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# An Assessment of the Changing Climate in Northern Nigeria Using Cokriging

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**Abstract** The aim of this paper is to test the applicability of Co-Kriging (CK) on the study of the changing climate in Northern Nigeria. Indices were derived from climatic variables (Rainfall and Temperature) obtained from Nigerian Meteorological Agency (NIMET) and remotely sensed data covering the period from 1981 to 2010 in the form of Normalised Difference Vegetation Index (NDVI) data derived from National Oceanic Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR). Because of the strong relationship between NDVI and Rainfall, CK method of data interpolation was tested with R-Statistical software. A digital elevation model (DEM) of the study area at 90-meter spatial resolution was used as a supplement in an overlay procedure using the IDRISI Remote sensing and GIS software so as to derive the correct altitude values of the Met stations for comparison with the coefficient of variation of the rainfall dataset. Results from the derived CK prediction maps showed that there are high variability in NDVI and rainfall across the time-series. Furthermore, spatial average variability in the growing season rainfall was 60% with a mean temperature of 4% although coefficient of variation in rainfall for the individual climatic station's ranged from 18.15 to 60.98 per cent. While the highest coefficient of variation in temperature for the entire time series (1981-2010) was located around Katsina area, the lowest was located around Minna. From the results of this analysis it is evident that the higher prediction variance values particularly for vegetation NDVI and rainfall are located in the southern part of the study area particularly around Kaduna, Minna, and Jos as compared to the northern part of the study area falling around Maiduguri, Sokoto and Katsina which indicated relatively lower prediction values. However, further studies should also be undertaken using the raster NDVI dataset in a GIS environment to buttress our view that there were changes in the general ecosystems within the study area as result of climatic impact.

***Keywords:*** *cokriging, normalized difference vegetation index, remotely sensed data, rainfall, GIS, DEM*

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## 1. Introduction

The issue of climate change is now presenting another challenge to development generally. It is now widely acknowledged that the impacts of the changing climate amplify existing unfavourable conditions for developing countries [1]. Accordingly, the generality of people from poor countries are more vulnerable and have less adaptive capacity to confront such changes [2]. Countries with lack of adequate resources, poor infrastructure, and unstable institutions have little capacity to adapt and are highly vulnerable [3].

Land degradation in the form of desertification in the arid and semi-arid areas particularly in Africa is increasing as a result of various factors such as climatic variations and other human activities [4]. The major desertification processes which include wind erosion, water erosion, reduction in vegetation cover are on the increase seasonally, while other processes such as salinization, acidity and compaction of the soil are increasing by the day [5].

According to [6], very significant changes in vegetation cover is directly responsible in the current global warming of the earth which in turn leads to redistribution of precipitation as well as the different temperatures on the earth surface. Although most of these changes in vegetation and land cover generally are being experienced in Southern parts America and Africa, such changes are also spreading to the high latitudes particularly in North America and Eurasia that are associated with temperature rise especially during the spring months. The Northern part of Nigeria on the other hand, is endowed with a large expanse of arable land that over the years served as vital resource for agriculture and other economic activities. However, according [7,8] and a more recent report by [9], the Sahara desert is encroaching and advancing southwards at the rate of 0.6 percent every year. It is observed in recent times that the weather condition and its consequences are even straining the agricultural relations between the communities of southern part of Niger

republic and their Nigerian counterparts. Thus, the role of prevailing climatic conditions on vegetation biomass in different regions of the world have been discussed extensively by different authors such as [10-16].

## 1.1. Theoretical Background

[17] compared the vegetation response to precipitation in Sahel and East Africa from 1982 to 1985 and found that the spatial patterns of annually-integrated NDVI are closely related to their mean annual precipitation. There are also a number of different studies that have analyzed the influence of precipitation, temperature, atmospheric circulation on vegetation dynamics and biomass at high latitudes such as [18,19]. However, when [20] analyzed the inter-annual trends in annual and seasonal vegetation productivity from 1982 to 1990 and its relationship to temperature and precipitation across the northern part of the mid-high latitudes, their study indicated increased vegetation greenness. On the other hand, [21] investigated the geographical distribution of global greening trends and their climatic correlates and reported that temperature was the primary climatic factor associated with greening in the northern high latitudes as well as western Europe, while precipitation was a strong correlate for greening in the fragmented regions only, but with decrease in greenness in the southern parts of America and Africa and central Australia.

