

Deforestation in the Sahel

Trends and Correlations

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Introduction

Situated between the vast dunes of the Sahara and the dense forests of Central and Western Africa, the Sahel is subject to the extreme variations of climate that come with its geography. Drought is commonplace in this borderland of the world's largest desert, and the extended drought of the 1970s and 1980s that killed more than one hundred thousand people also raised alarm about the longterm desertification of the region (Agnew and Chappell 1999, 299). Many researchers have also blamed human factors for what they perceive to be the retreating greenbelt in the Sahel. The rapid population growth common in less developed countries also characterizes the demographic trends of the Sahel, and researchers during the 1980s argued that these burgeoning population's slash-and-burn agriculture and dependence on woodfuels was contributing to the deforestation and desertification of the region.

By the 1990s studies had disproven the thesis that fuelwood use was driving deforestation in the Sahel and elsewhere. Tor Benjaminsen published several important papers proving that woodfuel use had little to no affect on deforestation in the Sahel. The droughts of previous decades also ended in the 1990s and satellite imagery actual shows a greening trend across the Sahel from the mid-1990s to early 2000s (Eklundh and Olsson 2003, 13-1). All indicators seemed to point away from desertification, either by potential environmental and human causes, but in 2010 this all changed when a severe drought not only plunged the region into another famine, but also renewed concerns about desertification. Especially when considered with the threat that global warming may cause further droughts in the future, there is growing fear that deforestation in the Sahel is on the rise.

This paper discusses the historic debate around deforestation in the Sahel and uses GIS as a tool to analyze relationships between deforestation and both human and environmental factors. The results of this study confirm the modern thesis that the so-called population pressure on the Sahel's forests are not nearly as important as the environmental pressures.

The Sahel

The Sahel is a ecoclimatic region that crosses through 14 African countries, reaching from the Atlantic Ocean in the west to the Red Sea in the east. Subsistence agriculture is the most important economic activity for the vast majority of the population and the region relies on only three to four months of rainfall each year to support its crops (UNEP 2006, 2).

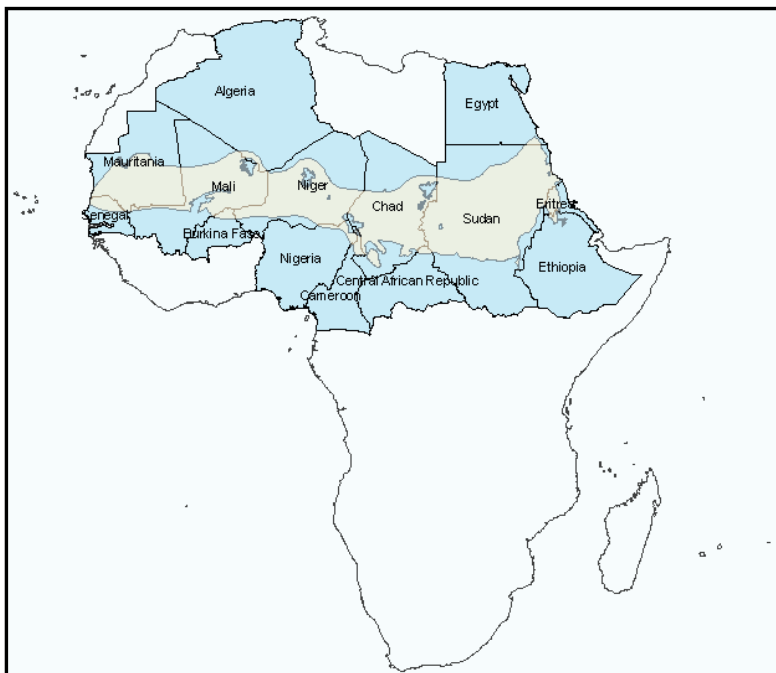


Figure 1-1: Countries of the Sahel ecoclimatic region.

Causes of Deforestation in the Sahel

Environmental Causes

The Sahel has a long history of droughts, but the longest in recent history lasted from the late 1960s to the early 1990s. According to the United Nations Environmental Programme (UNEP), average rainfall fell by as much as 50% during this period (UNEP 2006, 9). Figure 1-2 shows the trend of rainfall in the Sahel over much of the twentieth century.

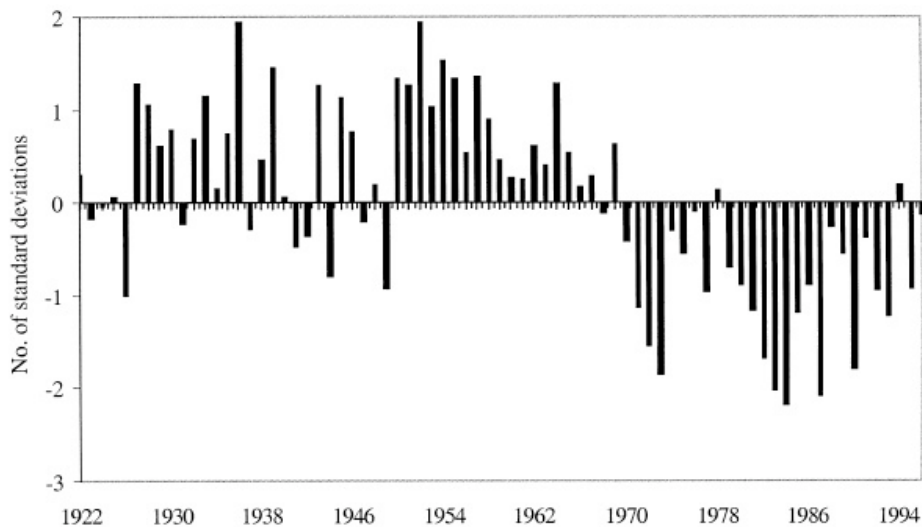


Figure 1-2: Rainfall in the Sahel, 1922-1996.

Vegetative greenness, as measured by Normalized Difference Vegetation Index (NDVI), is highly correlated with rainfall in the Sahel (Nicholson, Davenport, and Malo, 1990, 220-223; Hickler et al. 2005, 1). Eklundh and Olsson (2003) show that the Sahel exhibited a strong greening trend between 1982 and 1999 as the region slowly pulled out of the decades-long drought (13-1).

Although some authors (see Sissoko et al. 2011) are concerned that global warming will cause desertification in the Sahel, the International Panel on Climate Change (IPCC) concluded in its 2007 Assessment Report that it is unclear how climate change will affect

rainfall in the region (Christensen 2007, 866). It is possible that warming may increase rainfall and continue the recent greening trend.

Drought during the 1970s and 1980s reduced vegetation in the Sahel and satellite imagery in the 1990s showed that the end of the drought brought increased greening. Climate, then, is a clear driver of deforestation in this vulnerable ecoclimatic region, but the effects of long-term climate trends are less certain.

Human Causes

During the Sahel's long drought, researchers commonly believed that rapid population growth in the region put "population pressure" on an already fragile ecological region (Vierich and Stoop 1990, Ramaswamy and Sanders 1992). This Malthus-inspired argument explains how increasing population density puts pressure agricultural yields as well as woodfuel supplies, which is the primary source of fuel in the region.

Regarding agriculture, the "population pressure" theory explains how a growing population puts pressure on farmers to increase their yields, but how yields actually decrease. When the nutrients of the soil are depleted, farmers till more marginalized lands, often using slash-and-burn deforestation strategies to do so (Ramaswamy and Sanders 1992, 362-363). Deforestation because of the expansion of agriculture has been a seriously problem in many Sahelian countries, but has attracted most attention in northern Nigeria where population pressures and deforestation rates have been among the highest in the Sahel (Odihi 2003, 238).

By the 1990s new research discredited the theory that woodfuel use caused deforestation in the Sahel. Ribot (1999) explains that, although researchers in the 1980s

projected the depletion of Sahelian forests to cause a woodfuel shortage crisis in the 1990s, this crisis never came (291). Benjaminsen (1993) and Hansfort and Mertz (2011) conducted studies on deforestation and woodfuel use in Mali, and they came to the same conclusion: there is no clear connection between woodfuel use in areas of high population density and deforestation (Benjaminsen 1993, 407; Hansfort and Mertz 2011, 594).

GIS Approach

The goal of this study is not to determine the causes of deforestation in Sahel, but rather to simply discover where deforestation is happening in the region. Correlations between locations of deforestation and other spatial factors may shed light on the underlying causes of deforestation in the region.

This study conducts a GIS analysis of satellite imagery and vector map features to investigate relationships between spatial factors in the Sahel. The primary level of analysis is the relationship between deforestation and the human and environmental factors discussed above. Regarding the human factors, this study looks for correlation between population density and deforestation. This paper also explores the relationship between poverty and deforestation as well as the difference between deforestation near cities and deforestation near towns. Regarding environmental factors, this paper compares mean temperature and mean precipitation to deforestation rates, and explores the relationship between deforestation and land cover, soil type, proximity to water, and various measures of vegetative greenness.

This GIS analysis uses ArcGIS software to build a regression model of deforestation in the Sahel. Figure 1-3 shows the framework used to prepare the data for the model. The

study uses Ordinary Least Squares (OLS) regression to determine the global relationship between the dependent variable and the explanatory variables. After the OLS identifies the explanatory variables in the model, and once a Moran's I test on the residuals of the OLS determines that there is no spatial autocorrelation in the model, this study uses a Geographic Weighted Regression test to determine the local relationships between the dependent and explanatory variables.

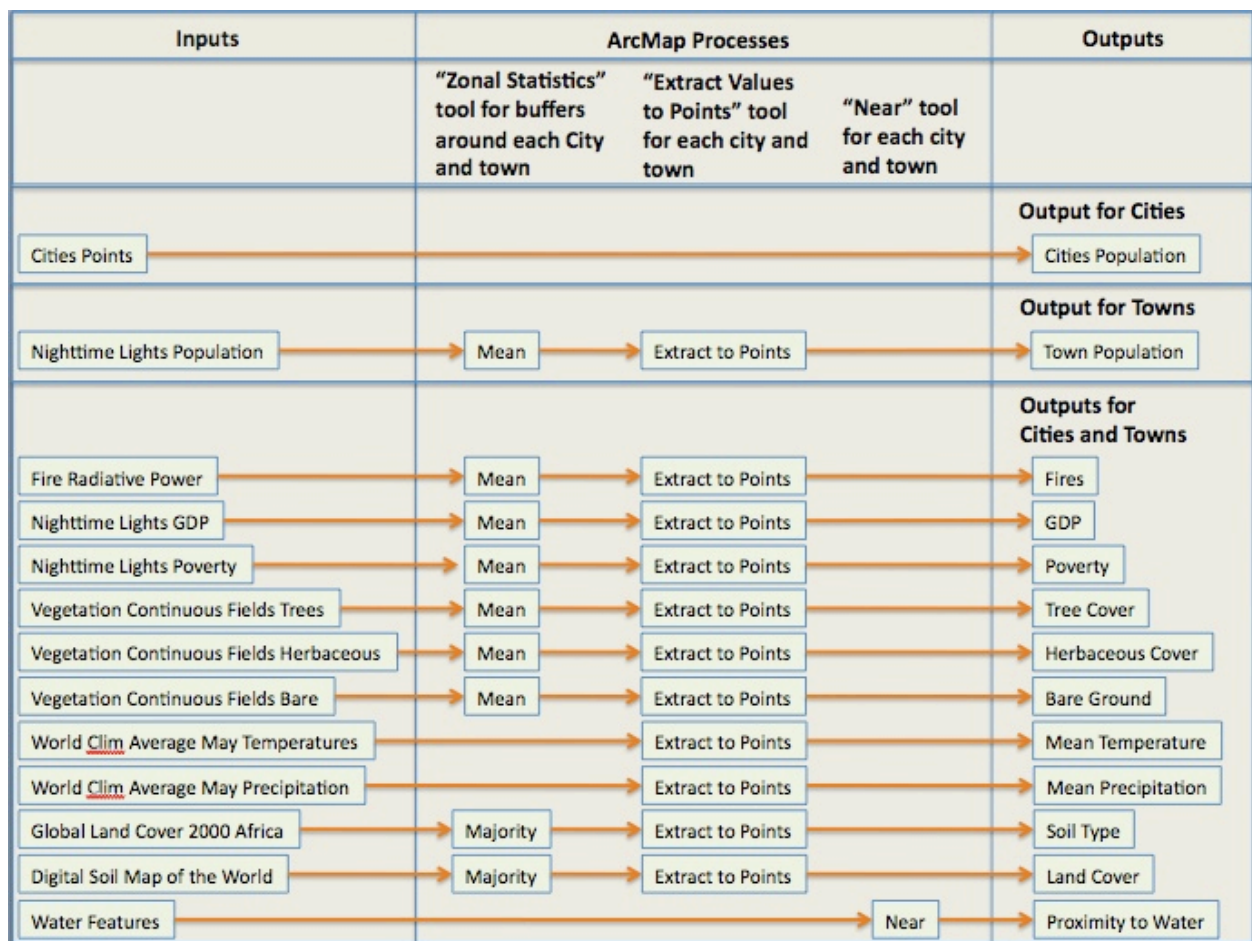


Figure 1-3: The four-part approach that incorporates four parameters: houses, roads, total visual exposure, and average visual exposure.

Data and Variables

Table 1-1 shows the dependent and independent variables and each of their sources. Much of the data comes from NASA's MODIS sensor on the Terra satellite, while other important sources include the Oak Ridge National Laboratory (ORNL), the Defense Meteorological Satellite Program's (DMSP), World Clim, FAO, and Esri.

Variable	Source
Population	ESRI World Map; ORNL LandScan
GDP	NOAA, using DMSP Nighttime Lights and ORNL LandScan
Poverty	NOAA, using DMSP Nighttime lights and ORNL LandScan
Fire Radiate Power	NOAA, MODIS Fire Radiative Power
Percent Tree Cover	GLCF, MODIS Vegetation Continuous Fields
Percent Herbaceous Cover	GLCF, MODIS Vegetation Continuous Fields
Percent Bare Ground	GLCF, MODIS Vegetation Continuous Fields
Mean Temperature	WorldClim 1950-2000 May Temperature
Mean Precipitation	WorldClim 1950-2000 May Precipitation
Land Cover	FAO, JRC Global Land Cover 2000 Africa
Soil Type	FAO, FAO-UNESCO Digital Soil Map of the World
Proximity to Water	ESRI World Map

Table 1-1: Dependent and independent variables and their sources.

