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STATISTICAL MODELING OF THE VARIATION OF SOME CLIMATIC VARIABLES FOR WEST AFRICA: TOWARDS FUTURE PREDICTION

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ABSTRACT
Globally, the obvious impact of climate change on human and ecosystem is of great concern. For agricultural productivity and sustainability, Africa especially the West Africa sub-region depend on apposite climate. However, the recent change in climate poses a challenge to the sub-region. Limited technical, institutional and financial supports in dealing with the impact of climate change also worsen the situation in this region. This work models the variation of some climatic variables in West Africa using Kalman Filter. Eight variables; maximum temperature, minimum temperature, rainfall, land use, population, solar radiation, relative humidity and wind speed were considered. Climatic data for West Africa spanning 1975–2015 were used. To model the impact/relationship, Kalman Filter, a recursive estimator that produces the optimal estimate of a dynamic system, was used. Control variables (population and land use) and transfer functions were introduced to control the dynamism of the model in MATLAB environment. Results show that there is a drastic variation in climate in the region within the period of the data. It also establishes the fact that population and land use pattern, especially loss of vegetation, had significant impact on the climatic variability in the West African climate system. This can be mitigated when institutional frameworks are effectuated in order to minimize the rapid change in population and land use pattern in West Africa.

KEYWORDS: *Climate Change, Kalman Filter, Land Use, Transfer Functions*

INTRODUCTION
Our planet has experienced changes since the creation of humankind. These changes can largely be attributed to human's struggle for survival. By exploiting its resources, mankind has tremendously impacted the earth's environment thereby causing issues of global concerns including but not limited to desertification, poor agricultural yields, droughts, floods, temperature rise, unpredictable rainfall pattern, and so on. No continent will be more severely hit with the consequences of climate change than Africa of which West Africa is of no exception. This is particularly because there is low level of understanding of climate change in the region, lack of institutional frameworks, high climate variability with high reliance on rain-fed agriculture (IPCC, 2014;Sultan*et al*.,

2016) and inconsistencies in model prediction (FCFA, 2016). A major challenge is limited adaptive capacity of people in Africa.

Amongst other things, increase in temperature (due to greenhouse gasses) has been identified as one of the major effects of climate change (IPCC, 2014). Adefisan (2018) investigates the climate change impact on monthly and seasonal distribution of rainfall and temperature of three scenarios of the Intergovernmental Panel on Climate Change (IPCC) between year 2000 and 2099. It was shown that temperature increases over West Africa in all the months under each of the scenarios. Precipitation which is any product of atmospheric water vapor that falls under the influence of gravity is also an important meteorological parameter in the West African Region (Zoungrana*et al.,* 2014;Djibo*et. al.,*2015).Existing regional models for precipitation showed high discrepancy, depicting large increases and decreases in monthly and annual values and there is no consensus on the direction of change in the future (Daron, 2014). In regions like the Sahel that receives precipitation below potential evapotranspiration, the prediction of rainfall is crucial to agriculture and water resources management.

El Houari*et al.,* (2014) used eight meteorological parameters (average temperature, maximum temperature, minimum temperature, pressure, moisture, visibility, wind speed and maximum wind speed) as predictors to model for precipitation. The researchers only considered precipitation but to properly simulate the climate system, the need for additional parameters becomes quite apparent.

There is a high correlation between temperature and solar radiation as their single origin is found in the absorption of radiant energy. Therefore, studying temperature necessitates the inclusion of solar radiation. Bazyomo*et al.,*(2016) used a set of eight climatic models to study the trends of solar radiation and temperature in West Africa. Results showed particular variation in different countries in the region. The work took precedence from global Climate Models (GCMs). GCMs do not account for fine-scale heterogeneity of climate variability and change due to their coarse resolution. Another concern over the approach of using GCM is that any error obtained in these models are propagated to the Regional Climate Models (RCMs).

Broman*et.al.,* (2014) investigated spatial and temporal variability of relative humidity over the West African Monsoon (WAM) region using cluster analysis. The research was able to model for relative humidity by exploiting the persistence of large-scale climate features including Sea Surface Temperature (SST), Sea Level Pressure and winds. The projected relative humidity was used to establish a link between meiningitis epidemics over the region.

Wind speed is another climate variable that should be considered when dealing with a climate system. This is because the rate of dispersion and diffusion can affect atmospheric concentration over an area (Largeron*et al.*, 2015). Akinyemi*et al.,*(2016)in a previous study examined wind dynamics of Ota, Nigeria to understand wind variation using statistical approach. The research showcased the behavior of wind during specific time of the year.

To fully understand variation in the West African climate system, there is a need for an empirical research leading to a model which may be used to predict the actual changes in climatic variabilities in the region. With the knowledge of the process, the future trend of the parameters will be determined. The aim of this study is to model climatic variabilities in West Africa using Kalman filter with climate data of 1975—2015. In addition to temperature and precipitation, this study employs additional parameters of wind speed, relative humidity and solar radiation to model the variabilities of the climatic variables. Kalman Filter was selected because of its ability to handle diverse data set within a long-term series which is typical of this study. It can approximate the true value of a system by taking few inputs and by understanding the variation and the uncertainties of the inputs (Grewal and Andrews, 2015).This study will provide additional information on relatioships among various climatic variables that could be used for predictive purposes and also working tools tofurther address the complex challenge of climate change in West Africa.

Study Area

West Africa is located between latitudes 4^{o}N and 28^{o}N and longitudes 16^{o}W and 15^{o}E (Fig.1). The region is bounded by the Atlantic Ocean to the West and South, by the North of the Sahel-zone at around 20^{o}N latitude to the north, and by 10^{o}E to the East. The climate in this region is predominantly influenced by the WAM(Riede *et al.*, 2016). The region occupies an area of 6,240,000 km^2, with approximately one-fifth of Africa’s landmass lyingbelow 300 meters above sea level with a population of approximately 362 millions people as of 2016(UNDP, 2017).

