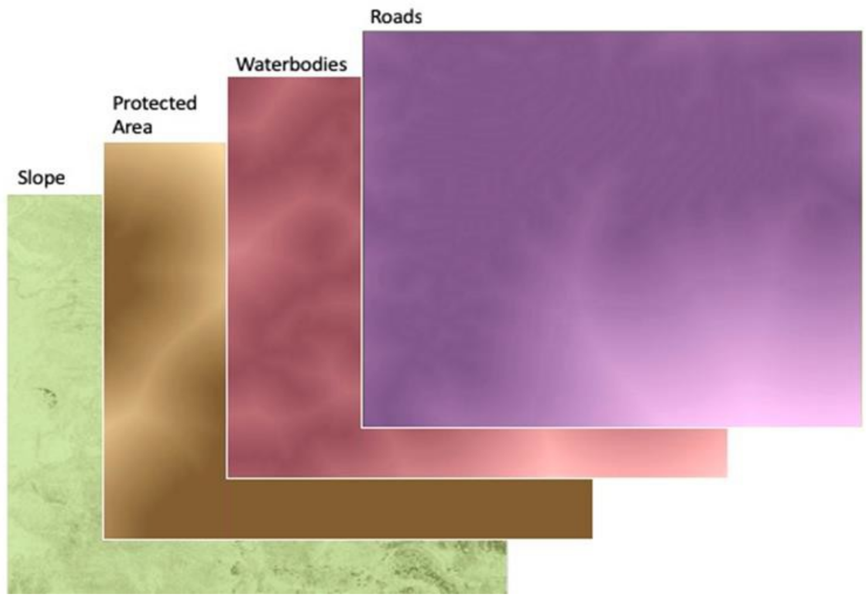
Analyzing the Factors of Deforestation in the Amazon using GIS and Logistic Regression



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Abstract

Deforestation is a shockingly destructive worldwide issue silently contributing to climate change. Unfortunately, in the Amazon, deforestation rates have been climbing since 2012, mainly due to agriculture expansion and institutionalized issues and remiss regulations. Using a GIS-based spatial analysis and logistic regression, this project aimed to explore different factors affecting deforestation (roads, waterbodies, protected area and slope) and create a predictive model. Analysis was conducted in southern Roraima, Brazil, to determine factor(s) most influential to deforestation in that location. It was found that the only main factor influencing deforestation at this site are the roads. Conclusions were supported by the *p* value for roads (*p* value = 9.49e-05) at a 95% confidence interval and the Akaike Information Criterion (AIC) evaluation of four models. Through this same analysis water bodies, protected areas and slopes were not determined to be statistically significant using spatial regression when used to compare predicted to actual deforestation. Further analysis which was not covered in the model included factors such as city size and land use. In addition, the application of the model to other sites in other areas of the world was not proven effective.

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Problem Definition and Significance of Research

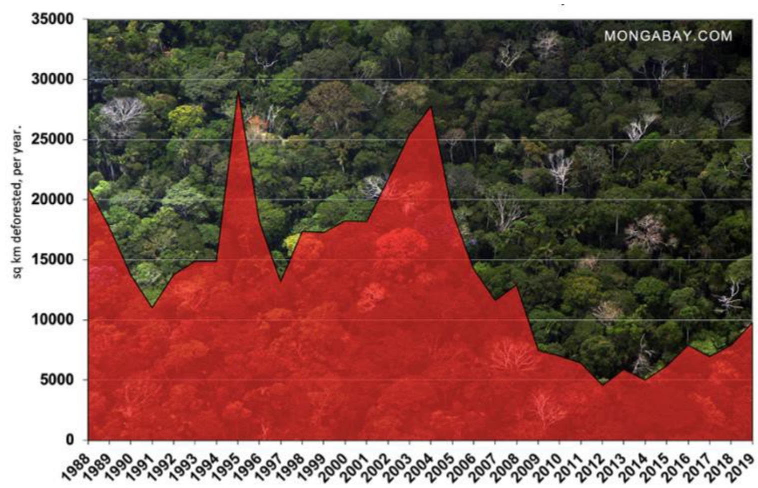

Figure 1 Deforestation in the Brazilian Amazon. There were significant spikes in deforestation in 1995 and from 2003-2004. Deforestation rates hit their lowest in 2012, but have been slowly climbing since then. Source: Hansen et al., 2019 via Mongabay

The world's forests provide humans and all life on Earth with air to breathe, and act as the lungs of our planet. The Amazon is a wonder of its own, home to 13% of the world's species and laying claim to 40% of South America (WWF, 2020 & Lewinsohn & Prady, 2005). It acts as a massive carbon sink and aids in the regulation of CO2 for all fauna and flora (Hashimoto et al., 2009). The IPCC(2019) predicts that forests absorb a third of all anthropogenic greenhouse gas emissions, and with unprecedented worldwide forest loss, the climate is likely to change even faster than previously thought.

There are many causes for the alarming rate of deforestation within the Amazon. Rates have declined since the early 2000's, but are slowly rising again (Hansen et al., 2019) (Figure 1). As stated by Geist & Lambin (2002), some of these factors include "proximate causes" and "underlying causes". Proximate causes include direct human actions that impact forests such as agricultural/infrastructure expansion, whereas indirect factors such as economic, technological and political advancements that lead to increased rates of forest cover loss are considered underlying causes.

The largest contributing proximate cause to deforestation of the Amazon is agricultural expansion, an overwhelming 63% caused by land clearing for pasture and cattle ranches (Marchand, 2012 & Rosa et al., 2013). Since the 1970's, ranches have been the top cause of deforestation. In addition, there is significant amounts of deforestation for small farms and soy crops (Figure 2)—in the 1990's a soy crop was genetically engineered to thrive in the rainforest climate. Due to this, this crop was planted across the rainforest at increasing rates (Mongabay, 2020).

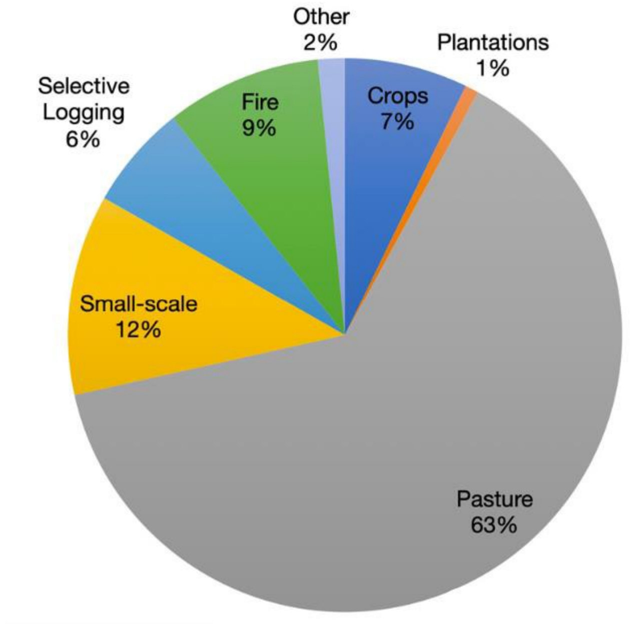

Figure 2 Drivers of deforestation in the Brazilian Amazon. Source: Hansen et al., 2019 via Mongabay.

Underlying causes of deforestation are more complex, institutional problems. In the past, farmers were incentivized by the Brazilian government to invest in ranches in the Amazon or grow a specific export crop (Fearnside, 1987). Today, there are issues surrounding the effective governing of forests in the Amazon creating the phenomenon of "paper parks" where the designation of a protected area is not respected (Figueiredo, 2007). One critical factor contributing is the expansion of illegal roads. It is believed that for every kilometer of road, there are three kilometers of illegal, undocumented roads (Barber et al., 2014). The Brazilian government lacks the necessary resources to properly police protected land and these illegal roads (Verburg et al., 2012). The Forest Code in Brazil recently ruled to forgive $2.2 billion USD in fines for illegal deforestation, giving agribusiness lobbies and land-grabbers even more incentive to continue clear cutting (Branford & Torres, 2018).

Knowledge and Research Gaps

A potential research gap we have identified is the effect that buffer zones have on the rates of deforestation outside of protected areas (PA) in the Amazon. Buffer zones are areas surrounding PAs that have been implemented to provide an extra source of protection surrounding a property (Wells et al., 1993). However, it has been found that the effectiveness of these buffer zones is highly variable, especially in the Amazon as they are often more ambiguous and have informal rules, stemming from the initial lack of resources to police the PAs (Weisse & Naughton-Treves, 2016 & Verburg et al., 2012). Therefore, it will be difficult to gauge the output model in relation to these buffer zones, and whether they influence deforestation rates.

Another potential research gap from preliminary analysis conducted is the indirect effect that the construction of roads has on deforestation. The clearing of trees to provide the needed space for roads contributes to the amount of deforestation but, roads also lead to many indirect factors that may further increase rates. These factors are difficult to quantify and account for in our model.

The research gaps that have been identified as important to this region do not necessarily require more advanced GIS-based techniques, but have required modified critical thinking methods based on other studies to display our results effectively.