Dependent Variable: Fire Radiative Power

This study uses the MODIS Fire Radiative Power product, available through the website of the National Oceanic and Atmospheric Administration (NOAA). The product measures fire locations and radiant heat output, measured in MWatts (NOAA 2012). For the purposes of this study, Fire Radiative Power serves as a proxy measure for deforestation. This study

uses the Mean function in the Zonal Statistics tool in ArcMap to calculate the average radiant heat output value within a 50 km radius of each city and town in the study area.

Exploratory Variable #1: Population

The LandScan product from the Oak Ridge National Laboratory (ORNL) is an innovative product that estimates population at a resolution of 30 arc-seconds by disaggregating census data on a country-by-country basis. Population is measured as the average number of people (in integers) per cell, which represents an estimate of where people are at any point during the day, and not just where they sleep (ORNL 2012). This study uses the Mean function in the Zonal Statistics tool in ArcMap to calculate the average population value within a 5 km radius of each town in the study area. The populations of cities in this study come from Esri's world map.

Exploratory Variable #2: GDP

Ghosh et al. (2010) created a map estimating Gross Domestic Product (GDP) at a resolution of 30 arc-seconds (150). They accomplished this by running regressions to determine the relationship between DMSP's Nighttime Lights and official national and sub-national estimates of GDP. Using the unique coefficient generated by the regression model, the authors disaggregated the GDP values for each country based on LandScan's population distribution map. The resulting map of GDP is measured in millions of 2006 US dollars (at Purchasing Power Parity) per square kilometer (Ghosh et al. 2010, 150-151). This study uses the Mean function in the Zonal Statistics tool in ArcMap to calculate the average GDP value within a 20 km radius of each city and within a 5 km radius of each town in the study area.

Exploratory Variable #3: Poverty

Elvridge et al. (2006) created a poverty index map at a resolution of 30-arc seconds by dividing the Landsat population count by the brightness of DMSP Nighttime Lights. Poverty on the map is expressed as a Normalized Poverty Index (NPI) that represents the percentage of the population living under \$2 per day (Elvridge et al 2006, 9). This study uses the Mean function in the Zonal Statistics tool in ArcMap to calculate the average NPI value within a 20 km radius of each city and within a 5 km radius of each town in the study area.

Exploratory Variable #4: Percent Tree Cover

This NDVI product is one of the three data layers that make up MODIS Vegetative Continuous Fields (the other two data layers are exploratory variables #5 and #6) (DeFries et al. 2000). While some land cover imagery products (such as the one used for exploratory variable #9) use discrete categories to mark boundaries between types of vegetation, this NDVI product shows tree cover as a continuous field represented as a percentage of the cell covered in trees. This study uses the Mean function in the Zonal Statistics tool in ArcMap to calculate the average percentage of tree cover within a 50 km radius of each city and town in the study area.

Exploratory Variable #5: Percent Herbaceous Cover

This variable represents the herbaceous cover data layer that comprises the MODIS Vegetative Continuous Fields product (DeFries et al. 2000). Herbaceous cover in this map is represented as a percentage of each cell covered in herbaceous cover. This study uses the Mean function in the Zonal Statistics tool in ArcMap to calculate the average percentage of herbaceous cover within a 50 km radius of each city and town in the study area.

Exploratory Variable #6: Percent Bare Ground

This variable represents the bare ground data layer that comprises the MODIS Vegetative Continuous Fields product (DeFries et al. 2000). Bare ground in this map is represented as a percentage of each cell that is bare ground. This study uses the Mean function in the Zonal Statistics tool in ArcMap to calculate the average percentage of bare ground within a 50 km radius of each city and town in the study area.

Exploratory Variable #7: Mean Temperature

This data comes from the WorldClim, an organization associated with the University of California, Berkeley. The product is a collection of interpolated surfaces of monthly mean temperatures collected by thousands of weather stations around the world. The data used in this study is from a world map mean temperatures for the month of May for all the years between 1950 and 2000 (WorldClim 2005). The reason this study uses May temperatures is that it represents neither the hottest nor the coldest time of year for the Sahel. This study simply used the Extract Value to Point tool in ArcMap to extract the mean temperature for each city and each town in the study area.

Exploratory Variable #8: Mean Precipitation

This data also comes from WorldClim and the methods behind the data are the same. This study simply used the Extract Value to Point tool in ArcMap to extract the mean precipitation level for each city and each town in the study area.

Exploratory Variable #9: Land Cover

The EU's Joint Research Council (JRC) produced this world map of land cover (Joint Research Center 2012). Unlike the Vegetative Continuous Fields layers, land cover in this map is comprised of discrete points. To prepare this data for the model, this study

calculates the most common land cover type within a 50 km radius of each city and town by using the Majority function in the Zonal Statistics tool in ArcMap.

Exploratory Variable #10: Soil Type

The FAO and UNESCO produced the Digital Soil Map of the World (FAO 2012). To prepare this data for the model, this study first converted the vector layer to raster and then used the Zonal Statistics tool in ArcMap to calculate the soil type that represented the majority of the soil within a 50 km radius of each city and town.

Exploratory Variable #11: Proximity to Water

The water features in this study come from Esri's world map data layer. To prepare this data for the model, this study used the Near tool in ArcMap to calculate the distance to water from each city and town.

Results

Ordinary Least Squares

The first test in this study is an Ordinary Least Squares (OLS) regression of all the exploratory variables against the dependent variable, namely Fire Radiative Power, which serves as a proxy for deforestation in the study. This first test shows which variables have a statistically significant relationship with the dependent variable, and in the case of this study, only one variable passed the tests. Mean precipitation was the only variable that showed a statistically significant relationship with fires in the Sahel, and this relationship was significant for locations surrounding cities but not for towns.

Fires near cities

The table below shows the results of the OLS exploring the relationship between fires near cities and the independent variables.

Variable	Coef	StdError	t_Stat	Prob
Intercept	126.181917	798.657971	0.157992	0.875785
POPULATION	0	0.000001	0.255462	0.800542
PROXIMITY_WATER	-0.000002	0.000002	-0.843475	0.407293
TREE_COVER	-1.23461	8.025293	-0.15384	0.879023
HERBACEOUS_COVER	-1.249672	8.020495	-0.15581	0.877487
BARE_GROUND	-1.242322	8.019071	-0.154921	0.87818
SOIL_TYPE	-0.018476	0.023092	-0.800106	0.4315
TEMPERATURE	-0.001739	0.014151	-0.122907	0.903205
PRECIPITATION	0.041229	0.018642	2.211629	0.036763
GDP	-0.045858	0.143397	-0.319797	0.751889
POVERTY	-0.005193	0.016924	-0.306816	0.761629
LAND_COVER	-0.042023	0.093532	-0.449291	0.657252

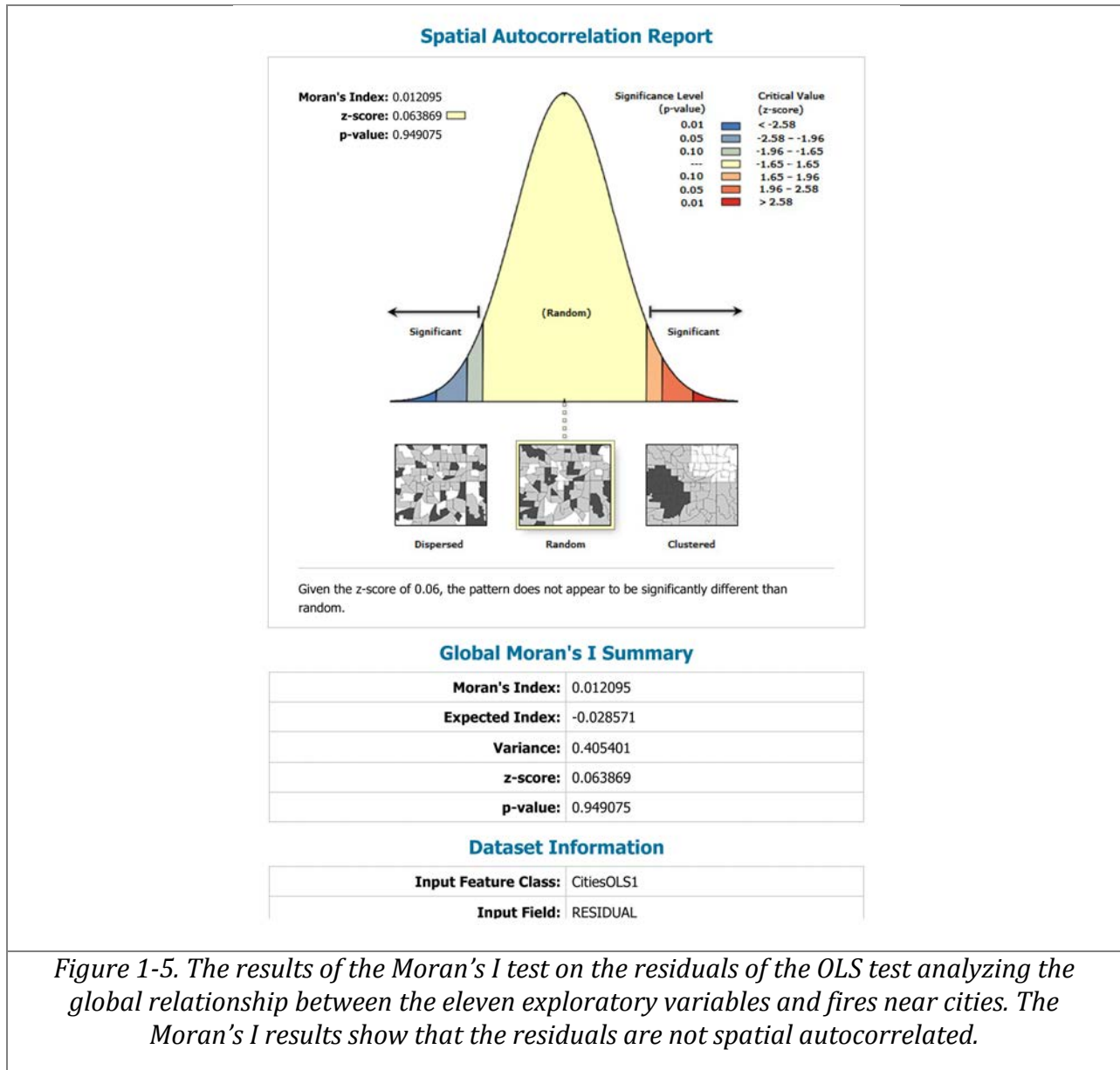
Diag_Name	Diag_Value
AIC	105.073306
AICc	121.618761
R2	0.572996
AdjR2	0.377286
F-Stat	2.927779
F-Prob	0.01344
Wald	32.765304
Wald-Prob	0.000574
K(BP)	16.052759
K(BP)-Prob	0.139183
JB	242.43269
JB-Prob	0
Sigma2	0.789835

Figure 1-4. The results tables of the OLS test analyzing the global relationship between the eleven exploratory variables and fires near cities.

The results table shows that only precipitation has a statistically significant relationship with fires near cities in the Sahel. Testing at a 95% confidence interval, none of the variables except precipitation come anywhere close to being significant, as indicated by their high p-values (“Prob” on the table). Precipitation has a p-value of 0.036763, which makes it significant, and the R-squared value of 0.57 indicates that the relationship is significant.

After finding this relationship, the next step is to run a Moran’s I test on the residuals of the OLS to determine if the results are spatially autocorrelated, which would represent

bias in the model. The Moran's I test for cities shows no spatial autocorrelation (see Figure 1-5).



Fires near towns

All the variables, including precipitation, failed the initial OLS for fires near towns. The table below shows the results of the OLS.

Variable	Coef	StdError	t_Stat	Prob
Intercept	497.466587	3366.652611	0.147763	0.883488
PROXIMITY_WATER	-0.000001	0.000001	-1.518595	0.138997
TREES_COVER	-4.976119	33.6634	-0.14782	0.883444
HERBACEOUS_COVER	-4.983662	33.664887	-0.148037	0.883274
BARE_GROUND	-4.990353	33.664296	-0.148239	0.883116
SOIL_TYPE	-0.00726	0.012751	-0.569363	0.573212
TEMPERATURE	0.003103	0.003505	0.885494	0.382709
PRECIPITATION	0.008549	0.008748	0.977237	0.336018
GDP	-0.58024	0.754	-0.769549	0.447392
POVERTY	-0.002959	0.004109	-0.720312	0.47673
POPULATION	-0.000083	0.000298	-0.279946	0.781379
LAND_COVER	0.040794	0.027876	1.463448	0.15341

Diag_Name	Diag_Value
AIC	51.561809
AICc	64.113534
R2	0.441789
AdjR2	0.243714
F-Stat	2.230416
F-Prob	0.039059
Wald	2548.26676
Wald-Prob	0
K(BP)	17.743136
K(BP)-Prob	0.087735
JB	118.131953
JB-Prob	0
Sigma2	0.147165

Figure 1-6. The Coefficient and Diagnosis results tables of the OLS test analyzing the global relationship between the eleven exploratory variables and fires near cities.

At a 95% confidence interval, only proximity to water and land cover come anywhere close to having significant P-values (at 0.138997 and 0.15341 respectively). None of the other variables come anywhere close to having a significant relationship, including precipitation, which has a P-value of 0.336018. With an R-squared of 0.441789, there is no statistically significant relationship between the independent variables and fires near towns.

The Moran’s I test for towns also shows problems with the data. Figure 1-7 below shows that the results for the towns OLS have a dispersed distribution. This result indicates that there is an element of bias in the portion of the study regarding towns, and that the results of this portion of the study are unreliable.

