Satellite Remote Rensing Monitoring of the Effects of Urban Forestry on Urban Heat Island using the Auto Regressive Moving Average (ARMA) model

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Abstract
Ibadan, located in South Western Nigeria is the third-largest city in Nigeria with an estimated population of over six million inhabitants. Cities such as Ibadan with a large population, myriads of economic activities and built infrastructures contribute to global warming through various anthropogenic activities. This research evaluated the positive effects of urban forestry on Urban Heat Island. The city was partitioned into five different microhabitats (Urban Forest, Peri-Urban Forest, Peri-Urban Sparsely Populated, Urban Farmland, Urban Densely Populated, urban Urban Sparsely, Populated, Peri-Urban, Farmland. Time-series data were extracted from the Moderate Resolution Imaging Spectroradiometer (MODIS, MYD11A2 V6) satellite using javascript in the Google Earth Engine (GEE) platform from each of the seven micro-climate habitats. Each location had 941 observations with the start date from the 18th of February 2000 to the 4th of August 2020. The Auto-regressive Moving Average (ARIMA) was used to model variation between the Land Surface Temperature of identified microhabitats within the city and the study also model future scenarios of Land Surface Temperature of various microclimate habitats of the study area. Accuracy was measured using mean absolute percentage error (MAPE). Monitoring the urban heat island in seven areas of Ibadan City, an average temperatures difference of 9.4^0C was observed between urban forest and densely populated areas, while temperature difference between urban forest and urban sparsely populated, urban forest and peri-urban sparsely populated was 1.0^0C and 3.99^0C respectively. The study re-enforces the importance of urban forest in climate mitigation, thus spatial development planning strategy that will include green open spaces should be created for comfortability and a friendly urban environment.

Keywords: Remote Sensing, Urban Forest, microclimate, Urban Heat Island, ARMA

Introduction
The increase in global warming is believed to be caused by anthropogenic induced land-use changes and these changes are known to cause incident radiation absorptivity, increase heat retention capacity and local heat conductivity of the region (Weng, 2012). Hypothesis abounds suggesting that anthropogenic induced land-use changes coupled with rapid urbanisation are contributory factors to temperature rise (Crum & Jenerette, 2017; Fabiyi, 2006). Studies have shown that an increase in urbanization could change the mechanism of the energy balance on urban in large cities and thus, expand Urban Heat Island (Effat *et al*., 2014). Urban heat island is one of the established examples of inadvertent modifications of climate (Arthur-Hartranft, 2003) . The expansion of Urban heat island (UHI) is based on incoming and outgoing energy flux from an urban system and this automatically affects the radiation of the urban interface.

The absorbed energy by this urban surface is generated through anthropogenic activities which causes surface warming or convectional and radiation. The release of anthropogenic energy, emissions from industrial activities, motor vehicles, and the heat capacity of building materials with natural structures affect the nature of the urban surface. It has been proven in recent research that increased Land Surface Temperatures (LST) is caused by UHI effects which inevitably affect the flow of materials and energy and also change the structure and function of the environment, thus affecting climate, hydrological situations, soil properties, atmospheric environments, biological habitats, material cycles, energy metabolism and population health (Yang *et al*.,2016).

Land Surface Temperature (LST) is one of the key climatic parameters and an important factor in the study of urban climate and this is widely used for a variety of environmental studies and its important role is in measuring surface urban heat islands, estimating building energy consumption and evaluating heat-related risks (Fabiyi, 2006; Khandelwal, Goyal, Kaul, & Mathew, 2017; Pu, Gong, Michishita, &

Sasagawa, 2006). Land surface temperature variation in different locations is due to albedo thus structures like buildings have a lower albedo than natural surfaces and absorb more visible radiation which implies that the urban surface tends to be hotter than the natural surface such as vegetation (Abera, Heiskanen, Pellikka, Rautiainen, & Maeda, 2018; Hu & Brunsell, 2013; Trlica, Hutyra, Schaaf, Erb, & Wang, 2017).

