Research article

The Interactions between Temperature and Relative Humidity: Results for Benin City, Nigeria Using Statistical Analysis

Israel Uzuazor Siloko[1]*, Kingsley Eghonghon Ukhurebor[2], Edith Akpevwe Siloko[3], Esosa Enoyoze[1] and Osayomore Ikpotokin[4]

[1]*Department of Mathematics, Edo State University Uzairue, Nigeria*
[2]*Department of Physics, Edo State University Uzairue, Nigeria*
[3]*Department of Statistics, University of Benin, Benin City, Nigeria*
[4]*Department of Mathematics and Statistics, Ambrose Alli University, Ekpoma, Nigeria*

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Abstract

The interactions between temperature and relative humidity are the main focus of this article. These two meteorological observations are of great significance due to their direct effects on humans and their environment. A series of studies on meteorological variables was carried out over a decade with emphasis on their effects on humans and their environment. Similar studies are going on due to the constant changes in the globe because of climate change. Appropriate measures can be provided for weather experts to curb some of the adverse effects of these variables. This article addresses the connectivity of temperature and relative humidity as well as their joint effects in Benin City, Nigeria for the period of ten years from 2010 to 2019 using nonparametric techniques that employ the Gaussian kernel estimator as analytic tool. The statistical analysis of the relationship between temperature and relative humidity vividly revealed that human activities were more successful in 2016 and 2017 under the period been studied with the asymptotic mean integrated squared error (AMISE) used as the performance measure.

Keywords

AMISE;
bandwidth;
humidity;
kernel;
temperature

1. Introduction

Weather variables like rainfall, temperature, light intensity, humidity, wind speed, pressure as well as other variables have direct impacts on the environment [1]. Consequently, studying their interactions

*Corresponding author: Tel.: +2348164830801
E-mail: suzuazor@yahoo.com, siloko.israel@edouniversity.edu.ng

is imperative especially for proffering proper understanding of their impacts that would be of assistance for decision making by weather experts. Globally, weather variables play a very significant role in agricultural activities upon which humanity directly depends for its existence and continuity. A study on consequences of some weather variables on crops yield was conducted with the conclusion that about 93% of poor performance was due to the harshness of weather variables. The interdependence of rainfall and temperature, which are essential variables for plant growth, was investigated by some researchers and the findings were made available to meteorologists to help them make appropriate decisions [2-5]. A special model that incorporated weather parameters was designed by Schlenker and Lobell [6]. The model dealt with crop performance within the Sub-Sahara Africa, and the findings indicated that a rise in temperature led to low yields owing to reduction in rainfall. Research on temperature impact by Feng *et al*. [7] on crop production revealed that higher temperature reduces crop yields.

Atmospheric temperature is simply the measure of the hotness or coldness of the atmosphere and this has either positive or negative effects on the environment. Temperature as a weather variable is of primary importance for the growth and development of plants owing to the fact that with warmer temperatures, which are associated with climate change, the productivity of plants will be eventually affected. Pollination that is fundamental to plants is regulated by temperature, which can occur either with minimum, maximum or optimum values for different plant species [8]. In a study conducted by Barlow *et al*. [9] on the effects of temperature on wheat crop (*Triticum aestivum L.*), the results divulged that frost can give rise to unproductivity and termination of grains forming while excess heat can bring about low rate of grain production. As a result of the negative impacts of lofty temperature on pollens suitability, several researchers advised that the production of some cereal crops such as rice should be done at cooler hours of the day in snug environment using the differences in flowering periods as a valuable phenotypic distinction for lofty temperature resilience.

High temperature has serious negative effects on human activities because reports on weather variables have shown that high temperatures induce social vices, and psychology and criminology studies showed the negative effects of high temperatures on household income [10]. High temperatures can result in serious heat that negatively affects agricultural activities and especially species that have difficulty in adapting to temperature rise. A rise in temperature also leads to evaporation that ultimately produces high precipitation but increases in precipitation do not result in an abundance of water for human activities. An investigatory study was experimented with elderly patients in twelve cities of United States and a positive correlation was established between temperature and the number of hospital admissions for heart and myocardial diseases [11].

Humidity measures the volume of water vapor present in the atmosphere and it is a vital weather variable. Humidity as a weather variable affects temperature because warmer temperature can produce intolerable environmental condition. The creation of clouds and precipitation that leads to rainfall vital for maximum productivity and sustenance of mankind is a function of humidity. Knowledge of the interactions between temperature and humidity with regards to the environment is paramount owing to the fact that humidity is a crucial global weather variable. There are different forms of humidity, such as relative humidity, which demonstrates a highly inverse relationship with dew-point. Relative humidity is the quantity of water vapor available in the atmosphere relative to the volume of water vapor that can be held by the atmosphere and is usually expressed in percentage. On the other hand, the dew point reveals the temperature at which water vapor in the atmosphere has become saturated. Relative humidity and dew point are both temperature dependent; however, dew point produces an exact result more than relative humidity [12].