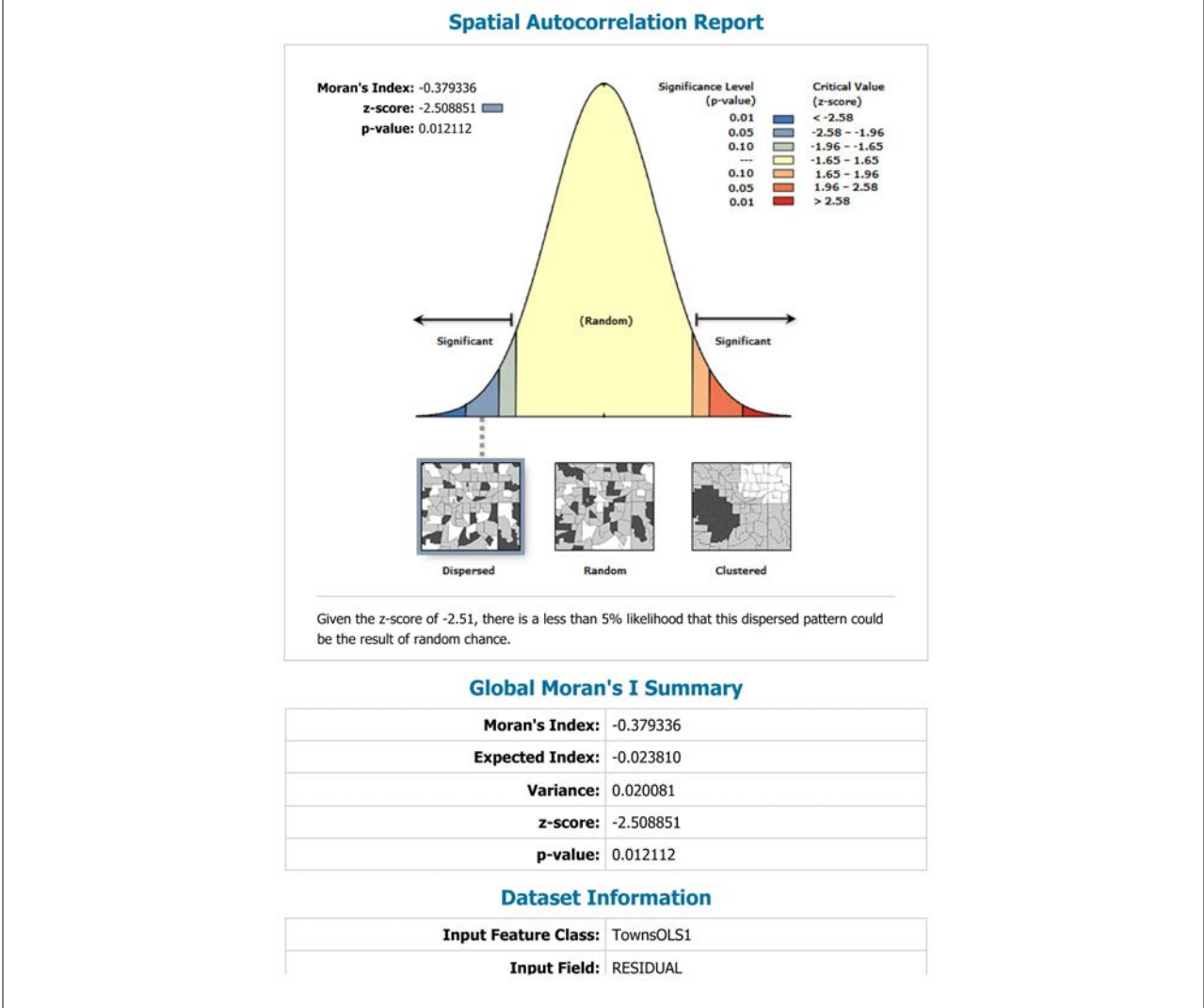


Figure 1-7. The results of the Moran's I test on the residuals of the OLS test analyzing the global relationship between the eleven exploratory variables and fires near towns. The Moran's I results show that the residuals have a dispersed distribution.

Ordinary Least Squares: Fires near cities and precipitation only

To confirm the relationship between fires near cities and precipitation, this study ran a second OLS test isolating the relationship between the two variables. See Figure 1-8 for the results of the test.

Variable	Coef	StdError	t_Stat	Prob
Intercept	-0.044253	0.072155	-0.61331	0.543752
CITIESEXTRACTPRECIP.PRECIP	0.012557	0.002288	5.489318	0.000004

Diag_Name	Diag_Value
AIC	29.04385
R2	0.469849
AdjR2	0.454256
F-Stat	30.132615
F-Prob	0.000004
Wald	9.365734
Wald-Prob	0.002211
K(BP)	13.802362
K(BP)-Prob	0.000203
JB	40.133212
JB-Prob	0
Sigma2	0.1243

Figure 1-8. The Coefficient and Diagnosis results tables of the OLS test analyzing the global relationship between precipitation and fires near cities.

The results tables show that the test confirms a relationship at an extremely high confidence interval. The precipitation variable has a P-value of 0.000004, which is far beyond the 0.05 level (95% confidence) used in this test. The R-squared for this test is not as impressive, but still shows that nearly 50% of the variation in fires can be accounted for by variation in precipitation. The Koenker’s BP statistic of 0.000203 also shows that the results have nonstationarity, which indicates that the variables are appropriate for a geographic weighted regression.

The equation for this model is as follows:

$$\text{Fires Near Cites} = 0.012557(\text{Precipitation}) - 0.044253$$

Having determined this relationship, it is important to once again check for spatial autocorrelation in the data. The Moran’s I test on the residuals of this OLS test once again show that the data have a random distribution, which indicates there is no bias in the results and that they are reliable (see Figure 1-9).

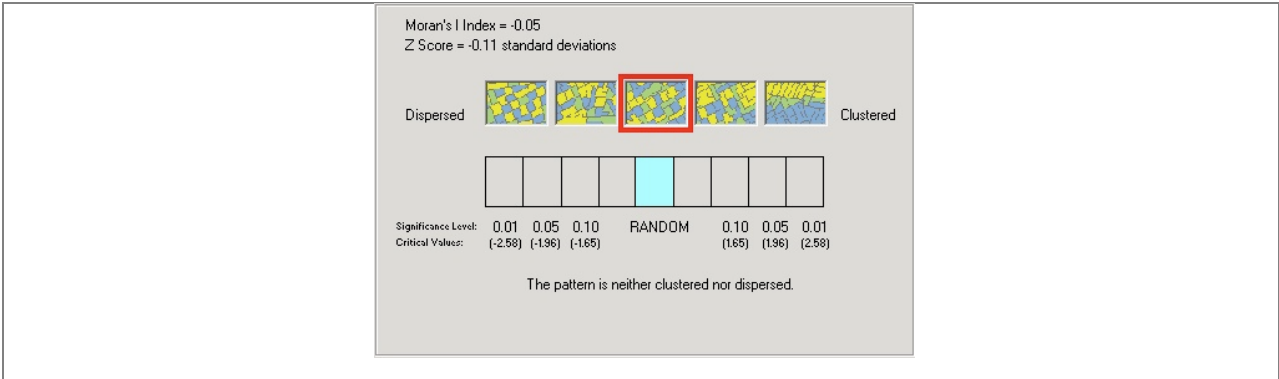


Figure 1-9. The results of the Moran's I test on the residuals of the OLS test analyzing the relationship between precipitation and fires near cities. The Moran's I results show that the residuals are not spatially autocorrelated.

Geographic Weighted Regression

The OLS tests showed global relationships across the study area. Geographic Weighted Regressions (GWRs) can be useful because they analyze local relationships and generate models for each location in the data set. Since the only statistically significant relationship in this study is between fires near cities and precipitation, and since Koenker's BP test showed nonstationarity for the relationship, this study conducts a GWR for these variables. See Figure 1-10 for the results of the test.

VARNAME	VARIABLE
Bandwidth	686386.441059
ResidualSquares	2.849761
EffectiveNumber	11.538761
Sigma	0.341323
AICc	40.276583
R2	0.935806
R2Adjusted	0.908149

Figure 1-10. The results of the GWR test analyzing the local relationships between precipitation and fires near cities.

The results show a surprisingly strong relationship between the variables. With an R-squared of 0.935806 and an adjusted R-squared of 0.908149, the test shows that nearly all of the variation in fires can be attributed to variations in precipitation.

Discussion

The results of this study confirm the research about deforestation in the Sahel. Population density does not seem to have an effect on deforestation in the region. Farmers do not seem to be more likely to engage in slash-and-burn agriculture near cities or in the remote countryside near only villages. Economics also does not have a positive or negative correlation with deforestation. This is also not surprising, considering there is very little wealth in the Sahel, either in cities or in towns. GDP is extremely low while poverty is everywhere in the region. Considering the relatively small range of wealth and poverty in the region, it is logical that there is no clear relationship between wealth and deforestation.

It is more surprising that there is no correlation between any of environmental variables and fires, except for precipitation. Deforestation is no more likely where there are trees than where there are no trees. Clearly there is more chance of deforestation in forested areas than in the desert. The global relationships analyzed in the OLS seem to fall short in this case. Perhaps a GWR would be better suited to this dataset, considering the vast differences in vegetation between the southern and northern parts of the Sahel.

Soil type does not seem to be an important factor, and neither does proximity to water. Presumably there are more trees near water than far away from water, but again, the model does not find this relationship to be significant. Temperature is not an important factor, and this is a reasonable conclusion considering the dataset has relatively little variation in latitude or altitude, which are two of the primary drivers of temperature change.

Finally, precipitation is the only variable to exhibit a relationship with fires in the Sahel. Although this was a surprising result at first since rains put out fires, upon further inspection, the result is reasonable. Fires are either caused by humans or by the lightning strikes, but whichever the case, both humans and lightning strikes tend to be where the rain is. It should be no surprise then that precipitation is highly correlated with fires.

Population does not correlate with fires though. These results confirm studies that show that forests near Sahelian cities are not being deforested any faster than forests in the countryside (Hansfort and Mertz 2011, 594). The only reasonable conclusion, then, is that the primary driver of deforestation in the Sahel is lightning strikes. Stepping back to look at fires in all of Africa (see Figure 2-5 in the Appendix), we see that fires are common through areas that have lots of rainfall (see Figure 2-5 in the Appendix), but are less common in the Congo rainforest where the most rainfall falls on the continent. Though this seems to oppose the theory that fires are primarily driven by lightning strikes, it actually shows that lightning strikes in semi-arid regions like the Sahel are more likely to cause fires than in extremely wet places like the Congo rainforest.

Additional Considerations

There are many ways to improve this study. The most obvious problem is that some of the town points are not centered directly over the towns in the satellite imagery. This is particularly a problem for the Nighttime Lights and LandScan layers. Many of the town points are positioned over dark areas of the satellite imagery, near to the lights of the towns. This study attempts to account for this problem by using a 5 km buffer around towns when calculating population, GDP, and poverty. It would be better yet to simply move the town points to center them over the towns in the satellite imagery.

Another problem is that two of the region's largest cities, Port Sudan and Saint Louis, were left out of the analysis because of their location on coasts. It was misleading to calculate average values of population, GDP, etc. within a 50 km radius when the ocean values distorted the results. With more time, this would be simple problem to fix.

The boundary of the project area could also have affected the results. The boundary for the Sahel comes from Esri's world map biomes layer, but it seems to have an irregular shape that doesn't necessarily reflect the actual Sahel region. For instance, the southeastern part of the project area incorporates large sections of forested area, while forest in the western part of the project area is sparse. This indicates that the Sahel boundary used in this study might need to be adjusted to accurately reflect the ecoclimatic region.

Conclusion

The results of this study confirm the research on deforestation in the Sahel. There is no correlation between population and fires, which indicates that slash-and-burn agriculture is not the primary driver of deforestation in the region. On the other hand, the results show that the only variable correlated with fires is precipitation. The results show this correlation between fires near cities and precipitation, and data problems are likely the reason that we do not see the same correlation between fires near towns and precipitation. For fires near cities, the relationship with precipitation has a p-value of 0.000004 and an R-squared of 0.47, which proves the relationship is considerable. This indicates that lightning strikes are the primary driver of deforestation in the Sahel.

References

- Agnew, C.T., and A. Chappell. 1999, "Drought in the Sahel." *GeoJournal* 48:299-311. Accessed June 1, 2012.
- Benjaminsen, Tor A. 1993. "Fuelwood and Desertification: Sahel Orthodoxies Discussed on the Basis of Field Data from the Gourma Region in Mali." *Geoforum*, 24(4):397-409. Accessed March 25, 2012. [http://0-dx.doi.org.bianca.penlib.du.edu/10.1016/0016-7185\(93\)90003-Z](http://0-dx.doi.org.bianca.penlib.du.edu/10.1016/0016-7185(93)90003-Z).
- Christensen, J.H., B. Hewitson, A. Busuioc, A. Chen, X. Gao, I. Held, R. Jones, R.K. Kolli, W.-T. Kwon, R. Laprise, V. Magaña Rueda, L. Mearns, C.G. Menéndez, J. Räisänen, A. Rinke, A. Sarr and P. Whetton. 2007. "Regional Climate Projections." In: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller, 847-940. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.
- DeFries, R., M. Hansen, J.R.G. Townshend, A.C. Janetos, and T.R. Loveland. 2000. 1 Kilometer Tree Cover Continuous Fields, 1.0. Department of Geography, University of Maryland, College Park, Maryland, 1992-1993.
- Eklundh, Lars, and Lennart Olsson. (2003). "Vegetation index trends for the African Sahel 1982-1999." *Geophysical Research Letters* 30: 1430. Accessed May 17, 2012. doi:10.1029/2002GL016772.
- Elvidge, Christopher D., Paul S. Sutton, Kimberly E. Baugh, Benjamin T. Tuttle, Ara T. Howard, Edward H. Erwin, Budhendra Bhaduri, and Edward Bright. 2006. "A Global Poverty Map Derived From Satellite Data." Paper submitted to AMBIO, December 27, 2006. http://www.ngdc.noaa.gov/dmsp/pubs/Poverty_index_20061227_a.pdf.
- FAO GeoNetwork. 2012. "Digital Soil Map of the World" <http://www.fao.org/geonetwork/srv/en/metadata.show?id=14116>.
- Ghosh, T., R. Powell, C. D. Elvidge, K. E. Baugh, P. C. Sutton, and S. Anderson. 2010. "Shedding light on the global distribution of economic activity." *The Open Geography Journal*, 3:148-161. Accessed 25 May, 2012. http://www.ngdc.noaa.gov/dmsp/pubs/Ghosh_TOGEOGJ.pdf.
- Hansfort, Sofie Louise, and Ole Mertz. 2011. "Challenging the Woodfuel Crisis in West African Woodlands." *Human Ecology*, 39:583-595. Accessed May 15, 2012. doi 10.1007/s10745-011-9417-8.
- Hickler, T., L. Eklundh, J. W. Seaquist, B. Smith, J. Ardö, L. Olsson, M. T. Sykes, and M. Sjöström. 2005. "Precipitation Controls Sahel Greening Trend." *Geophysical Research Letters*, 32:L21415. Accessed June 1, 2012. doi:10.1029/2005GL024370.
- Hijmans, R.J., S.E. Cameron, J.L. Parra, P.G. Jones and A. Jarvis. 2005. "Very high resolution interpolated climate surfaces for global land areas." *International Journal of*

Climatology, 25: 1965-1978. Accessed May 20, 2012.
http://www.worldclim.org/worldclim_IJC.pdf.