Several studies have posited that the solar radiation falling on the built area (asphalt, concrete) increases the surrounding air temperature because the heat capacity of asphalt and concrete is lower than other types of surfaces, thus land cover influences the spatial distribution of land surface temperature (Akbari, Damon Matthews, & Seto, 2012; Crum & Jenerette, 2017). Similarly, urban heat is derived from anthropogenic induced combustions such as home heating, cooking, industrial processes and internal combustion engines and poor ventilation systems(Ramdhoni, Rushayati, & Prasetyo, 2016).

The effects of Urban Heat Island in cities are usually higher than the surrounding rural or Peri-Urban areas (Ulpiani, 2020), thus studies on the nature and intensity of UHI between cities and Peri-urban or rural areas have a temperature difference of more than 5 ^{0}C. This has been adduced to the sparsely populated nature of the peri-urban habitat, few paved areas thereby reducing emissivity and presence of vegetations. A study by (Oleson, 2012) concluded that UH means temperatures in urban areas are on average of 2–5^{0}C higher than the surrounding Peri-urban areas. Also, the strong negative relationship between UHI and Normalized Difference Vegetation Index (NDVI) has been extensively reported in thermal remote sensing for urban and rural environments (Önder & Akay, 2014). Similarly, Urban Forest or vegetation provide reduce evapotranspiration and thereby reducing emissivity and temperature increase. Therefore, the temperature in areas with urban forests is lower than those of habitats without it. Several studies have established the correlation between an increase in green areas and a reduction in local temperature (Pu et al., 2006; Susca, Gaffin, & Dell'Osso, 2011).

Cities such as Ibadan with a large population, myriads of economic activities and built infrastructures have the potentials of contributing to global warming through various anthropogenic activities. Therefore, this study is drawn on the two key research questions, which are; is there variation between the Land Surface Temperature of identified microhabitats within the city and Peri-urban and what is the nature of the Land Surface Temperature between the different locations?

Study Area

The study area is Ibadan city, located in Southwestern Nigeria. It lies between 7°19'30''N to 7°27'30''N latitude and 3°50'0''E to 3°58'30''E longitude, its elevation ranges from 150 m in the valley area, to 275 m above sea level with a total area of 3,080 square kilometres.

The mean total rainfall for Ibadan is 1420.06 mm, while the mean temperature is 26.5 °C.