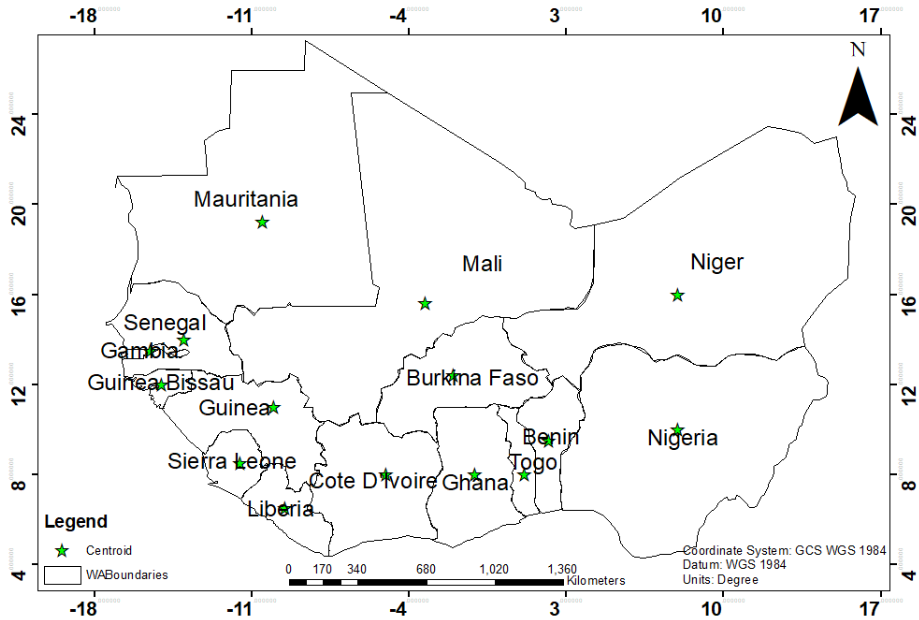

Fig. 1 Map of West Africa showing the centroid location for each country

MATERIALS AND METHODS

Data

The data used for this study spans all countries in West Africa except Cape Verde.

Table ***1*** shows all the datasets used and their sources.

Table 1 Data and Sources

No.	Data	Source	Period
1	Longitude, latitude, Elevation (m), Maximum Temperature (°C), Minimum Temperature (°C), Precipitation (mm), Wind Speed (m/s), Relative Humidity (%), Solar Radiation(mj/m^2)	National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) https://globalweather.tamu.edu	1979-2014
2	Land Use(km^2)	West Africa: Land Use and Land Cover Dynamics https://eros.usgs.gov/westafrica/land-cover/land-use-and-land-cover-trends-west-africa	Epochs 1975, 2000, 2013
3	Population (person)	United Nations World Population Prospects 2017 https://esa.un.org/unpd/wpp/	1950-2015

Methods

A number of parameters was used for future forecasting and prediction in this study usingKalman Filter. Kalman Filter is a state estimator that approximates the condition of a dynamic system using two distinct matrices; State Transition and Control Variable matrices. The filter uses series of measurements observed over time, containing statistical noise and other inaccuracies, to produce estimates of unknown variables that tend to be more precise than those based on a single measurement (Welch & Bishop, 2001)

State Transition Matrix

The State Transition Matrix of Kalman Filter is the matrix that relate the input of the system to the model. The parameters for the state transition matrix are contained in Table 2.

Control Variables

These are variables responsible to control the dynamics of any system under consideration.The choice of these variable is based on their correlation as indicated in previous literatures. Several authors have noted that only models that include anthropogenic forcing can simulate the observed patterns of warming.Models that rely explicitly on global natural forcing only reproduced the observed global mean warming (Hegerl, et al., 2007). Some authors are of the opinion that the natural processes alone cannot explain the increase in temperature (Hulme, 1996), thus making the argument for anthropogenic warming stronger especially in poor regions of the world (Jones, 1994). In addition, it has been proven that land use has changed and greater carbon dioxide has been released in recent time (Kalnay & Cai, 2003); (Zhou, et al., 2004). As a result, In this case, land use and population were selected as Control Variables, hence, their respective projections were made prior to the introduction of the Kalman Filter process using the formulae below.

The Pearson Population Projection equations were used to project for future years.

$$Growth\ Rate\ (r) = \frac{P_{present} - P_{past}}{P_{past} \cdot N} * 100\% \qquad \text{Eq. (1)}$$

$$P_t = P_0 \cdot e^{rt} \qquad \text{Eq. (2)}$$

Where P_t is the population at a particular time, P_0 is the previous population, e= euler number = 2.71828, t = time (years) and N = total number of years.

Table **2** shows all the parameters used in the study together with their symbolic representation.

Table 2 Symbolic Representation of Parameters used

Parameter	Symbolic Representation	Matrix
Maximum Temperature	*Mx*	State Transition
Minimum Temperature	*Mn*	
Precipitation	*Pr*	
Relative Humidity	*Rh*	
Wind Speed	*Ws*	
Solar Radiation	*Sr*	
Land Use (Forest Loss)	*Lu*	Control Variable
Population	*Po*	

As for the land use (particularly vegetation loss), the data was converted to polynomial after the initial interpolation.These polynomials were developed for each country which depicts the land use change over the period of the data using the technique of***Lagrange Interpolation***for unequal interval inEq. (3). Similarly, Eq. (3) was used as a hypothetical case to create transfer function between every two time series climatic parameter.

$$Mx(t) = \frac{(t-t_1)(t-t_2)}{(t_0-t_1)(t_0-t_2)}Mx_0 + \frac{(t-t_0)(t-t_2)}{(t_1-t_0)(t_1-t_2)}Mx_1 + \frac{(t-t_0)(t-t_1)}{(t_2-t_0)(t_2-t_1)}Mx_2 \quad \text{Eq. (3)}$$

Where Mx = Maximum Temperature and Pr = Precipitation, $t_1 \ldots t_n$ = various instances of time. When the data is supplied, Eq. (3) evaluates to a polynomial of the form:

$$Mx(t) = at^4 + bt^3 + ct^2 + dt + e \quad \text{Eq. (4)}$$

Eq. (4) is a best fitting polynomial with argument (time) and a,b,c,d are coefficients and e is a constant (if available). This equation is sufficient for the land use component involving forest loss. Degraded forest, gallery forest and riparian forest were used as indicators for land use. With each value of time, the forest loss can be determined using Eq. (4).

