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COMPARISON OF DIFFERENT INTERPOLATION TECHNIQUES TO MAP TEMPERATURE IN WEST AFRICA.

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ABSTRACT

Human actions have led to abnormal changes in temperature in the past 50 years due to climate variability. For efficient planning and management of agricultural and economic activities, understanding and forecasting the spatial variation of climate data particularly temperature is very important. Local technique and the geo-statistical procedure were assessed for temperature mapping in the study area, using 46 temperature stations in West Africa between the years 2002 to 2017. The annual temperature within the region was retrieved within two seasons, rainy and dry seasons, to justify the comparison between two interpolation methods. Distinct interpolation techniques reveal that all methods have similar performance considering the error statistics but at the same time give satisfactory results.

Keywords:
Annual temperature, Interpolation, Ordinary Kringing, IDW.

1.0 INTRODUCTION

The concentrations of greenhouse gases in recent time has increased due to anthropogenic activities which have led to abnormal changes in temperature in the past 50 years due to climate variability (Tiengrod & Wongseree, 2013). On many occasions, climate data are not available where they are most needed because spatial availability of climatic data is more problematic because the information recorded from various but dispersed weather stations are static (Vicente-Serrano et al., 2003). Due to effective planning and management of agricultural and economic activities, understanding and predicting the spatial variation of climate data especially temperature is very important (Ibrahim & Nasser, 2015). Interpolation technique can be either non-geo-statistical method (e.g. IDW) or geo-statistical techniques (e.g. kriging). So many scholars have employed either one or both of these interpolation methods to estimate and predict some values in order to gain insights into the study of a particular phenomenon.

According to Vicente-Serrano et al. (2003), different interpolation methods need to be tested before the most appropriate scheme for a given area and the climatic variables are selected since it is important to make a climatic map that corresponds closely to reality for agricultural and hydrological management and the improvement of the climatic model at local scales to ensure increased efficiency. The work of Ibrahim & Nasser (2015), which made comparisons between inverse distance weighted (IDW) and kriging, found that when precision is the goal of a project, the kriging technique of interpolation gives an excellent outcome than inverse distance weight; and also stress the assumption that kriging method underestimates the interpolated height value while IDW method overestimates values in their conclusion.

West Africa climate is controlled by the interaction of two air masses, the influence of which varies throughout the year with the North-South movement of the inter-tropical convergence zone. Predicting and understanding the spatial variation of climate data, particularly temperature is important to both agriculture and economic sectors for planning and management activities. Moreover, it will also make for better decision-making since agriculture employs the majority of the population in West Africa.

Temperature data across West Africa has increased over the last 50 years in line with an increase in global temperature (Niang et al, 2014). Temperature changes across the region are still poorly documented with global temperature data sets showing gaps in the region due to interpolation from few stations. The purpose of this study is to assess the spatial variability of annual average temperature in two seasons in five West African countries (Burkina Faso, Ivory Coast, Ghana, Togo, and Benin Republic) by comparing different interpolation procedures which are deterministic method (IDW) and geo-statistical method through error statistics or the Jack-knife cross-validation.

Study Area: West African Sub region

The area considered for the study is five West African countries: Burkina Faso, Ivory Coast, Ghana, Togo, and Benin Republic (Figure 1). This is because the stations are not evenly distributed and if all the countries in West Africa was used to carry out the analysis, the model generated will be inaccurate as a result of an overcompensation in the areas with limited data. These countries are located between 13.5317ºN, 2.4604º W.