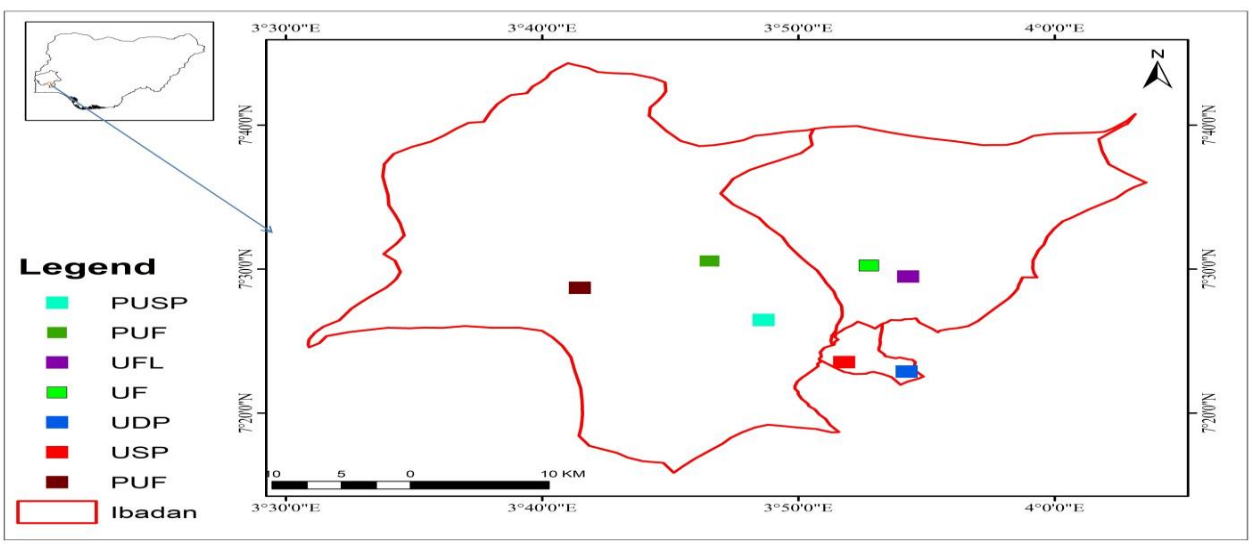

Figure 1: Study Area map. *PUSP (Peri-Urban Sparsely Populated), PUF (Peri-Urban Forest), UFL (Urban Farmland), UF (Urban Forest), UDP (Urban Densely Populated), USP (Urban Sparsely Populated), PUF (Peri-Urban Farmland)*

The study area was stratified into seven different locations, namely: Periurban Sparsely Populated (PUSP), Periurban Farmland (PUF), Urban Farmland (UFL), Urban Forest (UF), Urban Densely Populated (UDP), Urban Sparsely Populated (USP) and Peri-urban Farmland (PUFL).

Data Extraction

Land surface temperature datasets for the stratified areas were extracted from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data using javascript on the Google Earth Engine (GEE) platform. The MODIS (MYD11A2 V6) satellite data provide an average 8-day land surface temperature with 1 kilometre (km) spatial resolution. MODIS LST was extracted from seven different locations within Ibadan city and the Peri-urban. Five points were randomly created at each location; the points were used to extract the time series dataset for 20 years having 941 observations. The time series from the five points were then averaged for each location.

Methodology

A cross-correlation coefficient was performed to measure the positive or negative strength among the seven locations using Equation 1 below (Gubner, 2006).

$$R_{X_iX_j}(t_1,t_2) = E\left[X_{it_1}\bar{X}_{jt_2}\right] \text{------------------------------------ (1)}$$

Let X_{it} and X_{jt} be two-time series variables of interest, where t is a time index, $X_{it}, X_{jt} \in R$, and $i,j \in Z$, such that $i \neq j$. Assuming each time series have means $\mu_{xi}(t)$ and $\mu_{xj}(t)$ respectively and variances $\sigma^2_{xi}(t)$ and $\sigma^2_{xj}(t)$ respectively at time t for each t, then the cross-correlation between the times t_1 and t_2 is defined as the expected value of both time series at the respective times t_1 and t_2.

The Auto-regressive Moving Average (ARMA) was used to model the time series variables and predict future points in the variables.

ARMA model forecasts if variables which are time series by linearly combining their historic values (Dimri, et al., 2020).

ARMA model as a tool deals with all the aspects related to univariate time series model identification and its parameter estimation and forecasting ARMA model has the dual advantages of flexibility of use for modelling and its application to non-stationary time series data sets (TPL, 2016). It is made up of the autoregressive part which is used to forecast time series variables by regressing it on a combination of its past values (Shumway and Stoffer, 2010), the integrated part which indicates the stationary of the time series data by subtracting the observations from the previous values (Swain *et al*., 2018), and the moving average part which uses the combination of errors in the past values to forecast future values (Enders, 2004). Let $X(t)$ be the time series data of interest indexed by some set T, such that

$$\{X(t) : t \in T\} \text{------------------------------------ (2)}$$

and $X_t \in R$. The ARIMA (p, d, q) model – where p is the order of the autoregressive part of the model (Shumway & Stoffer, 2011), d is the degree of differencing, and q is the order of the moving average part of the model – for the time series is given by

$$(X_t - X_{t-1})^d + \emptyset_1(X_{t-1} - X_{t-2})^d + \ldots + \emptyset_p(X_{t-p} - X_{t-p+1})^d = \varepsilon_t + \theta_1\varepsilon_{t-1} + \ldots + \theta_q\varepsilon_{t-q} \text{ ………. (3)}$$

Which is equal to

$$\left(1 - \sum_{i=1}^{p} \emptyset_i \lambda^i\right)(1 - \lambda)^d X_t = \left(1 - \sum_{i=1}^{q} \theta_i \lambda^i\right)\varepsilon_t \text{ ……………………………………. (4)}$$

