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Simulation and Prediction of Land Surface Temperature (LST) Dynamics within Ikom City in Nigeria Using Artificial Neural Network (ANN)

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Abstract

Land Surface Temperature (LST) is one of the factors associated to urban heat rise and micro climatic warming within a city. Researches relating to the development new technologies or the improvement on the existing ones are very important in urban climate studies. This paper expounds our study on the simulation and prediction of specific future time LST quantitative trend in Ikom city of Nigeria using Feed Forward Back Propagation Artificial Neural Network technology. This study was based on time series ANN model that takes a sequence of past LST values, understand the pattern of change within the dataset and further predict or future time values. Similar studies have been carried out in this manner from our literature review but none used earth observation time series satellite data of a coarse resolution epoch interval for LST time series prediction using ANN. The novelty of this study centers on the attempt to predict some specific future time LST values city-wide using ANN from past LST values derived from earth observation remote sensing imagery (Landsat 7 ETM). The results derived from this study reaffirms the efficiency of ANN (part of deep learning technologies) in learning, understanding and making accurate predictions from a non-linear chaotic real world complex datasets.

Keywords: Land surface temperature prediction; Artificial neural network; Urban heat rise

Introduction

The city of Ikom in the south-southern part of Nigeria has experienced tremendous urban transformation since the last decade. The city has in recent time witnessed massive land use/land cover changes, increase in built-up, impervious covers, tarred roads and pavements, massive depletion of vegetation and forests as well huge rise in human and vehicle population. This has recently resulted in terrific Urban Heat Rise (UHR) and micro climatic warming within the city. This heat rise and warming can be attributed to many biophysical public health problems within the city such as heat stress, air pollution, and other health problems caused by excessive warming. In view of this, development of scientific and policy strategies to reduce this urban heat rise and mitigate future occurrence of worst micro urban climatic warming in this city is a key challenge.

There are quite a number of factors attributed to urban heat rise and micro climatic warming of which rise in land surface temperature (LST) is one of them. This study focuses on the LST component of this urban heat rise and micro climatic warming. Understanding of the trend and pattern with which LST has risen within the Ikom city for the past 28 years (1986-2014) and prediction of what LST pattern is going to look like in future time is key to this study.

Modeling, simulation and prediction of LST within a dynamic and chaotic urban environment based on time series remote sensed imageries is non-linear and chaotic. There are some soft simulation and prediction algorithms such as Markov Chain, Cellular Automata, and Logistic Regression. Artificial Neural Network (ANN) has proven to be highly suited for a case like this where the underlying processes are not well known [1]. For example, Markov Chain is better when the trend within the phenomenon is known but there is inadequate spatial dependency and spatial distribution of the phenomenon. The Cellular Automata method models the state of the phenomenon depending on the previous state of the cells within a neigh bourhood according to a set of transition rule. Artificial Neural Network which has recently become a component of deep learning technologies was originally developed to mathematically model the underlining working process of the human brain in learning and understanding complex real world patterns. ANN becomes interestingly powerful in cases where the underlying processes and relationships are hard to understand and display chaotic properties. ANN does not require too much of prior knowledge of the dynamics in the real world complex network under consideration to reconstruct the underlying process within the system in order to make predictions [2]. In Accordance with Galvao [3], ANN can comprehend complex data characteristics which present serious problems for traditional statistical techniques because of its nonlinear structure. Therefore in a time series system like this case study without much provision of external influencing factors, ANN presents the best approach to model, simulate and predict the system. In this study, a Multi-layer Feed forward back Propagation Neural Network method was adopted to model, simulate and predict future land surface temperature (LST) pattern from past time series LST information within the city of Ikom.

The Multi-Layer Perceptron MLP, neural network makes automatic decisions about the network parameters and how they should be changed to better model the network. MLP algorithm is based on the principle of error correction learning [4]. In MLP, when the network receives a pattern, at first, it processes and produces a possibly low accurate random output. It then does a self-computed error function by calculating the difference between this random output and the

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expected (target) output. Leveraging the back-propagation algorithm, correction weights are computed between the output layer and the hidden layer (s) and between from the hidden layer (s) to those of the input layers. This back and forth iterative process goes on until an acceptable error between the network output and the desired output is reached [5].