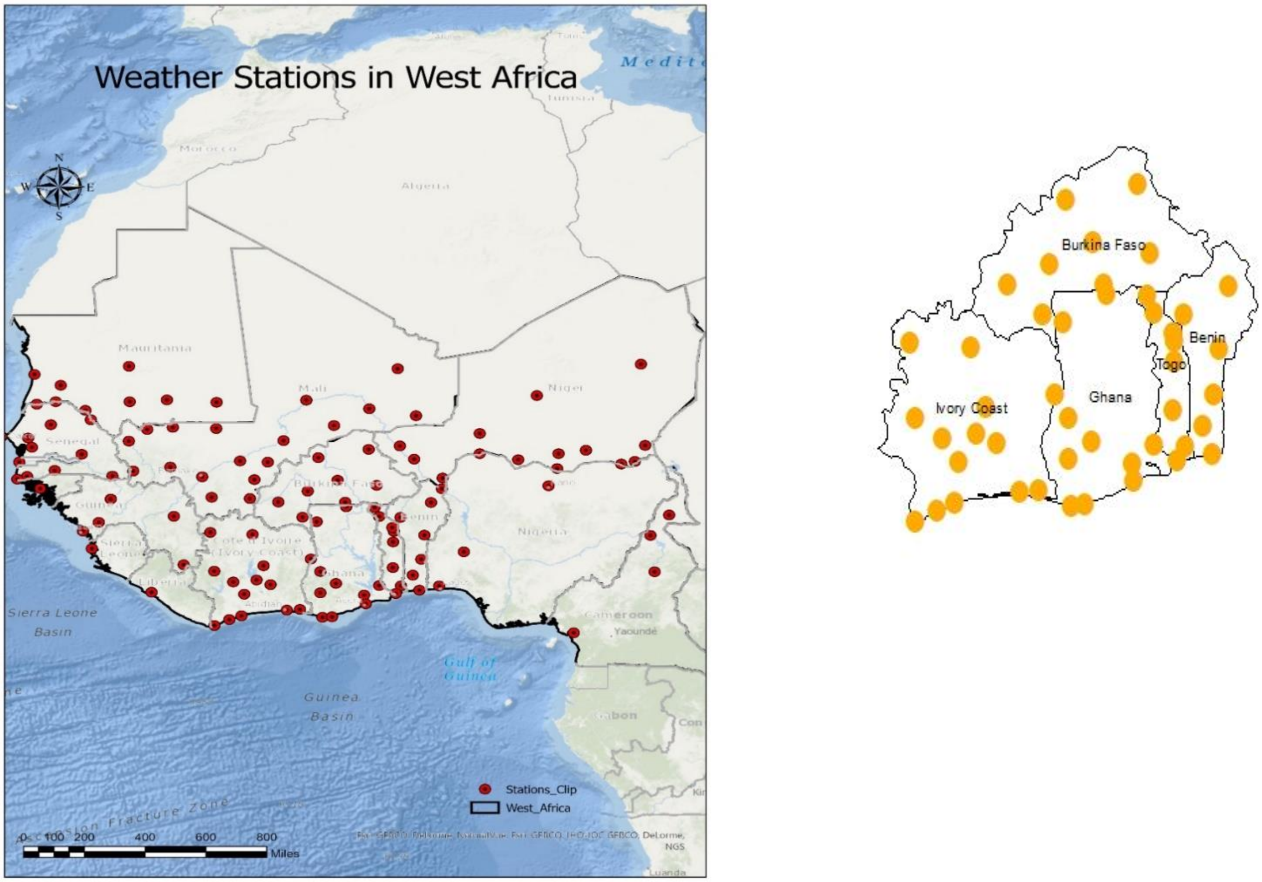


Figure 1: A map of West Africa showing the five countries and the locations of the weather stations (Source: National Oceanic Atmospheric Administration, 1981-2010

1.1 Study Methodology

In this project, we compared the local technique and the geo-statistical method for temperature mapping in the study area using 46 temperature stations between the years 2002 to 2017 provided by National Oceanic Atmospheric Administration. The authors pre-processed the datasets obtained from the 46 weather stations across the five West African countries (Table 1) in Excel to work on incomplete, noisy, and inconsistent figures. We inputted the data in ArcGIS 10.3 with a base map of the study area showing the spatial distribution of the weather station. Next we investigated the Statistical properties of the data set to ensure that the data is distributed normally. We determined the variogram for the data after ensuring the normality of the data. The authors then plotted the experimental variogram using the computed variogram, through the experimental variogram. The best variogram model was fitted. Spatial autocorrelation between sample points was examined using the model with a particular or defined radius. To determine the value points with appropriate technique of interpolation, IDW and Ordinary Kriging were used (refer to Figure 2).

SN	Station Name	NCDC_ID	Country	Region
1.	FADA N'GOURMA	30016050	Burkina Faso	Gourma
2.	BOUAKE	30017041	Ivory Coast	Bouake
3.	MAN	30017660	Ivory Coast	Man
4.	COTONOU	30018749	Benin	Aboisso
5.	ATAKPANE	30019009	Togo	Ogou
6.	SOKODE	30023518	Togo	Tchaoudjo
7.	SASSANDRA	30025394	Ivory Coast	Sassandra
8.	SAVE	30025988	Benin	Zou
9.	TABLIGBO	30036120	Togo	Yoto
10.	KANDI	30038806	Benin	Borgou
11.	BOROMO	30039523	Ivory Coast	Mouhoun
12.	DIMBOKRO	30047515	Ivory Coast	Dimborko
13.	OUAHIGOUYA	30050052	Burkina Faso	Yatenga
14.	GAOUA	30051246	Burkina Faso	Poni
15.	DORI	30054413	Burkina Faso	Seno
16.	GAGNOA	30054875	Ivory Coast	Gagnoa
17.	ADIAKE	30056426	Ivory Coast	Aboisso
18.	NATITINGOU	30061825	Benin	Atakora
19.	TABOU	30069624	Ivory Coast	Tabou
20.	ODIENNE	30069739	Ivory Coast	Odienne
21.	SEFWI BEKWAI	30095009	Ghana	Western
22.	DALOA	30095032	Ivory Coast	Daloa
23.	ABIDJAN FELIX HOUPHOUET BOIGN	30095054	Ivory Coast	Abidjan
24.	KOFORIDUA	30095161	Ghana	Eastern
25.	MANGO/SANSANNE	30095208	Togo	Oti
26.	KARA	30095246	Togo	Kozah
27.	WA	30095306	Ghana	Upper West
28.	BOHICON	30095387	Benin	Zou
29.	BONDOUKOU/SOKO	30095463	Ivory Coast	Bondoukou
30.	AXIM	30095471	Ghana	Western
31.	PARAKOU	30095489	Benin	Borgou
32.	NIAMTOUGOU INTERNATIONAL	30095749	Togo	Doufelgou
33.	YAMOUSSOUKRO	30095837	Ivory Coast	Yamoussoukro
34.	SUNYANI	30095838	Ghana	Brong-Ahafo
35.	SAN PEDRO	30095926	Ivory Coast	San-Pedro
36.	NAVRONGO	30095956	Ghana	Upper Eastern
37.	OUAGADOUGOU	30096060	Burkina Faso	Kadiogo
38.	GNASSINGBE EYADEMA INTL	30096158	Togo	Zio
39.	HO	30096177	Ghana	Volta

40.	KOTOKA INTL	30096242	Ghana	Greater Accra
41.	PO	30096310	Burkina Faso	Nahouri
42.	KUMASI	30096313	Ghana	Ashanti
43.	KORHOGO	30096322	Ivory Coast	Korhogo
44.	DAPAON	30096325	Togo	Tone
45.	BOBO DIOULASSO	30096360	Burkina Faso	Houet
46.	TAKORADI	30096407	Ghana	Western