Where ε_t, $\emptyset_i$, θ_i, and λ^i represent the independently and identically distributed error terms of the model, the coefficients of the autoregressive part of the model, the coefficients of the moving average part of the model, and the lag operator respectively. When the time series is stationary, equation (3) becomes:

$$X_t - \emptyset_1 X_{t-1} - \cdots - \emptyset_p X_{t-p} = \varepsilon_t + \theta_1\varepsilon_{t-1} + \ldots + \theta_q\varepsilon_{t-q} \text{ …………………………… (5)}$$

Which is equal to

$$X_t = \sum_{i=1}^{p} \emptyset_i X_{t-i} + \left(1 + \sum_{i=0}^{q} \theta_i\right)\varepsilon_{t-i} + k \quad (6)$$

Where $\theta_0 = 1$, and k is a constant term. Equation (6) is known as the ARMA model. For each location, the derived LST time series observations were divided into a 70/30 ratio for training and validation.

Mean Absolute Percentage Error (Mape)

Let X_t be the time series data of interest were t is indexed from $\{1, 2, \ldots n\}$, and $X_t \in R$. Let $X_{t_{train}}$ and $X_{t_{test}}$ be subsets of X_t such that $(X_{t_{train}}, X_{t_{test}}) \in X_t$, then $X_{t_{train}}$ is such that $t_{train} = \{1, 2, \ldots, k\}$ and $X_{t_{test}}$ is such that $t_{test} = \{(k+1), (k+2), \ldots, n\}$. Also, let $X_{t_{pred}}$ be the forecasted values of X_t indexed from $\{(k+1), (k+2), \ldots, n\}$. The mean absolute percentage error (MAPE) (de Myttenaere, et al., 2015) used to measure the accuracy of the forecasting method is expressed as:

$$MAPE = \frac{1}{(n-k)} \sum_{k+1}^{n} \left| \frac{X_{t_{train}} - X_{t_{pred}}}{X_{t_{train}}} \right| \quad (7)$$

Here, the absolute value in this calculation is summed for every forecasted point in time and divided by the number of fitted points n, multiplied by 100% makes it a percentage error. (de Myttenaere, *et al.*,2015). MAPE is a percentage; it can be easier to understand than the other accuracy measure statistics. For example, if the MAPE is 5, on average, the forecast is off by 5%.

Results

It was observed that Land Surface Temperature (LST) of Urban Densely Populated (UDP) was generally higher (36.43^{0}C) than LST from other locations, while LST from Peri-Urban Forest (PUF) and Urban Forest (UF) were significantly lower (27.75 and 27.56 degrees respectively). This was followed by the LST of PUFL and UF. The LST time series from the different locations were all stationary and no correlations or similarities were found between the LST of urban densely populated (UDP) and LST of other locations in this study (Table 1). While strong cross-correlation function (CCF) was found between pairs of LST of other locations at certain lags.