Humidity is an indispensable weather variable with direct effects on a wider scope of human and environmental health-related studies. A research study was conducted on relative humidity by Davis *et al*. [13] and the findings showed high levels of correlation with some cardiovascular and pulmonary diseases when the human respiratory system was continuously exposed to the environment. A high correlation level was established between relative humidity and hypertension by Yang *et al*. [14], and the findings suggested a potential threat for humanity as a consequence of some meteorological variables. A similar research investigation was made in Japan by Hayes *et al*. [15] to ascertain connectivity between relative humidity and asthmatic patients admitted to hospital with the results suggesting that asthmatic patients demonstrated bronchoconstriction with low relative humidity. High temperature and high relative humidity heightened the admissions of patients with cardiovascular and respiratory related diseases in New York [16]. A distinct analysis of the association between temperature and relative humidity was suggested by Montero *et al*. [17] stressing that relative humidity may occasionally exhibit a range of negative or positive relationships with temperature. The turgidities of plants can be affected by humidity due to transpiration, and the growth and spread of diseases like fungi can be supported by high humidity. A research study showed that a species of beans (*Phaseolus* spp.) was affected during fruit formation when the humidity was low. Low humidity is fundamental in long term storage of agricultural products particularly grains but fruits and vegetables require high humidity during storage to reduce water loss [18].

The knowledge of connections between weather variables is of great importance mainly for identification of their joint effects which can provide basic information about the environment, and accurate future predictions can be made on the basis of the structures and patterns discovered [19, 20]. Orderly presentation of weather variables is sacrosanct and their prominent role in environmental management must not be underestimated. Analysis and evaluation of weather variables usually involves graphical presentation of the variables for identification of the inherent features in the variables [21].

Hence, this study will attempt to graphically examine the connectivity between temperature and relative humidity in Benin City, Nigeria using the nonparametric kernel estimator on account of the advantages of computations of the estimator. Although there are other essential climate variables like rainfall, light intensity and pressure, temperature and relative humidity were chosen as the focal points of this study because of their peculiarity. Because of the constant variations of weather variables, a nonparametric technique that was devoid of imposition of distributional properties on the observations was appropriately used.

2. Materials and Methods

In this paper, the kernel method, which is one of the nonparametric density techniques used in the analysis of data without regards to their family of distribution, has been employed. Density estimation involves the construction of probability density estimates of random variables using either known probability distribution or unknown probability functions. The kernel estimator is a nonparametric method for analysing data without assuming the family of the observations. The two-dimensional Gaussian estimator is employed using the product technique in the analysis of temperature and relative humidity.

2.1 The kernel density estimator

This estimator is an extensively used in the nonparametric approach in statistics for the investigation of features and structures of observations. The one-dimensional form of the kernel estimator in its succinct form is

$$\hat{f}(\mathrm{x}) = \frac{1}{nh_{\mathrm{x}}} \sum_{i=1}^{n} K\left(\frac{\mathrm{x}-\mathrm{X}_i}{h_{\mathrm{x}}}\right), \tag{1}$$

where $K(\cdot)$ is the kernel function, n is sample size, h_{x} is bandwidth while x is the range of the observations, and X_i are the sets of observations. Kernel functions are usually probability density with certain sufficient axioms

$$\int K(\mathrm{x})d\mathrm{x} = 1, \quad \int \mathrm{x}K(\mathrm{x})d\mathrm{x} = 0 \quad \text{and} \quad \int \mathrm{x}^2 K(\mathrm{x})d\mathrm{x} \neq 0. \tag{2}$$

Every kernel function is a probability density function whose integral is unity with zero mean and variance greater than zero. Kernel methods are used for exploration of data and visualization; nonetheless, there is the challenge of accurate bandwidth selection especially with an increase in dimensions [22, 23].

The one-dimensional kernel estimator can be straightforwardly extended to the multi-dimensional kernel estimator but graphical illustrations can be better visually displayed with the two-dimensional estimator. The two-dimensional kernel estimator can be graphically presented as a surface plot with an additional dimension or contour plot that maintains the same dimension of the observations. Again, presentation of observations regarding their direction is better encapsulated with the two-dimensional symmetric kernel estimator, which is given by

$$\hat{f}(\mathrm{x}, \mathrm{y}) = \frac{1}{nh_{\mathrm{x}}h_{\mathrm{y}}} \sum_{i=1}^{n} K\left(\frac{\mathrm{x}-\mathrm{X}_i}{h_{\mathrm{x}}}, \frac{\mathrm{y}-\mathrm{Y}_i}{h_{\mathrm{y}}}\right), \tag{3}$$

where $h_{\mathrm{x}} > 0$ and $h_{\mathrm{y}} > 0$ are the bandwidths in the directions of X and Y, while x and y are the ranges of the observations in the different directions with $K(\mathrm{x}, \mathrm{y})$ representing the two-dimensional kernel estimator. The two-dimensional kernel estimator can be in product form or spherical form but in practice, the product kernel is mostly used when estimating data. The two-dimensional product kernel which involves multiplying two univariate kernel estimators is

$$\hat{f}(\mathrm{x}, \mathrm{y}) = \frac{1}{nh_{\mathrm{x}}h_{\mathrm{y}}} \sum_{i=1}^{n} K\left(\frac{\mathrm{x}-\mathrm{X}_i}{h_{\mathrm{x}}}, \frac{\mathrm{y}-\mathrm{Y}_i}{h_{\mathrm{y}}}\right), \tag{4a}$$

