Predicting At-Risk Areas for Deforestation in Malawi

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Abstract

One of the poorest nations in Africa, the small country of Malawi has recently experienced severe deforestation. From 1990-2010, Malawi lost 17% of its forest cover (FAO 2013). Malawi also has the 6th highest population growth rate in the world (3.3% per year) (CIA 2014). Given this information, our study aimed to predict areas of future deforestation in Malawi. We constructed a spatial model to predict deforestation using the following parameters: distance from roads, distance from major markets, and population density. Our model predicted tree cover loss from 2000-2010 with some degree of accuracy. We then applied this model to currently forested areas to predict areas at-risk for deforestation.

Introduction

Malawi is a small country of 17 million people located in southeastern Africa. One of the poorest nations in Africa, Malawi continues to experience rapid forest loss. From 1990-2010, Malawi lost 660 ha of forested area, around 17% of its total forested land (FAO 2013). With the 6th highest population growth rate in the world (3.3% increase per year), Malawi’s population will continue expanding for the foreseeable future (CIA 2014). Villagers living around forests contribute to deforestation, mainly by cutting trees, opening up gardens, grazing livestock, and burning charcoal (Minde et al. 2001). Expanding populations also results in a higher density of road networks, a factor linked to deforestation in Thailand (Cropper et al. 1997). With limited funding, conservation efforts must focus on the areas of highest risk for future deforestation. In this study we created a spatial model that could be tested on past deforestation trends in Malawi, in order to identify the currently forested areas that might be at risk for future deforestation.

Methods

We used ARCGIS 10.2 (ESRI) to model and predict the most at-risk forested areas for future deforestation in Malawi. We obtained Landsat images of forest cover for the year 2000, and forest cover lost from 2000-2013. These files came from the University of Maryland’s School of Geographic Science (Hansen 2013). These images were merged and clipped to only include the area within Malawi’s national boundaries. Diva-GIS provided a road network map, the ArcGIS website provided a population density map, and MASDAP provided the location of the three largest urban centers. The population density map was converted to a raster layer. We projected the data to UTM Zone 36 WGS84. We created a deforestation model. The model determined areas that could be at risk for deforestation based on the following parameters: distance from roads, distance from markets, and population density. Euclidean distance from roads resulted in index scores from (1-40), while Euclidean distance from major markets resulted in a score of (1-30). Population density was reclassified to give each forested area a value of (1-30). These factors were combined to create an additive model. The parameters were weighted based on previous deforestation research (Cropper (1997), Minde (2000), FAO (2013), Global Forest Watch (2015)). The tree cover data was then added to the model. We included all forest areas with a canopy density greater than 30% (Global Forest Watch 2015).Those with under 30% cover were reclassified as “No data”. Our model was then compared to the actual tree cover loss from 2000-2013. In order to determine how accurate our model was in predicting areas at risk for deforestation, we generated a box plot output using R Studio. To predict future at-risk areas, we reclassified our model to highlight areas

with scores of 50-75 (moderate risk), and 75-100 (high risk). The areas were clipped to the extent of existing tree cover in Malawi.

Results

The boxplot output showed our model was somewhat able to predict deforestation from 2000-2013. This output demonstrated the relationship between our data (tree cover vs. tree cover loss) and the corresponding model values associated with these pixels. The mean is depicted by bold black line, and 50% percent of our data falls within the grey boxes. We generated an output that showed that areas with a higher mean value were more likely to be deforested than those with a lower value at a slightly significant rate. Areas with extremely high values (90 - 100) were almost all deforested, as seen in Figure 3.

Discussion

Our model can be used to predict areas at risk for future deforestation, specifically by looking at the areas with high values that have not yet been deforested. The areas with high values indicated by orange and red in Figure 4 are at risk. However, our model does have several limitations. By solely factoring in three major parameters, our model does not consider the additional factors that may contribute to deforestation. While deforestation can be modeled and predicted to a degree, it does not solely occur as a direct impact of the aforementioned factors. Our model cannot predict if areas of land will be purchased and converted for agricultural purposes, or if they will be set aside and conserved as forest lands.