With regards to modelling of precipitation, [22] proposed two methods in modelling the space-time correlation of precipitation. The first method was the inference of spatial variogram models specific to a particular time and their subsequent combination. The second method was the inference of space-time variogram model by contouring experimentally, available variogram values for various spatial and temporal lags in a distance-time variogram graph. In both methods the global technique of Ordinary Least Squared (OLS) regression analysis was utilized. The OLS regression is based on the assumption of spatial stationarity, therefore, the use of this global technique over relatively wide areas is constrained by local level of spatial variability of the observed relationships [23]. Compared to the OLS method, there is the Geographically Weighted Regression (GWR) which is relatively a new method that takes into account spatially varying relationships in a regression analysis [24]. However, the potential use of GWR using remotely sensed data and GIS techniques was presented by [25]. Thus, [26] explored this potentiality by studying the relationships between NDVI and the local level atmospheric constituents consisting of precipitation and temperature in the state of Minnesota from 1990 to 1997 using the GWR and spatial interpolation techniques. That analysis focused on the summer months because such relationships are more apparent in northern mid-latitude regions. In comparison to traditional OLS, there was a substantial improvement in the analysis from this study by [26] because the average $R^2$ value increased from 24% to 67%. However, the overall relationship between the different atmospheric constituents and NDVI were broadly consistent with the different types of land use across their study area with the highest correlation located in forested locations.

In comparison to the arid and semi-arid climates which are characterized with high variability of climatic variables running from one year to another, such variability is particularly extreme with regards to rainfall. This was presented on a map of the inter-annual variability of rainfall across the globe by [27] where areas of greatest irregularities correspond to semi-arid and desert areas. In other development however, [28] studied the irregular urban development and green space destruction using NDVI, principal component analysis (PCA) and post classification methods using Saqqez city as a case study. These three techniques were employed to detect the green space changes. On the other hand Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) dataset from 1989 to 2009 were used to determine land use changes, especially the physical development of the area and its devastating effects on the green space. The result showed that green space has been reduced from 530 ha in 1989 to 198.3 ha in 2009. In that study, the capabilities of Landsat data oriented towards determining land use changes via the standard methods was examined. The result showed that NDVI and post classification analysis methods were better than PCA in detecting the devastating effects of unplanned constructions and forming projects on Saqqez's green space.

However, this was analysed within a GIS environment using remote sensing and GIS software rather than specifically a stand-alone statistical software.

With regards to Geostatistics which is based on the theory of regionalized variables [29,30,31], this is increasingly explored because it allows one to capitalize on the spatial correlation between neighbouring observations to predict attribute values at unsampled locations. Some authors [32,33] have shown that the geostatistical prediction technique (kriging) provides better estimates of rainfall than conventional methods. Recently, [34] found that the results depend on the sampling density and that, for high-resolution networks (e.g. 13 raingages over a 35 km2 area), the kriging method does not show significantly greater predictive skill than simpler techniques, such as the inverse square distance method. Similar results were found by [35] when they compared kriging and multiquadratic surface fitting for various gauge densities. In fact, besides providing a measure of prediction error (kriging variance), a major advantage of kriging over simpler methods is that the sparsely sampled observations of the primary attribute could be complemented by secondary attributes that were more densely sampled. For rainfall, secondary information was taken in the form of weather-radar observations. A multivariate extension of kriging, known as cokriging, has been used for merging rain gauge and radar-rainfall data [36,37]. However, [38] used another geostatistical technique with an external drift, to combine both types of information. In that study, another valuable and cheaper source of secondary information was considered ie, a digital elevation model (DEM). Precipitation tends to increase with increasing elevation, mainly because of the orographic effect of mountainous terrain, which causes the air to be lifted vertically, and the condensation occurs due to adiabatic cooling. For example [39,40] reported a significant 0.75 correlation between average annual precipitation and elevation recorded at 62 stations in Nevada and southeastern California. In that experiment, a multivariate version of kriging, called cokriging to incorporate elevation into the mapping of rainfall was utilised. A more straightforward approach consists of

estimating rainfall at a DEM grid cell through a regression of rainfall versus elevation [41]. Furthermore, [42] examined different models such as, thiessen polygons, inverse distance, second order polynomial, ordinary kriging and universal kriging for distribution of monthly rainfall in southern Florida. From that study ordinary kriging method had the lowest error (1.32).