The radially spherically bivariate kernel estimator is hinged on the Euclidean distance between the observations with the formula as:

$$\hat{f}(\mathrm{x}, \mathrm{y}) = \frac{1}{nh_{\mathrm{x}}h_{\mathrm{y}}} \sum_{i=1}^{n} K\left(\sqrt{\left(\frac{\mathrm{x}-\mathrm{X}_i}{h_{\mathrm{x}}}\right)^2 + \left(\frac{\mathrm{y}-\mathrm{Y}_i}{h_{\mathrm{y}}}\right)^2}\right). \tag{4b}$$

The two-dimensional kernel estimators bridge the gap between one dimensional and other higher dimensional estimators. One significant role of the two-dimensional kernel estimators is the easy presentation and interpretation of their estimates [24, 25].

2.2 Assessments of kernel estimator

The assessment of kernel performance is done with an error criteria function that depends on bandwidth. A plethora of performance measures exist in the literature but the asymptotic mean integrated squared error (AMISE) is more prominent due to the mathematical structure and the incorporation of dimensions while other performance measures are dimensionless. The AMISE with its two components; the integrated variance and integrated squared bias is

$$AMISE\left(\hat{f}(\mathrm{x})\right) = \int \mathrm{Variance}\left(\hat{f}(\mathrm{x})\right) d\mathrm{x} + \int \mathrm{Bias}^2\left(\hat{f}(\mathrm{x})\right) d\mathrm{x}. \tag{5}$$

The AMISE of the one-dimensional kernel estimator when approximated by Taylor's series expansion yields its components as

$$\int \mathrm{Variance}\left(\hat{f}(\mathrm{x})\right) d\mathrm{x} = \frac{R(K)}{nh_{\mathrm{x}}} \tag{6}$$
$$\int \mathrm{Bias}^2\left(\hat{f}(\mathrm{x})\right) d\mathrm{x} = \frac{1}{4} h_{\mathrm{x}}^4 \mu_2(K)^2 R(f'')$$

The combination of the terms in equation (6) gives the AMISE which is

$$AMISE\left(\hat{f}(\mathrm{x})\right) = \frac{R(K)}{nh_{\mathrm{x}}} + \frac{1}{4} h_{\mathrm{x}}^4 \mu_2(K)^2 R(f''), \tag{7}$$

where $R(K) = \int K^2(\mathrm{x}) d\mathrm{x}$ is called the roughness of kernel, $\mu_2(K)^2$ is known as kernel variance, while $R(f'') = \int f''(\mathrm{x})^2 d\mathrm{x}$ is the roughness of the function. The bandwidth that will produce the minimum AMISE is obtained from the differential equation

$$\frac{\partial}{\partial h} AMISE(h) = \frac{-R(K)}{nh_{\mathrm{x}}^2} + \mu_2(\mathrm{K})^2 h_{\mathrm{x}}^3 R(f'') = 0.$$

On solving the differential equation, the bandwidth with the minimum AMISE is

$$h_{\mathrm{x-AMISE}} = \left\{\frac{R(K)}{\mu_2(\mathrm{K})^2 R(f'')}\right\}^{1/5} \times n^{-1/5}. \tag{8}$$

The two-dimensional product kernel estimator has its AMISE which is

$$AMISE\left(\hat{f}(\mathrm{x},\mathrm{y})\right) = \frac{R(K)}{nh_{\mathrm{x}}h_{\mathrm{y}}} + \frac{h_{\mathrm{x}}^4}{4}\mu_2(K)^2 \int\int \left(\frac{\partial^2 f}{\partial \mathrm{x}^2}\right)^2 d\mathrm{x}d\mathrm{y} + \frac{h_{\mathrm{y}}^4}{4}\mu_2(K)^2 \int\int \left(\frac{\partial^2 f}{\partial \mathrm{y}^2}\right)^2 d\mathrm{x}d\mathrm{y} \tag{9}$$

The performance of the kernel estimator is determined by the bandwidths especially with the two-dimensional Gaussian distribution where the observations are presumed independently and identically distributed. The minimum of the AMISE of the bivariate product kernel is obtained with respect to the bandwidths in the two directions [26-30]. The Gaussian based bandwidth selector is employed in analyzing the observations mainly for visualization purposes. The two-dimensional Gaussian kernel function is

$$K(\mathrm{x}\,,\mathrm{y}) = \frac{1}{2\pi} exp\left(-\frac{\mathrm{x}^2+\mathrm{y}^2}{2}\right). \tag{10}$$