Data gaps

The period of the data availability varies with respect to the dataset, see

Table ***1***. Therefore, the data for 1975–2015 being the common period for all data were used. Most of the data obtained are daily records. They were averaged to determined monthly values. The linear interpolation formula in Eq. (5) was used to account for data gaps.

$$(y - y_1) = \left(\frac{y_2 - y_1}{x_2 - x_1}\right)(x_2 - x_1) \quad \text{Eq. (5)}$$

Where y = the value to be interpolated, y_1 = the previous y value, y_2 = the next y value, x_1 = the previous value of time and x_2 = the next value of time.

Transfer Functions

These are functionsthat relate input to output of a system.For a continuous system, it is the Laplace Transform of output to input. To determine the transfer functions which will be used for the State Transition and Control Variable matrices, the Laplace Transform was of Eq. (4)without initial condition using Eq. (6). To convert the polynomial to its equivalent rational form, the concept ofPadé Approximant was introduced. Padé approximant is a way of converting polynomials to rational expression usingEq. (7).

$$\mathcal{L}\{t^n\} = \frac{1}{s^{n+1}}, n \text{ is an integer} \qquad \text{Eq. (6)}$$

$$a + bx + cx^2 + dx^3 + \cdots + Z_n = \frac{P(x)}{Q(x)} \qquad \text{Eq. (7)}$$

The expression in Eq. (7) then take the form in Eq. (8) with the highest exponent determining the extent of Padé Approximant.

$$as^{-4} + bs^{-3} + cs^{-2} + ds^{-1} + e = \frac{P_0 + P_1 s^{-1} + P_2 s^{-2} + P_3 s^{-3} + P_4 s^{-4}}{Q_0 + Q_1 s^{-1} + Q_2 s^{-2} + Q_3 s^{-3} + Q_4 s^{-4}} \qquad \text{Eq. (8)}$$

Setting P_o = Q_o = 1 and expanding Eq. (8), like terms are collected using partial fraction decomposition and the unknowns (Ps and Qs) are determined using Least Squares,Eq. (9)

$$X = (A^T PA)^{-1} A^T P\mathrm{L} \qquad \text{Eq. (9)}$$

Where X = unknowns, A = design matrix, P = unit weight (same dimension as A), L = augmented matrix. Eq. (8)becomes a set of M linear equations N unknowns denominator coefficients (columns).The solution from Eq. (8) in Ps and Qs is substituted back into Eq. (8)to reduce the equation to its frequency domain form as indicated in Eq. (10). In cases where the result equation is not found in the table involving the Inverse Laplace, little algebraic manipulation are normally carried out to obtain the proper format represented in the table. The appropriate inverse Laplace Transform will be taken to convert the series to time domain.

$$Mx(t) = \frac{ds^2 + es}{cs + bs^2 + as^3} \qquad \text{Eq. (10)}$$

The resulting expression is the differential equation representing the transfer function in time domain without initial conditions for the series.

$$Mx(t) = \frac{dt + e}{ct + bt^2 + at^3} \qquad \text{Eq. (11)}$$

This process is repeated until transfer functions are determined for each set of climatic parameters. The State Transition and Control variable Matrices which are typical of a Multiple-Input-Multiple-Output (MIMO) system where each element is a Single-Input-Single-Output (SIMO) system with poles of 2 and zeros of 1. All climatic variables for every country were mapped as input-to-output to determine these matrices. This entire process is coded in MATLAB for ease of computation. The state transition matrix (A) for the Kalman Filter process becomes all transfer function as determined usingEq. (11).

$$A = \begin{bmatrix} MxMx & MxMn & MxPr & MxWs & MxRh & MxSr \\ MnMx & MnMn & MnPr & MnWs & MnRh & MnSr \\ PrMx & PrMn & PrPr & PrWs & PrRh & PrSr \\ WsMx & WsMn & WsPr & WsWs & WsRh & WsSr \\ RhMx & RhMn & RhPr & RhWs & RhRh & RhSr \\ SrMx & SrMn & SrPr & SrWs & SrRh & SrSr \end{bmatrix} \qquad \text{Eq. (12)}$$

NOTE: Eq. (12)should not be misconstrued for a covariance or correlation matrix but rather a transfer function between every two climatic variables.

Similarly, the control variable matric for the prediction equation becomes

$$B = \begin{bmatrix} LuMx & PoMx \\ LuMn & PoMn \\ LuPr & PoPr \\ LuWs & PoWs \\ LuRh & PoRh \\ LuSr & PoSr \end{bmatrix} \qquad \text{Eq. (13)}$$

The State Transition Matrix (A), Eq. (12) and Control Variable Matrix Eq. (13) are then infused into the Kalman Filter process Table 3 to give an approximation of the future state of the climate system.

Kalman Filter Process

Table 3 below summarizes the entire Kalman filter process; starting with the prediction equations and later the update equations. The process commences by first making a rough estimate of the state using the state transition, control variable and initial process covariance matrices. The rought estimates is updated using the Kalman Gain and consecutive data inputs.