Another study by [51] showed that the method of thin plate smoothing splines was the most accurate method for interpolation of soil salinity. However, when [52] compared the performance of three interpolation methods (nearest neighbour, ordinary kriging, and cokriging) for soil moisture retention curves they found that ordinary kriging and cokriging were the most accurate.

The aim of this study focused on Northern Nigeria is to determine the applicability of modelling using Co-kriging (CK) with remotely sensed data so as to assess how vegetation distribution are affected by climatic impacts.

## 2. The Study Area

The study area is centred on twelve climatic stations located in the Northern part of Nigeria namely, Birinin-Kebbi, Funtua, Gusau, Jos, Kaduna, Kano, Katsina, Maiduguri, Minna Sokoto Yelwa and Zaria falling between Latitude 9º to 14º N and Longitude 2º to 14.5º E. The study area falls in the arid and semi arid areas characterised with low rainfall and less vegetation cover in the extreme northern Nigeria except in the central and montane parts of the country where rainfall is much higher and vegetation more greener. Average annual temperature is 29ºC, average minimum temperature is 13ºC in January while average maximum temperature is 38ºC in April. The Average daily sunlight duration is 9 hours while mean annual rainfall is 72mm which comes between June to October (Figure 1).

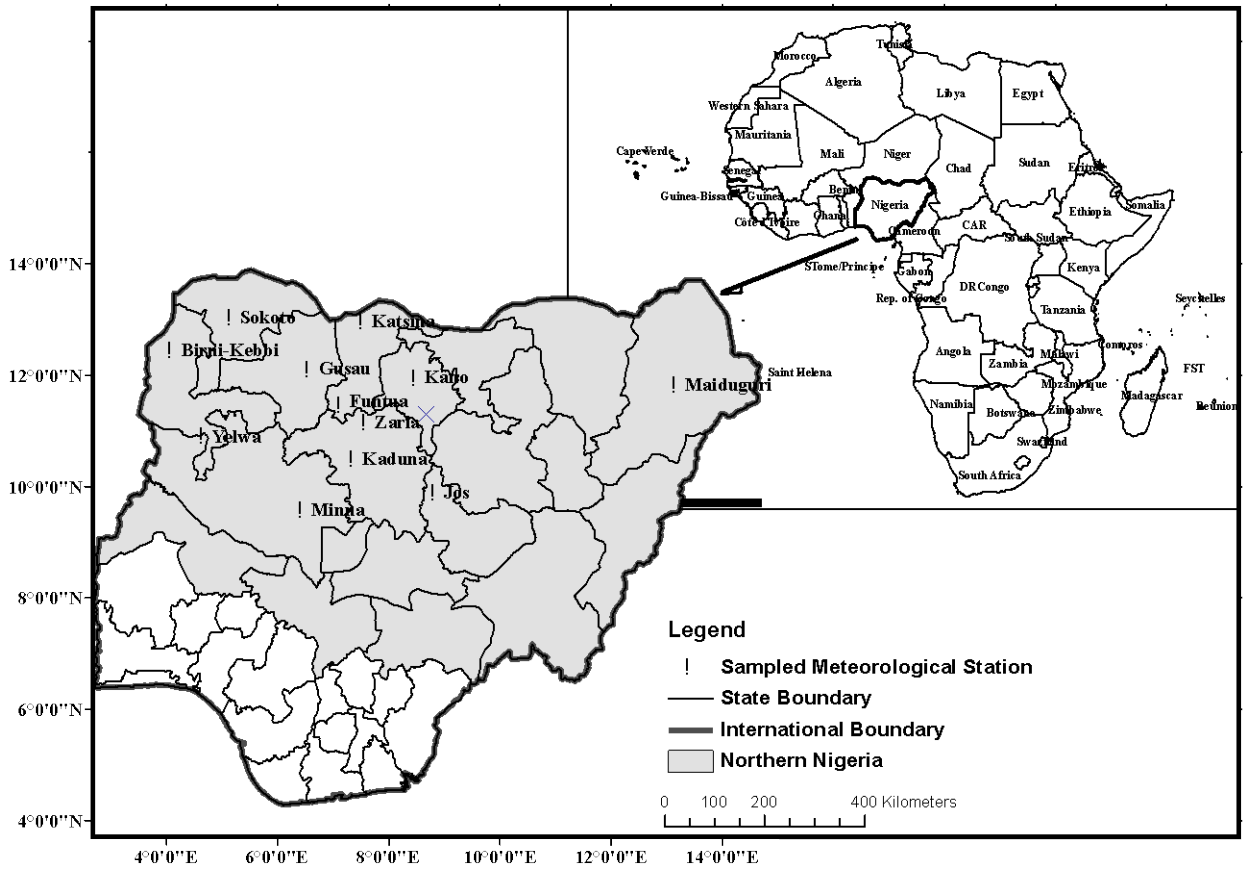


**Figure 1**. The study area covering the selected climatic stations in Northern Nigeria

### 2.1. Data and Methods

In this study climatic data in the form of rainfall, minimum and maximum temperatures, obtained from 12 climatic stations managed by the Nigerian Meteorological Agency (NIMET) were utilised. The dataset contain monthly records for growing seasons (June- September) covering the period of 1981-2010 and were used as input variables for the analysis. The climatic stations though not evenly distributed over the study area, are located across the representative land cover types found there. Other dataset utilised in this study was obtained from National Oceanic Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR) in the form of raster monthly maximum value (MVC) NDVI composite data sets of the same time-series (with the exception of September-December 1994 months which were contaminated with cloud cover). Their yearly averages, standard deviations and coefficient of variations were computed. A map of the study area was also prepared in a GIS environment so as to clearly indicate the locations of the climatic stations. A 90-meter spatial resolution digital elevation model (DEM) of the study area was also windowed from a DEM of Nigeria obtained from the Shuttle Radar Topography Mission (SRTM) instrument provided by the United States Geological Survey (USGS). This DEM image of the study area was used as a supplement in an overlay procedure using the