Works Cited

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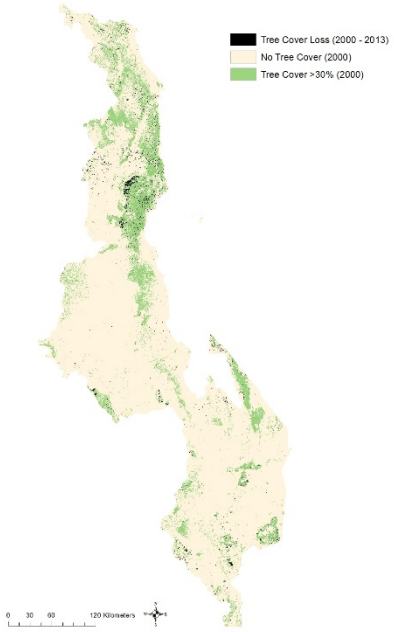

Figure 1: This map shows tree cover (2000) and tree cover loss from 2000-2013 in Malawi

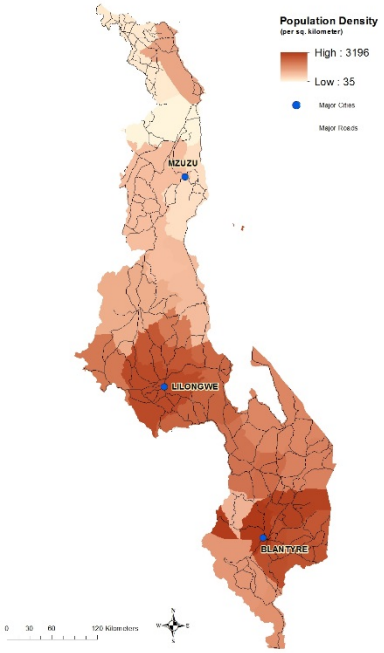

Figure 2: Population density, major roads and major cities in Malawi

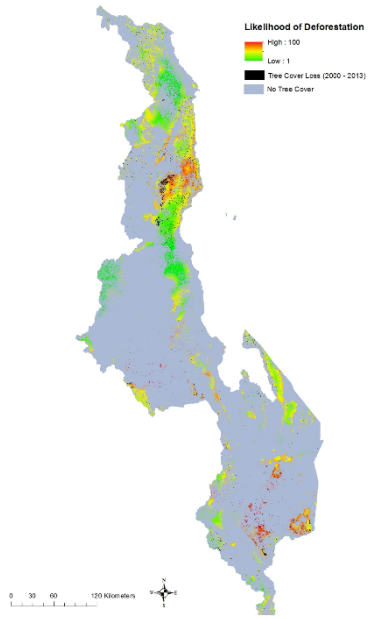

Figure 3: This map illustrates the relationship between our deforestation model and actual tree cover loss from 2000-2013 in Malawi

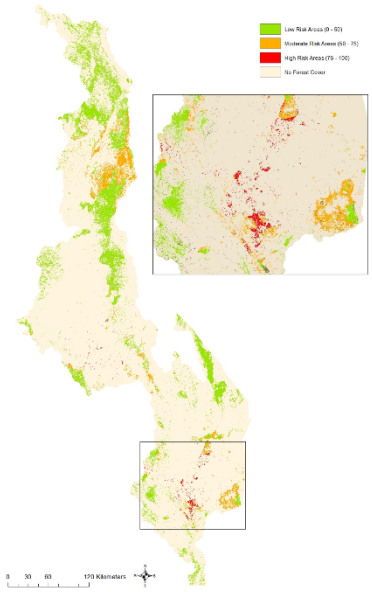

Figure 4: This map illustrates the areas our model shows to be at-risk for deforestation, with an inset of the high risk areas in the southern region of Malawi