In a nutshell, the interesting biologically inspired model of ANN at this stage of this paper would be worthwhile for the readers of this paper to get refreshed with. ANN which has become part of deep learning state-of-the–art technologies was modeled to mimic a biological process of signal processing in the human brain. Neurons receive signals through synapse located on the membrane of the neuron, the dendrites. When the signals received by a neuron are strong enough, the neuron gets activated and fires, releasing signals through the axon to another synapse which might activate more neurons. This biological abstraction can be translated in ANN terms as basically consisting of the inputs (signals) which are multiplied by weights (synaptic weights). The inputs and their corresponding weights at the summation junction are computed by a mathematical function (activation function) which then determines the activation of the neuron [2]. At the output layer, another activation function computes the output of the neurons to generate a result. The ability of an input signal to activate an artificial neuron to fire depends on the strength of the associated weight as described in Figure 1 below.

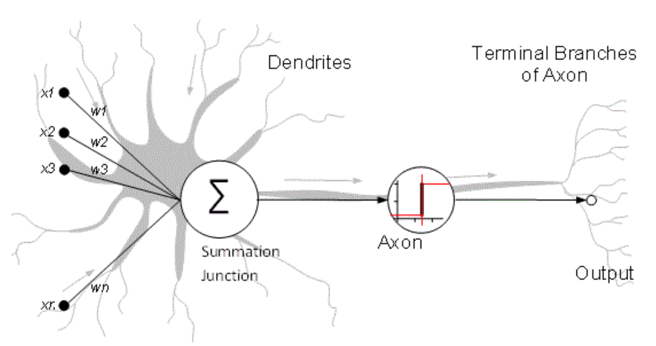

Figure 1: Diagram of biologically inspired artificial neuron network.

Materials and Methods

Study area

The study area, Ikom City is in the Central Senatorial District of Cross River State in Nigeria. The present geographical entity called Ikom City dates back to the 16th Century during the pre-colonial era when the area extended to some communities now enclosed in Boki Obubra, Abi and Etung Local Government Areas. Like other typical traditional societies, Ikom was governed by Chief priests or Village heads that were both ceremonial and religious. Modern day Ikom City began as a constituent part of the Afikpo Division in the early 1950s when it was together with Afikpo now in Ebonyi State. In 1976, Ikom local government was created with headquarters at Ikom. Ikom City with a large size of 1,861.926 square kilometers is bounded Ogaja on the North, Boki on North-East, Etung on the East and on the South is Obubra Local Government Area as shown in the map in Figure 2.

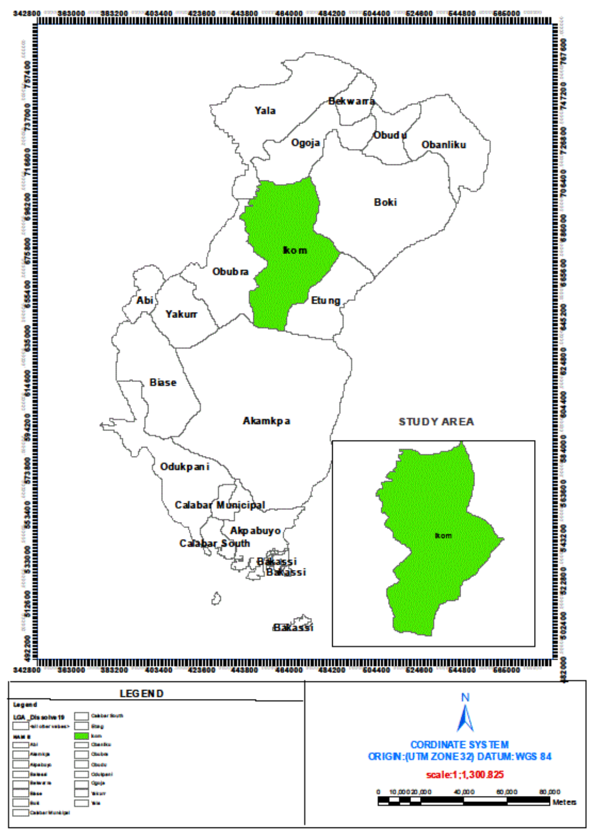

Figure 2: Map showing the study area.