IDRISI Andes Remote sensing and GIS software so as to derive the correct altitude values of the climatic stations.

## 2.2. Co-kriging Modeling

Co-kriging is a geostatistical technique developed to improve the prediction of a variable using the information on other spatially correlated variables which are generally more densely sampled. The variables are called co-regionalized and are spatially dependent [43]. Co-kriging is an extension of ordinary kriging in a case of two or more spatial or spatio-temporal variables. In Cokriging, the explanatory variables are spatial, temporal or spatio-temporal with expected values and variograms as compared to ordinary kriging in which explanatory variables are fixed [44].

The matrix formulation of co-kriging has been described by [29,44,45]. A cokriging estimate is a linear combination of both primary and secondary data values as shown by [46] in given equation :

$$\hat{y}(s_0) = \sum_i^n a_i U_i + \sum_j^m b_j V_j \quad (1)$$

Where $\hat{y}(s_0)$ is the estimate of $y$ at location 0; $u_1,\ldots,u_n$ are the primary data at $n$ nearby locations; $v_1,\ldots,v_n$ are the secondary data at $m$ nearby locations; $a_1,\ldots,a_n$ and $b_1,\ldots,b_m$ are the co-kriging weights to be determined.

The development of the co-kriging system is identical to the development of the ordinary kriging system. The definition of estimation error is stated as :

$$R = \hat{y}(s_0) - y(s_0) = \sum_i^n a_i U_i + \sum_j^m b_j V_j - y(s_0) \quad (2)$$

Where $U_1,\ldots,U_n$ are the random variables representing $U$ at the $n$ locations and $V_1,\ldots,V_n$ are the random variables representing $V$ at $m$ locations.

An expression for the variance of the estimation error in terms of the co-kriging weights and the covariances between the random variables are:

$$\begin{aligned} &Var(R) \\ &= \sum_i^n \sum_j^n a_i a_j Cov(U_i U_j) + \sum_i^m \sum_j^m b_i b_j Cov(V_i V_j) \\ &+ 2\sum_i^n \sum_j^M a_i b_j Cov(U_i V_j) - 2\sum_i^n a_i Cov(U_i U_0) \\ &- 2\sum_j^m b_j Cov(V_j U_0) + Cov(U_0 U_0) \end{aligned} \quad (3)$$

Where $Cov(U_i U_j)$ is the auto covariance between $U_i$ and $U_j$, $Cov(V_i V_j)$ is the auto covariance between $V$ and $V_j$ and $Cov(U_i V_j)$ is the cross-covariance between $U_i$ and $V_j$.