Table 1: Weather Stations and their locations (Source: National Oceanic Atmospheric Administration, 1981-2010)

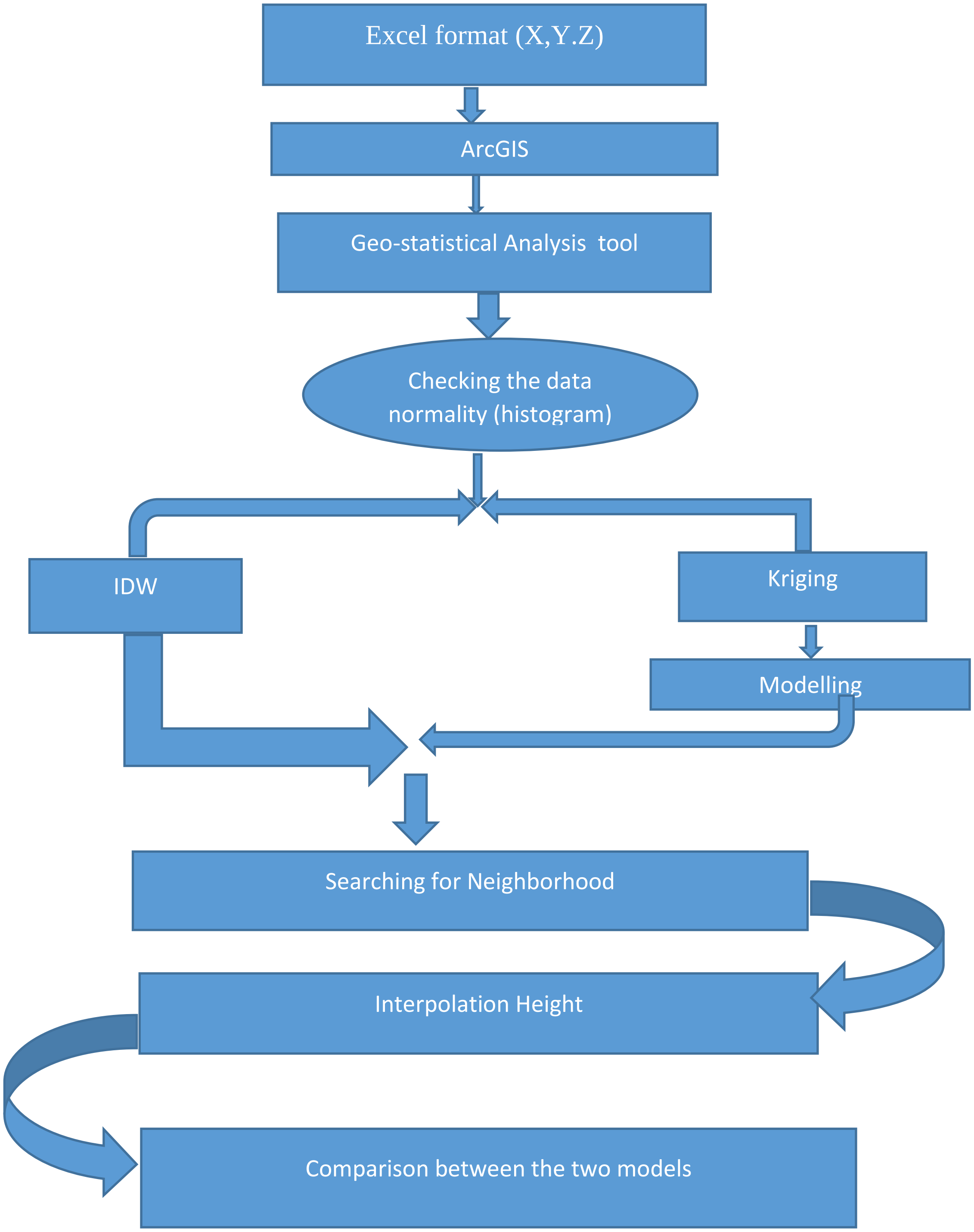
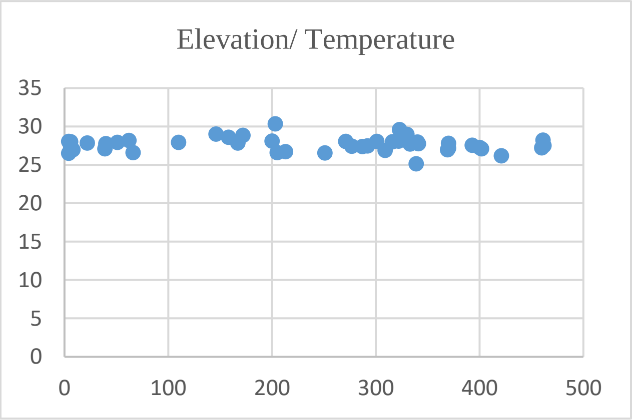


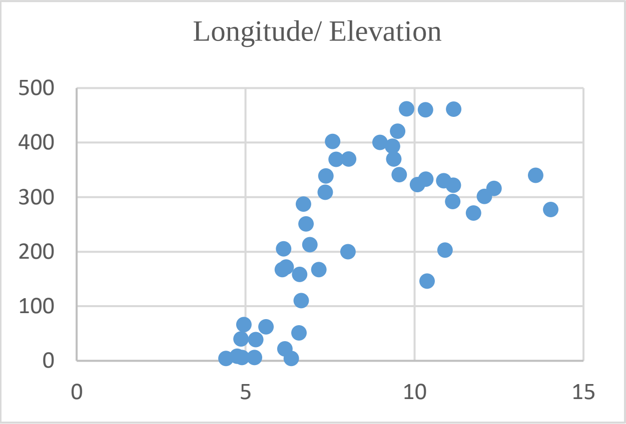
Figure 2: A flow chart of the study methodology showing the adopted steps and processes (Authors' drawing, 2020).