Table 3 Chronology of the Kalman Filter Process

Name and Equation	Definition of terms	Equation No.
Prediction Equations		
Predicted State $X_{k_p} = Ax_{k-1} + B\mu_k + w_k$	X_{k_p} is the Current State, A is the State Transitional Matrix x_{k-1} is the previous state B is a transition Matrix μ_k Control Variable Matrix w_k Error	Eq. (14)
Process Covariance $P_{k_p} = AP_{k-1}A^T + Q_k$	P_{k_p} is the Process Covariance Matrix P_{k-1} Previous Covariance Matrix Q_k Process Covariance Error	Eq. (15)
Update Equations		
Kalman Gain $\boldsymbol{K} = \frac{P_{k_p}H}{HP_{k_p}H^T + R}$	K is the Kalman Gain H is an identity matrix the same dimension as A R is the error. Note $0 < K < 1$	Eq. (16)
Measurement update $Y_k = CY_k + Z_k$	Y_k the New Measurement C is a vector which is the same as the Identity matrix Y_k Measurement from sensor (data) Z_k Error related to the sensor	Eq. (17)
State Update $X_k = X_{kp} + K\left[Y_k - HX_{k_p}\right]$	X_k Updated measurement X_{k_p} is the predicted state Y_k measured value	Eq. (18)
Process Covariance $P_k = (I - KH)P_{k_p}$	P_{k_p} predicted previous process covariance matrix	Eq. (19)

The model was run for all countries in West Africa for all months of the data period. Predictions were made up to 2050 producing results for all climatic parameters used in this study.

Rate of Change

The rate of change formula was used to determine the change in each parameter expressed as a percent.Eq. (20) was used to determine the variation in each climatic variable.

$$Y = \frac{x_2 - x_1}{x_1} * 100\% \qquad \text{Eq. (20)}$$

Where Y is the percent change, x_2 is the value at the previous year and $x_1$is the value at the current year.

Model Validation

This is the process of establishing the degree of agreement between the result of the model and real life data or atleast accurately represents the model specification. Studies (such as) have shown that proving absolute validity is a non attainable goal. Therefore, a high degree of *"face validity"* is often achieved. Face Validity means, from outward indications, the model appears to be an accurate representation of the system(Carson, 2002).To validate the model used in this work, the dataset was divided into 20 years each amounting to 50% for both testing/evaluation and implementation. For the testing and evaluation phase, 50% of the data was subjected to the model. The model predicted for the remaining 20 years as indicated in Table 4.

Table 4 Data Usage

Item	Year	Duration	Percentage
Testing and Evaluation	1975 – 1994	20 years	50%
Implementation	1995 – 2014	20 years	50%

The residuals were computed between predicted and observed for each climatic variable.

Correlation Analysis

Although the covariance of two random variables provides information regarding the nature of their relationship, their magnitude σ_{PO} does not indicate anything regarding the strength of the relationship since σ_{PO} is not scale-free. Its magnitude depends on the units measured for both ***P*** and ***O***. As a result, there is a scale-free version of the covariance called the ***correlation coefficient*** that is used widely in statistics. The Pearson's product-moment correlation coefficient was used to determine the correlation coefficients between the model-predicted and observed for each climatic variable in the region.

$$\rho_{PO} = \frac{cov(P, O)}{\sigma_P \cdot \sigma_O} \qquad \text{Eq. (21)}$$

Where ρ_{PO} is the Correlation Coefficient, $cov(P, O)$ is the covariance between P (predicted) and O (Observed) and $\sigma_P \cdot \sigma_O$ are the standard deviations of P and O respectively. The Correlation Coefficient is a dimensionless quantity which satisfies the inequality $-1 \leq \rho_{PO} \leq 1$ and standardizes the measure of interdependence between two variables and, consequently, tells how closely the two variables move.

The Refined Wilmott Index

Since obtaining absolute validity is a non attainable goal, that is, residual equals 0, it is however important to attain a value that is very close to 0. Literally, this means that the model should be close to the real system. To do this, models are validated and examined for their performance under known conditions. The Refined Wilmott Index is a nontrivial improvement over earlier version of the index and is quite flexible, making it applicable to an extremely wide range of model-performance applications (Willmott*et al.*, 2011). Mathematically, the index is expressed as

$$dr = \begin{cases} 1 - \frac{\sum_{i=1}^{n}|P_i - O_i|}{\sum_{i=1}^{n}|O_i - \bar{O}|}, \text{when} \sum_{i=1}^{n}|P_i - O_i| \leq 2\sum_{i=1}^{n}|O_i - \bar{O}| \\ \frac{\sum_{i=1}^{n}|O_i - \bar{O}|}{\sum_{i=1}^{n}|P_i - O_i|} - 1, \text{when} \sum_{i=1}^{n}|P_i - O_i| > 2\sum_{i=1}^{n}|O_i - \bar{O}| \end{cases} \quad \text{Eq. (22)}$$

Where P = predicted, O = Observed, $\bar{O}$ = mean value of the observed, n = size of the data and *dr* is the refined wilmott index of agreement.*dr* is dimensionless and it is bounded by -1.0 and 1.0. Interpretation of the index ranges from weak to strong across the interval.

RESULTS AND DISCUSSION

Results from the study are outlined below in two groups: results from climatic variables which constituted the state of the system and, those of controls (land use and population).Decadal values (observed and predicted) are presented. Despite observed values are presented, the emphasis will be on predicted values.

Results of Climatic Variables

The results from the six (6) climatic variables that constitute the state of the climatic condition in this study were grouped in decades beginning at 1975 and ending 2050. Table 5 shows decadal results from the computation of all six climatic parameters where **Table 6** shows the rate of change in each climatic parameter used in the study. Vectorized maps were also included for visualization purposes.