The set of cokriging weights thus, must satisfy two conditions. First, the weights must be such that the estimate given in Equation (1) is unbiased. Second, the weights must be such that the error variances given in Equation (3) are the smallest possible. One way of guaranteeing unbiased ness is to ensure that the weights in the first term sum to 1 while those in the second sum to 0 [47,48]:

$$\sum_{i=1}^n a_i = 1 \quad and \quad \sum_{j=1}^m b_j = 0 \quad (4)$$

The Lagrange multiplier method may be used to minimize error variance with two constraints. To implement the method we simply equate each nonbiased condition to 0, multiply by a Lagrange multiplier and add the result to Equation (3). This gives the following expression:

$$Var(R) = w^t C_z w + 2\mu_1\left(\sum_{i=1}^n a_i - 1\right) + 2\mu_2\left(\sum_{j=1}^m b_j\right) \quad (5)$$

Where $\mu_1$ and $\mu_2$ are the lag range multiplier. The minimized error variance can be calculated using equation (3) or it can be simplified by making substitutions using the Lagrange multipliers. The simplified version is:

$$\begin{aligned} Var(R) &= Cov(U_0 U_0) + \mu_1 \\ &- \sum_i^n a_i Cov(U_i U_0) - \sum_j^m b_j Cov(V_j U_0) \end{aligned} \quad (6)$$

Cokriging is the method having the best theoretical foundation, meaning that no assumptions are made on the nature of the correlation between the two variables. It exploits more fully the auxiliary information by directly incorporating the values of the auxiliary variable and measuring the degree of spatial association with the primary variable through the cross-semivariogram. The technique of cokriging improves the estimation and reduces the variance of the estimation error, but at the same time is much more demanding than ordinary kriging. The calculation of the cross-semivariogram and the fitting of a theoretical model becomes very difficult, particularly when the two variables are not strongly correlated [49].

# 3. Results and Discussion

A summary result of the analysis for the rainfall and temperature variability for the 30-year period covering the area within the 12 climatic stations is presented in Figure 2. However, the spatial average of variability in the growing season rainfall account to 60% with a mean temperature of 4% although the coefficient of variation in rainfall ranged from 18.15 to 60.98 per cent for the individual climatic stations. While the highest coefficient of variation in temperature for the entire time series (1981-2010) was located within Katsina area, the lowest was located around Minna. Thus, based on the threshold value of coefficient of variation of rainfall reported by [50] the border between equilibrium and non- equilibrium dynamics of ecosystem for this study area can be suggested to fall approximately around latitude 13ºN. By implication, this suggests that areas around Sokoto and Katsina experienced more changes in vegetation NDVI, and possibly their ecosystems. However, further studies using the whole time series NDVI dataset within GIS environment is more likely to prove this assertion. In Figure 3 a comparison between the coefficient of variation of the rainfall and altitude data derived from a digital elevation model (DEM) of the climatic stations is presented, suggesting that the lower the altitude, the higher the coefficient of variation in rainfall for most stations except for Zaria, Funtua and Jos. This may also

require further analysis to clearly confirm this. On the other hand, results from the prediction model using Co-Kriging for NDVI and other climatic dataset are presented in Figures 4-9.