Why GIS is the Correct Method Choice for Analysis

This analysis inherently requires a Geographical Information Systems (GIS) based approach as we are looking to determine if it is possible to predict forest cover loss considering proximity to road, water and PA and slope. We used ArcGIS, a software developed by ESRI that is used for spatial analysis to “model problems geographically, derive results by computer processing, and then explore and examine those results” (ESRI, 2018). The ability to quantify the spatial connectedness of the forest cover loss to the four variables is a spatial analysis and will require GIS-based analysis and tools (Bavaghar, 2015).

Study Area

This analysis was conducted in the Southern portion of the Northern Brazilian Province of Roraima, Brazil within the reaches of the Amazon Rainforest (Figure 3a). Based on Google Earth imaging and past Landsat data, this area has seen major development in the past 20 years, and has substantially expanded its urban presence with the construction of new roads every year, further accelerating forest loss. This area was chosen as the area of interest due to its combination of the noted important factors.

Figure 3a. Overview of where the study site is located, in central Northern Brazil, just North of the Equator. It is in the state of Roraima, which borders the State of the Amazonas. To the North are Venezuela and Guyana, and the Amazon River is about 500 kilometers to the South.

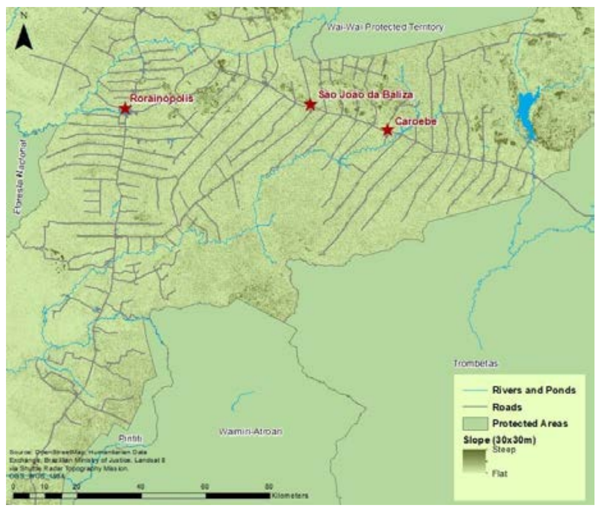

Figure 3b. Detailed location of our study site and relevant variables such as major cities, rivers, ponds, roads, slope and protected areas. Fishbone road patterns emerge where land parcels are narrow, long and regularly distributed, and are often deforested in a similar pattern surrounding these roads due to ease of access (Filho and Metzger, 2006). This layout causes the roads to take shape as pictured. There are 5 PAs in total, one pond and a small network of rivers. Topography has some minor variations in isolated areas, with a slope up to 74 degrees. The total area of the study site is approximately 180km by 160km, or 28,800km2.

The study area contains the cities of Rorainópolis (pop. 10,673), São João da Baliza (pop. 7,516) and Caroebe (pop. 7,400) (CityPopulation, 2019). The cities are within a triangular road pattern that contains roads in a fishbone layout (Figure 3b). There is PA to the North, West and South, small to medium-sized rivers and one lake. Overall, this area was chosen because it has all the variables we require to conduct our analysis, and has experienced significant change over the last 20 years.

Extent Choice

We chose our extent because we wanted to include the three major factors including PA's, roads and water features. We opted for a rectangular extent for our processing instead of political boundaries as our study area falls on the edge of two states in Brazil (Roraima & State of the

Amazonas). We chose a rectangular extent to remove administrative biases in spatial patterns (Thapa & Murayama, 2009).

Purpose of the Research

The purpose of this research is to create a predictive deforestation model using a logistic regression-based analysis which will determine which factor(s) is most influential to deforestation.

- O1 Identify: Identify variables associated with forest loss in Roraima, Brazil in the past 30 years.
- O2 Develop: Develop a statistical model relating various spatial variables and forest loss.
- O3 Assess: Assess the accuracy of predicted forest loss using the model developed in O2.
- O4 Evaluate: Evaluate the results for strengths and weaknesses regarding selection of study site and chosen deforestation variables.

Research Approach

Objective 1

The purpose of the first objective was to identify the various factors that influence forest cover loss within our study area. The four factors determined to play a significant role are proximity to roads, water bodies, PAs and topography (slope). Table 1 outlines the source of the variables obtained, as well as details some of the preprocessing steps.

Roads

The construction of roads themselves are not the main driving cause of forest cover loss and change, but they allow areas that were previously inaccessible to become within reach (Barber et al., 2014 & Freitas et al., 2009). This often contributes to the forest land to be cleared for various activities, like farming, logging and housing (Barber et al., 2014 & Freitas et al., 2009). While the increased number of roads may have many economic and social benefits to the residents nearby (Boston, 2017), it encourages and promotes clearing out the forests for further personal economic gain. Therefore, roads do tend to contribute to patterns of forest loss as an underlying cause (Angelstam et al., 2017, Barber et al., 2014 & Freitas et al., 2009).

Waterbodies

Waterbodies (rivers and lakes) are attractive for settlement for a variety of reasons. Water is used for drinking, agriculture and industry, and provides transportation, food sources, mineral extraction and tourism (Hari, 2016). Water is a massive economic driver (it's estimated that 3/4 jobs heavily rely on water) (UNwater, 2016), therefore it provides incentive for people to settle in an area, which ultimately leads to clearing of the surrounding forest in order to be able to make space for dwellings and agriculture development (Hari, 2016 & Curtis et al., 2018).

Protected Area

In the Brazilian Amazon, the government establishes natural and indigenous areas as conservation units (CU's) (Verburg et al., 2012), which have therefore been combined for the sake of this analysis as 'protected area' (PA). The Brazil government uses these designations to maintain biodiversity and natural characteristics of the forest. Unfortunately, these CU's often succumb to unsound policies and a lack of proper surveillance, leading to illegal logging and deforestation and "paper parks" (Figueiredo, 2007 & Verburg et al., 2012). Over 60% of the borders of PAs are not respected, primarily because they are lacking implementation of initiatives.

Topography/Slope

Topography and variations in slope influence the ease of travel. Generally, areas with steeper slope tend to experience less deforestation, whereas areas of lower elevation with gentler slopes are often used for sugarcane plantations and ranches in the Amazon, contributing to clear-cutting (Freitas et al., 2009 & Ranta et al., 1998). In addition, areas with steeper slopes often have lower-quality soil and therefore experience less human use (Silva et al., 2007). Construction of the Transamazon Highway and others in the Amazon tended to avoid areas with high slope (Arima et al., 205), therefore slope and topography are likely contributing factors to rates of forest loss.

Table 1. Data sources and pre-processing requirements for data preparation.

Required Data	**Data Type**	**Scale**	**Year**	**Source**	**Pre-Processing Required**
Forest Loss *(lossyear)*	Raster	30mx30m	2000-2018	University of Maryland (Landsat & Landsat 8 OLI)	Download the lossyear raster for three areas (10N70W, 10N60W, 0N,70W) and mosaic them to encompass our study area and clip. Derive a binary raster for deforested areas and forested areas. *Important to note that this data is based on Landsat 8 imaging that identifies tree cover change over time and is subject to minor error.*
Protected Area *(5 files in total – one for each area of protected land)*	Vector (Shapefile, polygon)	N/A	January 2020 (updated monthly)	Brazil's Ministry of Justice and Public Security	Combine 5 shapefiles. Clip the protected areas to our necessary study area. Rasterization to 30mx30m. Generate a Euclidean distance raster.
DEM (slope) *(six files in total)*	Raster (TIFF)	30mx30m	2000	USGS – Shuttle Radar Topography Mission	Create a mosaic of six DEM sections. Clip to study area. Derive slope.
Roads *(Roraima_roads)*	Vector (shapefile, line)	N/A	Most Recent	OpenStreetMap; user community	Clip the roads to our necessary study area. Rasterization to 30mx30m. Generate a Euclidean distance raster.

Required Data	Data Type	Scale	Year	Source	Pre-Processing Required
Water Features *(Roraima_rivers & Lago_jatapu)*	Vector (shapefile, line and polygon)	N/A	2019	OpenStreetMap; user community	Clip the rivers to our necessary study area. Rasterization to 30mx30m. Generate a Euclidean distance raster.

Objective 2

The second objective was to create and design a model which considers the four variables that were predicted to influence forest loss. This model was achieved using a similar technique to Bavaghar (2015), as his methodology included the identification of variables that may be contributing to deforestation, as well as a final logistic regression to generate a map of predicted deforested areas. Preparation of data can be seen in Figures 4, 5 and 6. The final workflow to yield the end product can be seen in Figure 7. A logistic regression was performed in RStudio that yielded the beta values to input into the raster calculator to produce an output model which showed the probability that an area will experience forest loss (Bavaghar, 2015 & Mohammadi et al., 2013) (Table 3). This output model was then validated against the forest loss data from the University of Maryland, which can be seen in Figure 9.