Dataset

The dataset used in this study were LST coverage derived from Landsat band 6 imageries of the study area from 1986 to 2014. For the Landsat ETM+ sensor, images in the thermal band are captured twice; low-gain mode (band 6L) and high-gain mode (band 6H). Band 6L is used to capture surfaces with high brightness, whereas Band 6H is used to capture surfaces with low brightness [6]. In this study images acquired in December month of the years were considered and this period presents relatively high brightness period hence bands 6L were used. Time series LST data of a coverage period of 28 years (1986-2014) at 7 years interval, 1986, 1993, 2000, 2007 and 2014 were generated from Landsat band 6 imageries. The Neural Network was also modeled to make predictions at 14 years interval, twice the input training time-scale interval. In addition we added longitude and latitude of the defined sample spatial units to increase the model efficiency, the more the input parameters the higher the efficiency of the network model [7].

Retrieval of Land Surface Temperature (LST) from Landsat Band 6

LST derivation from Landsat Band 6 satellite imageries used in this study involved the following image processing operations.

Conversion of digital number to spectral radiance

The first step for calculating Land surface temperature from Landsat ETM+ data is to convert the Digital Numbers (DN) of band 6 to spectral radiance using the equation below;

Lλ=[(LMAXλ - LMINλ)/(QCALMAX=QCALMIN)] × [(QCAL - QCALMIN)]+LMINλ (1)

Where;

Lλ – is spectral radiance at sensor's operative in

Wm-2Sr-1UM-1

LMIN – is the spectral radiance that is scale to QCALMIN.

LMAX – is the spectral radiance that is scale to QCALMAX.

LMAX and LMIN are obtained from the Meta data file available in the image file.

QCAL – is the digital number (DN)

QCALMIN – is the minimum quantized calculated Pixel value in DN.

QCALMAX – is the maximum quantized calculated pixel value is DN (255).

Conversion of spectral to radiant surface temperature

Spectral radiance values were then converted to radiant surface temperature under the assumption of uniform emissivity using pre-launch calibration constant for Landsat ETM+ sensor and inserting into the formula stated below;

TB=K2/[ln((Kl/Lλ) + l)] (2)

TB is radiant surface temperature in kelvin, K2 is calibration constant 2, K1 is the calibration constant 1 and Lλ is the spectral radiance at the sensor in Wm-2Sr-1 Um-1.

Conversion of radiant surface temperature to LST

The radiant surface temperature (TB) was then converted to land surface temperature using the equation below.

LST=TB/ [1 + (λ TB /P)lnε (3)

Where TB=Radiant temperature, λ=Wavelength of emitted radiance, P=Plank's constant, C=Velocity of light, σ=Stefan Boltzmann's constant, ε=Emissivity

The LST were converted into Celsius by subtracting 273.15 from the values calculated in equation (3). Also a graphical model estimating Land Surface Temperature was developed to automate the processes in ERDAS Imagine.

Spatial sample points

The study area is about 1,861.926 square kilometers in size and was too much in size in term of total number of pixels to be processed in a single computer by the ANN model. Therefore, the study area was sub-divided into a spatial grid size of 500 m × 500 m to generate a sample point size of 3,723 spatial units. The 500 m square size was chosen considering the minimum space range at which characteristics of one point can significantly affect a change in LST [8]. The mean LST pixel values of these 500 m square spatial units and the centroid coordinates (longitude and latitude) generated from QGIS software were the input parameters of the ANN.

Design of the ANN and network modeling

The ANN model is that of a Feed Forward Back Propagation (MLP). Every neuron in the hidden and output layer sums up the weighted input vectors adds a bias constant input to it and transfers the result through the transfer function and produces the output [9]. This is shown in Figure 3.

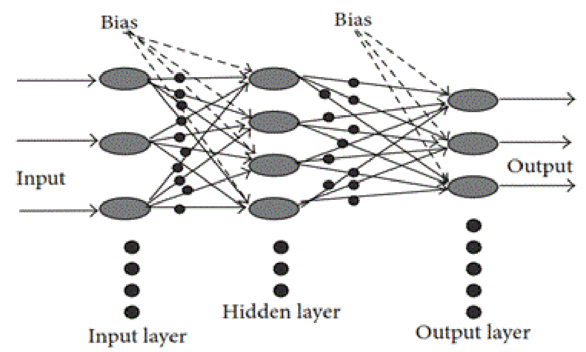

Figure 3: Diagram showing Feed Forward ANN model [9].

ANN prediction model

This is a case of ANN in time series forecasting of present and future LST. A sequence of past years values of LST at an epoch interval of 7 years within a time scale of 28 years (1986-2014) are supplied to the network as input vectors so that the system would recognize the hidden pattern within the dataset and produce the forecast by moving along the time scale [9]. The LST predicted output of a spatial unit of the next 7 years, t+7 is a function of the past values of that spatial unit within the time scale, mathematically and figuratively shown in Equation 4 and Figure 4 respectively.