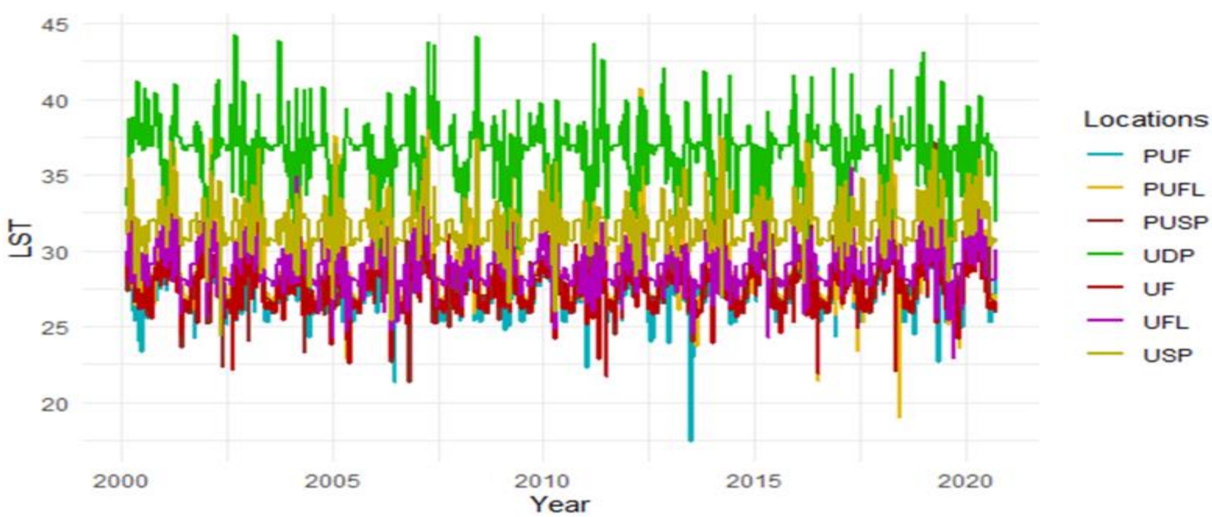

Figure 2: Peri-urban Forest (PUF), Peri-urban Farmland (PUFL), Peri-urban Sparsely Populated (PUSP) Urban Densely Populated (UDP), Urban Forest (UF), Urban Farmland (UFL), Urban Sparsely Populated (USP)

Monitoring the urban heat island in delineated microhabitats of Ibadan city, an average temperatures difference of 9.4^0C was observed between densely populated areas and urban forest, while temperature difference between urban forest and urban sparsely populated, peri-urban sparsely populated was 1.0^0C and 3.99^0C respectively.

Accuracy was measured using mean absolute percentage error (MAPE); the lower the error, the better the fitness of the model. Table 2 shows that all models were more than 95% accurate in both training and forecasting. The Coefficients of Time Series Models in table 3 are the Auto-Regressive Integrated Moving Average models deduced for the various locations and each was used to predict future temperature scenarios from the year 2020 to 2025. The forecast means average for the five years prediction was 95% accurate. `

Table 1: Cross – correlation Coefficients of the locations under study

LOCATIONS	CCF	LAGS VALUE
PUFL, UDP	-0.305	0.0435
PUFL, USP	0.518	0.0000
PUFL, PUSP	0.655	0.0000
PUFL, UFL	0.572	0.0000
PUFL, PUF	0.729	0.0000
UDP, USP	0.361	0.0000
UDP, PUSP	0.308	-0.5000
UDP, UFL	0.268	-0.4783
UDP, PUF	0.296	-0.4565
USP, PUSP	0.613	0.0000
USP, UFL	0.610	0.0000
USP, PUF	0.580	0.0000
PUSP, UFL	0.640	0.0000
PUSP, PUF	0.728	0.0000
UFL, PUF	0.617	0.0000
UF, PUF	0.742	0.0000
UF, PUSP	0.718	0.0000
UF, UDP	0.312	0.4130
UF, USP	0.632	0.0000
UF, UFL	0.774	0.0000

Table 2: Auto – Correlation Function, Mean and Accuracy

LOCATIONS	ACF	MEAN	**FORECAST MEAN	TRAINING MAPE	TEST MAPE
PUSP	0.0126	28.1873	29.5869	3.5597	4.2507
PUFL	0.0283	29.1017	28.3938	3.9357	4.3557
UF	-0.0137	27.7565	27.8113	3.0252	4.2313
UFL	-0.0018	29.1017	29.4732	3.2143	4.0263
UDP	-0.0004	36.4318	36.3209	3.0858	4.1439
USP	-0.0016	31.7082	31.7398	3.2980	3.6263
PUF	0.0005	27.5661	27.9436	3.4449	4.1142