1.2 Result and Discussion.

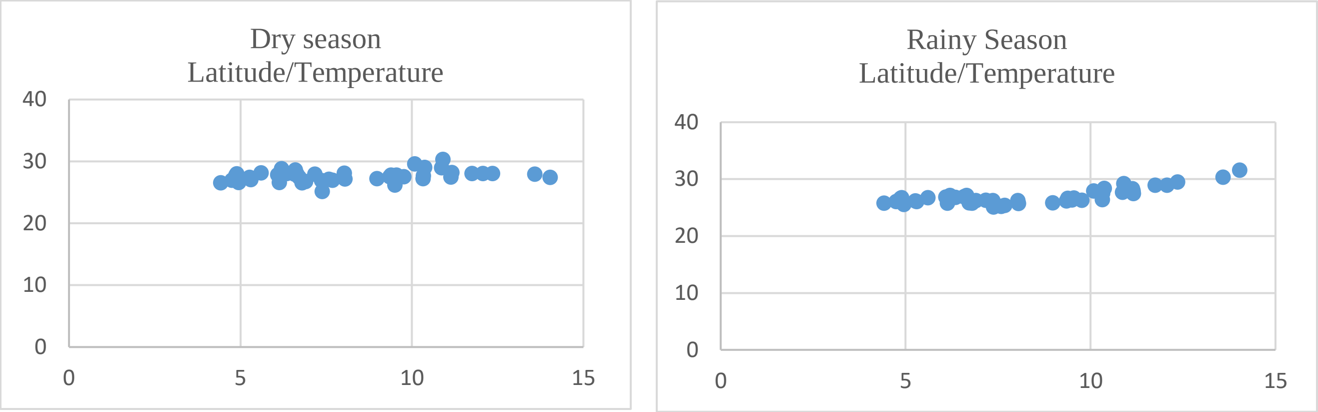
From the exploratory analyses carried out on the dry and rainy season average data from 1981 to 2010, we discovered that there is no correlation between the elevation of the station and the temperature (Figure 3a). The temperature of the region during both season is fairly homogenous with an increase of less than 7ºC all over. However, the temperature of the rainy season in West Africa increases with Longitude (Figure 3d), and the pattern shows that during the rainy season, the temperature increase as one travels farther from the Equator. The mean temperature during the dry season during the period under study 27.64451ºC and the mean temperature during the rainy season is 26.97349ºC. The station with the highest monthly average during the dry season is Navrongo, Ghana with 30.31075ºC and the lowest is Man, Cote d'Ivoire with 25.14132ºC. During the rainy season, the highest temperature is recorded in Dori, Burkina Faso with 31.56926ºC and, the lowest is Man, Cote d'Ivoire with 25.13031ºC (Figure 4).



a Scatter plot of the elevation and temperature



b. Scatter plot of longitude and elevation



c. *Scatterplot of latitude and temperature*

d. *Scatterplot of longitude and temperature*

Figure 3: Correlation between elevation and temperature (a), longitude and elevation (b), latitude and temperature in dry season (c) and latitude and temperature in rainy season (d) (source: Authors' analysis, 2020)

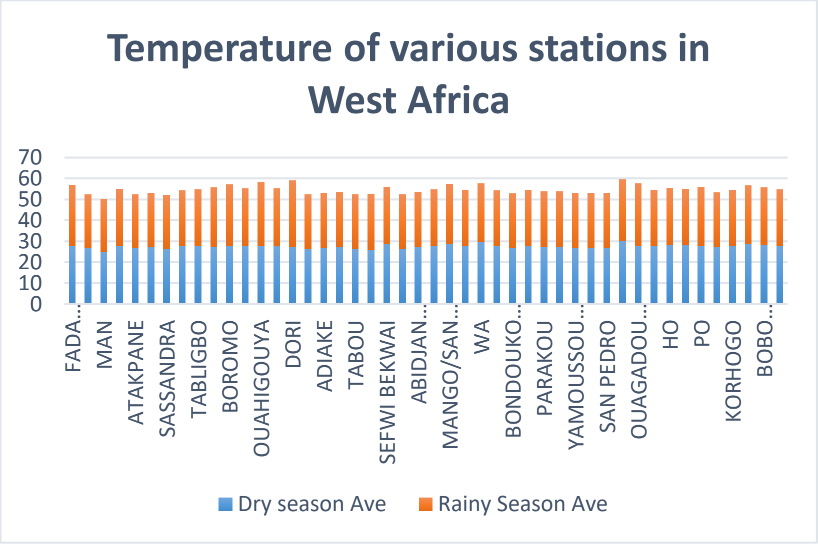


Figure 4: A bar chart showing the temperature distribution in both the rainy and dry season (Source: Authors' analysis)

Further analyses were carried out on the data, illustrated by the Voronoi map in Figure 5, showing that the distribution in both cases was not anisotropic. During the dry season, the temperature is highest in the regions around the Northern part of Ghana due to the long dry season in the region, and southern Ghana because it is parallel to the southeast trade wind.