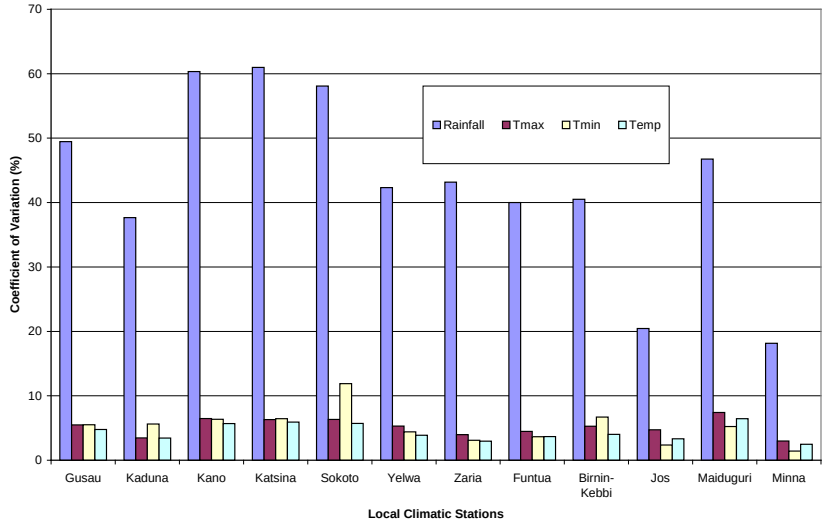


**Figure 2.** Computed Coefficient of Variation of the climatic variables (1981-2010)

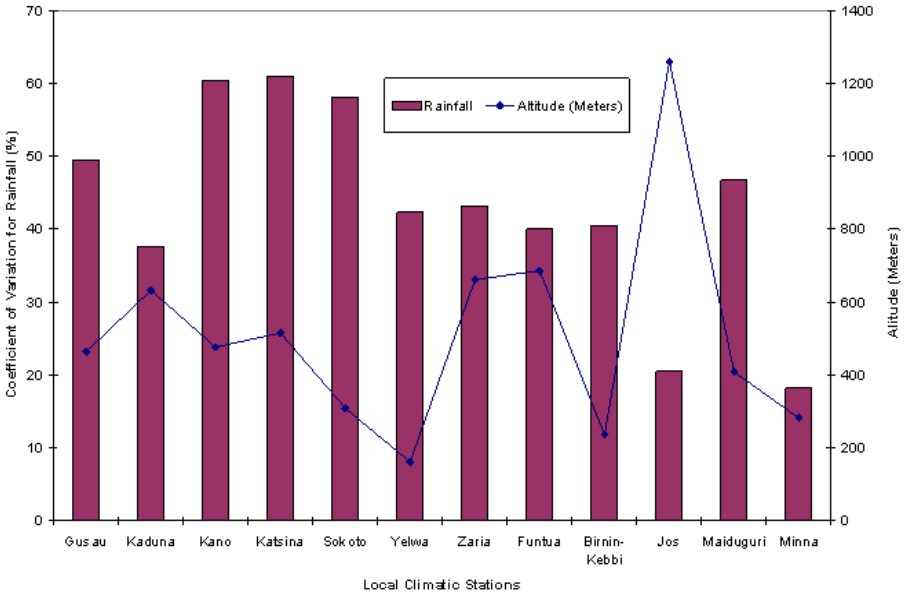


**Figure 3.** Comparison of Coefficient of Variation of rainfall and altitude for the climatic stations (1981-2010)

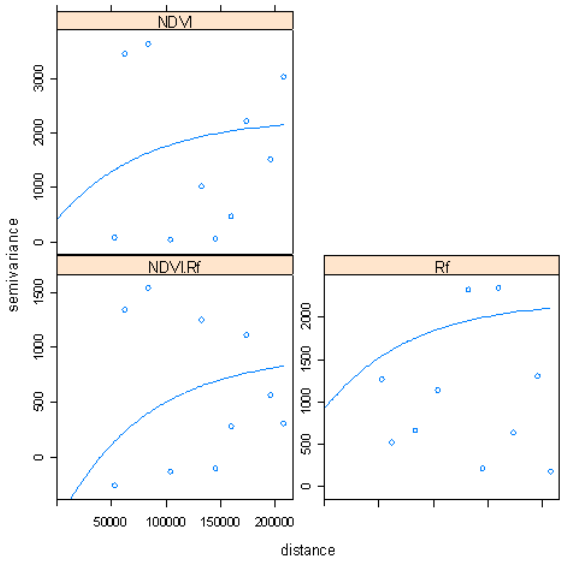


**Figure 4.** Fitted direct and cross variograms for NDVI and Rainfall

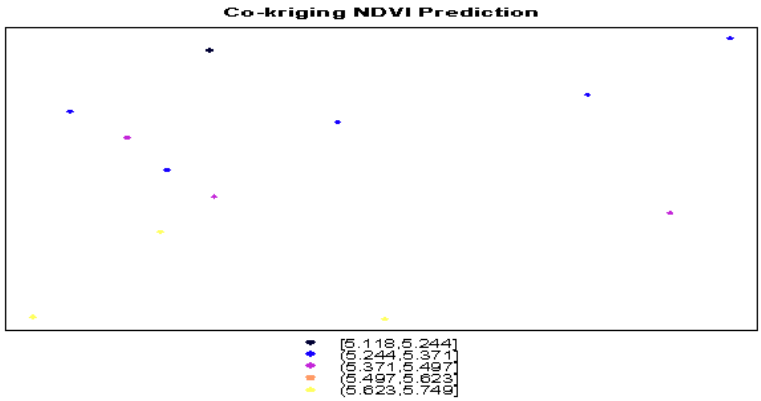


**Figure 5.** NDVI Co-kriging Prediction

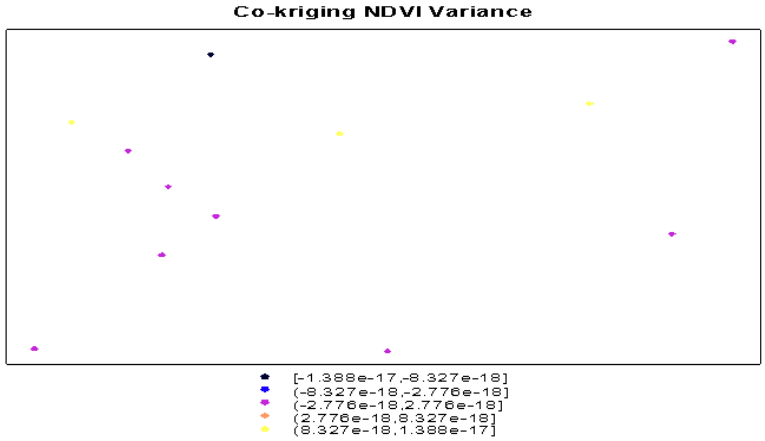


**Figure 6.** NDVI Co-kriging Variance

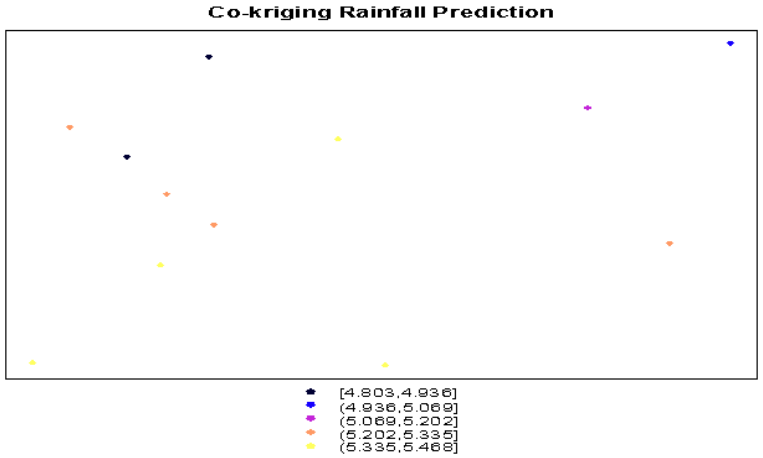


**Figure 7.** Rainfall Co-kriging Prediction

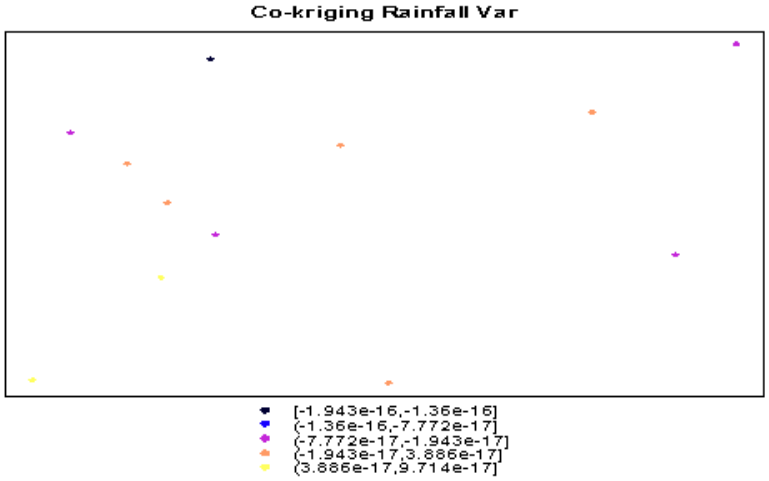


**Figure 8.** Rainfall Co-kriging prediction variance

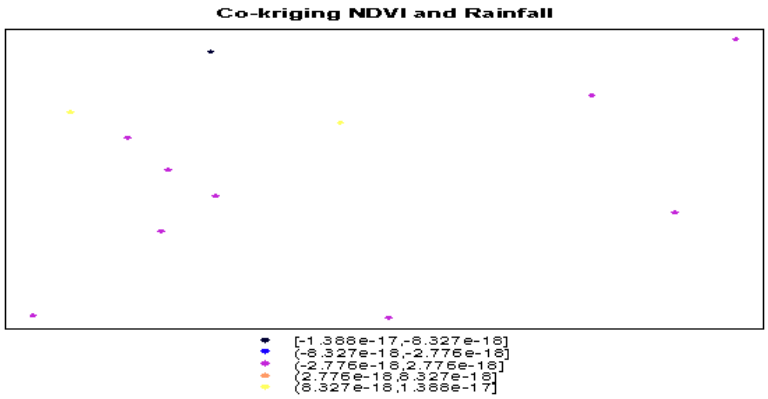


**Figure 9.** NDVI and Rainfall Co-kriging predictions error

From the results presented in Figures 5 and 7, NDVI and Rainfall prediction are higher for Jos, Kaduna, Yelwa and Minna falling in the southern part of the study area with lower values portraying northern part of the study area falling in Sokoto, Kano, Katsina and Maiduguri. With regards to the variance (Figures 6 and 8), the northern part of the study area has higher NDVI variance, while the southern part of the study area has moderately NDVI variance, and for rainfall, there were significantly lower variability around Sokoto than what