**Forecast mean temperature changes varying from 0.15^0C to 1.4^0C

Table 3: Coefficients of the Time Series Models

	ar_1	ar_2	ar_3	ar_4	ar_5	ma_1	ma_2	ma_3	ma_4
PUFL	1.9506	-0.9697	-	-	-	-1.6739	0.694	-	-
UDP	1.0343	0.5719	-0.7240	-	-	-0.8859	-0.5273	0.6170	-
USP	0.7572	-	-	-	-	-0.5538	-	-	-
PUSP	0.5860	0.0570	0.1669	-	-	-0.2298	-	-	-
UFL	0.6378	0.0184	0.1064	-0.0554	0.0360	-0.3707	-	-	-
UF	0.8045	-	-	-	-	-0.5279	0.0606	0.1080	-0.0647
PUF	-0.6309	0.5336	0.6301	-	-	0.9854	0.0564	-0.2493	-

Discussion

Meteorological data has been the conventional means of studying urban heat and its antecedent consequences. However, the major limitation is the lacks the capacity for spatial distribution studies of urban heat islands, making it difficult to extend information to the entire region () With the advancement of remote sensing technology, a large number of academics have begun to investigate urban heat islands using land surface temperatures or brightness temperature derived from remote sensing images. Satellite Remote Sensing (RS) technology has introduced a new and broader dimension to the study and understanding of the impact of urban forestry on Urban Heat Island (UHI) using land surface temperature (LST) to define the surface (Voogt & Oke, 2003).

Studies using Satellite Remote Sensing data has shown that vegetation plays a role in regulating temperature through photosynthesis and transpiration processes, thus reducing temperature and increasing humidity (Xiaoming, et al., 2010). A negative correlation between vegetation cover and temperature was observed by numerous researches on the relationship between vegetation cover and urban heat islands from various land cover types using Satellite Remote Sensing. Results from such studies depict that urban heat island has a relationship not only with the distribution of vegetation but also with other land use types.

Considering the strong relationship between LST and air temperature, UHI has been modelled using various satellite data sources. Remote sensing data has proved to be the most appropriate tool for studying spatial pattern and temporal dynamics of urban thermal landscape, as well as urban surface energy budget. Remote sensing studies of vegetated surfaces in general—and urban green vegetation in particular—showed cooler temperatures than the impervious surface of cities. Monitoring the urban heat island in delineated microhabitats of Ibadan city, an average temperatures difference of 9.4^0C was observed between densely populated areas and urban forest, while temperature difference between urban forest and urban sparsely populated, peri-urban sparsely populated was 1.0^0C and 3.99^0C respectively. UHIs are generated by the replacement of vegetated regions with non-evaporating and impermeable materials such as asphalt and concrete, which results in a human-induced urban/rural contrast (in physical features of the surface, such as albedo, thermal capacity, and heat conductivity). This UHI phenomenon leads to changes in radiative fluxes and the near-surface flow (Pu et al., 2006).

Therefore, urban vegetation can have a role in local and global climate change mitigation not only through several mechanisms of cooling simultaneously (shading, increasing albedo and evapotranspiration) but also through lower summertime energy demand to cool the indoor climate, which decreases CO2 emissions. “Urban greening” has also been proposed as one approach to mitigate the human health consequences of increased temperatures resulting from climate change. However, urban vegetation not only regulates climate but also acts as a supporting fact in the social cohesion and wellbeing of urban life.

Conclusion

This research evaluated the positive effects of urban forestry on Urban Heat Island using time series data. Densely populated (UDP) with little vegetation; the urban heat in that area increases at some point which could be as a result of human activities but, in some areas maintained a certain mean with little outliers. The increases in temperature within the area are a result of anthropogenic within the Urban areas. (I: e. activities from industrial activities, motor vehicle heat capacity of building materials, high-density parking lots and solid waste disposal sites (Pu, et al., 2006). In densely populated, almost all spots have scarce or lack of green areas which makes the location hotter compared to the sparsely and green areas that can retain water because of its little or more availability of natural surfaces.

ARMA model was used to predict the land surface temperature for five years using the available observations. The prediction shows a 95% confidence interval using the observed values. Conclusively, there is an obvious temperature increase in densely populated (UDP) thus, a spatial development planning strategy, which controls the growth of the built area and adds green open spaces should be created for comfortability and a friendly urban environment.

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