Table 5 Observed and Predicted Annual Average for Climatic Parameters

Year	Maximum Temperature (°C)	Minimum Temperature (°C)	Precipitation (mm)	Wind Speed (m/s)	Relative Humidity (fraction)	Solar Radiation (MJ/m^2)
1975	35.632	20.086	96.796	2.849	0.608	19.817
1980	34.814	20.603	88.348	2.330	0.636	19.187
1990	35.651	20.748	81.331	2.379	0.610	19.331
2000	36.759	20.475	92.180	2.422	0.570	19.962
2010	35.878	21.654	108.333	2.222	0.622	19.642
2020	35.219	21.730	97.594	2.531	0.738	18.946
2030	36.227	21.253	96.071	2.622	0.699	19.209
2040	37.262	21.598	105.749	2.656	0.680	19.736
2050	37.054	22.352	96.698	2.554	0.689	19.194

In the first three decades (1975-2010), annual average decadal temperature in the region increased by approximately 0.91°C. Precipitation in the region increased byabout 11.54 mm. In the same period, there was a reduction in Wind Speed -0.627m/s, relative humidity experienced a slight increase of 0.014%, while, Solar Radiation changed by -0.175MJ/m^2. From 2020 to 2050, the model predicted a change in average temperature of approximately 2°C, a predicted value which is consistent with the projected values of Sylla *et. al* (2016) and IPCC (2014) reportof 1.5° to 4.5°over West Africa and -0.0484 percent for relative humidity. This combination of findings provides some support for the conceptual premise that increase in temperature results to decrease in relative humidity (Coffel*et al*., 2017). With such variation (increase in temperature and decrease in relative humidity) and agricultural yields will be gravely affected (Hatfieldet al., 2014).For example, Parkes *et. al*,(2015) investigated the benefits of breeding cultivars of groundnuts with heat and water stress and found out that heat stree is the main cause of crop failure in Nigeria, Southern Mali, Ivory Coast, Burkina Faso, Ghana and Senegal. These changes could affect the ecosystem (Woodand Pidgeon, 2015). Increase in temperature at this magnitude could compromise structural integrity and on the overall, prejudice economic growth (Dunneet. al., 2013; Lyet. al., 2013).

The values in column 4 of Table 5 are annual average precipitation for all countries over the period of the observed and predicted data. On average, precipitation in the West Africa region is anticipated to increase by approximately 10% and by 2050, a downward trend of -0.896mm which is approximately -0.1%

of the annual average precipitationas indicated in Table 5. The projected precipitation values in this work disagrees with Sylla *et. al* (2016) whose results show no significant change in the region.This could be attributed with the involvement of population increase and vegetation loss as contained in this work. Result from the model shows Wind Speed in the region increased by 0.0233m/s which is far more than that experienced during the period of observation covered by the data. A change of -0.050% and 0.248MJ/m^2 is predicted for relative humidity and solar radiation. Like temperature, extreme changes in solar radiation is dangerous to living organism as the possibility of ridges, skin cancer, cataracts can occur (Gosselinand Jones, 2010).In **Table 6**, the corresponding annual changes were computed for each climatic parameter.

Table 6 Changes in Climatic Parameters for the Study Area

Year	Maximum Temperature (%)	Minimum Temperature (%)	Precipitation (%)	Wind Speed (%)	Relative Humidity (fraction)	Solar Radiation (%)
1980	0.023	-0.025	0.096	0.223	-0.044	0.033
1990	-0.023	-0.007	0.086	-0.021	0.043	-0.007
2000	-0.030	0.013	-0.118	-0.018	0.070	-0.032
2010	0.025	-0.054	-0.149	0.090	-0.084	0.016
2020	0.019	-0.003	0.110	-0.122	-0.157	0.037
2030	-0.028	0.022	0.016	-0.035	0.056	-0.014
2040	-0.028	-0.016	-0.092	-0.013	0.028	-0.027
2050	0.006	-0.034	0.094	0.040	-0.013	0.028

The table shows that annual average temperature in the region is on the increase by 0.076% annually. It is expected that there will be a reduction in precipitation in the region from 2040 to 2050. By 2050, precipitation will be increased by 0.094%. However, wind speed will be reduced up to 2040. Relative Humidity will also be high in the region until 2050 when it is expected to drop by 0.013%. The region is expected to have a loss of -0.027% in Solar Radiation by 2040.

Results of Control Variables (Land Use and Population)

Projections were made for the control variables (land use and population) which were found to be contributing factors for these variabilities. **Table 7** shows changes in Land Use and Population whereas **Table 8** shows the corresponding changes in percent over the study area for the period of observation and prediction.

Table 7 Land Use and Population Values (1975 – 2050)

Year	Land Use (km^2)	Population (person)
1975	404477	122,792,954
1980	392287	140,720,930
1990	367907	184,739,536
2000	343741	240,769,837
2010	318564	315,089,488
2020	300926	407,831,693
2030	292946	522,011,575
2040	285292	669,180,215
2050	277942	859,238,599

Table 8 Changes in Land Use and Population in the region

Year	Land Use (%)	Population (%)
1980	-0.038	0.183
1990	-0.621	3.128
2000	-0.657	3.033
2010	-0.732	3.087
2020	-0.554	2.943
2030	-0.265	2.800
2040	-0.261	2.819
2050	-0.258	2.840

The links between climate change and population dynamics are often complex as population dynamics have not been fully integrated systematically into the science of climate change (Stephenson*et. al.*, 2010). However, the values in **Table 7** give an insight into the contribution of population increase and vegetation loss to change in the climatic condition of the West African subregion. As indicated in **Table 7**, the population of West Africa has increased by approximately750 Million whereas there has been a drastic loss in vegetation which can be approximated to 126 thousand squared kilometers 1975 to 2050. With the increase in the values of population and reduction in land use in the region coupled with the results obtained in Table 5 suggests that the variations in the climatic variables can be attributed to change in population and land use. While these variations do not necessitate causal factors, they however depict that there is a correlation between these phenomena in addition to other factors. While these findings are in line with that of Cao *et al.*, (2015), they also support theIPCC (2014) report that population and economic growth, technological change and changes in patterns of energy and land use are the major driving forces of the growth of the greenhouse gas emissions.