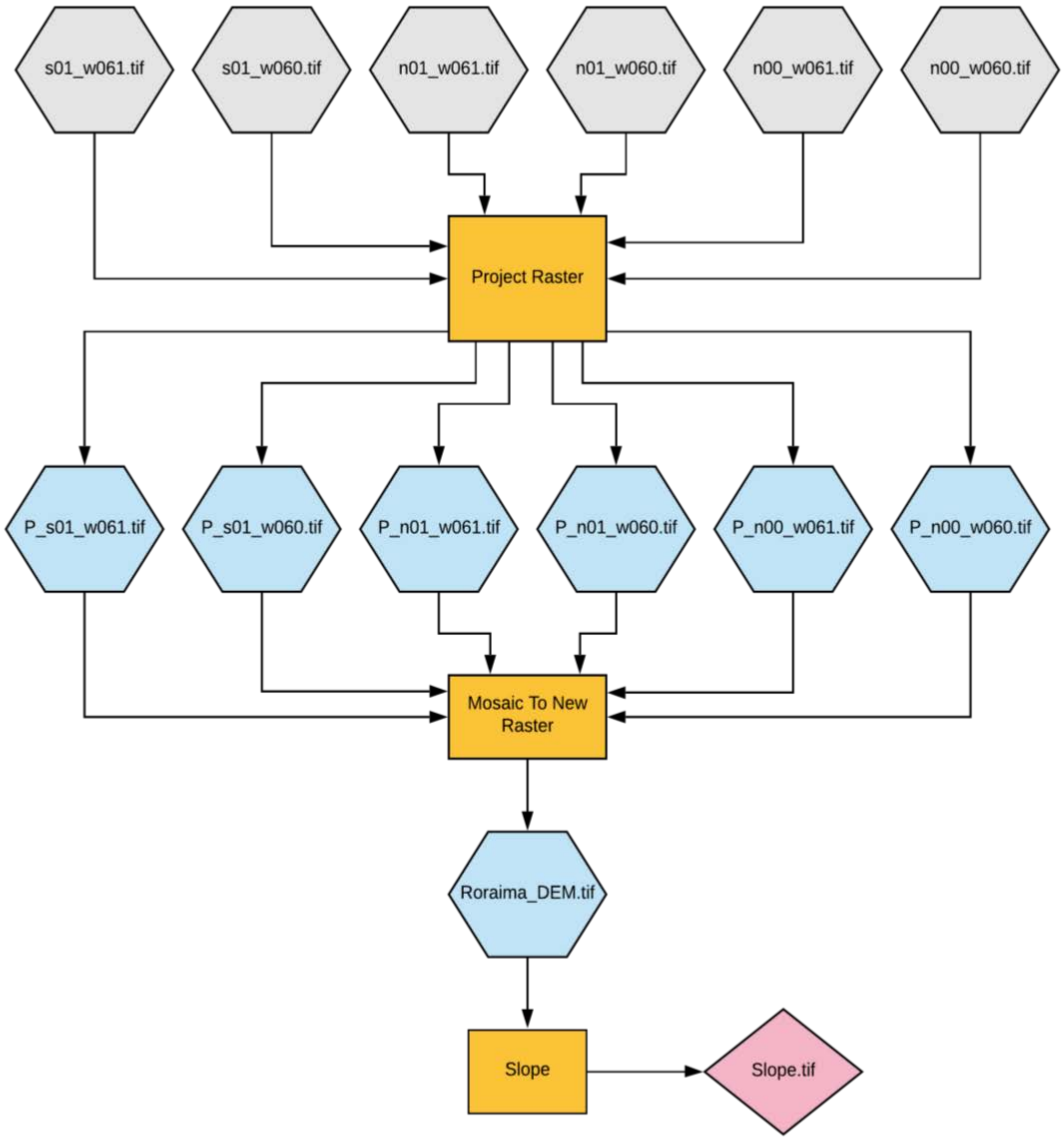

Figure 4. Workflow to create the slope raster (Slope.tif). This raster acted as the extent for the analysis, therefore was created first. Six files were downloaded from the USGS' Shuttle Radar Topography Mission, projected, mosaiced together, and then the slope was derived using the Slope Tool to yield the final slope.tif raster.

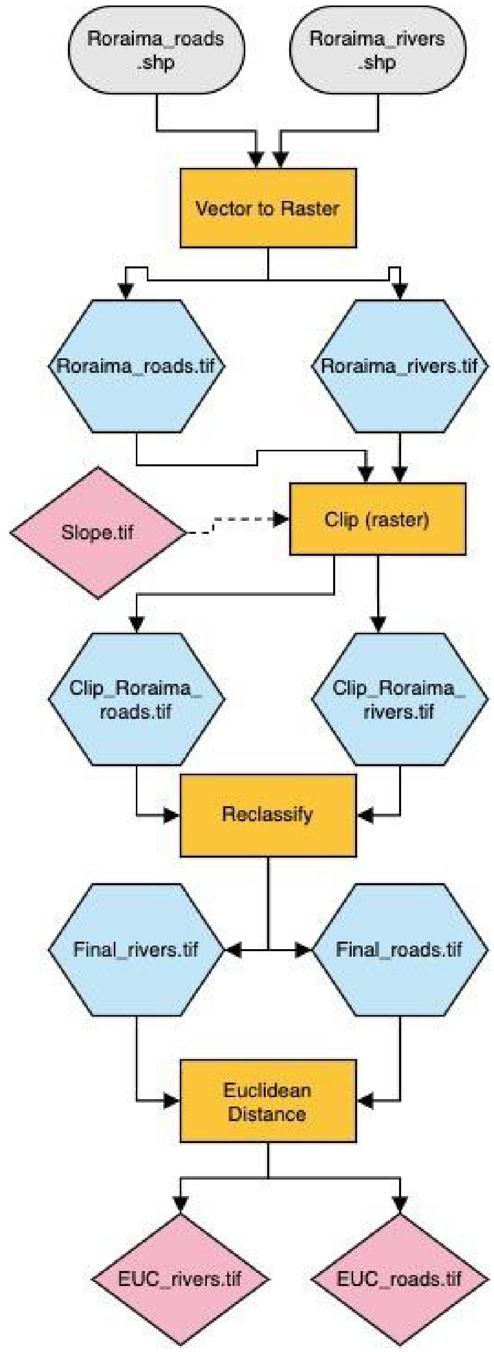

Figure 5. Workflow to obtain the Euclidean distance rasters for both waterbodies (EUC_rivers.tif) and roads (EUC_roads.tif).The process for both followed the same method. Vectors were converted to rasters, clipped to the slope.tif extent, reclassified into binary rasters and then a Euclidean distance raster was derived from each one.

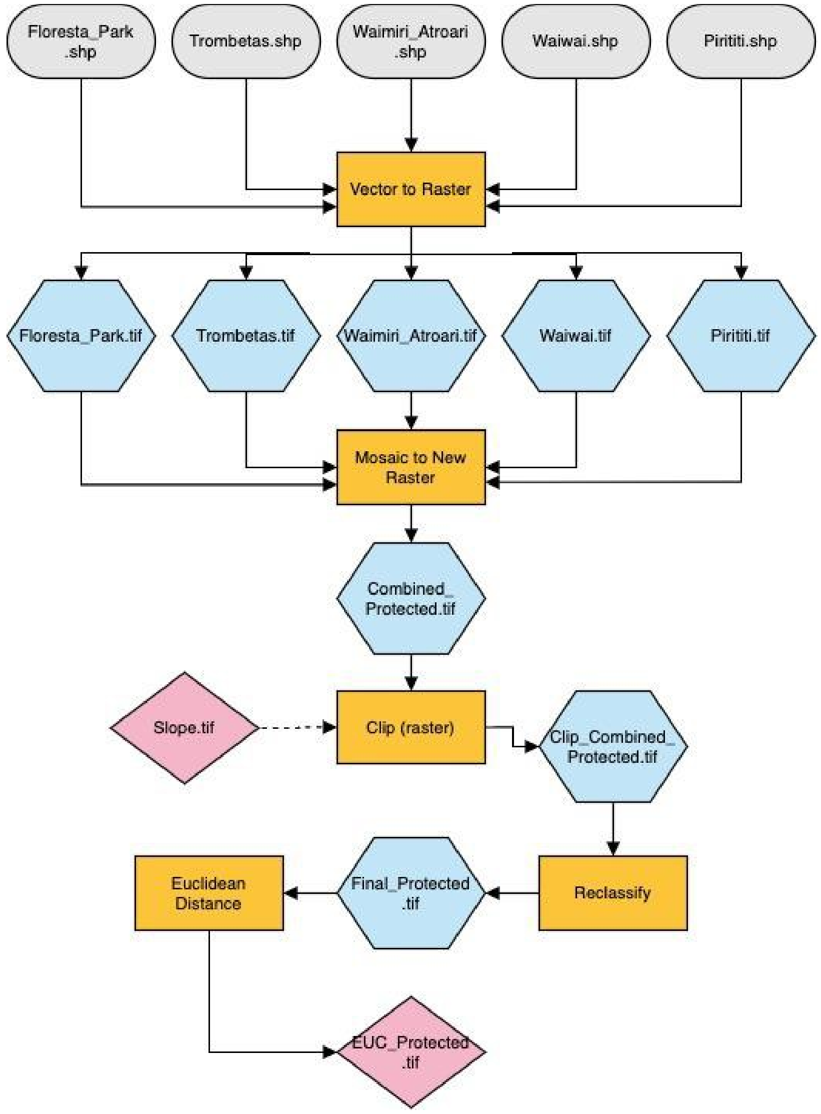

Figure 6. Workflow to obtain the Euclidean distance raster for PAs, EUC_protected.tif. Five shapefiles (one for each PA) were converted to rasters, ad mosaiced to a new raster which was then clipped to the slope.tif extent. The combined PA raster was then reclassified to become binary, and a Euclidean distance raster was generated.