The continuous differentiability and possession of higher order derivatives of the Gaussian kernel function has supported the wide applicability of the function. The Gaussian kernel estimator is also very prominent in social and medical sciences due to the comprehensibility of its mathematical estimations with unambiguous expressions and production of smooth estimates. The bandwidths of the bivariate product kernel with respect to the Gaussian kernel function for the x-axis and y-axis are given as

$$h_{\mathrm{x}-AMISE} = \left\{\frac{dR(K)^d}{\mu_2(K)^2\left(\frac{d(d+2)}{4\left(2\sqrt{\pi}\right)^d}\right)\sigma_{\mathrm{x}}^{-(d+4)}}\right\}^{1/6} \times n^{-1/6} \tag{11a}$$

$$h_{y-AMISE} = \left\{\frac{dR(K)^d}{\mu_2(K)^2\left(\frac{d(d+2)}{4\left(2\sqrt{\pi}\right)^d}\right)\sigma_{y}^{-(d+4)}}\right\}^{1/6} \times n^{-1/6}, \tag{11b}$$

where σ_{x} and σ_{y} are the standard deviations of variables X and Y with d representing the dimension, which is two in the bivariate case. Generally, the bandwidth with regards to the Gaussian kernel function is known as the Normal reference rule. The AMISE of the two-dimensional Gaussian kernel function for observations that are correlated can be computed as

$$\mathrm{AMISE}\left(\hat{f}(\mathrm{x},\mathrm{y})\right) = \frac{3}{8\pi\sigma_{\mathrm{x}}\sigma_y(1-\rho^2)^{5/6}}\left(1-\frac{\rho^2}{2}\right)^{-1/3} n^{-2/3}, \tag{12}$$

where ρ is the correlation coefficient of the variables [21, 22]. The AMISE in this case is dependent on the standard deviations of the observations, size of the observations and the correlation coefficient of the observations. Equation (12) is of wide applications especially in the bivariate normal distribution where the observations are independent.

2.3 Location and data collections

Benin City is the administrative headquarters of Edo State situated in rain forest of Southern Nigeria in the region called Niger Delta and lies between longitude 5°E and 6°42"E and latitude 5°45"N and 35"N. Geographically, Benin City is located at Edo South and lies between latitude 6°20′17″ N and longitude 5°37′32″ E with elevation level of 88m above sea level, which is 288 feet. Benin City is the commercial hub of the State with a population of 1,125,058 positioning the City as the largest in Edo State and operates in the West Africa Time (WAT) zone. Edo State has boundaries with three states which are Kogi towards the North, while Delta and Ondo states are to the Southern and Western part, respectively. The state is bounded to the east by the River Niger [31].

The climatic condition of Edo State is humid, and it experiences dry and wet seasons with savannah vegetation and a topography that is comparatively mountainous towards its North. The National Population Census of 2006 positioned the population of Edo State to be 3,218,332 which consisted of 1,640,461 males and 1,577,871 females with a current population projection of about five million people [32].

Data were retrieved from the archives of the Nigeria Meteorological Agency (NiMet) for ten successive years from 2010 to 2019, with data collected from January 1st to December 31st of each year. A map of Nigeria showing the location of Benin City in Southern part of Edo State is in Figure 1.

Figure 1. Map of Nigeria indicating the study area in Edo State (Benin City)

The average daily temperature and relative humidity in Benin City are 27°C and 70% throughout the dry season. Nevertheless, during the rainy season, the average relative humidity is around 86% and even in some situations is almost 100%. The dry season is experienced between the months of November and March while the rainy season is from April to October with modest differences in the temperature and relative humidity in the seasons.

3. Results and Discussion

Temperature and relative humidity are vital weather variables whose joint effects are presented graphically using the Gaussian kernel estimator. All graphical demonstrations of the observations and further statistical analysis were implemented using Mathematica version 12 software. The determinant of performance in kernel density estimation is the bandwidth that regulates the contributions of the bias and variance terms to the AMISE where performance is the ability of the kernel function to produce the minimum AMISE value. Kernel performance is also illustrated in the estimates' ability to retain vital information regarding the data like multimodality of observations for accurate decision making and implementation. As generally observed, inaccurate information about data could lead to wrong policies by policy makers; hence interdependence of the observations must be critically examined [33-35]. The two dimensional kernel density estimators usually employ two random variables for its implementation. Temperature and relative humidity are the two variables considered with temperature representing the x-axis while relative humidity represented the y-axis, respectively. Table 1 shows the statistical properties and AMISE value of temperature and relative humidity for the period under consideration.