Joint Research Center, Global Environment Monitoring Unit. 2012. "Global Land Cover 2000." <http://bioval.jrc.ec.europa.eu/products/glc2000/products.php>.

Kandji, Serigne T., Louis Verchot, and Jens Mackensen. 2006. *Climate Change and Variability in the Sahel Region: Impacts and Adaptation Strategies in the Agricultural Sector*. Nairobi: United Nations Environment Programme.
<http://www.unep.org/ecosystemmanagement/Portals/7/Documents/ClimateChangeSahelCombine.pdf>.

Nicholson, Sharon E., Michael L. Davenport, and Ada R. Malo. 1990. "A Comparison of the Vegetation Response to Rainfall in the Sahel and East Africa, Using Normalized Difference Vegetation Index for NOAA AVHRR." *Climate Change* 17: 209-241.

NOAA. 2012. "MODIS Fire Radiative Power."
http://www.ngdc.noaa.gov/dmsp/download_MODIS.html.

ORNL. 2012 "LandScan." <http://www.ornl.gov/sci/landscan/>.

Odihi, J. 2003. "Deforestation in Afforestation priority zone in Sudano-Sahelian Nigeria." *Applied Geography*, 23:227-259. Accessed June 5, 2012. <http://0-dx.doi.org.bianca.penlib.du.edu/10.1016/j.apgeog.2003.08.004>.

Ribot, Jesse C. 1999. "A History of Fear: Imagining Deforestation in the West African Dryland Forests." *Global Ecology and Biogeography*, 8:291-300. Accessed May 30, 2012. doi: 10.1046/j.1365-2699.1999.00146.x.

Ramaswamy, Sunder, and John H. Sanders. 1992. "Population Pressure, Land Degradation and Sustainable Agricultural Technologies in the Sahel." *Agricultural Systems*, 40:361-378. Accessed June 1, 2012. [http://0-dx.doi.org.bianca.penlib.du.edu/10.1016/0308-521X\(92\)90047-R](http://0-dx.doi.org.bianca.penlib.du.edu/10.1016/0308-521X(92)90047-R).

Sissoko, Keffing, Herman van Keulen, Jan Verhagen, Vera Teeken, and Antonella Battaglini. 2011. "Agriculture, livelihoods and climate change in the West African Sahel." *Regional Environmental Change* 11 (Suppl 1): S119-125. Accessed May 28, 2012. DOI 10.1007/s10113-010-0164-y.

Vierich, H.I.D., and W.A. Stoop. 1990. "Changes in West African Savanna Agriculture in Response to Growing Population and Continuing low Rainfall." *Agriculture, Ecosystems and Environment*, 31:115-132. Accessed June 1, 2012. [http://0-dx.doi.org.bianca.penlib.du.edu/10.1016/0167-8809\(90\)90214-X](http://0-dx.doi.org.bianca.penlib.du.edu/10.1016/0167-8809(90)90214-X).

Appendix

Africa and the Sahel

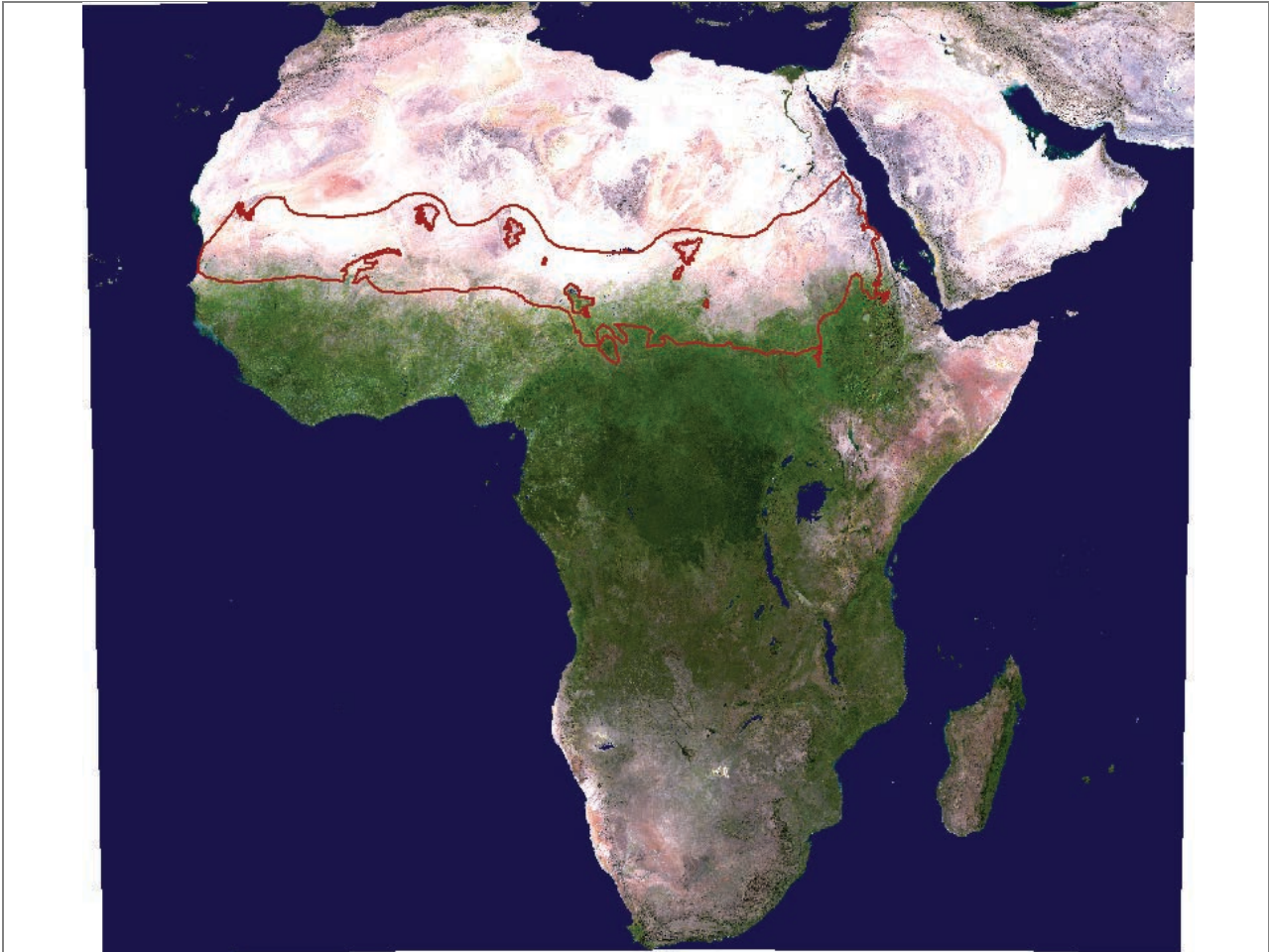


Figure 2-1: Flowchart showing the steps for calculating the visual exposure from houses to harvest block locations.



Figure 2-2: Flowchart showing the steps for calculating the visual exposure from houses to harvest block locations.

Cities and Towns



Figure 2-3: Cities of the Sahel.

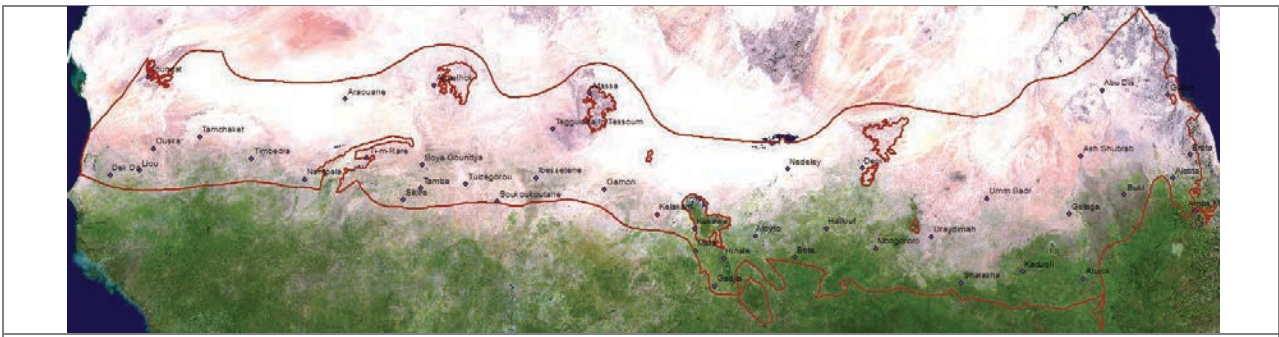


Figure 2-4: Towns of the Sahel.

Fire Radiative Power

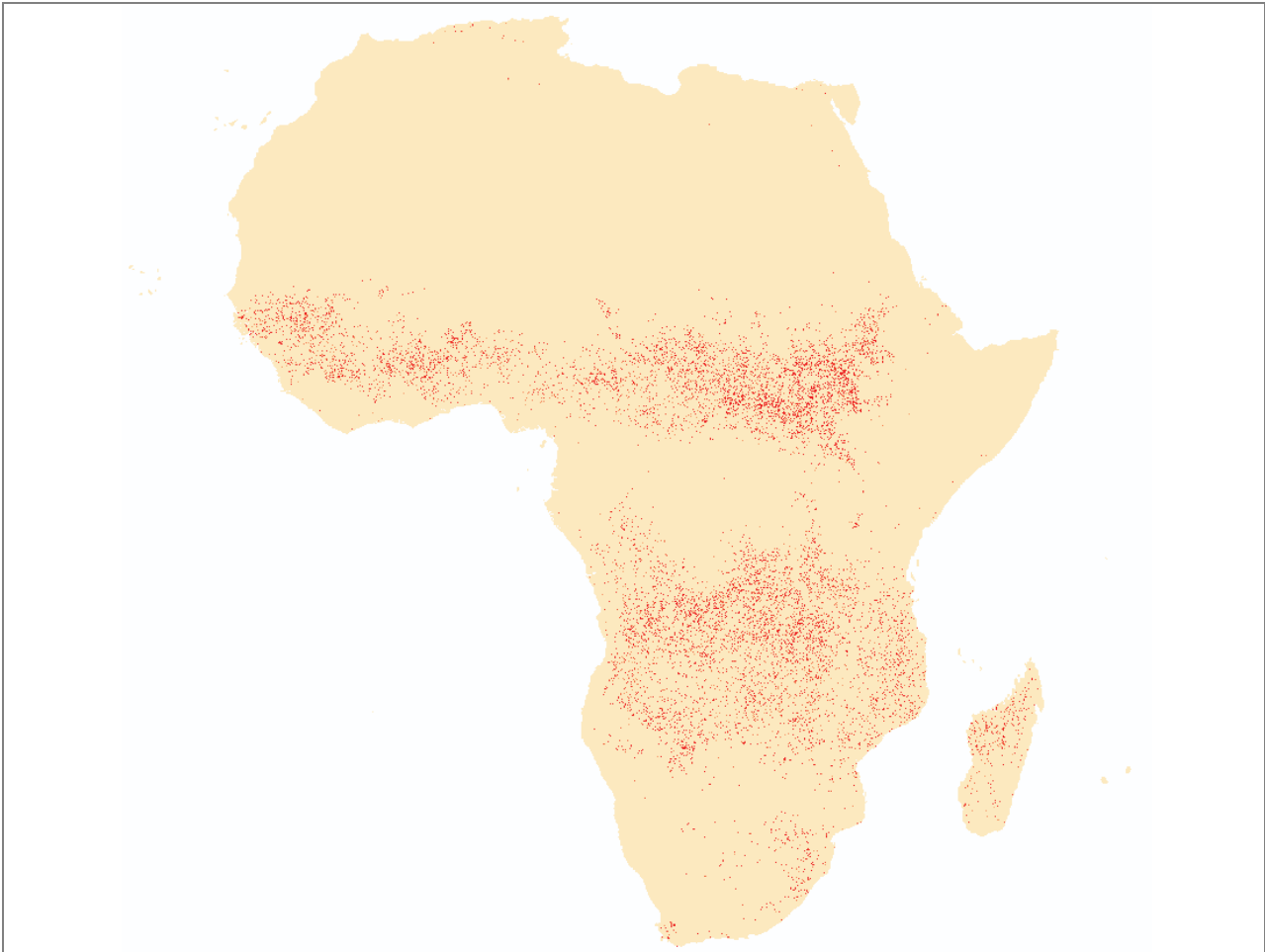


Figure 2-5: Fire Radiative Power in Africa.