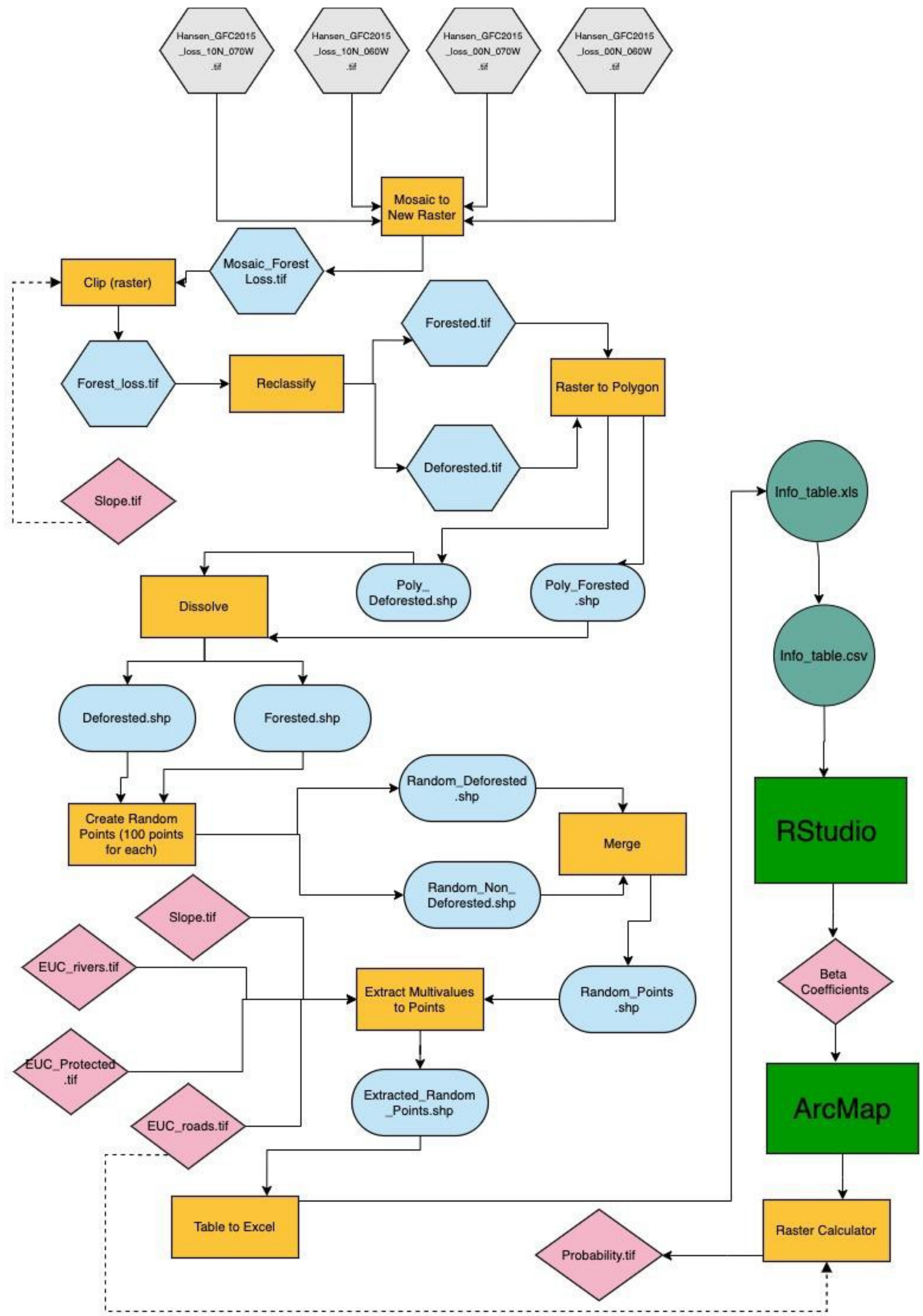

Figure 7. Workflow to create the forest loss raster. Beginning with four files from the Hansen et al. University of Maryland dataset, they were mosaiced and clippedto the slope.tif extent. The raster was split into forested and deforested, then each one was converted to a polygon. 100 random points were selected from both polygons, and the point files weremerged. Multivalues were extracted and outputted as an excel table. Beta coefficients were then determined in R and the raster calculator was used to create the final raster, probability.tif.

Objective 3

The purpose of the third objective was to assess the accuracy of predicted forest loss using the model developed in *Objective 2*. In order to validate our results, we followed a similar methodology to Bavaghar (2015) as well as Hosmer & Lemeshow (2000). We validated the significance of each factor and then determined the accuracy of the model when compared to the forest loss data. Factors were validated based on the *p* coefficients. *p* coefficients, given by the output of the logistic regression, that have a value lower than 0.05 are considered to be significant factors and any value higher will be deemed insignificant (Hosmer & Lemeshow, 2000). The accuracy of the overall model was determined through an Akaike Information Criterion (AIC), which is a statistical model that estimates out of sample prediction error and therefore can determine the most appropriate model (Akaike, 1973). Four different models were generated (Table 3) in order to determine the lowest AIC value, and the model with the lowest value was therefore the model we used (Akaike, 1973). The probability values were then acquired and compared to the University of Maryland Forest Loss data.

Objective 4

The purpose of the fourth objective was to evaluate the results of *Objectives 2* and *3* for strengths and weaknesses regarding selection of study site and chosen deforestation variables. Although chosen for their perceived impact on deforestation, variables slope, rivers and PAs were found to have insignificant impact. This remainder of objective is met in the following sections.

Research Findings

Through our analysis in both ESRI's ArcMap and RStudio, we were able to yield a deforestation probability raster using beta coefficients based on our four variables. From our four variables, Euclidean distance rasters were generated for PAs, roads and waterbodies, and a slope raster was calculated from the DEM (Figure 8). These four rasters were stacked, and 100 points were sampled from both deforested and forested land (Figure 10). The four variablesderived at these points were used to perform the logistic regression. Immediately, it is visually evident that the predicted deforestation and the deforested land data from the University of Maryland (Figure 9) are spatially similar (Figure 11).

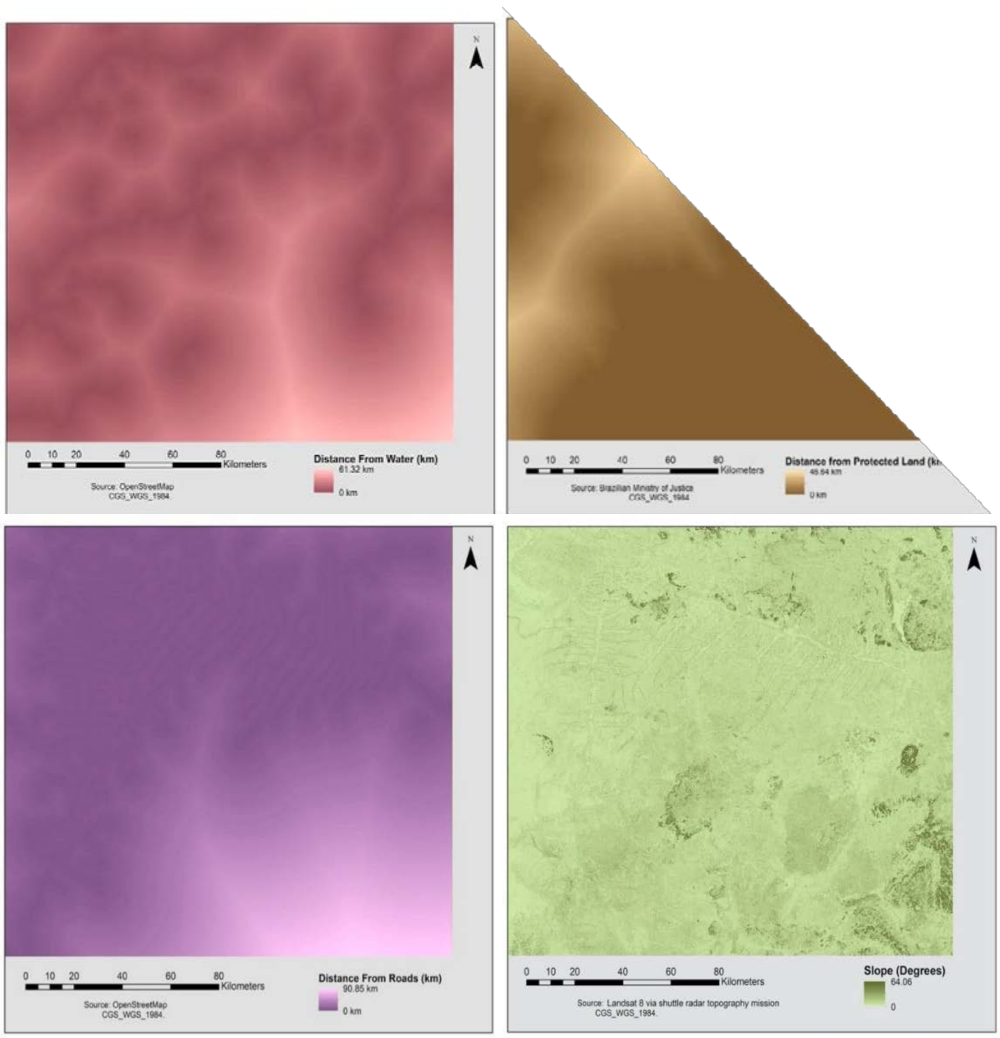

Figure 8. A grid of four rasters depicting the Euclidean distance to water (A), protected Areas (B), roads (C), and a raster of the slope in degrees (D). These represent the four analysis variables used in the construction of the model. Full size image can be found in the appendix. Euclidean distance rasters measure the ordinary straight line distance between two points. Therefore, The rasters A, B and D have a glow radiating from the respective feature being measured

