Assessing terrain dependency of deforestation in Borneo (2001-2019)

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Contents

1. Introduction

Deforestation is one of the major challenges for the future and currently threatens more than one million animal and plant species with extinction, while 1.6 billion people are dependent on forest resources for their livelihood (Diaz et al*.,* 2019; FAO, 2013). Because of this, it has been named as one of the 17 Sustainable Development Goals by the United Nations to “Sustainably manage forests, combat desertification, halt and reverse land degradation, halt biodiversity loss”. According to a report published by Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem services (Diaz et al., 2019) between 2010 and 2015 a total of 33,000 square kilometers of forest was lost.

This effect is even more pronounced on the island of Borneo, which has lost almost 22% of its total forest area between 2004 and 2017 according to a report published by the World Wide Fund for Nature (Pacheco et al., 2021). The same report states that “Deforestation may continue expanding, but likely to slower rates”, indicating that deforestation will remain a prevalent issue on the island. The author goes on to state that the primary drivers of forest loss are tree plantations, for wood and pulp, and large-scale oil palm plantations, with secondary drivers being smallholder farming, fires and construction of infrastructure. Three of the five drivers are considered agricultural in nature, giving credit to the fact that many forest types have been diminished in the recent decades on the island, with intense logging of Dipterocarp forests causing a loss of 29,000km^2 between 1985-2001, conversion of peat swamp forest to drainage-based agriculture and exploitation of mangrove for forest products or aquaculture development (Curran et al., 2004; Cooper et al., 2020; Polidoro et al., 2010).

It is likely that most of this deforestation has been happening at lower altitudes and flat terrain as this terrain is more suitable for industrial agriculture, commercial plantations and urban expansion. This is reflected in a research from Sandel and Svenning (2013) which found a strong relationship between slope and deforestation. The author states “As the human population increase and land use demands intensify over the next century of the Anthropocene, slopes are likely to become increasingly important refuges for forest”. Although this research only uses one variable, slope, it is expected that a similar trend is observed with elevation, since elevation has a major influence on average temperature which in turn, has a considerable influence on the average temperature.

For these reasons, it is hypothesized that deforestation in the last two decades (2001-2019) has increased on less accessible terrain on the island of Borneo. This drive has been caused by the lack of available space on flat terrain due to extensive clearing of lowland forests, resulting in an increased need for suitable space at higher elevation and steeper slopes. This paper aims to create more insight in the terrain dependency of deforestation in Borneo and see if patterns have changed over the last two decades. This is done through two main terrain parameters, slope (%) and elevation, to answer the research questions (1) to what extent does the slope influence the rate of deforestation on Borneo and (2) to what extent does elevation influence the rate of deforestation on Borneo.

2. Material and methods

To analyze the relationship between the terrain parameters, slope and elevation, several data source had to be processed. This was done using Python (v3.8.5) to allow for modifications in the classification parameters and re-use for similar research. First the paper will process the annual deforestation data acquired from the Global Forest Watch to remove redundant vegetation classes. Secondly, using data from the Shuttle Radar Topography Mission, we categorize the slope and elevation into four different categories. At last, the relative deforestation is calculated which is used to perform a simple linear regression between deforestation and the defined elevation and slope categories.

2.1 Data sources

To explore the relationship between terrain characteristics and deforestation rates, it is important to select the right datasets covering the necessary variables. The main dataset for this purpose is the deforestation raster (‘*lossyear*’) covering the change from the state of forest to non-forest between 2001 and 2019. Although the methodology and data were first published in 2013 by Hansen et al., the dataset and methodology are still being changed, with the newest version (v1.7) being updated in 2019. The same dataset includes the product of tree canopy cover in the year 2000 (‘treecover2000’) which is used as a baseline in this research. However, as of June 2021, the data covering the period from 2000 to 2011 has not been updated yet.

The terrain parameters are derived from the Shuttle Radar Topography Mission (SRTM), version 3 published by NASA (Farr et al., 2007). The slope was derived from the elevation data using the Slope function in ArcGIS Pro (v2.7). In addition, to make sure the relationship is only measured on the island of Borneo, a vector dataset served as mask. In this case, the Global Islands Explorer created by Sayre et al (2018).

Variable	Title	Author	Spatial resolution
Deforestation	Tree cover loss (‘lossyear’)	Hansen et al., 2013	30m
Base tree cover	Tree cover loss (‘treecover2000’)	Hansen et al., 2013	30m
Slope		Derived from SRTM	30m
Elevation	SRTM (v3)	Farr et al., 2007	30m
Borneo mask	Global Islands Explorer	Sayre et al., 2018	--

Table 1. Table indicating the different datasets used during the research for each variable.

2.2 Processing of deforestation data

Forest was defined as pixels with substantial tree cover (>30%) based on a variety of studies focusing on deforestation, e.g Margona et al. (2014), 30%; Sandel and Svenning (2013), 25%; Turubanova et al. (2018), 50%; Gaveau et al. (2018), 30%; Hansen et al. (2013), 25%. In addition, the data available from Hansen includes only cells where the trees are taller than 5 meters, excluding small shrubs and crops. Using the *treecover2000* product available on Global Forest Watch, all pixels are converted to Boolean values where tree cover above 30% is set as ‘Forest’, whereas all values less than the criteria set, are transformed to ‘non-forest’.