Table 1. Bandwidths, standard deviations, ρ and AMISE for the ten years period

Years	h_x	h_y	σ_x	σ_y	ρ	$AMISE$
2010	0.40977	3.54386	1.09544	9.47383	−0.053822	0.000225638
2011	0.53237	3.99397	1.42319	10.6771	−0.182199	0.0001573132
2012	0.51710	4.09951	1.38238	10.9592	−0.133602	0.0001561347
2013	0.47076	3.78792	1.25905	10.1309	−0.379826	0.0002031187
2014	0.45791	3.29320	1.22413	8.80380	−0.471827	0.0002571842
2015	0.38916	3.98843	1.04034	10.6623	−0.180220	0.0002153969
2016	0.76706	6.26737	2.05058	16.7546	−0.417205	0.0000773934
2017	0.66537	6.37279	1.77955	17.0442	−0.415254	0.0000873883
2018	0.76039	4.92158	2.03275	13.1569	−0.880520	0.0002575149
2019	0.45603	4.35468	1.21910	11.6414	−0.497015	0.0001996362

Generally, temperature and relative humidity are inversely related and this inverse relationship is demonstrated by the negative values of the correlation coefficient. The relationship that exists between temperature and relative humidity is best established by the values of the correlation coefficient. When the correlation coefficient value is close to -1 as noticed in 2018, then the two observations are highly negatively correlated. The correlation coefficient value is a statistical indicator in the establishment of connection between many natural phenomena. Regarding performance as seen in Table1, the years with the least AMISE values are 2016 and 2017, respectively and this is attributable to their bandwidths and standard deviations. Statistically, human activities that were temperature and relative humidity dependent thrived the most in 2016 and 2017 due to their production of minimal AMISE values, notwithstanding the fact that this might not be true in practice because of the interference of other atmospheric variables. Other years where activities that were connected to temperature and relative humidity were expected to be successful besides 2016 and 2017 were 2011, 2012 and 2019 as can be deduced from Table 1. The year with the highly negatively correlation coefficient value was 2018 and in conjunction with the standard deviations of the two variables produced a colossal AMISE value. The colossal AMISE value implies that ventures that hinge on the studied observations in 2018 may perform poorly provided all other atmospheric variables are constant. Kernel density estimation is basically for data analysis and visualization which is the graphical presentation of the observations. The graphs or estimates can be displayed in surface plot and contour plot especially for the two-dimensional case.

Kernel methods usually involve graphical display of the observations being investigated for the purpose of examining essential features present in the observations. The kernel estimates for the ten years period are clearly displayed in Figure 2 to Figure11 and the estimates of the ten years period as illustrated seems similar and unimodal, which in most cases are centered on temperatures between 25°C and 27°C while the relative humidity is between 75% and 85%. The unimodality of the kernels estimates depicts the fact that temperature and relative humidity are inversely connected with only one peak known as the mode. The two years with the minimal AMISE value, that is 2016 and 2017, both attained their peak with probabilities of 0.002 and 0.003, respectively. This implies that the kernel estimates of temperature and relative humidity with smaller probability values will produce minimal AMISE values and by interpretation, temperature and relative humidity projects will perform well when other weather variables are constant. Nevertheless, attainment of the mode (peak) of kernel estimates with respect to smaller probability values is also attributable to the correlation value as noted in the kernel estimates of 2018 observations. With highly negatively correlation values, smaller probability values will be required in attaining the estimates' peak as in 2018 with 0.003 as the probability at the mode but it translates to production of colossal AMISE values amongst the studied years. The surface plots and the contour plots of 2016 and 2017 vividly displayed the joint probabilities of the variables, which are 0.002 and 0.003, respectively. Again, the joint probability value of the variables for 2018 that produced the largest AMISE value in the studied variables is 0.003 as depicted by the contour plots. The implication of these probability values is that both minimum and maximum AMISE values are associated with lower probabilities while minimum AMISE value is an indication of better performance of the kernel estimates of the variables. Statistically, all activities that depend on temperature and relative humidity particularly for 2018 may have performed poorly owing to its production of the largest AMISE value. In general, note, higher probability values of temperature and relative humidity of the bivariate kernel estimator as displayed by the estimates is an indication of poor performance with respect to the AMISE as an error criterion function.

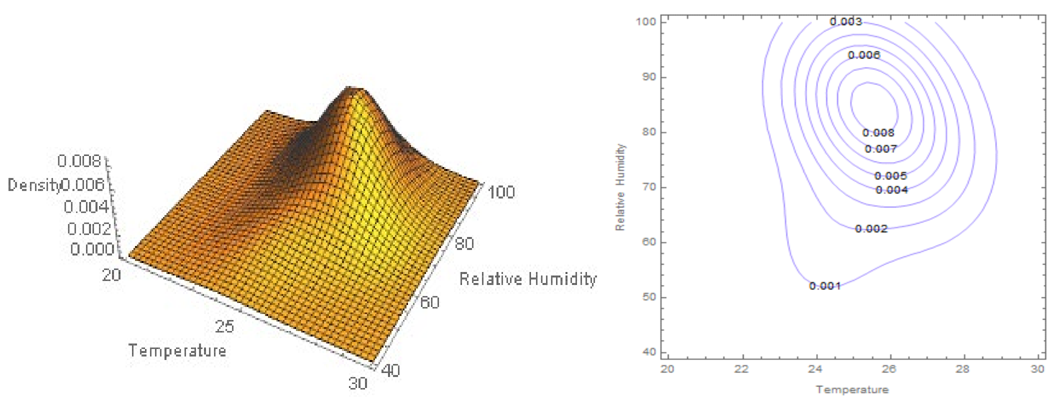

Figure 2. Surface plot and contour plot of bivariate kernel density estimate of 2010 data