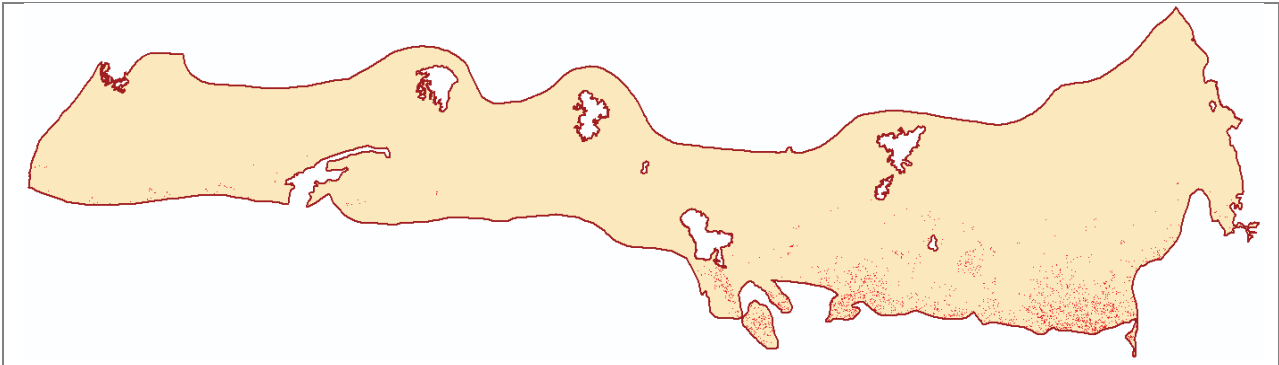


Figure 2-6: Fire Radiative Power within the boundary of the Sahel.

Population

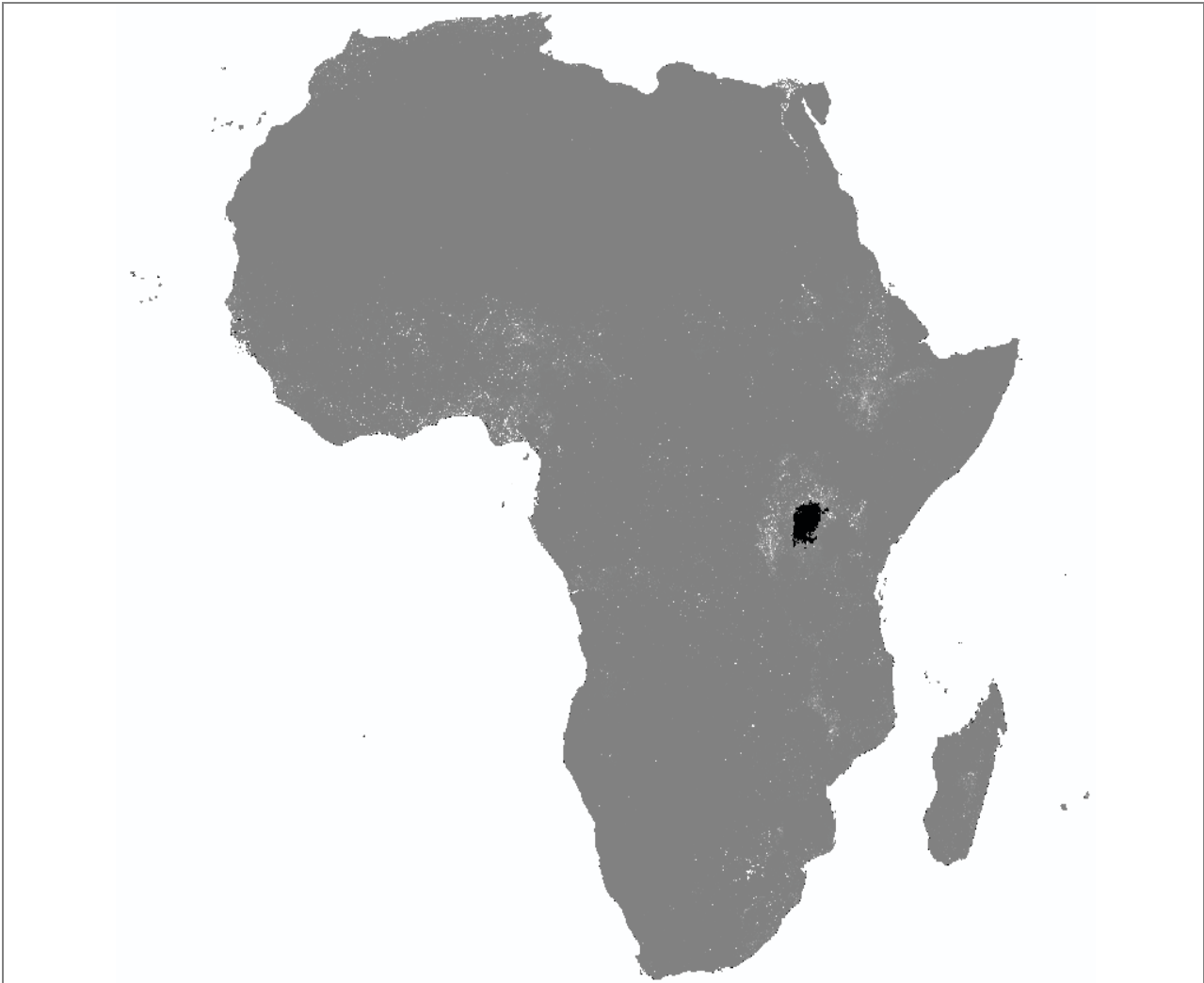


Figure 2-7: Population distribution in Africa.



Figure 2-8: Population distribution within the boundary of the Sahel.

GDP

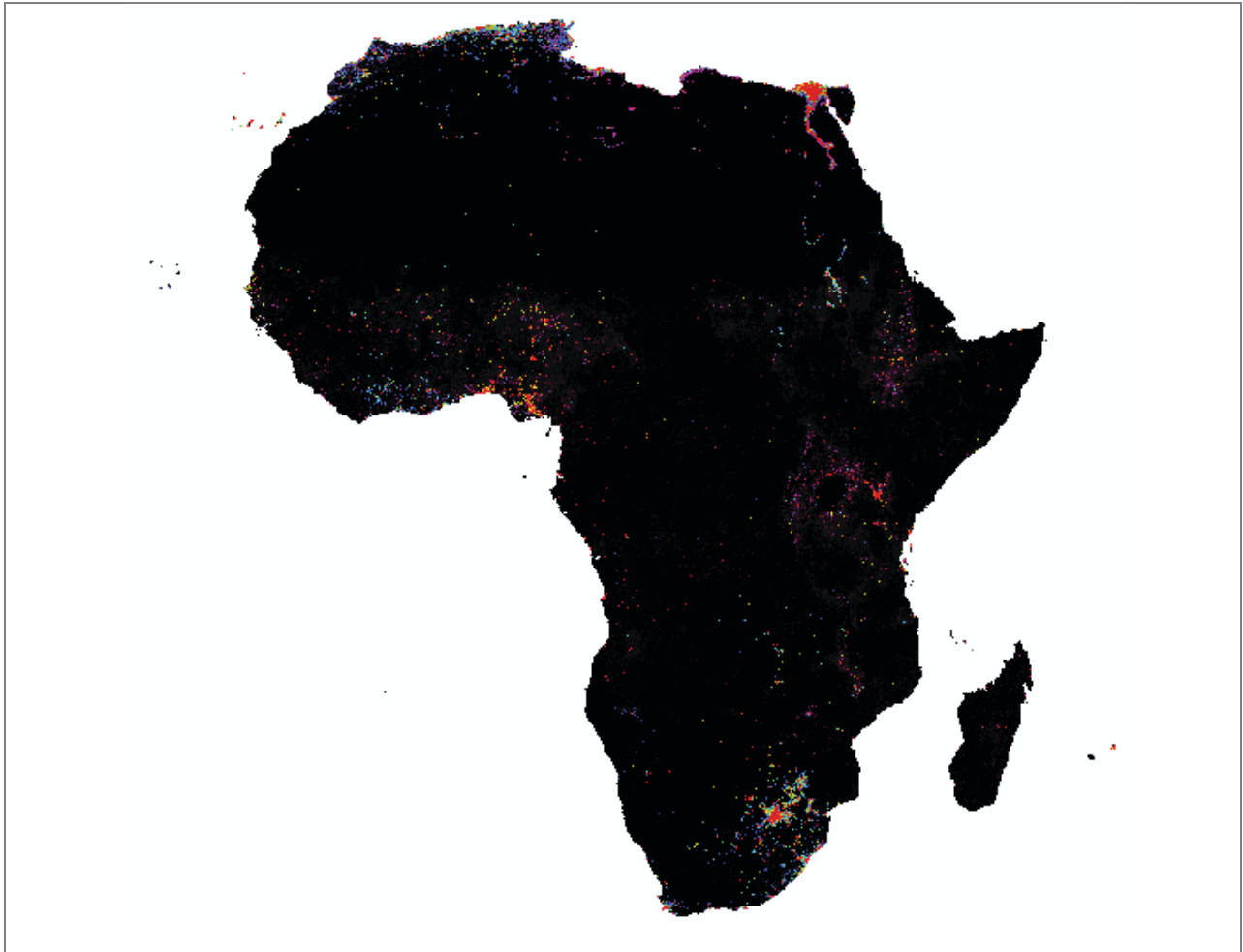


Figure 2-9: Nighttime lights as an estimate of GDP in Africa.



Figure 2-10: Nighttime lights as an estimate of GDP within the boundary of the Sahel.

Poverty

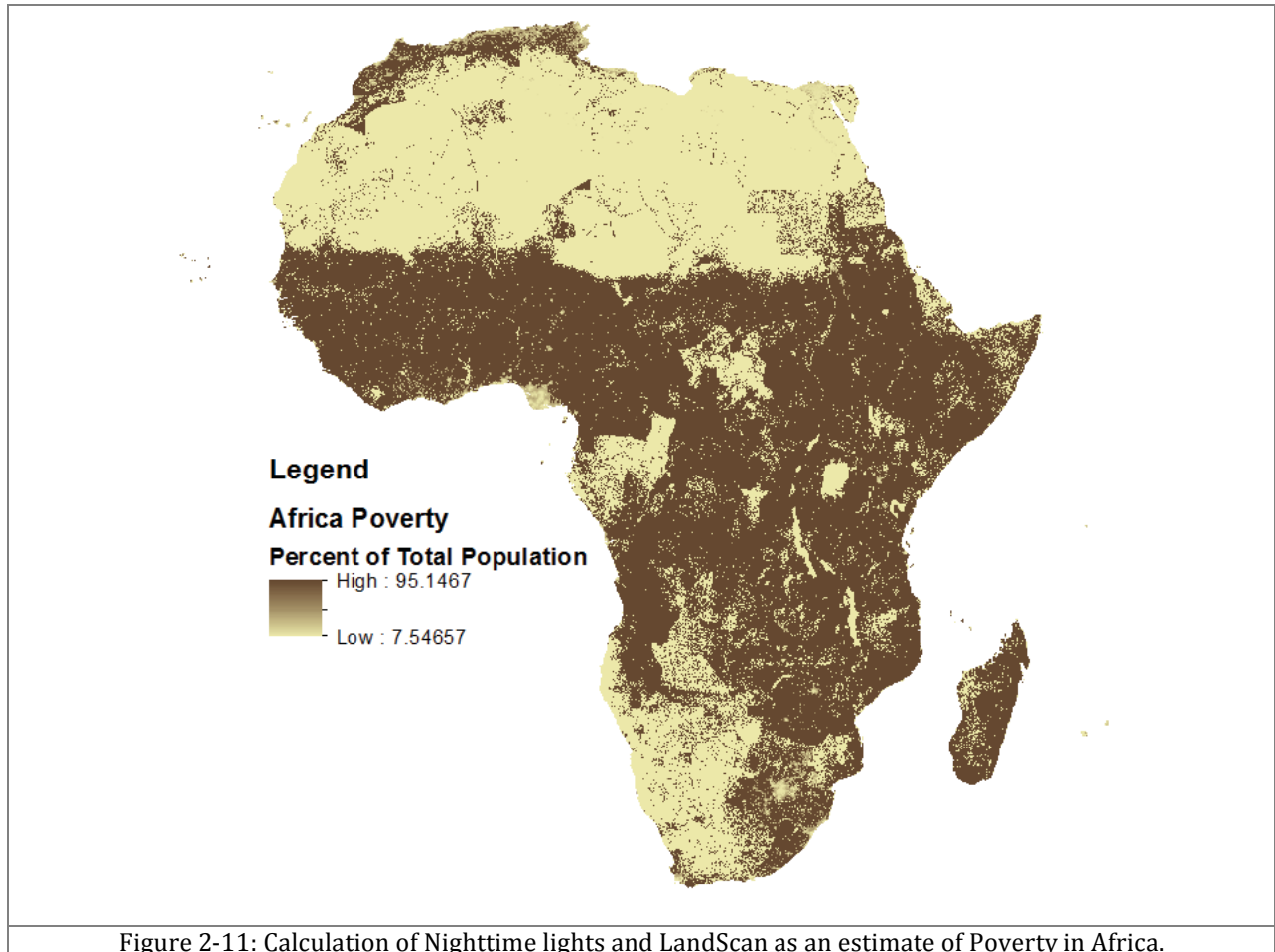


Figure 2-11: Calculation of Nighttime lights and LandScan as an estimate of Poverty in Africa.