LST (t +7)=f [LST(t), LST(t-7), LST(t-14), LST(t-21), LST(t-28)] (4)

The present year of study, t=2014.

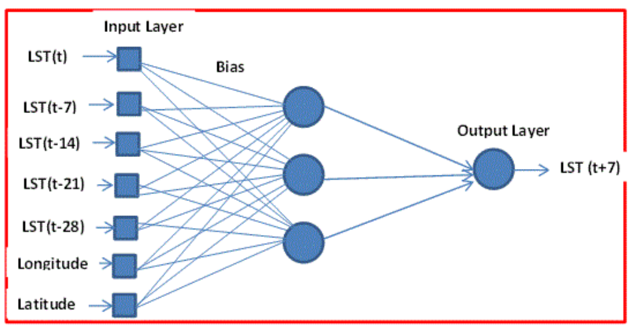

Figure 4: Diagram depicting ANN prediction Model for this study.

Choosing the number of hidden layers and neurons

As much as the selection of the correct number of hidden layers and hidden neurons is important and a critical decision to take yet there are no set out standards for choosing them for a specific ANN model.

It could be determined by experimenting on many trials with respect to the significant changes in the RMSE and R2 values. It is important to keep in mind that the number of the hidden layers and neurons affect the networks ability to understand the dataset very well [2]. Many hidden layers with larger number of hidden neurons will result to correct learning and correct prediction by the network. However, this may leads to over-familiarity with the trained dataset and the network performance on an entirely new dataset is compromised [7]. On the other hand with a hidden layer and too few hidden neurons, the network may fail to learn the pattern and trend within the dataset and the error minima will eventually fail to fall to an acceptable threshold. In this study after some few trials, the network was modeled to use 3 hidden layers and choose between 1-5n hidden neurons in each hidden layer [8], where the n is the number of time series layers of LST used in the network. 5 epochs in years was used at 7 years interval, so n is equal to 5.

Choice of the initial weights (w), learning rate (μ) and decay rate (β)

For this study, the first random feed forward vectors were set at the same condition (weight). The learning rate which is a very key parameter in ANN controls the number of steps to be taken in multidimensional weight space as each weight is adjusted. If the learning rate is too large, the local minima may be skipped constantly which results in oscillations and slow convergence of the minimum error point. And if the learning rate is too slow, the number of iterations needed to reach the local minima will be too large hence a slow performance network model [2]. In this study, the initial learning rate (μ) was set to 0.1 and decay rate (β) was used to control it. The decay rate which ranges from 0 to 1 ($0<\beta<1$). Decay rate of 0.9 was used to update the learning rate as thus; if the error function between the present iteration and the previous one is on the decrease, the β updates the learning rate μ by multiplication while it divides it when the error function is on the increase in order to reduce the μ.

Network creation in MATLAB

Network creation involves creating a subroutine that specifies number of layers, number of neuron in each layer, and a chosen learning or training rule. A callback function (Net) was developed to call a function which created a feed forward back propagation network process in Matlab.

The Backpropagation network function is of the form:

NET=NEWFF(P,T,S,TF,BTF,PF,IPF,OPF,DDF)'

NEWFF(P,T,S,TF,BTF,PF,IPF,OPF,DDF) takes,

P - the matrix of the input vectors

T - the matrix of target vectors

Si - Size of hidden layers

TF - Transfer function

BTF - Backprop network training function,='trainlm'

PF - Performance function,='mse'

IPF-Rowcell array of input processing functions={'fixunknowns','remconstantrows','mapminmax'}.

OPF - Row cell array of output processing functions={'remconstantrows','mapminmax'}.

DDF - Data division function='dividerand' (divides the data in the ratio of '6: 2: 2'; and returns an N layer feed-forward back propagation net.

Where, P is the input vector matrix of 37238 × 7 (3723 spatial units and 5 epochs in years (LST 1986, 1993, 2000, 2007 and 2014) in addition to longitude and latitude). T is the target vector matrix 3723 × 1 which is made up of 3723 spatial units by derived LST values of 2000 or 2014. Si is the size of the hidden layer which we concluded to be 3 after some experimental trials of different sizes. TF is the transfer function which was set to sigmoid function. The DDF, data division function is the function that divides the input dataset in case into 3 portions, one for the training process and the other two for validation and testing. The most common and optimum data division method from our literature review is the 60:20:20 ratios, 60% for training, 20% for validation and the reaming 20% for testing.