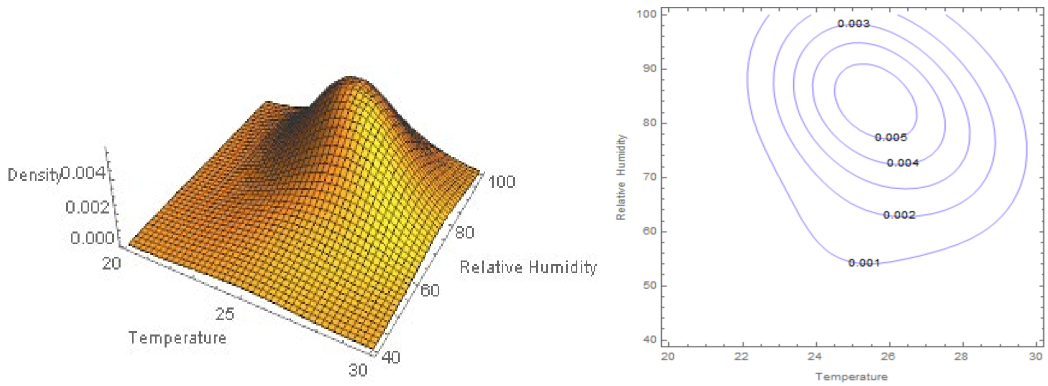

Figure 3. Surface plot and contour plot of bivariate kernel density estimate of 2011 data

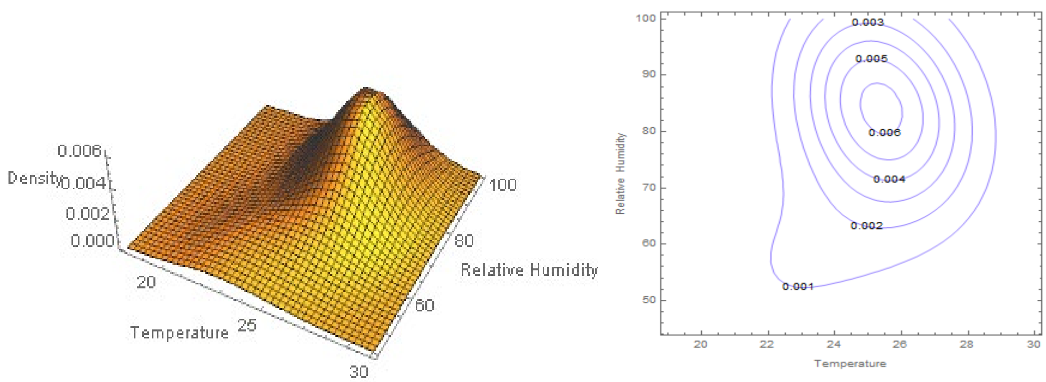

Figure 4. Surface plot and contour plot of bivariate kernel density estimate of 2012 data

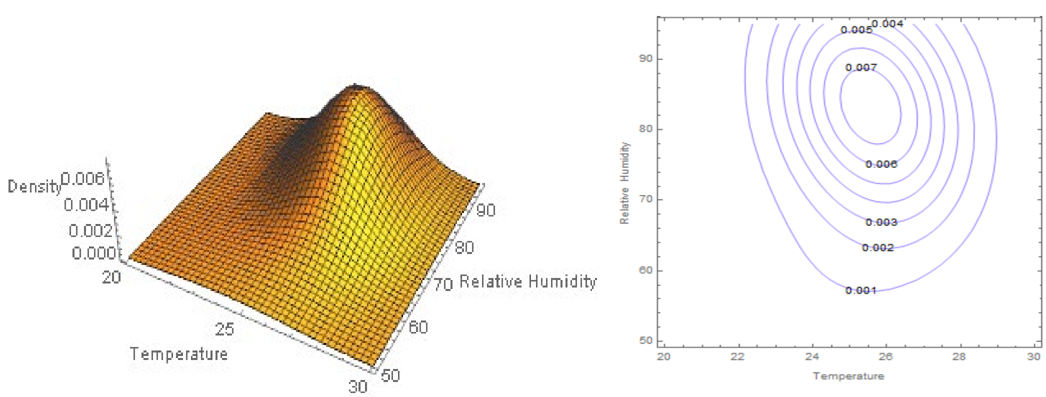

Figure 5. Surface plot and contour plot of bivariate kernel density estimate of 2013 data