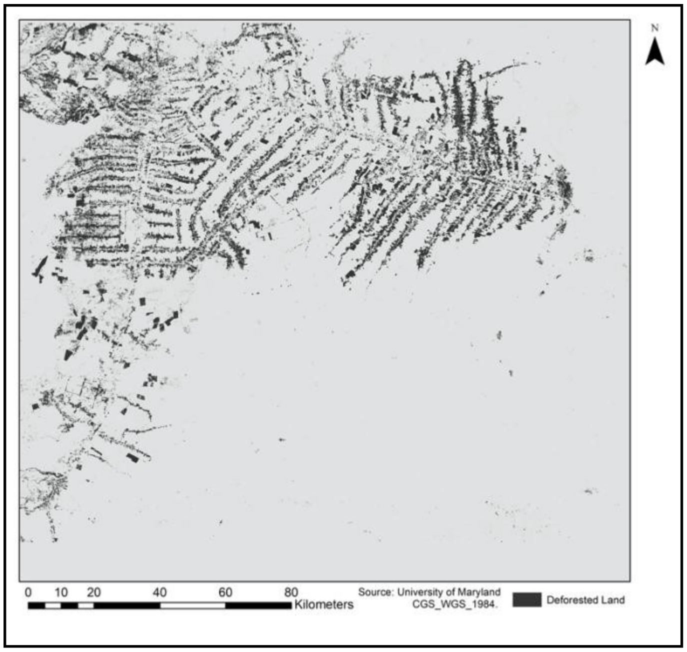

Figure 9. Deforested land within the study area. Data was acquired from the University of Maryland, via the Landsat Satellite and remote sensing techniques that identify tree cover change over time, from 2000 to 2018.

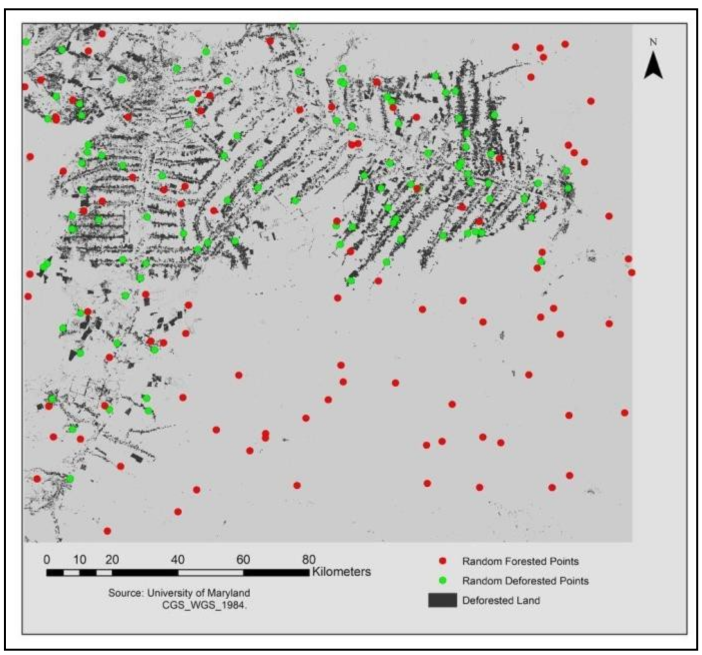

Figure 10. Deforested and forested points used for regression analysis in the study site in Roraima, Brazil. Data used for each point was determined through use of the University of Maryland dataset. Points were selected using stratified sampling and the random points tool.

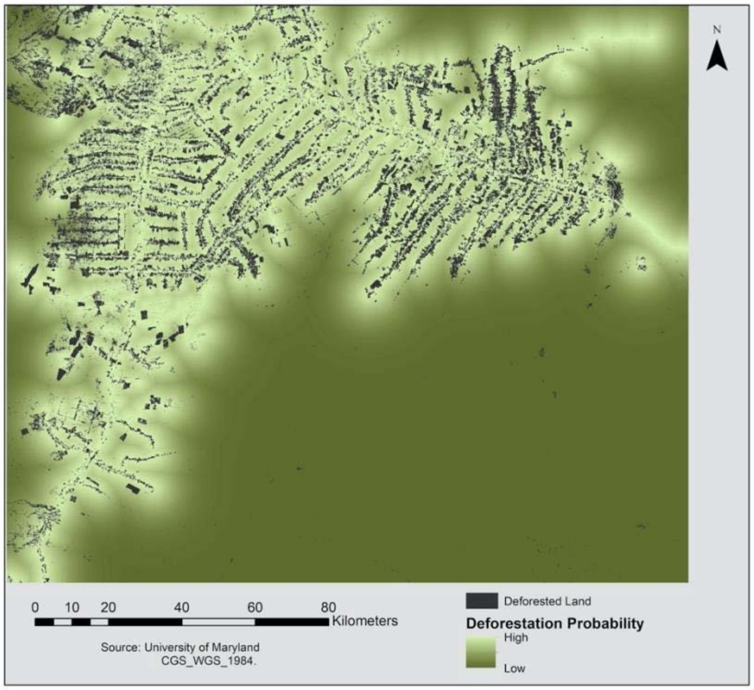

Figure 11. Deforestation data from the University of Maryland in comparison to the predictive raster that was generated from the model. The predictive raster has a glow that radiates from the areas of current deforestation, immediately showing that the model was effective.

Based on the results from the logistic regression performed in R, we were able to determine which of our predicted variables contributed to deforestation in our chosen study site. Roads overwhelmingly had the highest correlation to deforestation, with a *p* value of 9.49e-05. Following this, none of our other variables were determined to be statistically significant at a 95% confidence interval in causing deforestation (PAs: *p* value of 0.527, slope: *p* value of 0.711 and water: *p* value of 0.861) (Table 2). The best model to predict deforestation in our study area does not include any variable besides roads. This was determined based on the AIC (Akaike Information Criterion) (Table 3), which determines which model is the best fit (Mohammed et al., 2015). Our findings show that a model using only roads has the lowest AIC value and therefore was determined to be the best model (Figure 12).

Table 2. Four variables and their p values: output from R. Roads had a p-value of 0.0000949, water had a p-value of 0.861, protected area had a p-value of 0.527 and slope had a p-value of 0.711. A lower p-value is indicative of better results.

Variable	**Estimated Std.**	**Error**	**Z value**	***P* value**
Roads	-2.498e-04	6.398e-05	-3.903	9.49e-05
Water	-5.372e-06	3.058e-05	-0.176	0.861
Protected Area	1.048e-05	1.657e-05	0.633	0.527
Slope	2.293e-02	6.189e-02	0.371	0.711

Table 3. The four different models that were run, where model 4 (M4) was determined to be the most appropriate based on an AIC value of 212.5259. Model 1 (M1) contained all four variables, and had the highest AIC at 217.8941. With waterbodies removed, M2 had an AIC of 215.9249. Upon the removal of slope, M3 composed of roads and PA had an AIC of 214.0723. Finally, the most appropriate was M4. This model included only roads as the singular variable.

Model Number	**Variables in the Model**	**AIC value**
M1	Roads, waterbodies, PA and slope	217.8941
M2	Roads, PA and slope	215.9249
M3	Roads, PA	214.0723
M4	Roads	212.5259