Network training

Network training forms the central core activity in all phases of Neural Network modeling. The training process requires some set of examples of proper network behavior, the network inputs p, (input vector matrix, designated as input) and target outputs t (input vector matrix designated as target, LST-target). During the training the weights are iteratively adjusted to reach the error minima and update network performance function (pff). This network was trained using the common and standard Levenberg-Marquardt training process.

The standard Levenberg-Marquardt algorithm used in this work is described as follows:

1. Initialize the weights and parameter μ (μ=0.1)

2. Compute the sum of the squared errors over all inputs, F (w)

3. Solve (2) to obtain the increment of weights, Δw.

4. Recompute the sum of squared errors, F (w):

Using w+Δw as the trial w, and judge:

IF trial F(w)<F(w) in step 2 then

W=w+Δw And

μ=μxβ, for (β=0.9)

Go back to step 2

ELSE

μ=μ/β

END IF

The μ is the learning rate which is to be updated using the β, the decay rate. In our algorithm above μ is multiplied by decay rate β (β=0.9) whenever F(w) decreases, while μ is divided by β whenever F(w) increases in a new step, in other words reducing the learning rate for the error minima not to be overstepped.

The training subroutine function that reads the input vector data matrix into the network and runs the training in the Matlab environment is expressed as follows:

[Net, Tr]=Train (NET, P, T)

Train (NET,P,T,) takes,

NET - Network.

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P - Network input vector.

T - Network target vector.

Net – saves the new trained network (network used for prediction)

Tr – saves the training report (epochs and performance)

Performance evaluation of the network

The network training obtains the Net as described in the preceding section which subsequently was used to carry out the forecast of what the LST would be in a future epoch. The confidence to use this Network training result (Net) for prediction was based on the Regression (R) analysis and Mean Square Error (MSE) that resulted.

The regression analysis provides the measure of how well the variation in the output result is fully described by the target dataset. If this number is equal to 1, then there is perfect correlation, between the target and the output. However, the result most times is not usually 1. The Network Graphic User Interface (GUI) developed for this study works in such a way that the user is allowed to check these performance indicators with ease before adopting the network. The subroutine functions for these indicators were encapsulated in the network program.

Once these performance indexes are satisfactory the network (Net) is saved for simulation and subsequent prediction. The threshold values that gave good predictions were 0.8 and 0.5 for Regression and MSE respectively.

Simulation and prediction

Immediately the network performance analysis is considered satisfactory, the trained network is engaged for prediction. The simulation function takes the trained network (Net) as argument and returns the simulated LST with respect to the supplied input vectors. Afterwards the result of simulation is compared with the observed LST dataset; then prediction or forecast to future epochs is carried out using the saved parameters of the trained network.

A call_back function was encapsulated to carry out the simulation and prediction functions in the Matlab network program. All these were developed and compiled into an application with a functional user interface; the program flow chart is illustrated in Figure 5.

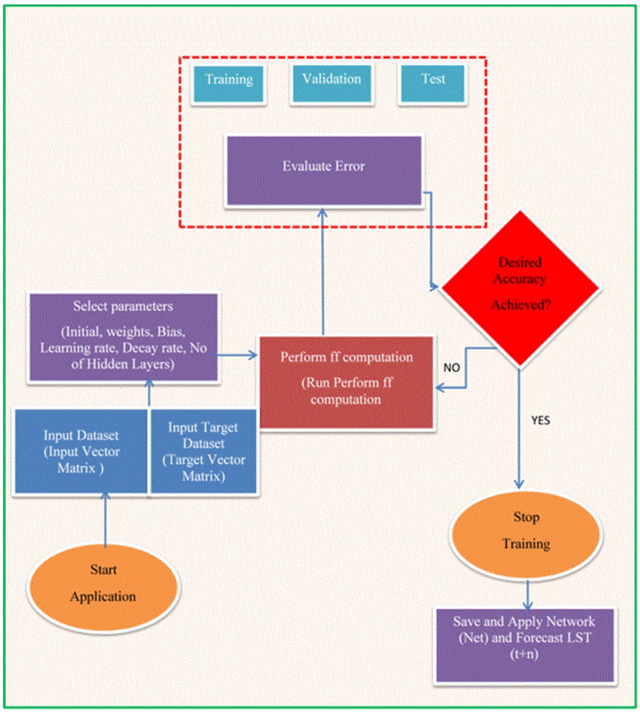

Figure 5: The flow diagram of the ANN Application developed in MatLab Environment.