Table 8 shows the corresponding decadal changes in Land use and population. These findings demonstrate that population is on the increase with specific reduction between 2010 and 2020. This reduction is insignificant considering the fact that the later parts of the results indicate consistent increase population and reduction in land use.

Fig. 2that shows Land Use, Population and Choropleth maps for each climatic parameter in the region for the year 2050 with legends indicating variations across latitudes.

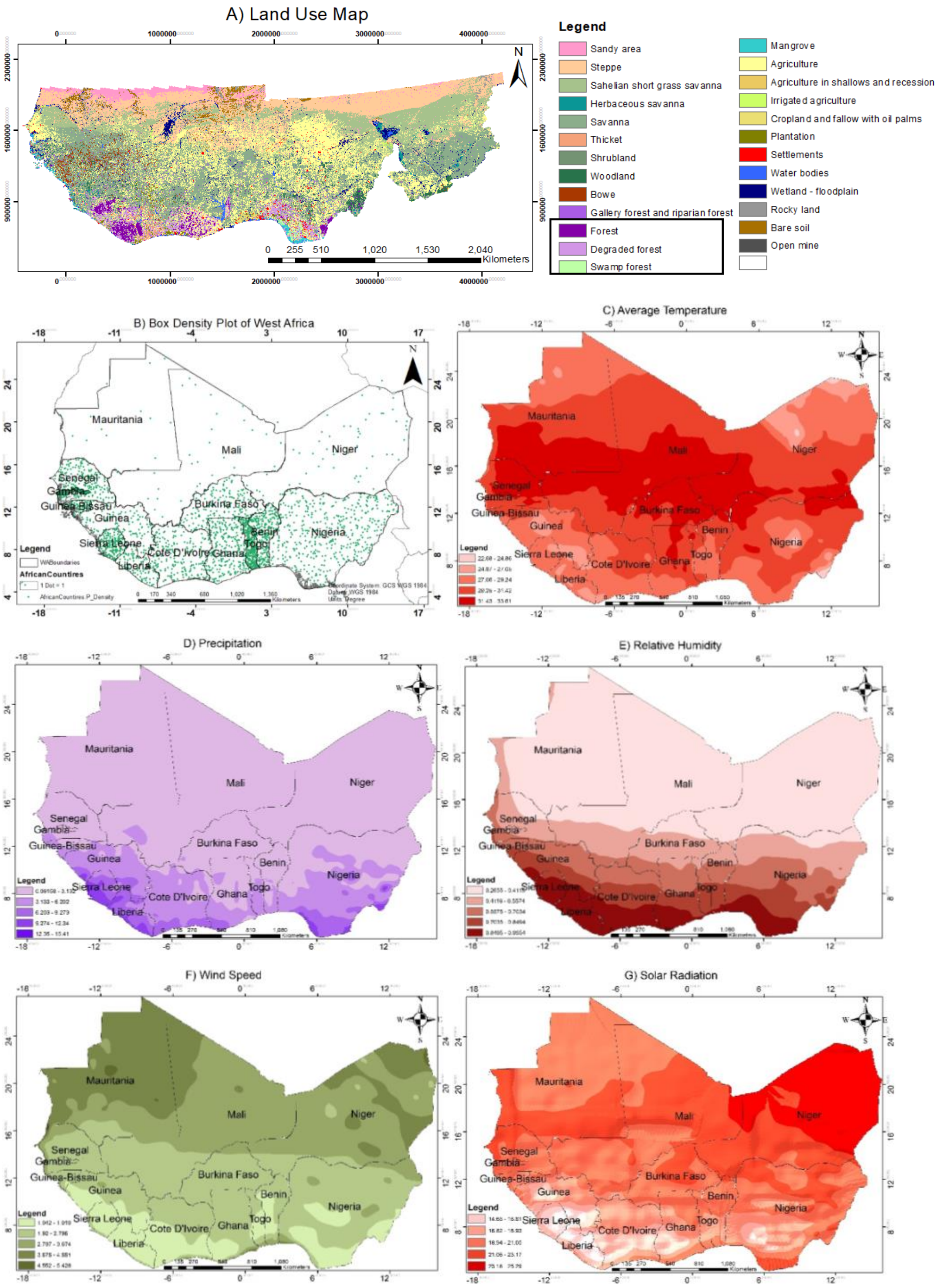

Fig. 2 Choropleth maps of projected parameters for the year 2050

It can be seen in
Fig. 2that Burkina Faso, Senegal, Mali, Niger, Ghana, Nigeria, Togo are expected to receive the highest amount of annual average temperature (>30^{o}C) while Liberia, Sierra Leone, Guinea, Cote D'Ivoire all receiving the lowest predicted values (<28^{o}C). It is worth noting that the countries predicted to receive the highest amount of annual average temperature are those with the highest predicted population and highest loss in vegetation. The only exception is Niger with the lowest available forest loss due to the desert. Consistent with the results of Sylla *et. al* (2016)and Sarr (2017) Liberia, Sierra Leone, Guinea, Cote D'Ivoire, Guinea-Bissau are expected to experience the highest annual precipitation values (>120mm) whereby Mauritania, Niger, Mali, Senegal, Burkina Faso, Gambia are all expected to receive the least precipitation value (<90mm).**In addition, countries earmarked to receive the highest values in precipitation are those with the more virginvegetation** available which are Liberia, Sierra Leone, Guinea and Cote D'Ivoire.

The Southern parts of Nigeria will experience the highest precipitation values as compared to the Northern parts. This has a negative correlation with annual average temperature which suggests that increase in population and loss of forest have stress on these climatic variables (IPCC, 2014). Mali, Niger and Mauritania will experience the highest predicted values (>3.5m/s) for Wind Speed. On the contrary, Liberia, Sierra Leone, Cote D'Ivoire, Ghana will have the lowest predicted values (<2.05m/s). Liberia, Sierra Leone, Cote D'Ivoire, Ghana will have the highest predicted value of relative humidity (>0.76%) whereas Niger, Mali, Burkina Faso and Mauritania shall all receive the lowest values in relative humidity (<0.34%).