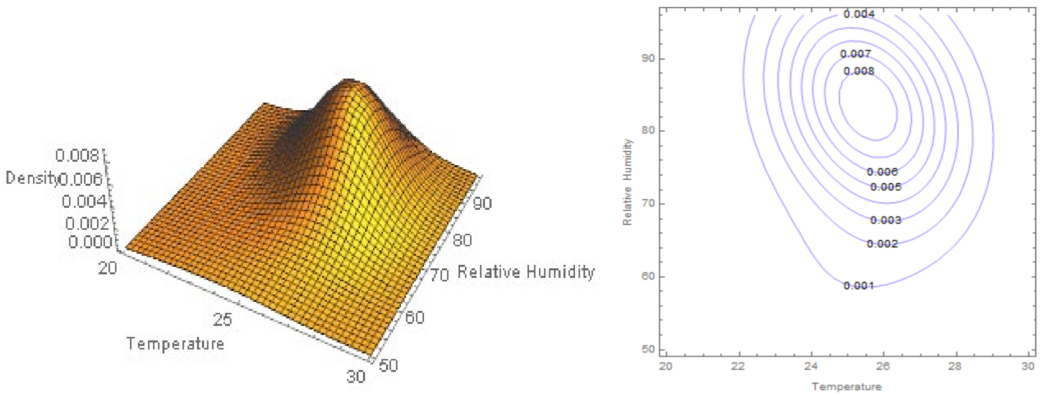

Figure 6. Surface plot and contour plot of bivariate kernel density estimate of 2014 data

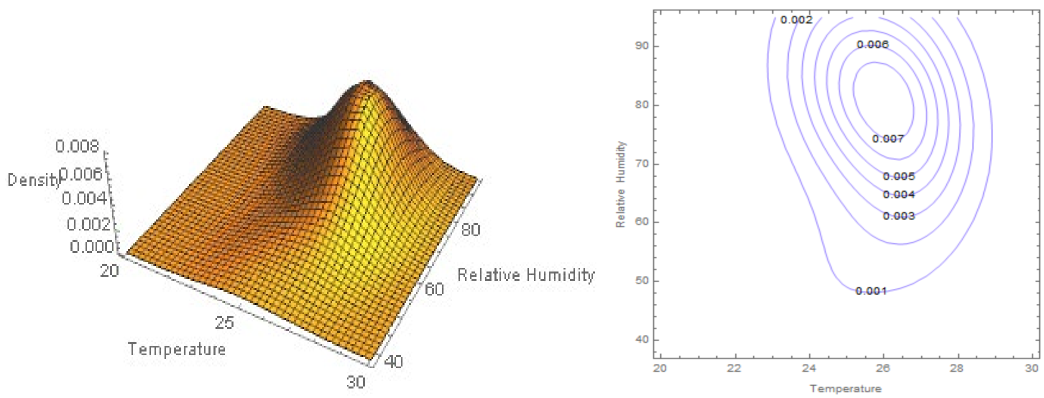

Figure 7. Surface plot and contour plot of bivariate kernel density estimate of 2015 data

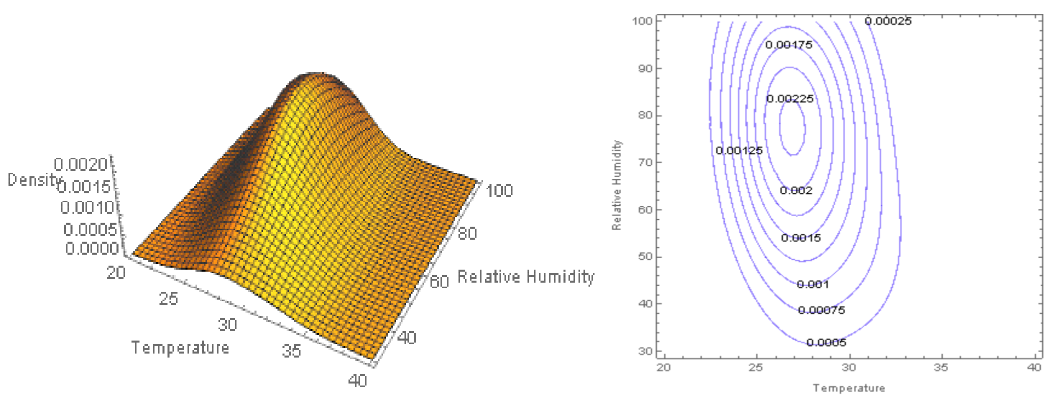

Figure 8. Surface plot and contour plot of bivariate kernel density estimate of 2016 data