Results and Discussion

The performance assessment of the developed LST prediction ANN system was based on the scatter plot comparison between the predicted and observed LST values, correlation coefficient values (R), Mean square error (MSE), quantitative and qualitatively assessment of the predicted LST raster maps in relation to the observed. All these assessments indexes showed that the Network was able to simulate and predict LST values over the future year epochs satisfactorily as shown by the closeness between the observed and predicted LST values. The scatter plots and graphs of LST 2000 and 2014 observed and predicted as depicted in Figures 6, 7, 8 and 9 indicate very good agreement. The statistical correlation coefficient (R) and mean square error (MSE) quantitative values of predicted and observed LST 2014 were 0.85 and 0.525 which indicate a strong correlation between the observed and predicted LST with reasonably low MSE value. Figures 10 and 11 show LST 2000 and 2014 raster maps respectively with the observed and predicted having strong agreement in closeness of values across the maps. Based on these good results from predicted LST 2000 and 2014, the network forecasted LST scenarios for 2028 and 2042 as shown in Figure 12.

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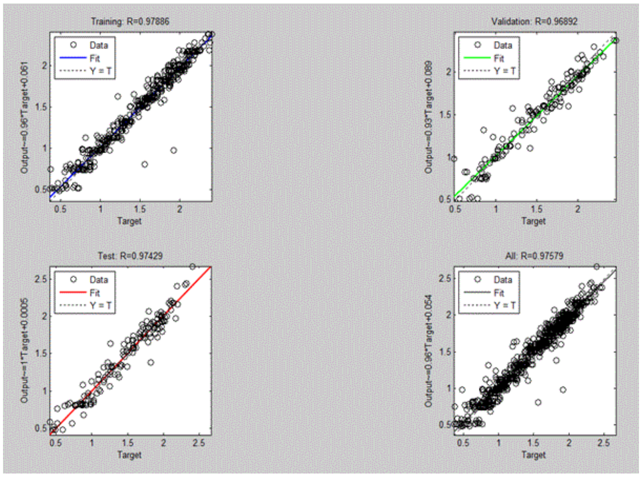

Figure 6: Scatter plot diagram describing the Correlation Coefficients between Predicted output and Observed LST data of year 2000.

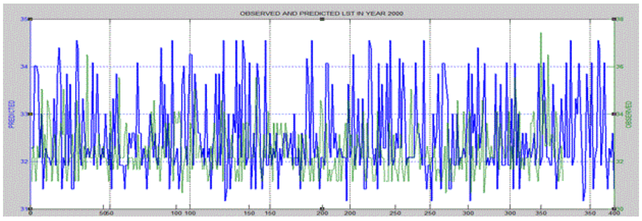

Figure 7: Graph showing the variation between Predicted and Observed LST values for the year 2000.

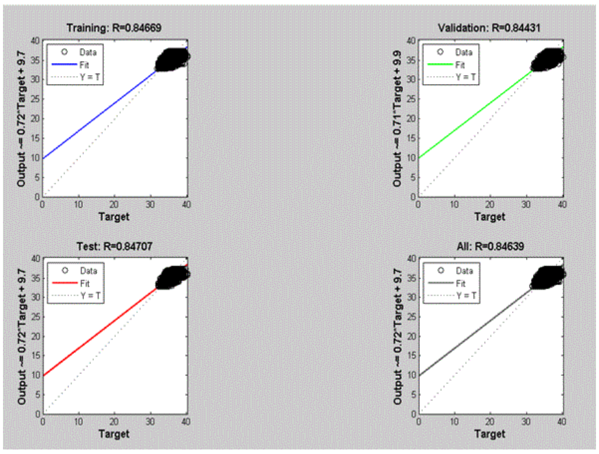

Figure 8: Scatter plot diagram describing the Correlation Coefficients between Predicted output and Observed LST data of year 2014.