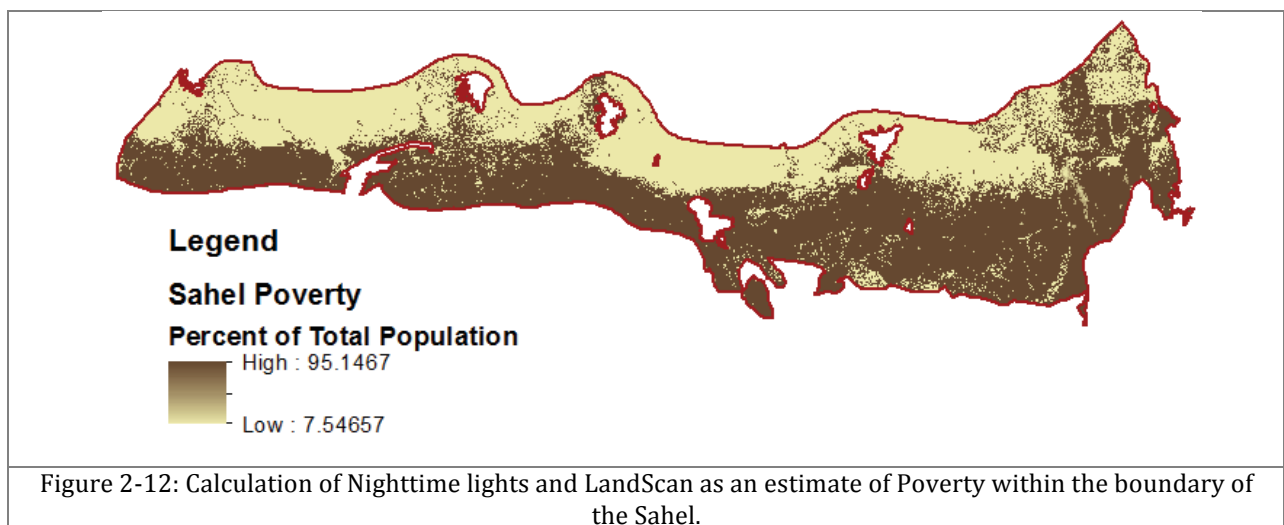


Figure 2-12: Calculation of Nighttime lights and LandScan as an estimate of Poverty within the boundary of the Sahel.

Tree Cover

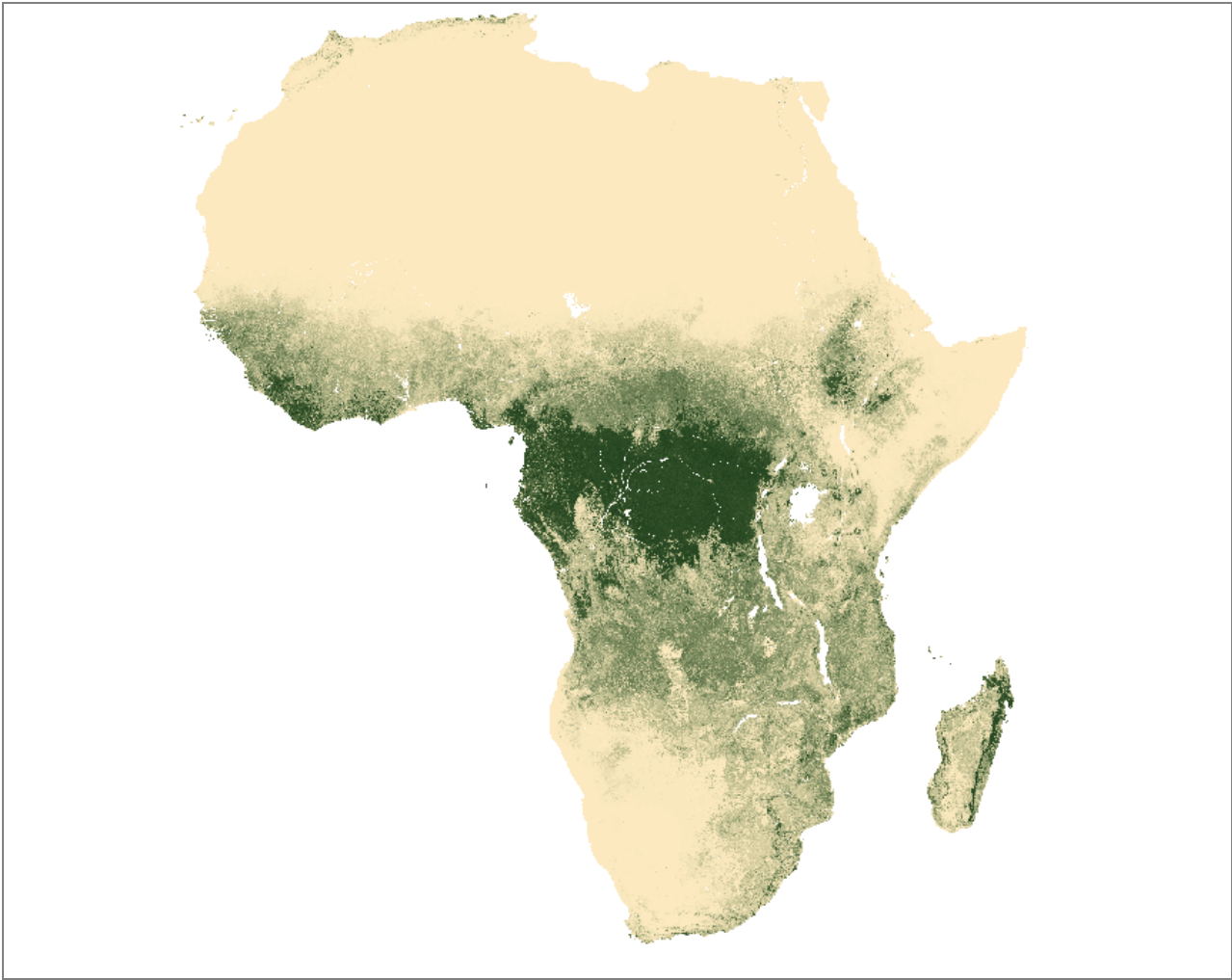


Figure 2-13: NDVI tree cover in Africa.

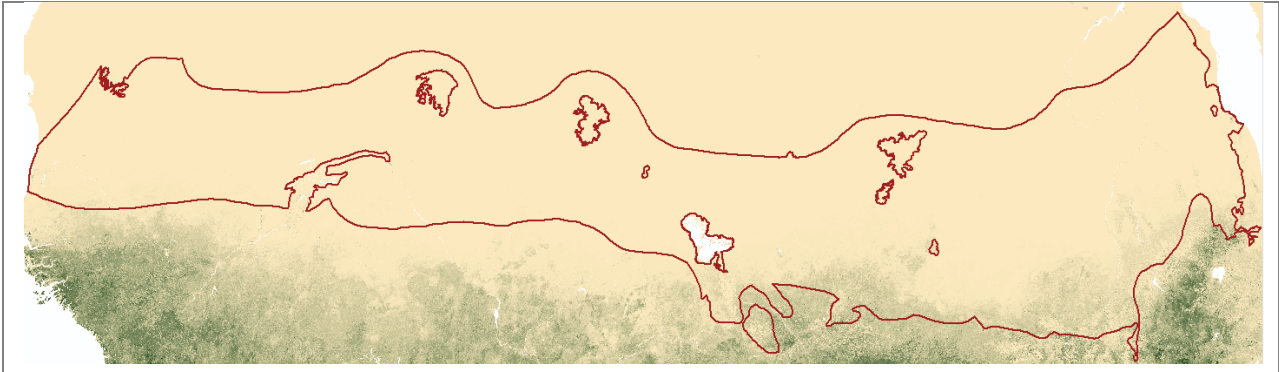


Figure 2-14: NDVI tree cover within the boundary of the Sahel.

Herbaceous Cover

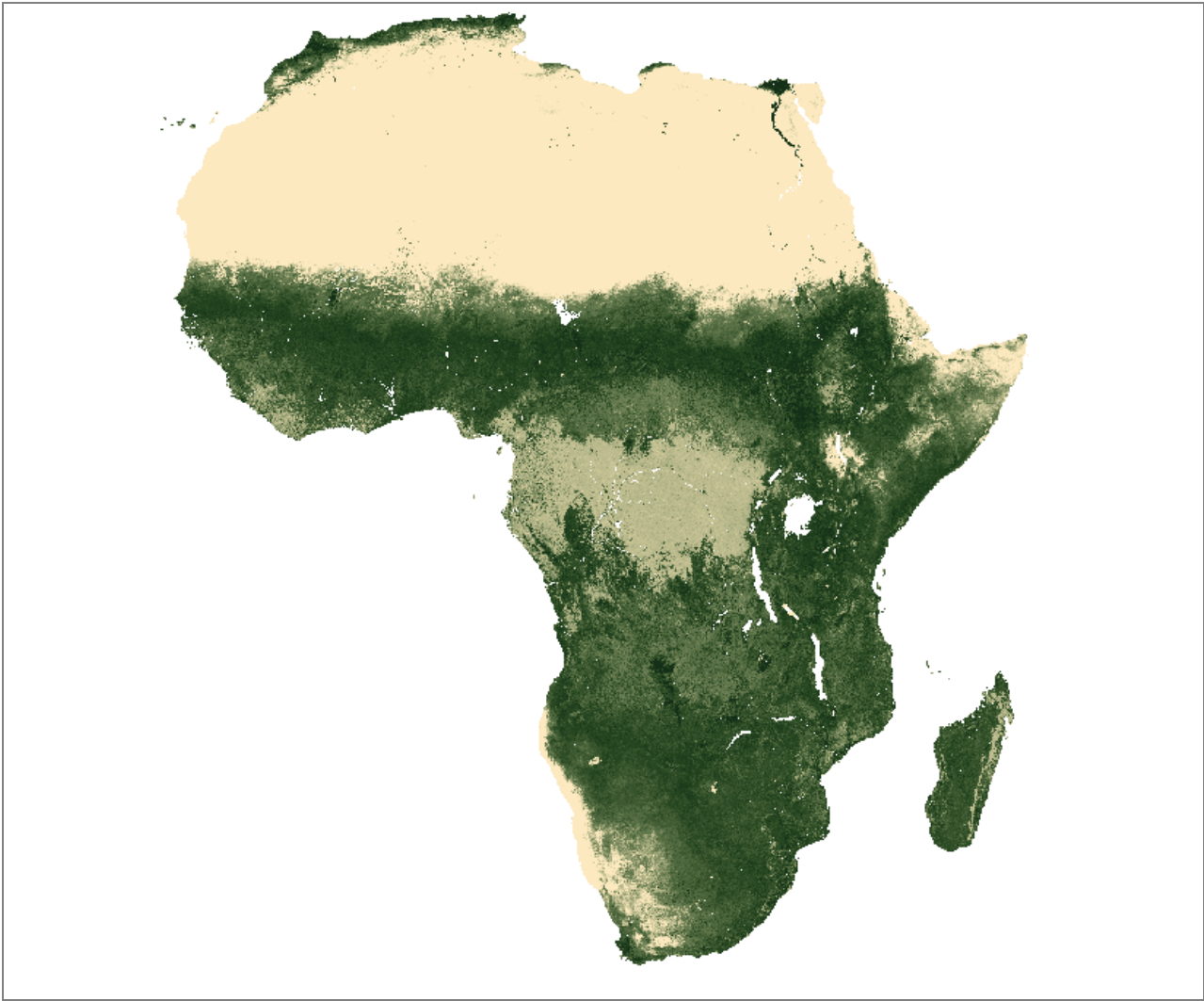


Figure 2-15: NDVI herbaceous cover in Africa.



Figure 2-16: NDVI herbaceous cover within the boundary of the Sahel.

Bare Ground

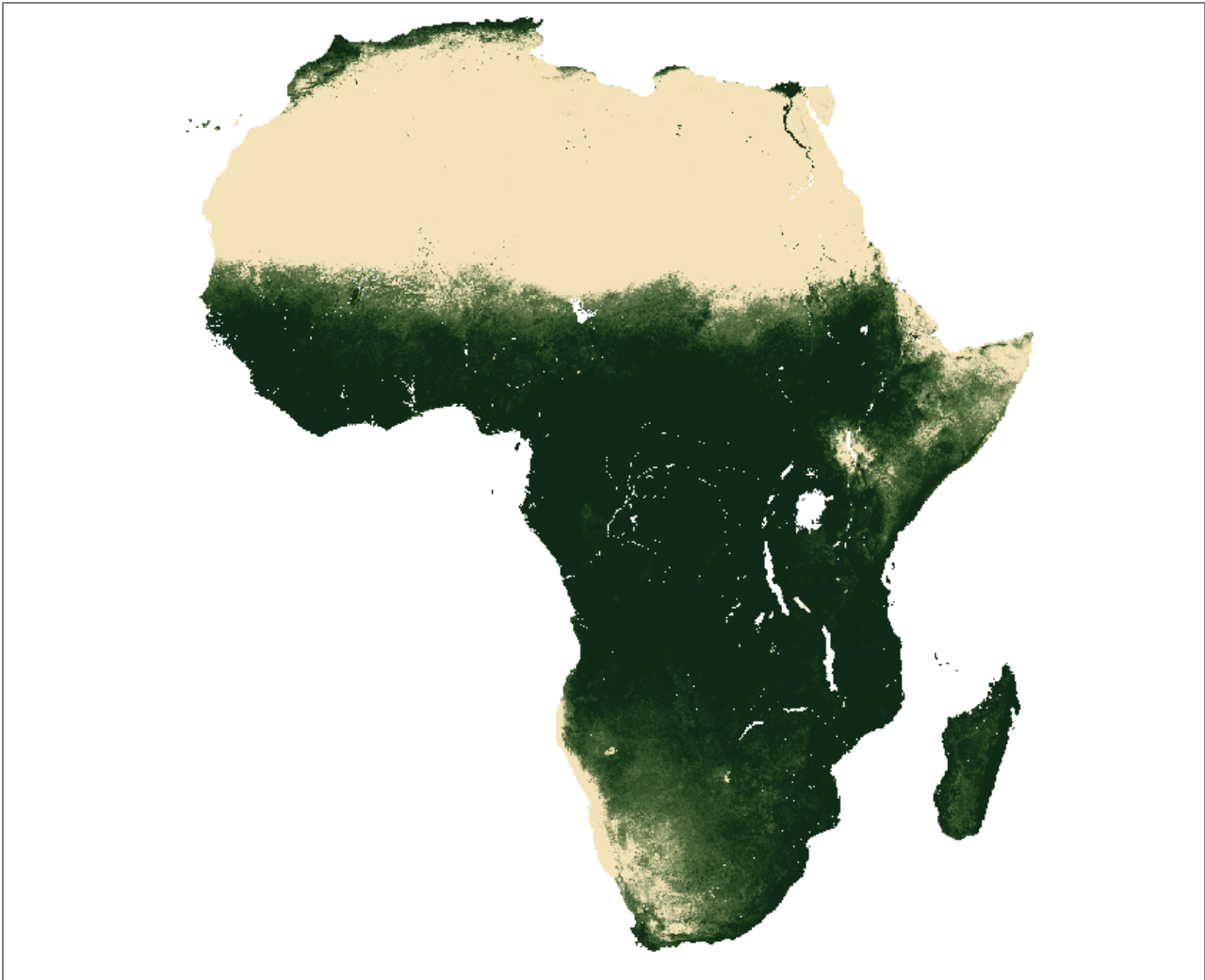


Figure 2-17. NDVI bare ground in Africa.