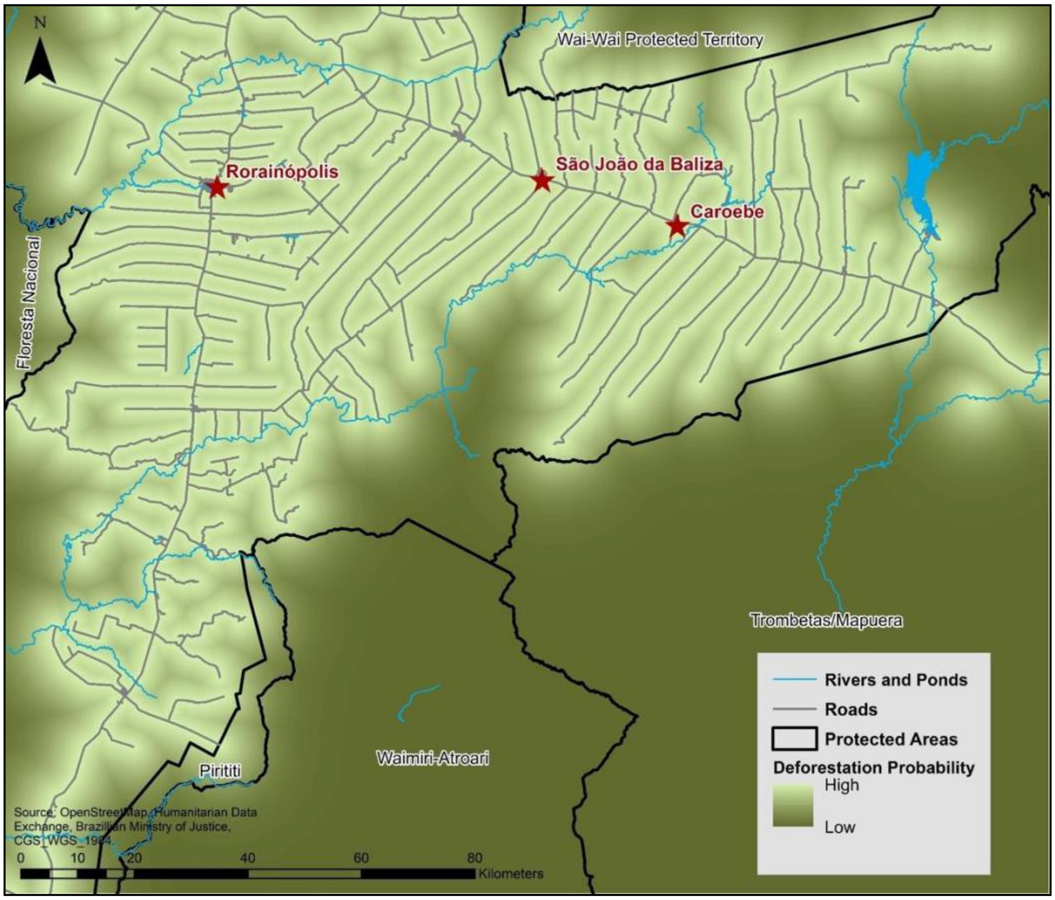

Figure 12. Study area depicting the predicted deforestation raster with the roads, waterbodies and protected land as reference. Note that the roads were the most statistically significant to be a predictor of deforestation, and there is a significant amount of evident buffering around the road features.

The model and the results generated contains strengths and weaknesses (Table 4). Immediately, it is important to note that the model and logistic regression performed in this analysis are unique to this study area and beta coefficients may not be applicable to other study sites, even in other areas of Roraima, Brazil.

Table 4. Overall strengths and weaknesses of our model.

Model Strengths	Model Weaknesses & Limitations
➢ Able to predict deforestation probability with reasonable accuracy ➢ Highlighted which variable contributed most to deforestation (roads) ➢ Simple to compute and visualize	➢ Not necessarily applicable in other deforestation scenarios ➢ Inherently a spatial problem, therefore spatial autocorrelation will likely impact our model. ➢ Cannot predict exactly where deforestation *will* occur, predicts only the probability of deforestation

Model Evaluation

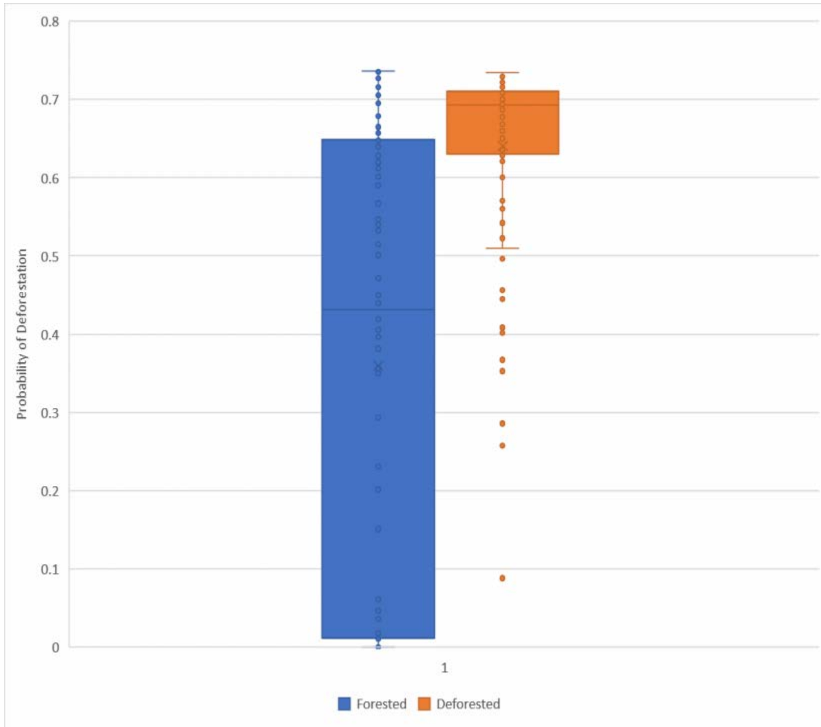

Figure 13. Box and whisker plot depicting the distributions of probability for forested and deforested land. Plot for forested land contains a large area which is indicative of a larger deviation amongst probability values. Plot for deforested land contains a much smaller area which indicates a lower deviation amongst acquired values.

Once the predictive deforestation map was generated, a box and whisker plot was then created to aid with assessing the accuracy of our results. Based on Figure 13, there can be seen two plots on the same graph describing the distribution of point probabilities that were selected on both deforested and forested land. The line contained within each box is the median of that range of probabilities, which would indicate that 50% of points lie above and below that line. The median probability of deforestation of the forested and deforested points were found to be 0.4318 and 0.6931, respectively. Assuming a threshold probability value of 0.5 (values with probabilities below this representing likely forested and areas above representing likely deforested areas), our model contains 88% of the points above 0.5 for deforested areas and 55% of points below 0.5 for forested areas. Based on this assumption, we have determined the model to make a reasonably accurate prediction of where deforestation is likely to occur.

Discussion

Roads were determined to be the most impactful on deforestation. Distance to water, protected areas (PAs) and relative slope were determined to have an insignificant effect on deforestation in our study site with given analysis methods. These results contradict the results from Bavaghar (2015), which claimed that slope was a significant factor. One explanation for this could be that the land is relatively flat in our study area compared to that of Bavaghar (2015) which took place in Iran. This could indicate that relative steepness of the slopes plays a much larger impact. PAs having an insignificant impact on deforestation could indicate that these areas are not being protected. We would assume that the PAs would have an inverse relationship with deforestation due to the sites being preserved. This could be indicative of our selected PA's being part of the "paper parks" phenomenon where an area is selected for protection, but is not protected due to lack of resources (Figueiredo, 2007 & Verburg et al., 2012). Water also having insignificant impact on deforestation in this area is interesting, as it could mean that the study area's economy does not heavily rely on water specifically from rivers and ponds for agriculture development. The study area falls within the Coastal Plain groundwater province in Brazil, where large amounts of groundwater can be easily obtained from artesian wells (Schneider, 1963). This could imply that the study area already has an effective irrigation and water system, meaning being in close proximity to water is not a concern. However, it is important to note that the direct presence of water was not deemed a significant driving factor of deforestation.

Conclusions

The purpose of this research was to create a predictive deforestation model using a logistic regression-based analysis which would determine which factor(s) is most influential to deforestation. Roads were determined to be the most significant factor contributing to deforestation in our study area based on our model and our outputs. This points to roads as the lead driver in deforestation, however, our model does not explain why the deforestation was heavily reliant on the presence of roads. Waterbodies, PAs and slope were not found to significantly contribute to the probability of deforestation.

The overall goal of this project was not to compute a model applicable worldwide, but to be predictive in nature for the selected study site. In continuing this work, selection of study site and evaluation model will change results. Going forward, there are still gaps in our research regarding other variables that can potentially impact deforestation such population density and cites. Furthermore, analysis should be conducted into a possible connection between tree cover type (species) and deforestation, as well as why deforestation is occurring. Further studies should be conducted to better understand what other variables may drive deforestation to help mitigate biological effects on the environment and climate.

Table 5. Some potential changes to consider when choosing future study sites and variables.

Original Method/Choice	**Change to be Made**	**Reason**
Study area selection	Choose an area with less roads	Could have allowed for a more interesting result if variables were in the study area in even amounts
Study area selection	Choose an area with more topographic variation	Areas with greater variations in slope could have potentially had a greater impact on the model.
Model evaluation: Box Plot	Compute an ROC (Receiver Operating Characteristics) probability curve	Could distinguish between true and false positives, and determine how effective our model is.
Deforestation Factor	Consider cities and city size	Adds another variable to model.
Deforestation Factor	Consider land use post-deforestation	Analysis of reasons for areas of deforestation (i.e logging, farming) could provide insight into which practices have more of an impact on the rate of deforestation.