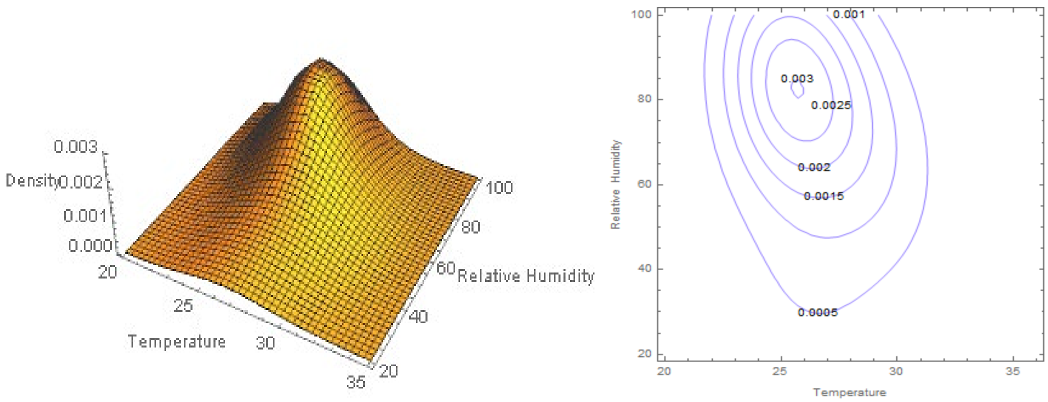

Figure 9. Surface plot and contour plot of bivariate kernel density estimate of 2017 data

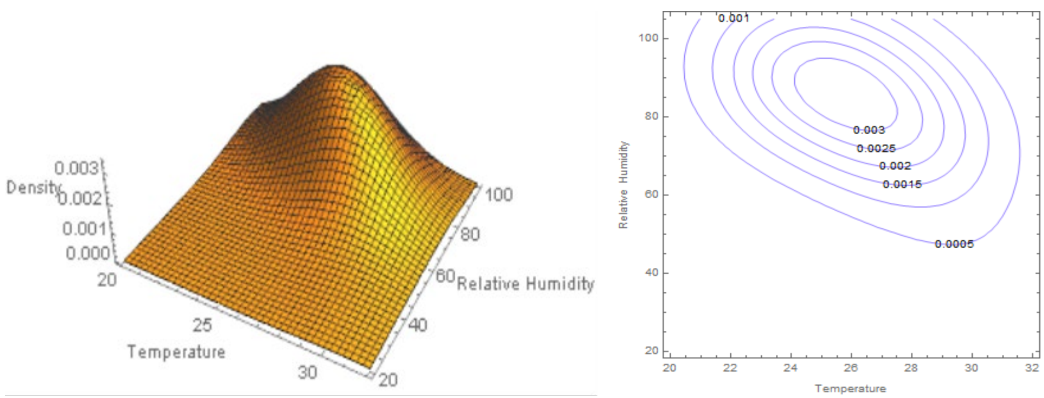

Figure 10. Surface plot and contour plot of bivariate kernel density estimate of 2018 data

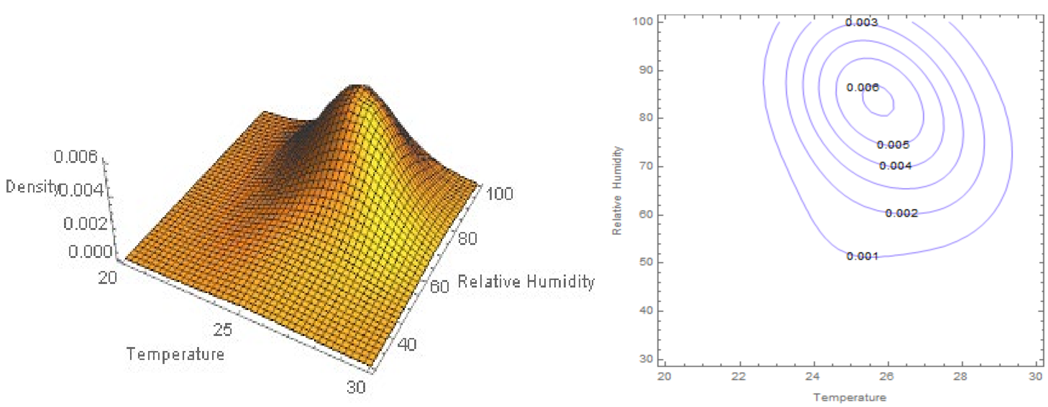

Figure 11. Surface plot and contour plot of bivariate kernel density estimate of 2019 data

The investigatory role of kernel estimation is seen in the Figures and the connectivity of the observations under consideration is revealed by the values of the correlation coefficient and kernel estimates of the observations. The analysis of the observations is done with the kernel method owing to the fact that weather-related variables exhibit constant variations with respect to time and only methods that are data dependent should be employed in such analysis to avoid imposition of statistical properties on the observations. The relationship between the observations and their respective probabilities are graphically shown with higher probability values lying between 25°C and 27°C for temperature and 75% and 85% for relative humidity which is the modal region of the observations.

4. Conclusions

This article investigated the interactions between temperature and relative humidity in Benin City over a period of ten years using two-dimensional Gaussian product kernel estimator. The results of the investigation revealed that human activities that were temperature and relative humidity dependent thrived the most in Benin City for two consecutive years being 2016 and 2017 when other weather variables were held constant. Inferentially, the determinant of the performance of the years (in which agricultural and human activities related to temperature and relative humidity) to be successful is to hinge on the probability values of the kernel estimates. The probability value determines the mode of the observations except for the years with high negative correlation value of the observations.

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