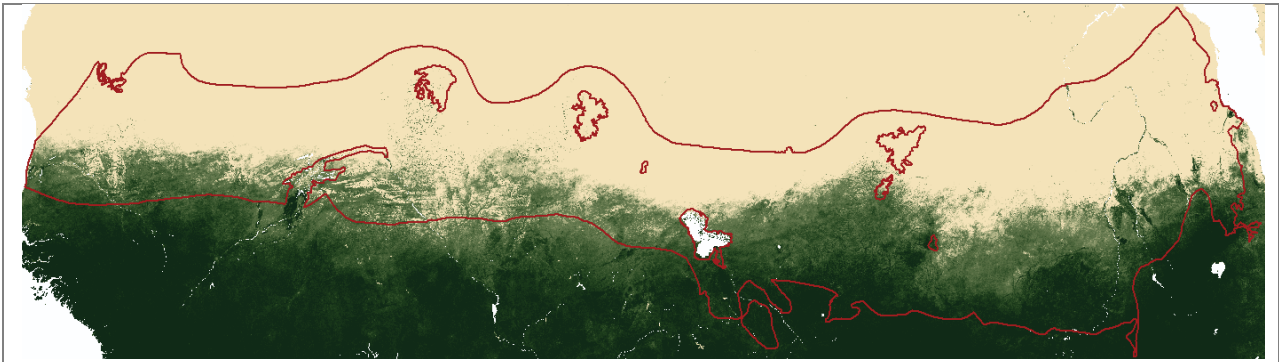


Figure 2-18. NDVI bare ground within the boundary of the Sahel.

Mean Temperature

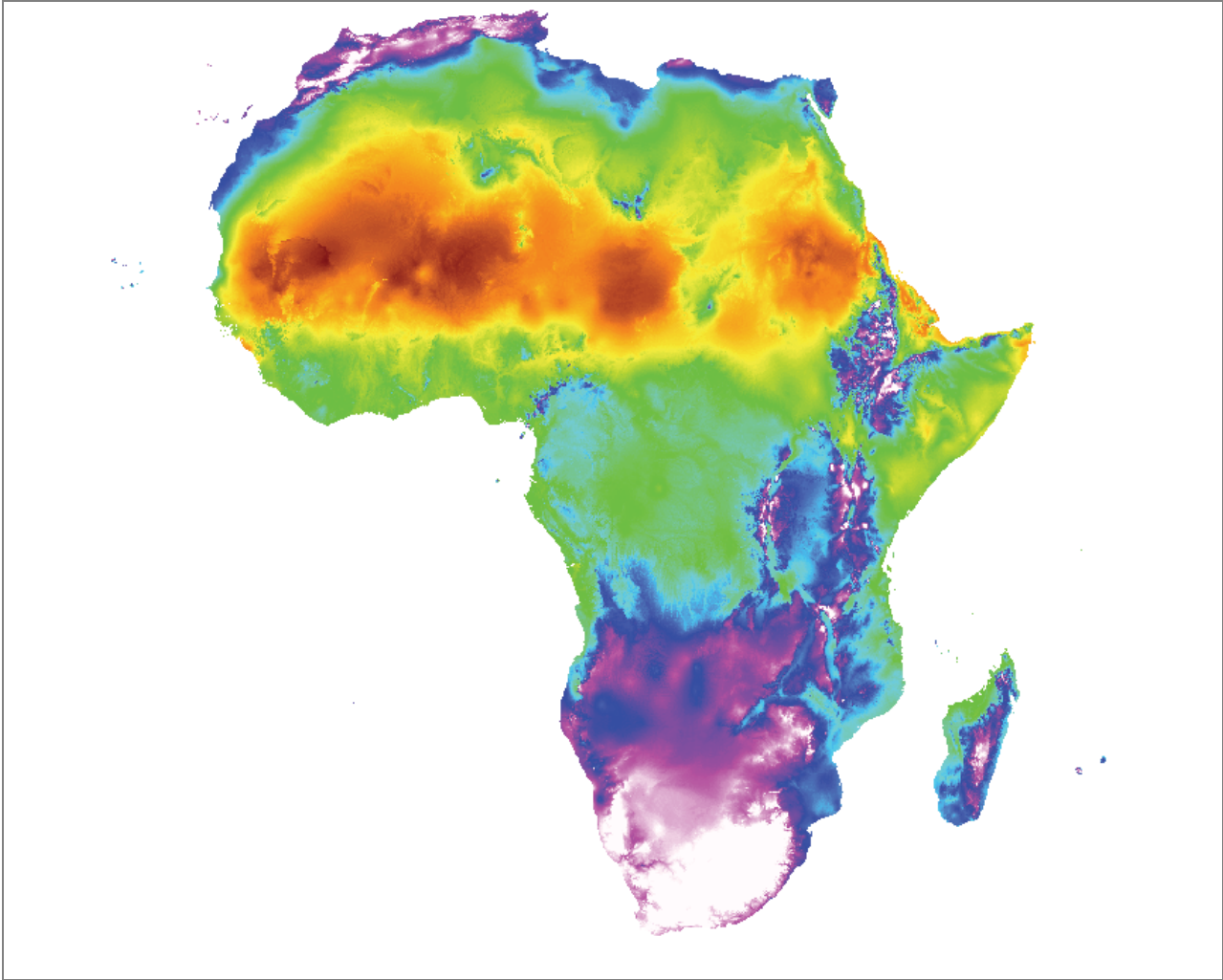


Figure 2-19: Mean temperatures between 1950 and 2000 for May in Africa.

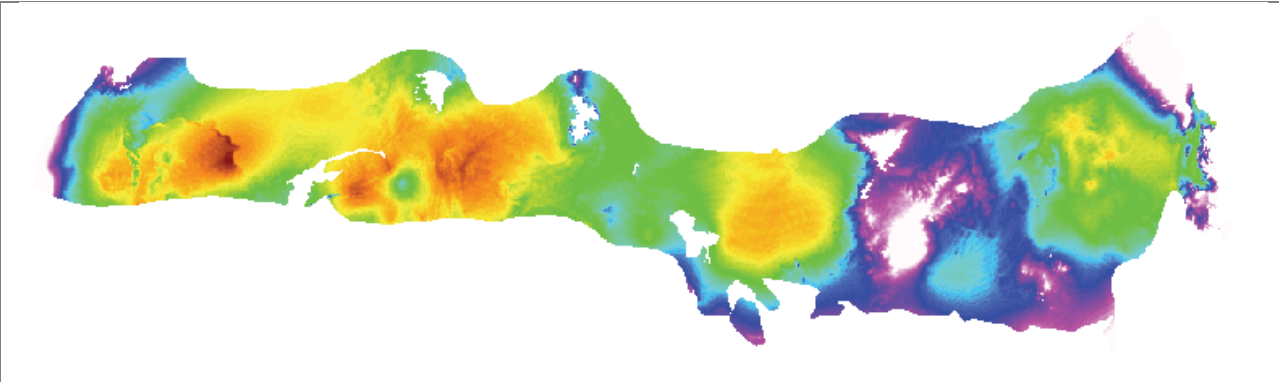


Figure 2-20: Mean temperatures between 1950 and 2000 for May within the boundary of the Sahel.

Mean Precipitation

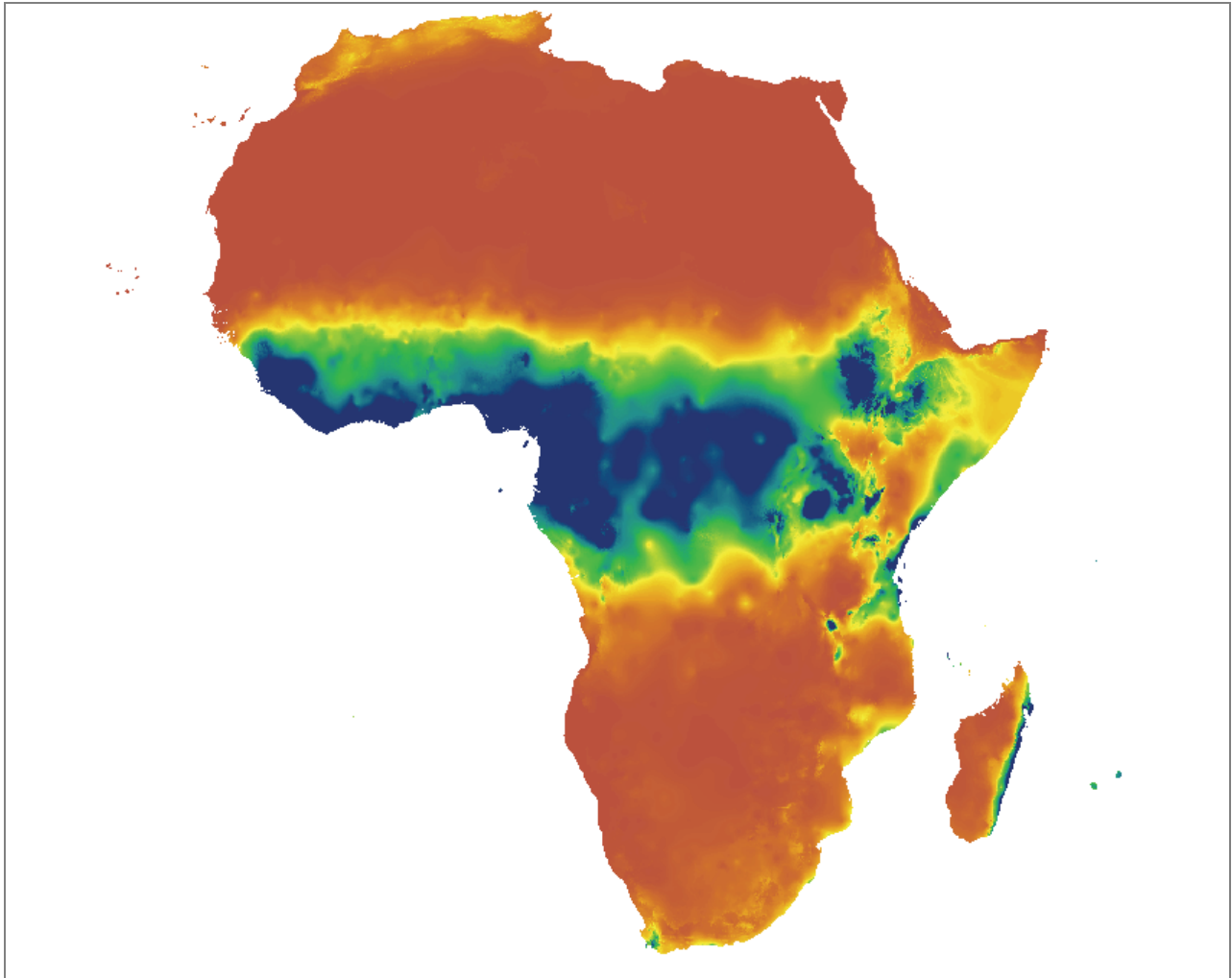


Figure 2-21: Mean temperatures between 1950 and 2000 for May in Africa.

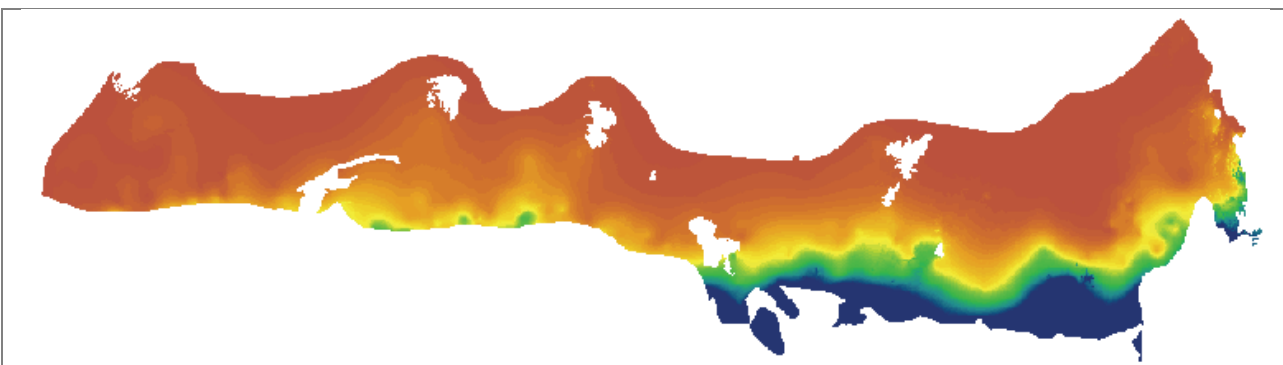


Figure 2-22: Mean temperatures between 1950 and 2000 for May within the boundary of the Sahel.

