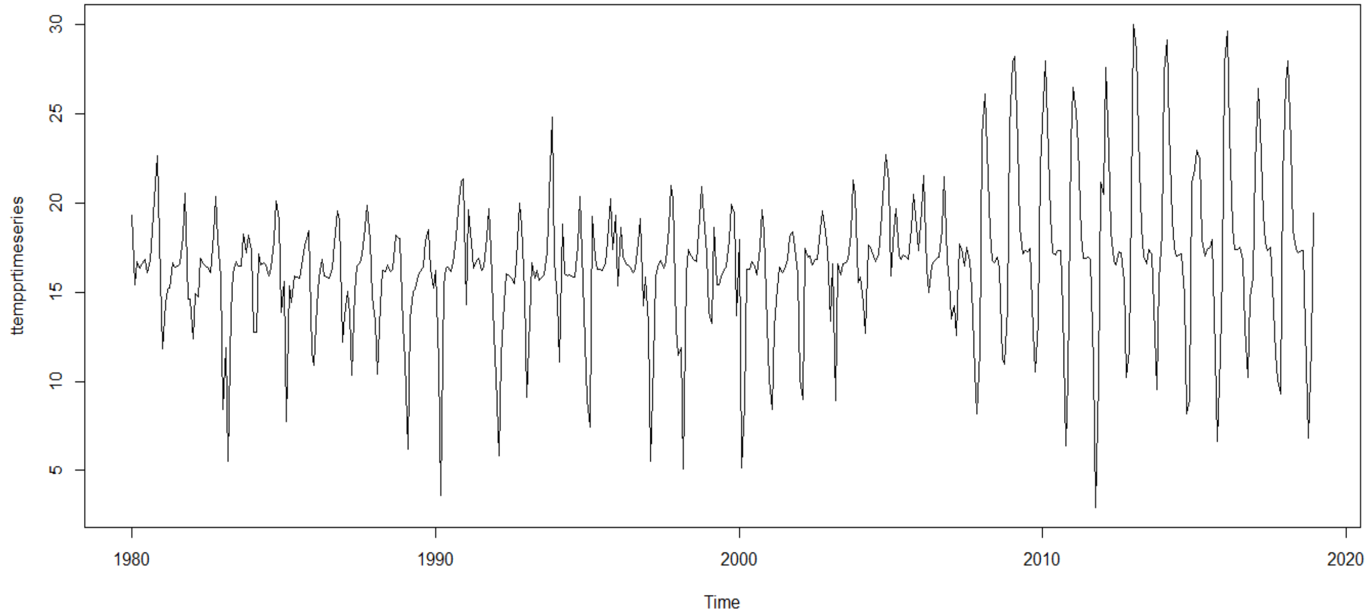


Fig. 11. Adjusted dew point temperature, combining the trend and fluctuation

The analysis of spectral density curve does not show regular cycles. The periodogram is represented in Fig. 9a. The lag plots show a slight trend at lag 1 with sinusoidal-type fluctuations (Fig. 9b).

Fig. 10 illustrates the additive decomposition of dew point temperature data series. The trend has been upward since the beginning of period, becoming more pronounced over the years, especially towards the end. The random component of structure displays a regularity that reverses towards the end of period and increases in intensity.

The combination of trend and random component of series show significant variability starting from year 2010 (Fig. 11).

Benin has two types of climate: a sub-equatorial climate with four seasons, including two rainy seasons and two dry seasons in the south; and a Sudanian climate with two seasons, one rainy and one dry, in the north. The central part of the country has a transitional climate which is similar to a sub-Sudanese climate. The average annual temperature is estimated at 27°C, [65, 66]. The highest temperatures occur in March, April and May, and the lowest in December and January, when the harmattan rages, [66]. In northern Benin, the rainy season extends from April-May to September-October, and the dry season from October-November to March-April, [66]. During the dry season, temperatures reach 40°C and the harmattan blows dry, dust-laden air.

Analysis by day of the month indicates an irregular change in values at the beginning of the month. This result is in agreement with the results obtained by other authors such as [2, 3]. This is also justified by the type of climate in the area. The days of the week show a minimum at the beginning of the week and a maximum at the end of the week. Relative humidity plays a role in mitigating the water deficit. It maintains relatively high monthly and annual values throughout the year. The averages decrease from south to north. A comparison of average monthly rainfall and relative humidity shows that rainy months are generally those with high relative humidity. In the north, the differences between the annual average and the monthly values are greater, [66].

Analysis of dew point temperature data as a function of months of year shows a bell-shaped distribution with a plateau covering the months from May to September. This plateau corresponds exactly to the rainy season in the study area, [66]. The average temperature at dew point increases over the years. This observation can be explained by climate change over the last few decades.

4. CONCLUSION

Several studies around the world have looked at the analysis of dew point temperature. Some of these studies focus on modelling this parameter. With the data used, this study appears to be a first. The studies covering our study area and dealing with the dew point temperature approach it as a parameter that is calculated for a given moment or for a defined period. This study analyses the dew point temperature on several time scales, identifying the links that are established. The aim of this initial study is to identify the intrinsic qualities of the data.

The results obtained are comparable to those of previous studies. They are useful for identifying the seasons and for finding hydro- and agro-climatological solutions, etc. Analysis of the descriptive statistics on the data shows that the distribution has several modes. Three groups seem to have emerged. The first can be interpreted as the dry season months with the harmattan (November, December and January); the second group covers the rainy season (April-May to September-October) and the third group follows the dry season months (February, March and April) before the rainy season. It is also easy to identify the two main seasons, the rainy season and the dry season (Fig. 2b). The distribution is asymmetrical (Fig. 2a). This is confirmed by Fig. 2b. The different cycles obtained (days of the week, days of the month, months of the year and years) provide coherent information that can be exploited. The data also describe a non-stationary periodic series approved by statistical tests. The absence of an inflection point in the data and in the trend means that the distribution is evolving and cyclical but not regular. The data can reflect the current realities of the phenomena it can model.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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