This support the conclusion that increase in precipitation leads to increase in relative humidity as these countries also share similar correlation between precipitation and relative humidity. Mauritania, Mali, Burkina Faso and Niger shall have the highest values of solar radiation (>21mj/m^2). Liberia, Sierra Leone and Cote D'Ivoire are expected to have the lowest predicted value in Solar Radiation (<18mj/m^2). This suggests that there is a positive correlation between annual average temperature in the region and solar radiation in the region. The variations suggest that increase in population and loss of forest could be contributing factors to climatic variabilities in the region.

Results from Model Verification

This session presents summary of the statistical analysis done on all climatic parameters in the region as indicated in this study.**Table 9** depicts the correlation coefficient between all climatic parameters used in the study whereas **Table 10** shows additional statistical analysis based on Root Mean Square Error and Refined Wilmott Index of Agreement.

Table 9 Correlation Coefficient of Climatic Parameters used in the study

Variables	Max. Temp.	Min. Temp.	Precip.	Wind Speed	Rel. Hum.	Solar Rad.
Max. Temp.	1.0000	0.4084	0.3890	0.2964	0.0276	0.4344
Min. Temp.	0.4084	1.0000	0.5037	-0.1367	0.7103	-0.4611
Precip.	0.3890	0.5037	1.0000	0.1473	0.3059	0.2724
Wind Speed	0.2964	-0.1367	0.1473	1.0000	0.2677	0.1497
Rel. Hum.	0.0276	0.7103	0.3059	0.2677	1.0000	-0.7349
Solar Rad.	0.4344	-0.4611	0.2724	0.1497	-0.7349	1.0000

It is shown that there is a negative correlation between minimum temperature and Solar Radiation. Also, there exist a negative correlation between minimum temperature and Wind Speed and also between minimum temperature and solar radiation. All other variables in **Table 9** have positive correlation. The diagonal element indicates the variance in each case.

Table 10 Summary of Statistical Analysis

Climatic Parameter	Root Mean Square Error	Refined Wilmott Index of Agreement
Maximum Temperature	2.5842	0.3498
Minimum Temperature	1.5399	0.0813
Precipitation	23.4213	-0.3529
Wind Speed	0.0924	-0.2843
Relative Humidity	0.4276	-0.6732
Solar Radiation	1.1830	-0.1295

With the exception of precipitation with a high RMSE value of 23.4213 (as a result of randomness over the region), the RMSE for the other parameters are closer to 0.The RMSE value of precipitation is an indication of the huge disparity between monthly precipitation value. This suggests that there is a high degree of agreement between test data and predicted values. The values of the Refined Wilmott Index of Agreement suggest that the predicted values are in agreement with observed values because the inequality is satisfied ($-1 \leq dr \geq 1$).

CONCLUSION & RECOMMENDATION

Conclusion

This study presented a novel approach in modelling climatic variability using six climatic variables (Maximum Temperature, Minimum Temperature, Precipitation, Relative Humidity, Wind Speed, Solar Radiation), Land Use and Population to model variabilities in West Africaand employed Laplace transform to determine Transfer functions for each parameter. These transfer functions were later used to determine the State Transition and Control Variable Matrices. These matrices were later called in the Kalman Filter process to determine a dynamic system which models climatic variability in the region.

The study has established analytically that the changes in these parameters can be attributed to changes in Land Use and Land Cover Change pattern in the region and also the drastic increase in population.

Recommendation

Based on the findings of this study, the following recommendations might be of great importance when implemented:

1. West African nations should consider enacted ordinances that will protect forests in the region;
2. The issue of reforestation should be strongly encouraged and measures to ensure that it is fully practiced should be put in place;
3. It is about time that population controlled mechanisms be considered;
4. Additional research should be done that will involve the usage of additional parameters like aerosol, atmospheric pressure, and so on and also to quantify the effects of population and land use on climate change variability.

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REFERENCES

Adefisan, E. (2018). Climate Change Inpact on Rainfall and Temperature Distributions Over West Africa from Three IPCC Scenarios. *Journal of Earth Science & Climate Change, 9*(476). doi:10.4172/2157-7617.1000476

Akinyemi, M.L., Emetere, M.E. and Akinwumi, S.A.,. (2016). Dynamics of Wind Strength and Wind Direction on Air Pollution Dispersion. *Asian Journal of Applied Sciences, 4*(2), 422-429.

Bazyomo, S.D.Y.B, Lawin, E.L., Coulibaly, O. and Ouedraogo, A. (2016). Forecasted Changes in West Africa Photovoltaic Energy Output by 2045. (Y. Zhang, Ed.)

Broman, D., Rajagopalan, B. and Hopson, T. (2014). Spatiotemporal Variability and Predictability of Relative Humidity over West Africa Monsoon Region. *Journal of Climate, 27*(14), 5346-5363. doi:10.1175/JCLI-D-13-00414.1

Cao, Q., Yu, D., Georgescu, M., Han, Z., & Wu, J. (2015). Impacts of land use and land cover change on regional climate: a case study in the agro-pastoral transitional zone of China. *Environmental Research Letters, 10*, 1-12. doi:10.1088/1748-9326/10/12/124025

Carson, J. (2002). Model Verification and Validation. (E. Yücesan, C.-H. Chen, J. L. Snowdon, & J. M. Charnes, Eds.) *Proceedings of the 2002 Winter Simulation Conference*.