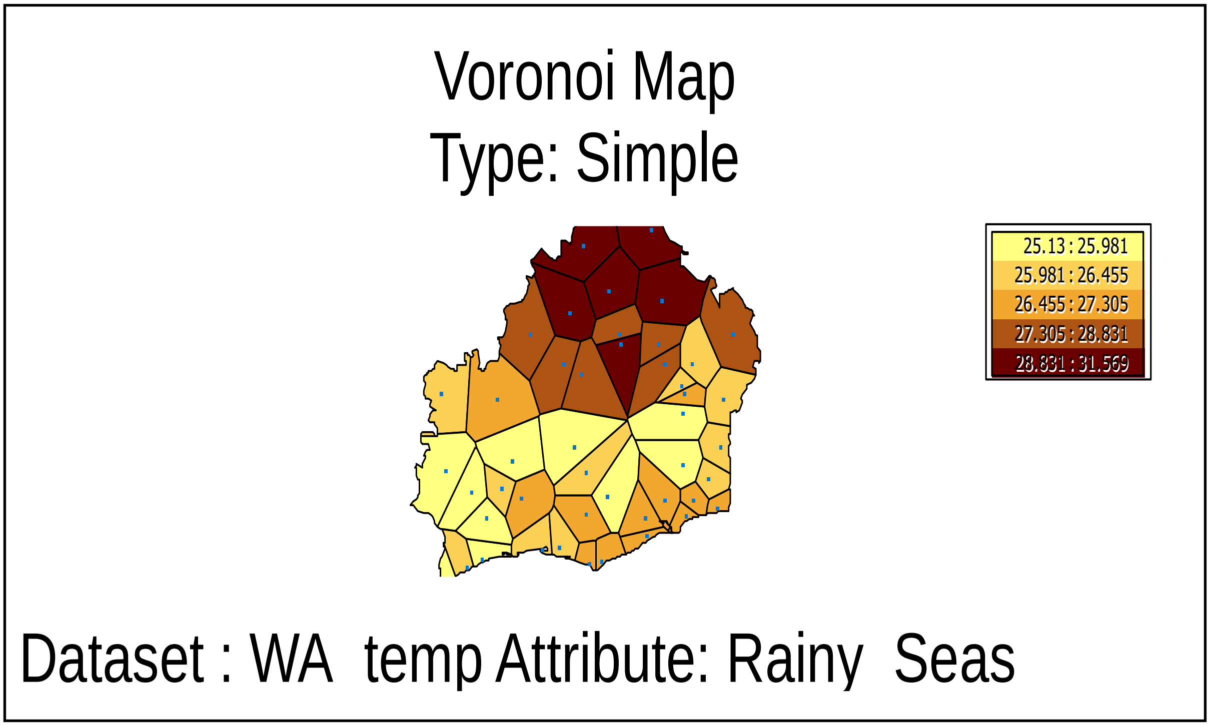


Figure 5: Voronoi Map showing the distribution of the average rainy season temperature in the study area (source: Authors' analysis, 2020)

1.3 Prediction Model.

1. **Rainy season**:
    i. Inverse Distance Weighed

We carried out a cross validation of the parameters of the model; sector type, maximum neighbours and minimum neighbours; to yield a model with a small mean error, as shown in table 2a, the best fit parameters are thus: circle 4 sectors, 10 maximum neighbours and 5 minimum neighbours.

Sector type	Maximum neighbours	Minimum neighbours	Mean error	Root-Mean-Square error (RMSE)
circle 1 sector	15	10	-0.0839	0.7753
circle 4 sector	10	5	-0.0692	0.7568
4 sectors 45 degrees offset	13	6	-0.0854	0.7815
circle 4 sector	10	6	-0.0742	0.7746
circle 8 sector	10	2	-0.077	0.75251
4 sectors 45 degrees offset	15	3	-0.0783	0.7382

Table 2a: IDW cross validation for rainy season

The cross validation of the parameters, table 2b, gave the best fit parameter as circle 8 sectors, 6 maximum neighbours and 1 minimum neighbours.

Sector type	Maximum neighbours	Minimum neighbours	Mean error	Root-Mean-Square error (RMSE)
4 sectors 45 degrees offset	5	2	-0.0584	0.7544
4 sectors 45 degrees offset	10	3	-0.0326	0.7258
circle 4 sectors	10	5	-0.0332	0.7228
circle 8 sectors	6	1	-0.0294	0.7278
4 sectors 45 degrees offset	5	1	-0.0584	0.7544
4 sectors 45 degrees offset	15	10	-0.0311	0.7319

Table 2b: Kriging cross validation for rainy season

The prediction models, created from the best-fit parameters, of the two interpolation methods, investigated, differ in that the kriging models (Figure 6) are smoother than the IDW models (Figure 7). The cross-validation for the rainy season, the mean error was smaller for the IDW (Table 2a) than the Kriging model (Table 2b).