was obtained from remaining part of the study area. This is suggest that the southern part of the study area experienced less changes in both vegetation and possibly climatic impacts spatially compared to the northern part of the study area. However, a comparison between rainfall and altitude in Figure 3 suggests that the higher the altitude the lower the variability in rainfall particularly for Birnin-Kebbi, Yelwa and Jos.

It can also be seen generally from the prediction results in Figures 6 and 8 that for all the areas under study, that the higher prediction variance values particularly for vegetation NDVI and rainfall are located in the southern part of the study area particularly around Kaduna, Minna, and Jos as compared to the northern part of the study area falling around Maiduguri, Sokoto and Katsina which indicated relatively lower predictive values in variability.

## 4. Conclusion

From this assessment it can be seen that the applicability of cokriging to the study of vegetation NDVI and other climatic variables in northern Nigeria is possible. The spatial distribution of climate variables in the study area was shown to be influenced by external forces and possibly by elevation and topography which ranges from 161 meters around Yelwa to about 600m in the mid-northern portion of the study area and over 1200 meters around Jos. This relationship between NDVI and some climatic variables for this study area is hereby tested using CK method of data interpolation. However, it has to be pointed out that the modelling approach utilised a limited number of available climatic stations within the study area, although this could have been extended for more spatial spread towards the North-eastern part of the country for better predictive results if data and more stations were available. Further studies should be undertaken using the NDVI dataset (since they are rastersised time-series dataset) in a GIS environment to buttress the view that there were changes in the general ecosystems within the study area.

## Acknowledgements

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## List of Abbreviations

| | |
|---|---|
| CMD | Climate Modelling Grid |
| CK | Cokriging |
| DEM | Digital Elevation Model |
| EVI | Enhanced Vegetation Index |
| GIS | Geographical Information Systems |
| GWR | Geographically Weighted Regression |
| IGPB | International Geosphere Biosphere Programme |
| MODIS | Moderate Resolution Imaging Spectrometer |
| NASA | National Aeronautics Space Administration |
| NDVI | Normalised Difference Vegetation Index |
| OLS | Ordinary Least Square |
| SRTM | Shuttle Radar Topography Mission |
| Tmax | Maximum Temperature |
| Tmin | Minimum Temperature |
| USGS | United States Geological Survey |

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