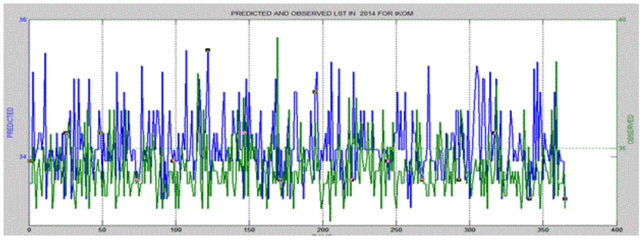

Figure 9: Graph showing the variation between Predicted and Observed LST values for the year 2000.

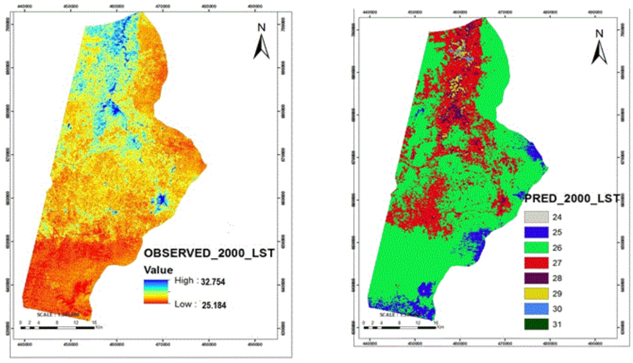

Figure 10: Observed and ANN Predicted LST maps year 2000 of the study area.

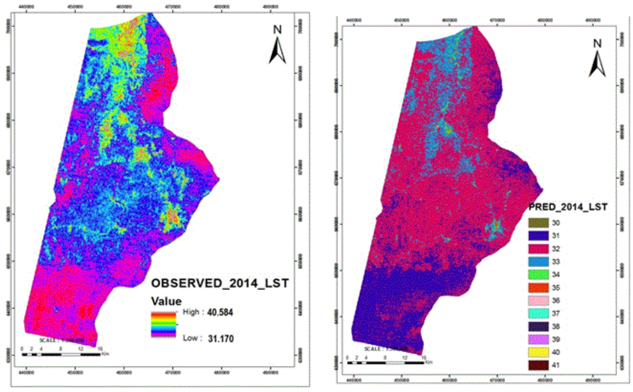

Figure 11: Observed and ANN Predicted LST maps year 2014 of the study area.

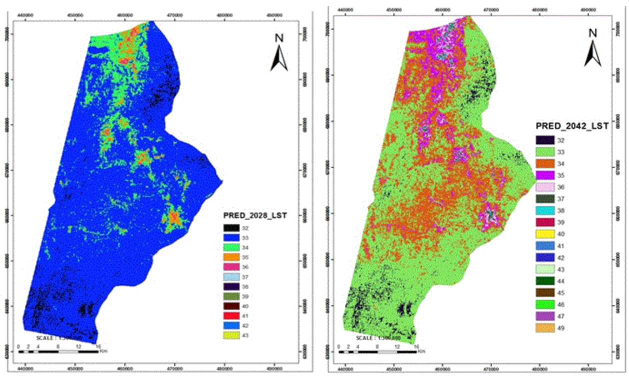

Figure 12: Forecasted LST maps of the study area for years 2028 and 2042 respectively.

Conclusion

The study explored the use of Artificial Neural Network (ANN) to simulate and forecast LST values from a sequence of past years values at an epoch interval of 7 years within a period of 28 years (1986-2014). The novelty of this work could be seen that from thorough literature review, no study has used earth observation satellite data (e.g., Landsat) to carry out this type LST forecasting using ANN. Past studies in this subject used discrete temperature time series data from in-situ sensors such as weather monitoring stations Smith et al. [10] and Patil et al. [9]. The study has further reaffirmed that FFBP ANN model can accurately forecast LST when larger training sample size, more input parameters and more than one hidden layer are provided. There is a need for further studies to improve the accuracy obtained in this work by increasing the number of past years' time series LST earth observation satellite data. In other words, the epoch interval will be reduced in order to increase the size of time-series training set with an aim to reduce prediction errors to a certain degree.

The results of this study show that LST is continually on the rise within the city of Ikom. Average temperature in the city in 2014 rose by more than 10 percent of what it was in 2000, from 29 degree Celsius to 35 degree Celsius as shown in the maps above. The ANN forecast suggests that this will continue to rise to about 37.5 and 40.5 degree Celsius in 2028 and 2042 respectively. This is not a good trend for the city of Ikom as it is a factor contributing to the micro climatic warming being experienced right now in this city. If nothing is done to mitigate this trend in LST rise, the city might experience severe Urban Heat Rise (UHR) which will adversely affect livelihood in there.

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