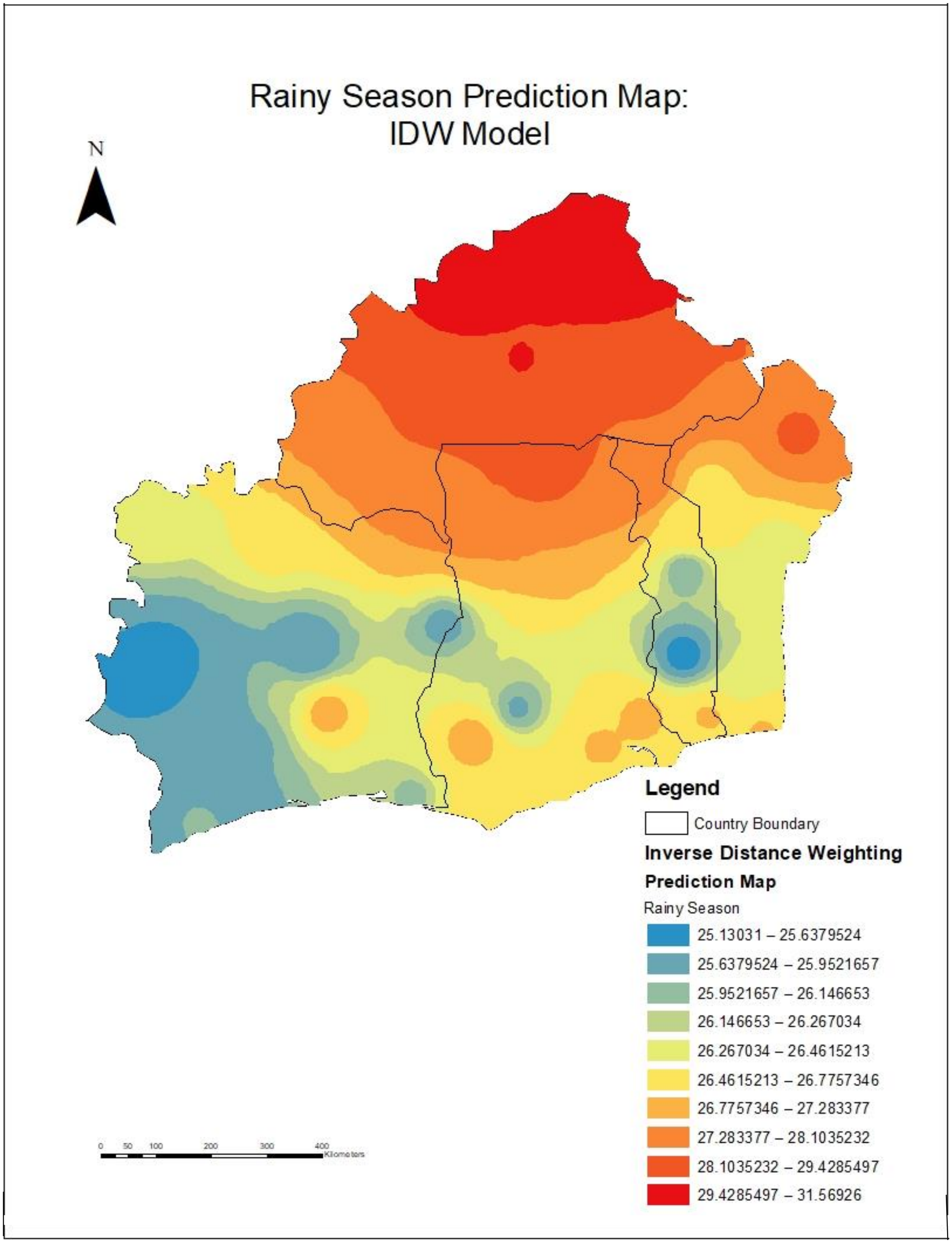


Figure 6: IDW model for the rainy season (Source: Authors' analysis, 2020)