Land Cover

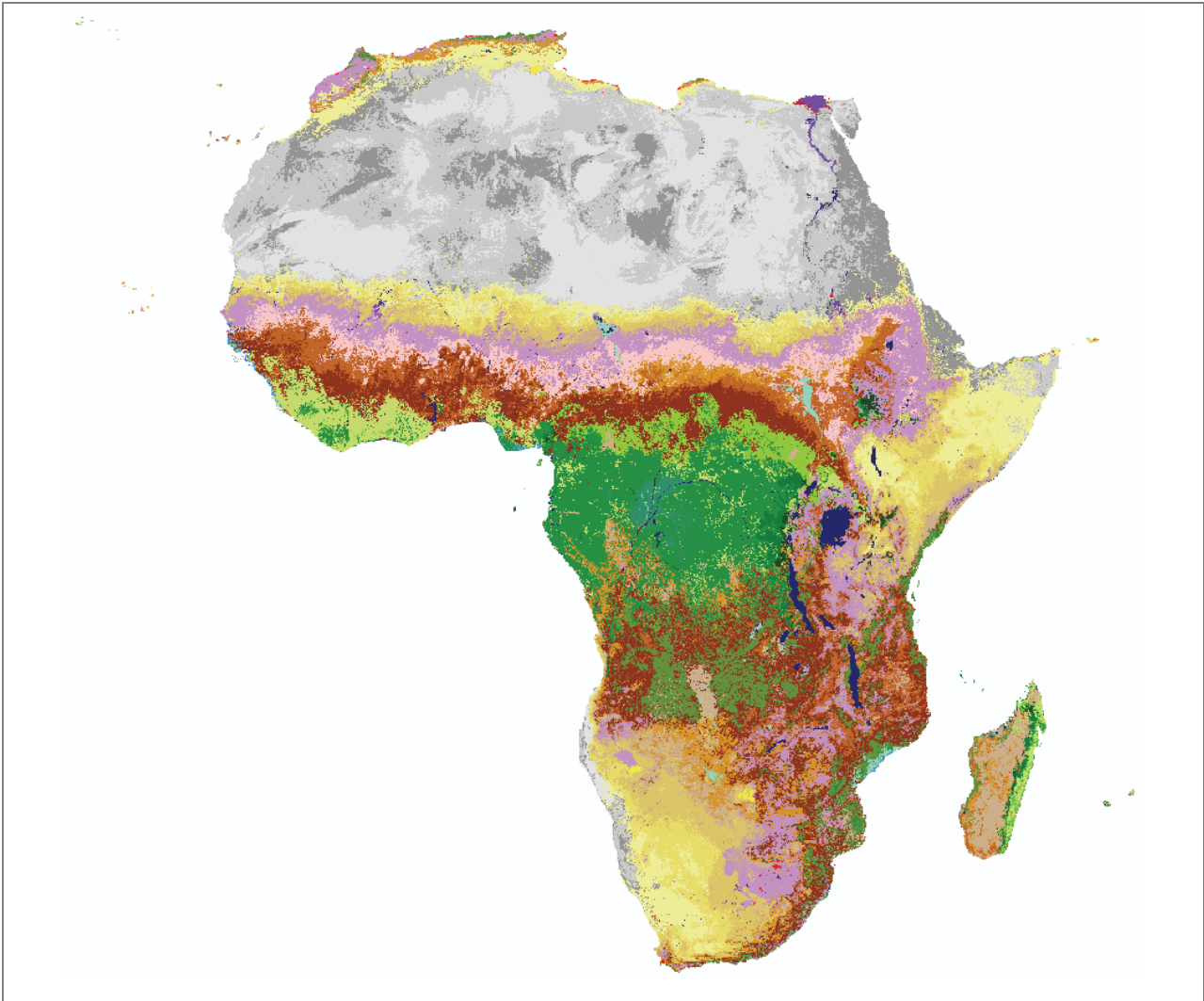


Figure 2-23: Land cover in Africa.

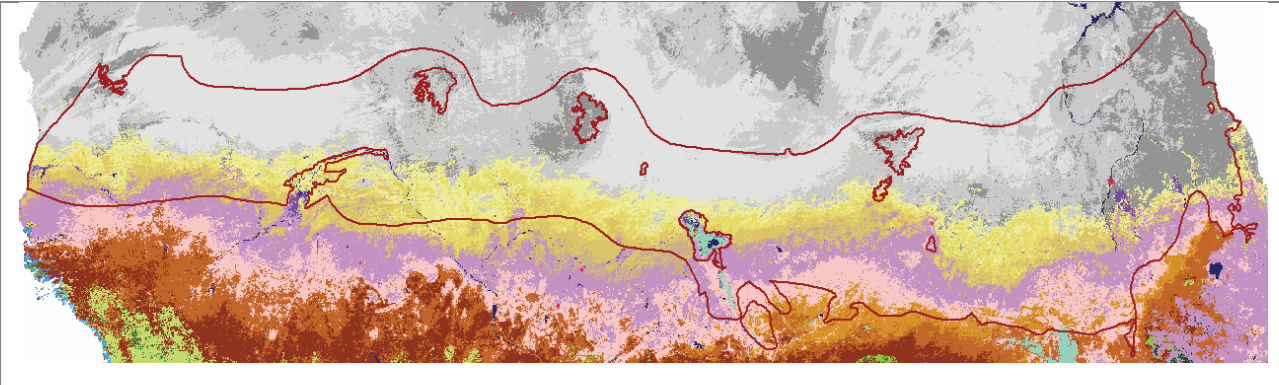


Figure 2-23: Land cover within the boundary of the Sahel.

Soil Type



Figure 2-24. Soil type in Africa.

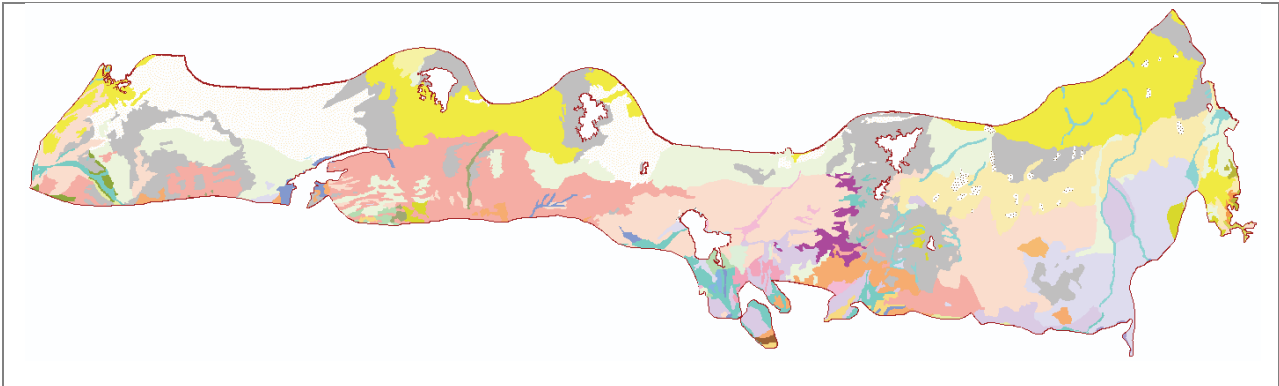
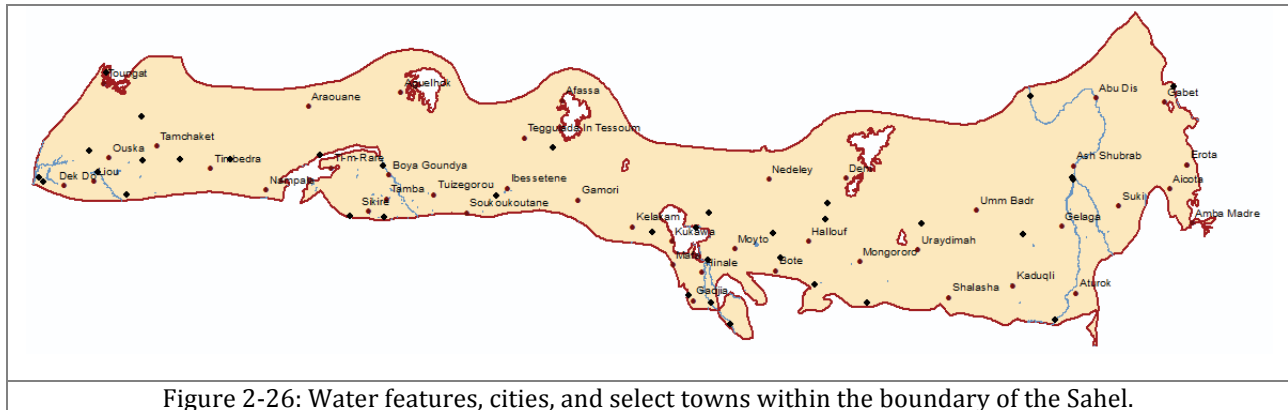
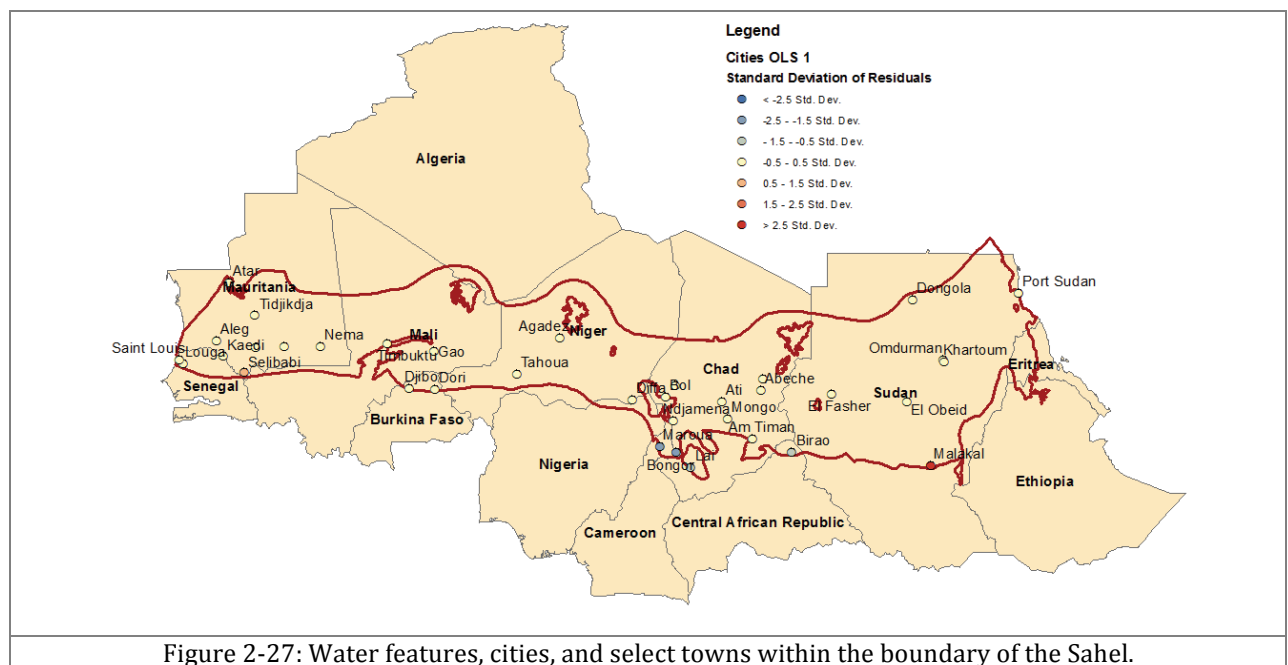


Figure 2-25: Soil type within the boundary of the Sahel.

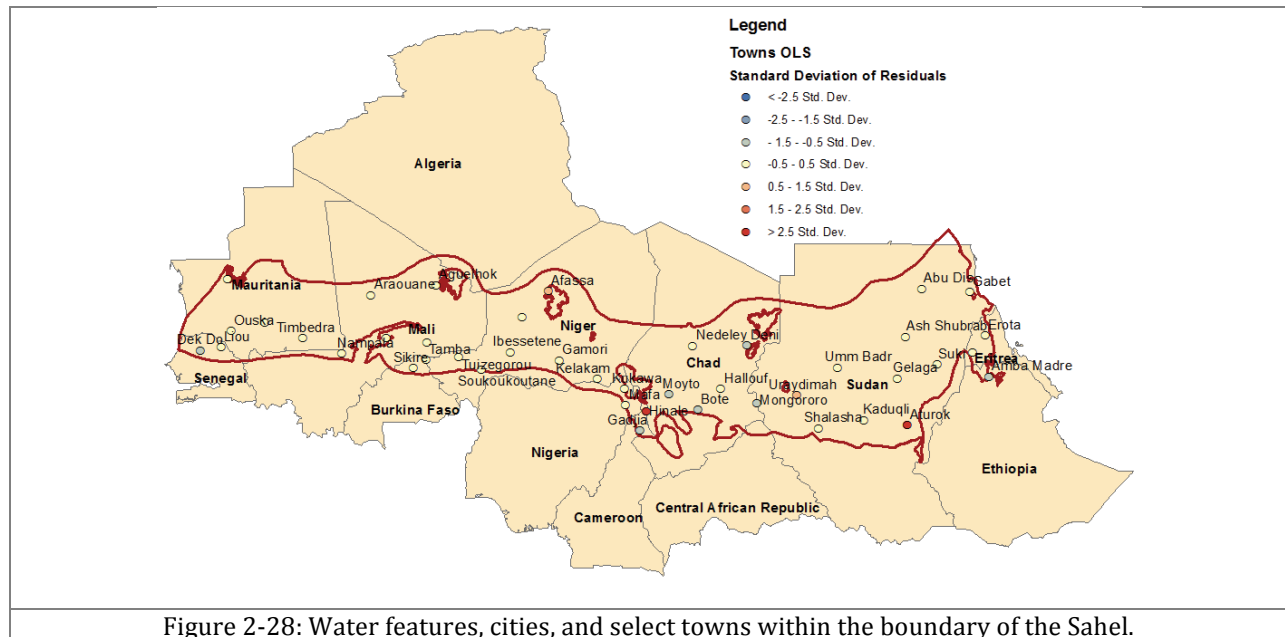
Proximity to Water



Cities OLS exploring the relationship between fires near cities and the independent variables



Towns OLS exploring the relationship between fires near cities and the independent variables



Cities OLS exploring the relationship between fires near cities and precipitation