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Appendices

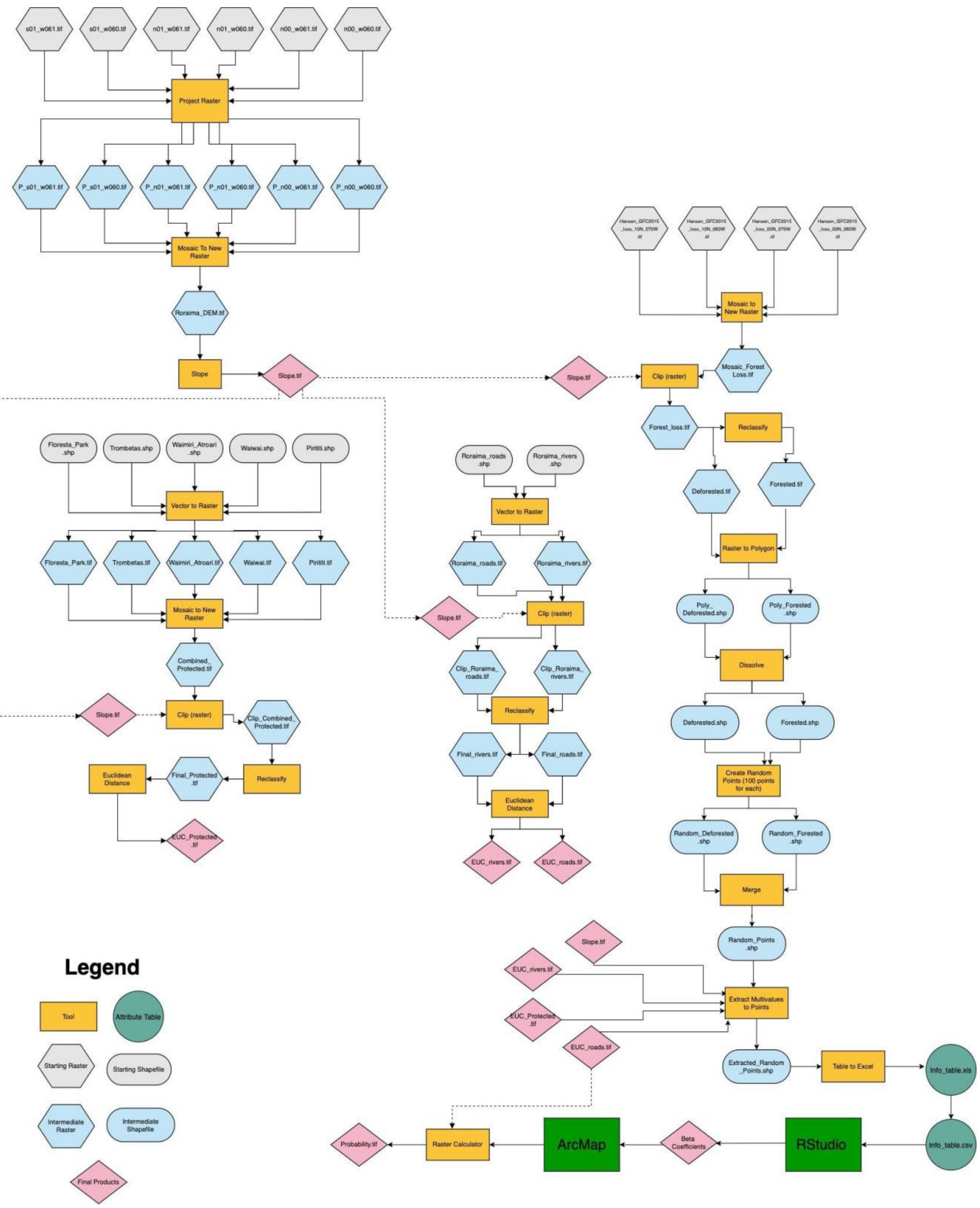

Figure 14. Full flow chart depicting the entire workflow.

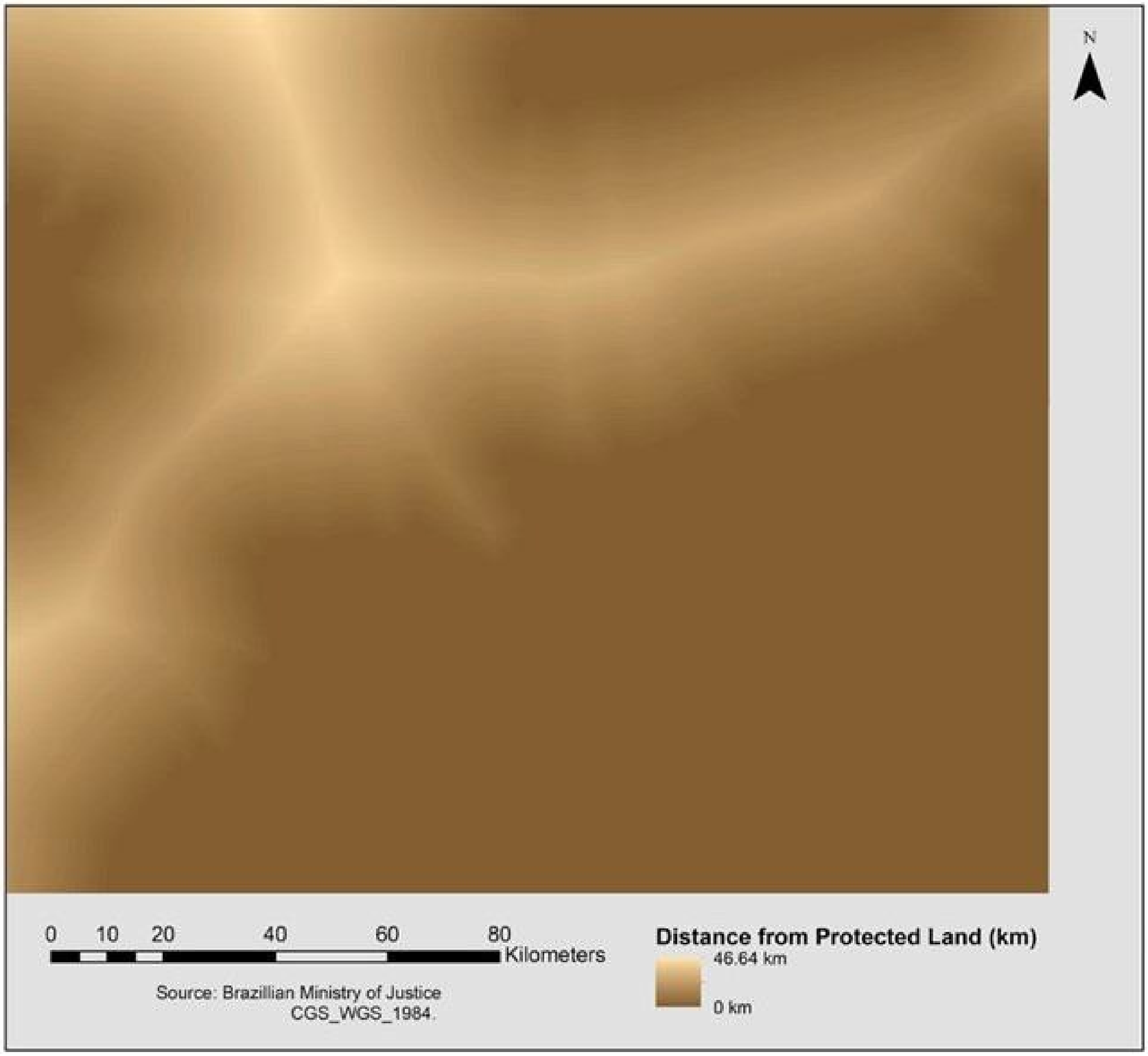

Figure 15. Distance from protected land raster.