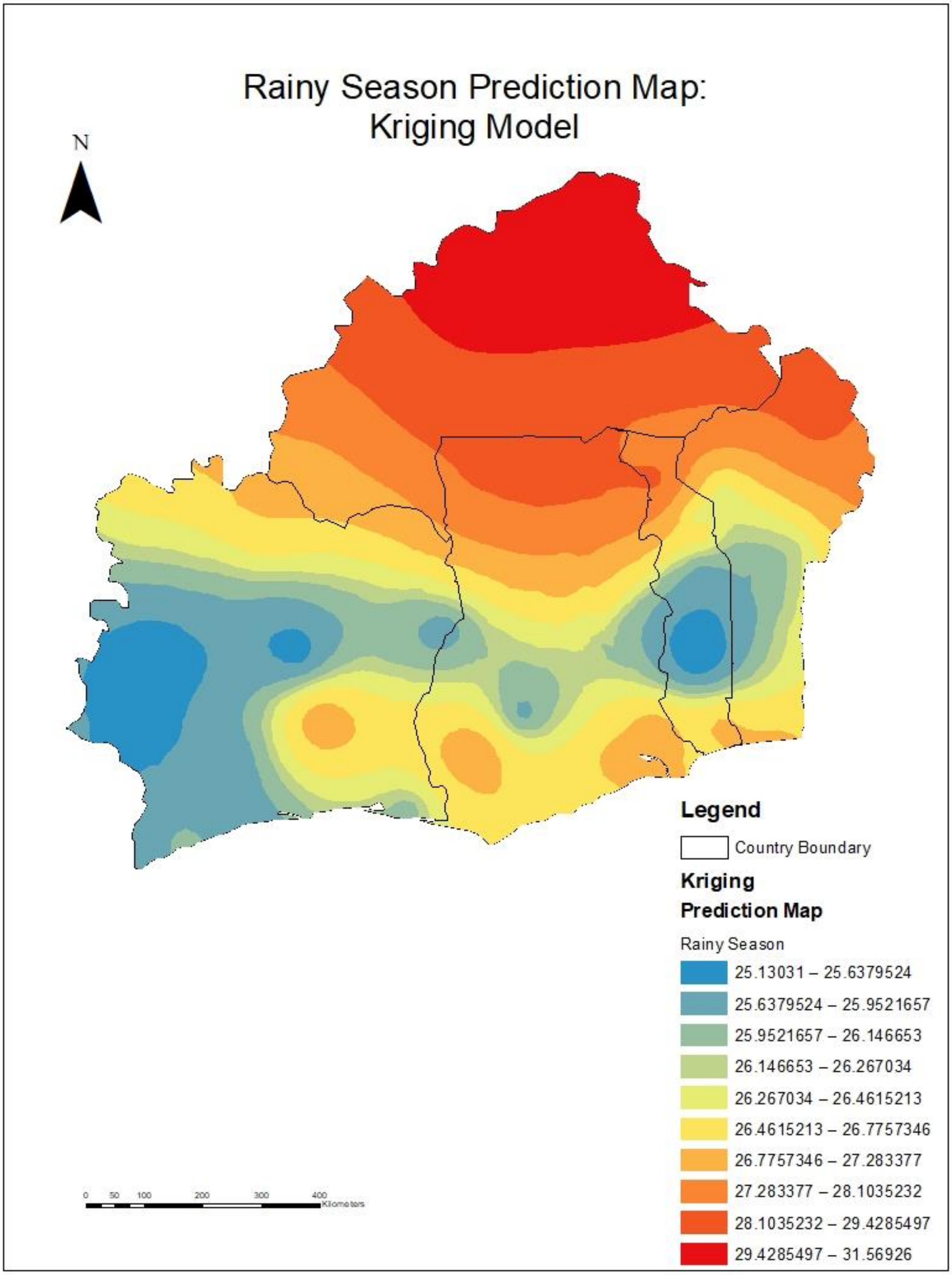


Figure 7: Kriging model for the rainy season (Source: Authors' analysis, 2020)

A. Dry season

i. Inverse Distance Weighted

The cross validation of the parameters, table 3a, gave the best fit parameters as 4 sectors 45 degrees offset, 12 maximum neighbours and 5 minimum neighbours.

Sector type	Maximum neighbours	Minimum neighbours	Mean error	Root-Mean-Square error (RMSE)
circle 1 sector	15	10	0.0764	0.7374
circle 4 sectors	10	5	0.0775	0.7418
4 sectors 45 degrees offset	12	5	0.0381	0.7474
circle 8 sector	13	4	0.0656	0.7308
4 sectors 45 degrees offset	17	7	0.0599	0.7303
4 sectors 45 degrees offset	10	2	0.0557	0.7307

Table 3a: IDW cross validation for dry season

ii. Kriging

When the cross validation of the parameters was carried out, table 3b, the best fit parameters were circle 8 sectors, 17 maximum neighbours and 5 minimum neighbours

Sector type	Maximum neighbours	Minimum neighbours	Mean error	Root-Mean-Square error (RMSE)
4 sectors 45 degrees offset	5	2	0.0257	0.7182
circle 4 sectors	10	2	0.0288	0.7148
4 sectors 45 degrees offset	10	5	0.0265	0.722
4 sectors 45 degrees offset	7	3	0.0282	0.7793
circle 8 sectors	17	5	0.0265	0.7193

Table 3b: Kriging cross validation for dry season

For the dry season model, the mean error was smaller for the kriging (Table 3a) than the IDW (Table 3b).

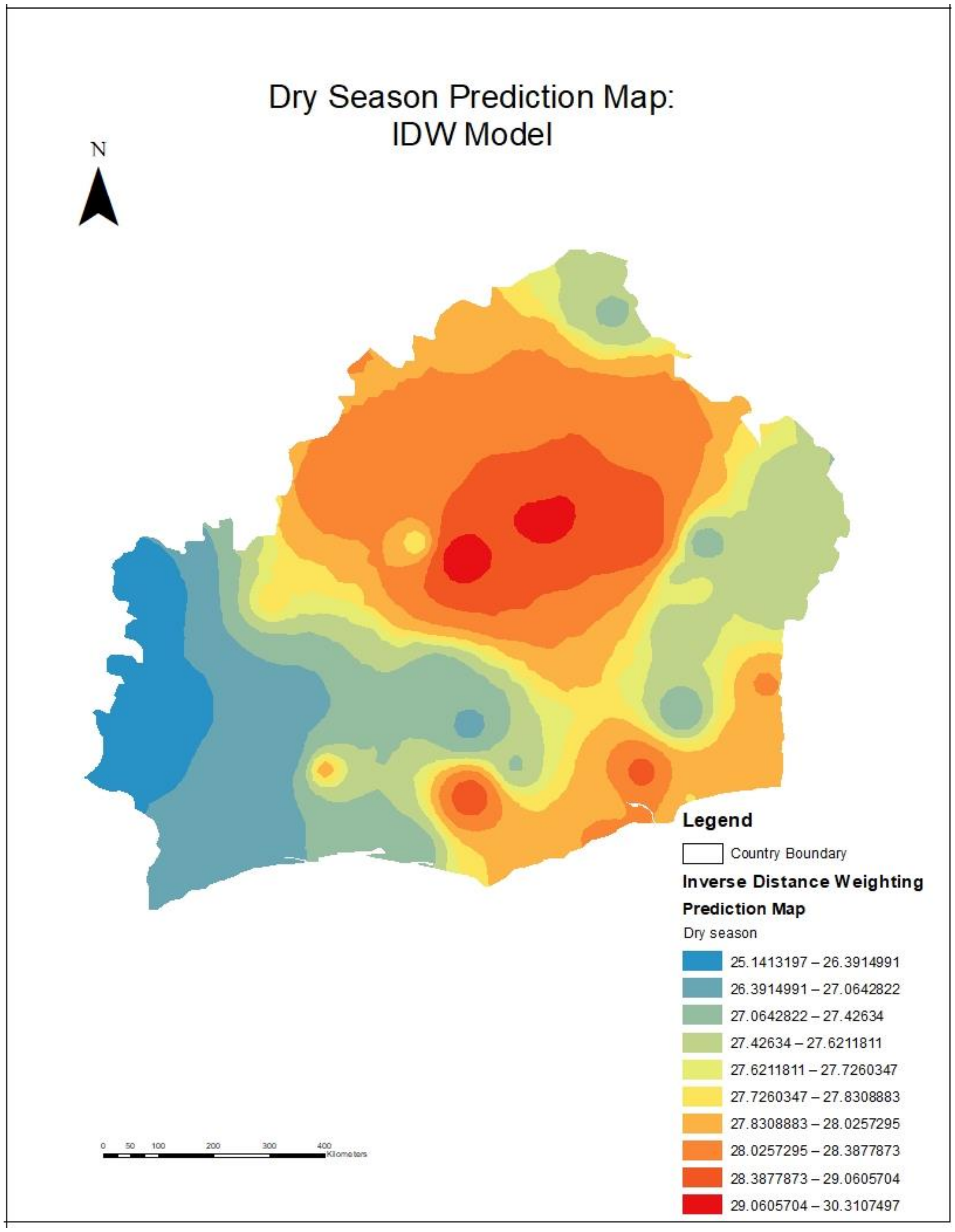


Figure 8: IDW model for dry season (Source: Authors' analysis, 2020)