Coffel, E.D., Horton, R.M. and Sherbinin, Alex. (2017). Temperature and humidity based projections of a rapid rise in global heat stress exposure during the 21st century. *Environmental Research Letters, 13*(2018). doi:10.1088/1748-9326/aaa00e

Daron, J. (2014). Regional Climate Messages: West Africa. Scientific report from the CARIAA Adaptation at Scale in Semi-Arid Regions (ASSAR) Project.

Djibo, A.G., Seidou, O., Karambiri, H., Sittichok, K., Paturel, J.E. and Saley, H.M. (2015). Development and assessment of non-linear and non-stationary seasonal rainfall forecast models for the Sirba Watershed, West Africa. *Journal of Hydrology: Regional Studies, 4*(1).

Dunne, J.P., Stouffer, R.J. and John, J.G. (2013). Reductions in labour capacity from heat stress under climate warning. *National Climate Change, 3*(563-6). doi:10.1038/NCLIMATE1827

El Houari, B., Zegaoui, O. and Abdelaziz, A. (2014). Development of Mathematical Models to Forecasting the Monthly Precipitation. *American Journal of Engineering Research (AJER), 3*(11), 38-45.

FCFA. (2016). Africa's Climate - Helping Decision-Makers make sense of Climate Information. (A. Creese, & W. Pokam, Eds.)

Gosselin, L.A. and Jones, L.A. (2010). Effects of solar radiation on barnacle settlement early post-settlement mortality and community development in the intertidal zone. *Marine Ecology Progress Series, 407*(140-158). doi:10.3354/meps08567

Grewal, M. S. and Andrews, A.P. (2015). *Kalman Filter - Theory and Practice using Matlab* (Fourth ed.). New Jersey: John Wiley & Sons.

Hatfield, J., G. Takle, R. Grotjahn, P. Holden, R. C. Izaurralde, T. Mader, E. Marshall, and D. Liverman. (2014). Climate Change Impacts in the United States: The Third National Climate Assessment. In J. Melillo, R. Terese, & G. W. Yohe (Eds.). doi:10.7930/J02Z13FR

Hegerl, G. C., Zwiers, F. W., Braconnot, P., Gillett, N. P., Luo, Y., Orsini, J. M., Scott, P. (2007). Understanding and Attributing Climate Change. In S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. Averyt, . . . H. Miller (Eds.), *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Hulme, M. (1996). Climate Change within the period of meteorological records. (W. Adams, Ed.) *The Physical Geography of Africa*, 88-102.

IPCC. (2014). The IPCC's Fifth Assessment Report, What's in it for Africa?

Jones, P. (1994). Hemispheric Surface air temperature variations: A reanalysis and an upate to 1993. *J. Climate, 7*(1794).

Kalnay, E., & Cai, M. (2003). Impact of urbanization and land use on climate change. *Nature, 423*, 528-531.

Ly, M., Traore, S.B., Alhassane, A. and Sarr, B.,. (2013). Evolution of some observed climate extremes in the West African Sahel. *Weather and Climate Extremes, 1*(19-25).

Parkes, B., Challinor, A. J., & Nicklin, K. (2015). Crop failute rate geoengineered climate: impact of climate change and marine cloud brightening. *Environmental Research Letter, 10*(8). doi:10.1088/1748-9326/10/8/084003

Riede, J.O., Posada R., Fink, A.H. and Kaspar, F. (2016). What's on the 5th IPCC Report for West Africa? (A. Fink, J. Yaro, & J. Hesselberg, Eds.) *Adaptation to Climate Change and Variability in Rural West Africa*. doi:DOI 10.1007/978-3-319-31499-0_2

Sarr, A. (2017). Multi-Scale Characteristics of Precipitation and Temperature over West Africa using SMH1-RCA Driven by GCMs under RCP8.5. *American Journal of Climate Change, 6*, 455-486. doi:10.4236/ajcc.2017.63024

Stephenson, J., Newman, K., & Mayhew, S. (2010). Population dynamics and climate change: what are the links?*Journal of Public Health, 32*(2), 150-156. doi:10.1093/pubmed/fdq038

Sultan, B. and Gaetani, M. (2016). Agriculture in West Africa in the Twenty-First Century: Climate Change and Impacts Scenarios, and Potential for Adaptation. *Frontiers in Plant Science, 7*(1262).

Sylla, M. B., Nikiema, P. M., Gibba, P., & Kebe, I. (2016). Climate Change over West Africa: Recent Trends and Future Projections. (J. Yaro, & J. Hesselberg, Eds.) *Adaptation to Climate Change and Variability in Rural West Africa*, 25-40. doi:10.1007/978-3-319-31499-0_3

UNDP. (2017). World Population Prospects: The 2017 Revision. *United Nations Department of Economic and Social Affairs*. Retrieved September 10, 2017, from https://esa.un.org/undp/wpp/DataQuery/

Welch, G., & Bishop, G. (2001). An Introduction to the Kalman Filter.

Willmott, C.J., Robeson, S.M. and Matsuura, K. (2011). Short Communication, A refined index of Model Performance. *Internal Journal of Climatology*. doi:10.1002/joc.2419

Wood, E.M., and A.M. Pidgeon. (2015). Extreme Variations in spring temperature affect ecosystem regulating services provided by birds during migration. *Ecosphere, 6*(11). doi:10.1890/ES15-00397.1

Zhou, L., Dickinson, R. E., Tian, Y., Fang, J., Li, Q., Kaufmann, R. K., Mynen, R. B. (2004). Evidence for a significant urbanization effect on climate in China. (J. E. Hansen, Ed.) *Goddard Institute for Space Studies, 101*(26), 9540-9544. doi:10.1073

Zoungrana, B.J.B., Conrad, C., Amekudzi, L.K., Thiel, M. and Dapola, E.,. (2014). Land Use/Cover Response to Rainfall Variability: A Comparing Analysis between NDVI and EVI in the Southwest of Burkina Faso. (Tarendra Lakhankar, Ed.) *Climate*, *3*(63-77). doi:10.3390/cli3010063