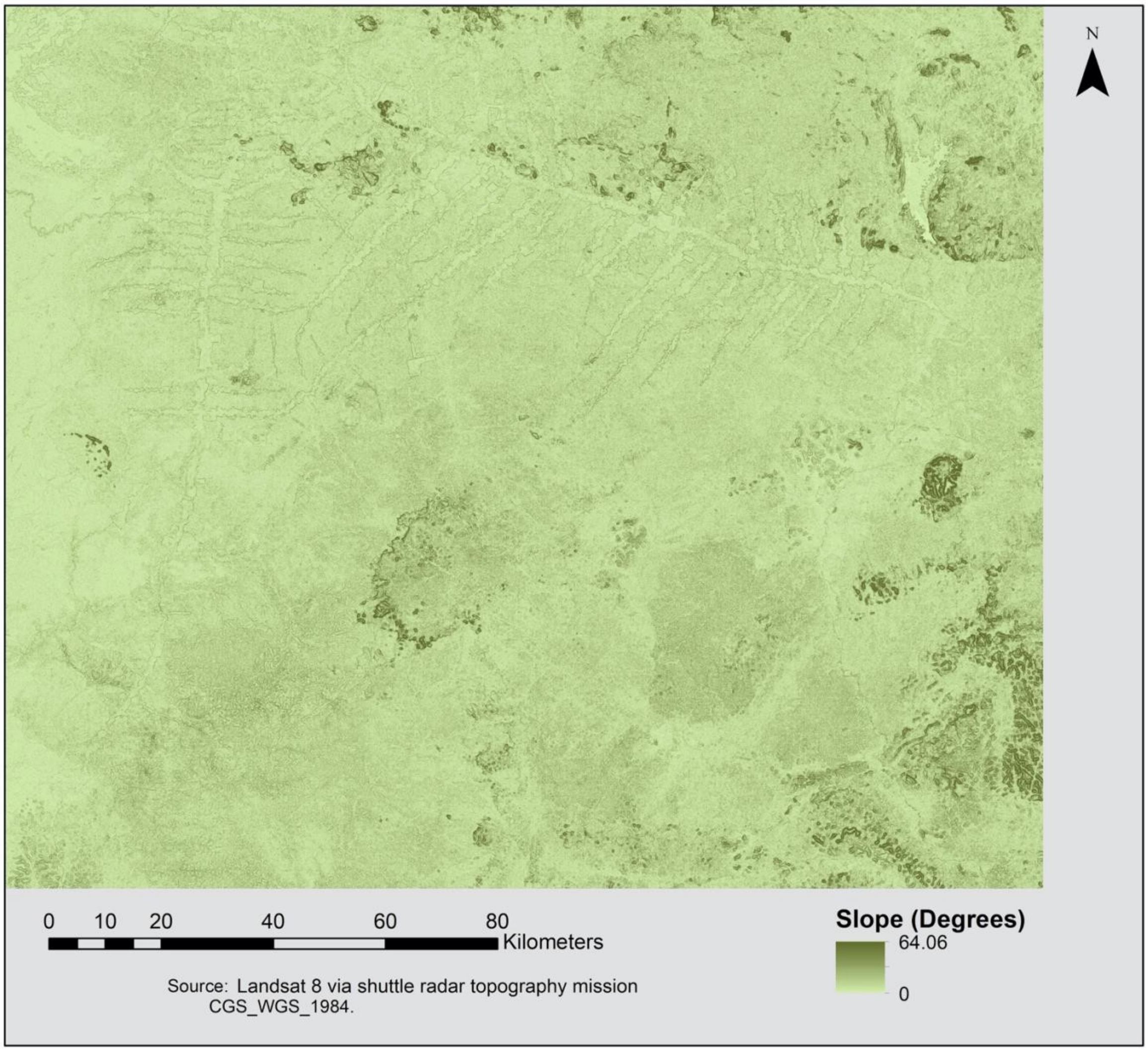

Figure 16. Slope raster.

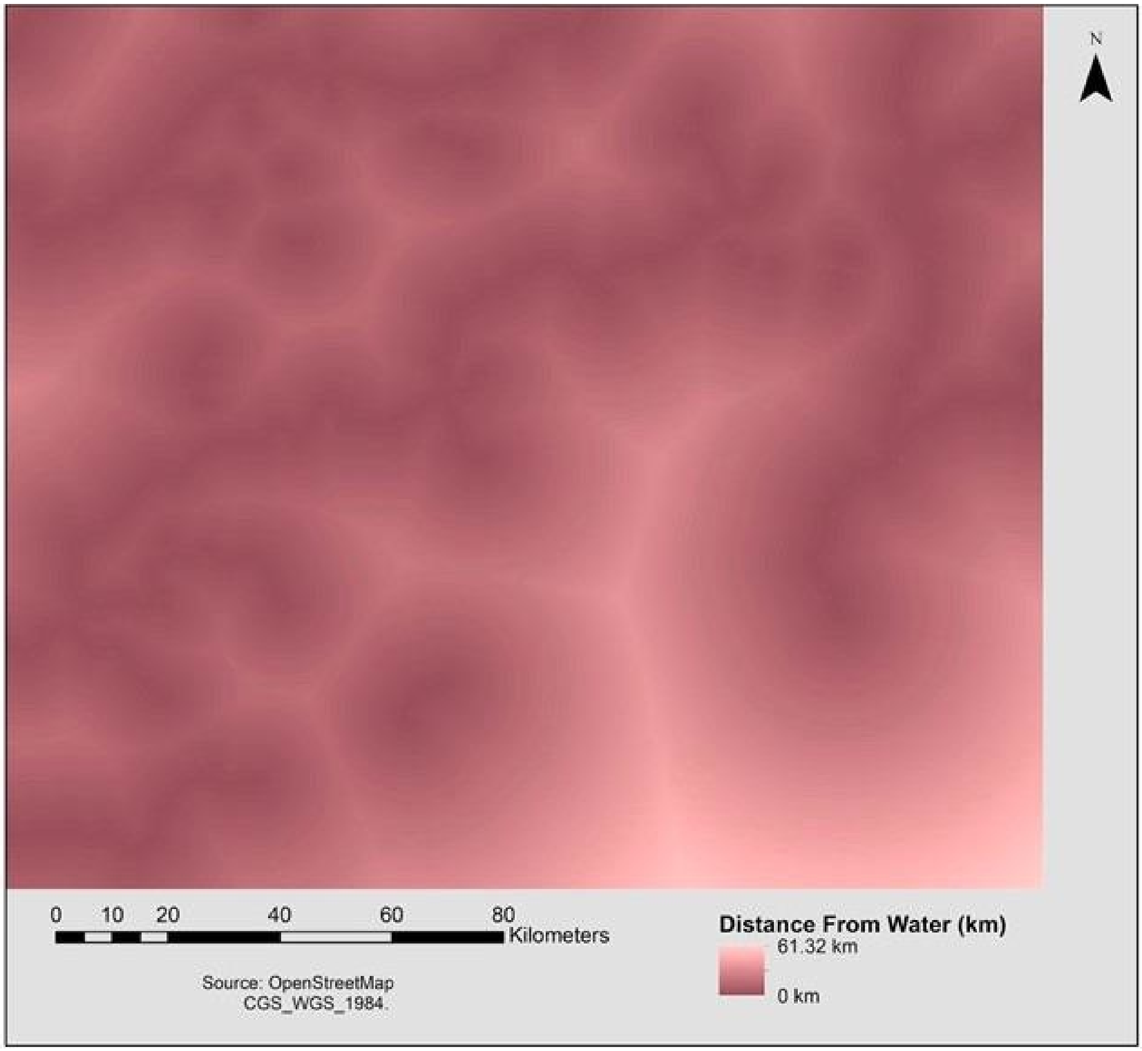

Figure 17. Distance from water raster.

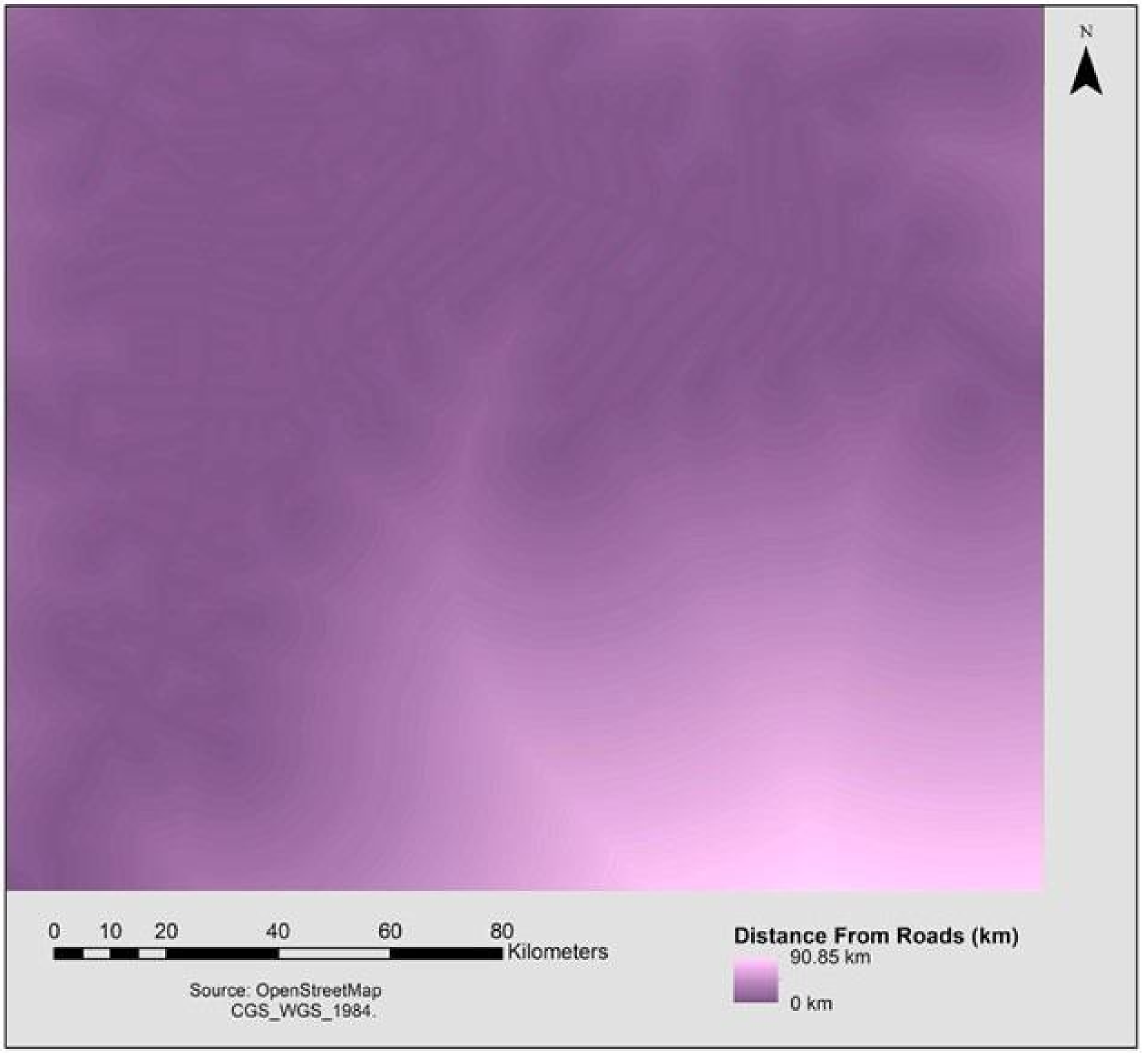

Figure 18. Distance from roads raster.