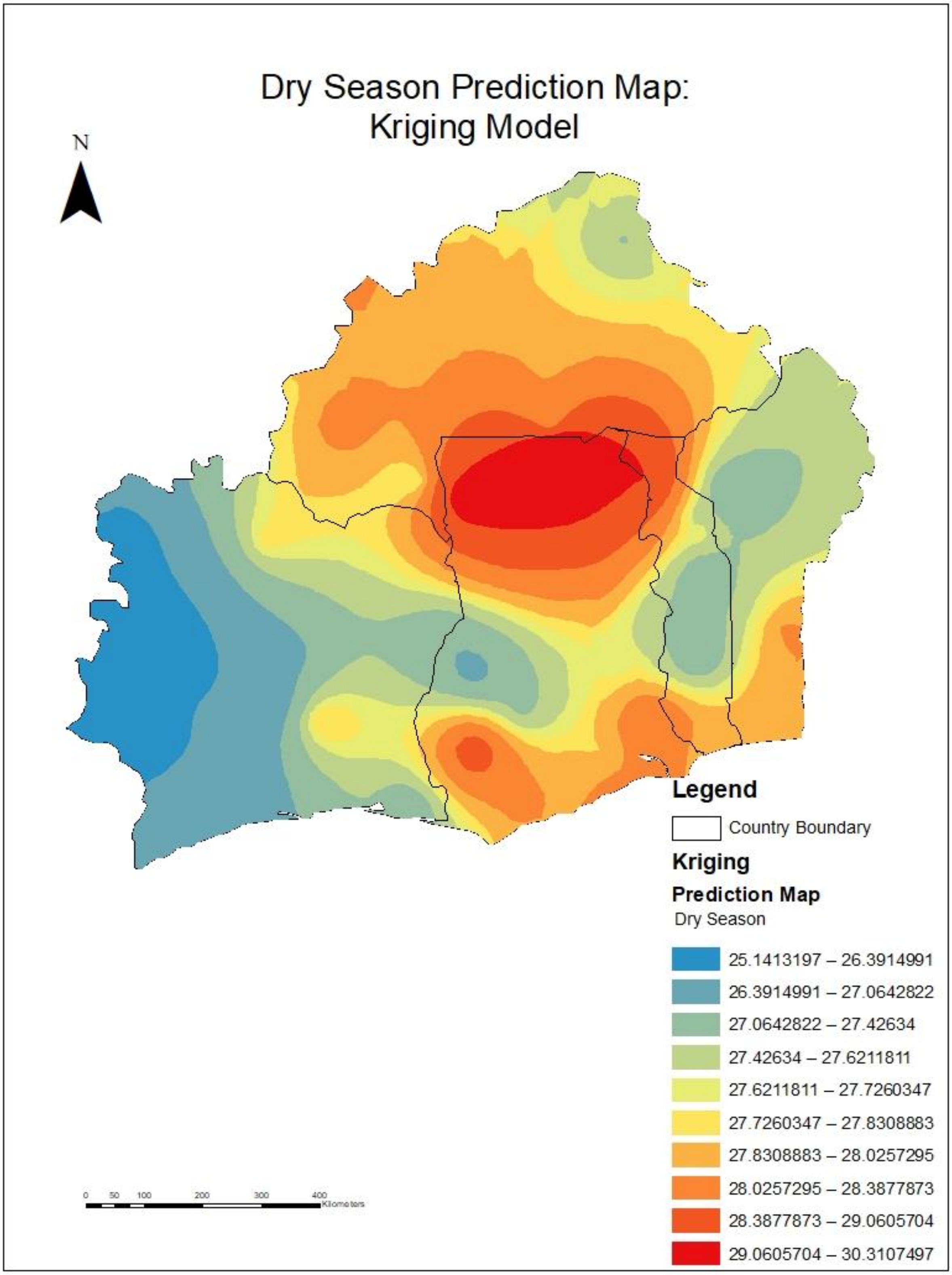


Figure 9: Kriging model for the rainy season (Source: Authors' analysis, 2020)

2. CONCLUSION

The conclusion is drawn from the project to justify the importance of making climatic maps that correspond closely to reality through different interpolation. Different interpolation techniques reveal that all methods have similar performance considering the error statistics but at the same time given acceptable results. Cross-validation may be a useful factor for predicting the relative performance of ordinary kriging and IDW, but ordinary kriging was a better choice than IDW with a nugget model. Cross-validation should not only be used as the sole criteria for deciding whether to use an interpolation procedure over another (Mueller et al., 2004).

The study revealed the significance of using GIS in mapping and modeling temperature data in the regions of West Africa. Temperature modeling is important in policy making for efficient planning and management of agricultural and economic activities. It provides temperature information for areas with no climatic data.

In concussion, this study supports the hypothesis that in West Africa, the average temperature during the dry season is higher than the average temperature during the rainy season. One limitation of this study is that the weather stations are not evenly distributed, which will cause a stretch of overcompensation on the models predicted.

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