The annual deforestation was retrieved from the ‘lossyear’ product from Hansen et al. (2013) with data from 2001 up to 2019. To ensure that the relationship between deforestation and terrain parameters is analyzed correctly, all pixels overlapping the previously established ‘non-forest’ category are removed. This threshold is created to remove non-forest vegetation classes from the analysis, mainly herbaceous habitats with aquatic hydrophytes and shrubs which typically occur in sparse forest cover (<20%) according to a land cover classification system developed by the Food and Agriculture Organization (Gregorio and Jansen, 2001).

This study was conducted on the island of Borneo, however, all datasets used within this research have a spatial scale covering the entire globe. For this reason, a vector mask had to be applied to remove all deforestation data outside the study area. Therefore, the Global Islands Explorer developed by Sayre et al. (2018) was used to select the polygon covering the study area. Subsequently, all deforestation loss outside the main island was removed. See figure 1.

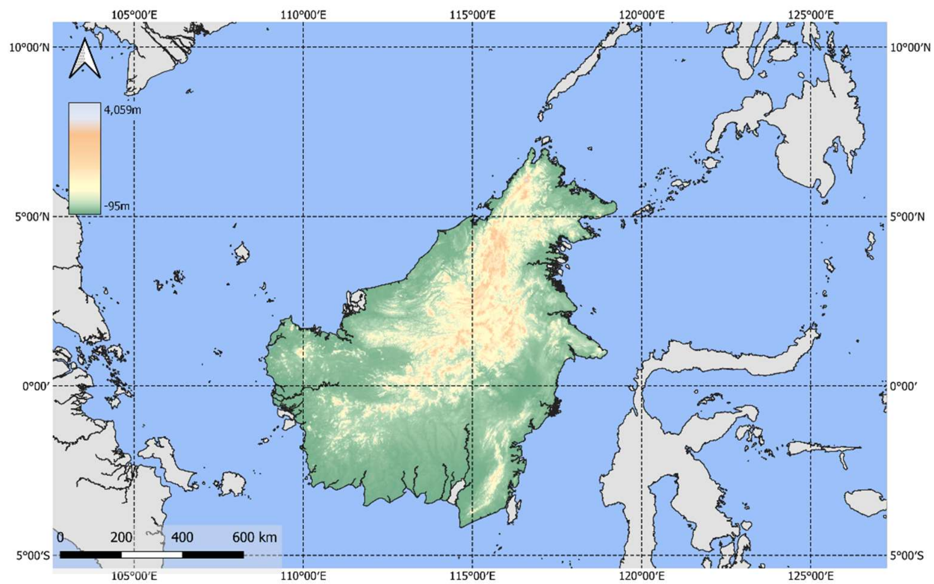

Figure 1. Map indicating the study area of Borneo with elevation from the Shuttle Radar Topography Mission. Landmass data is from the Global Island Explorer.

2.3 Classification of terrain parameters

For this research it was decided to use two main terrain parameters: slope and elevation, which are common predictor values to analyze, and predict, deforestation (Mayfield et al., 2017). Slope was split into four different categories to represent the range from flat lowland areas to steep mountainous terrain. As no scientific classification exists, the ranges were chosen to be relatively comparable to previous research, e.g Bałazy et al. (2019); Birhanu et al. (2019).

The approach was different for the elevation categories, as with slope, literature exists with defined intervals, but they are highly context-specific and vary greatly between studies. Therefore, the elevation ranges were divided into equal zones of approximately 500 meters. It is important to note that the peak elevation in Borneo is much higher, at 4,059 meters, but 99.6% of the landmass has an elevation lower than 1500 meters.

Variable	Classification	Minimum	Maximum
Slope (in %)	<10	0	9.99
	10 – <20	10	19.99
	20 – <30	20	29.99
	>30	30	100
Elevation (in meters AMSL)	<500	-95	499
	500 - <1000	500	999
	1000 - <1500	1000	1499
	>1500	1500	4059

Table 2. Classification of terrain categories.

2.4 Data analysis

The deforestation data has a high variance in the amount of land changed from forest to non-forest per year, this effect is even more pronounced when comparing deforestation in different classifications. Therefore, it was decided to use relative deforestation instead of absolute values. The relative deforestation is calculated by summing up all deforestation pixels in a single year per terrain category and dividing this value by the total of all deforestation pixels in that year. This can be seen in the equation below.

$$Relative\ deforestation = \frac{\sum Pixel_{year^{-1}\ category^{-1}}}{\sum Pixel_{year^{-1}}} * 100$$

At last, a simple regression was calculated to determine the relationship between the terrain parameters and deforestation. The inputs for the regression were the calculated relative deforestation $year^{-1}$ $category^{1}$ and the temporal range from 2001 to 2019. Using SciPy, a simple regression using the Ordinary Least Squares method was calculated. In addition, the same library was used to calculate the P-value using a Wald Test with null hypothesis.

3. Results

3.1 Slope

On observation of deforestation in each slope category, it becomes apparent that the rate of deforestation greatly differs between each classification. While deforestation within the first category (<10%) seems to decreasing, the opposite effect is seen in the second and third category where the rate of deforestation seems to be increasing. Notable is the high variance between the total forest area lost per year (see figure 2).

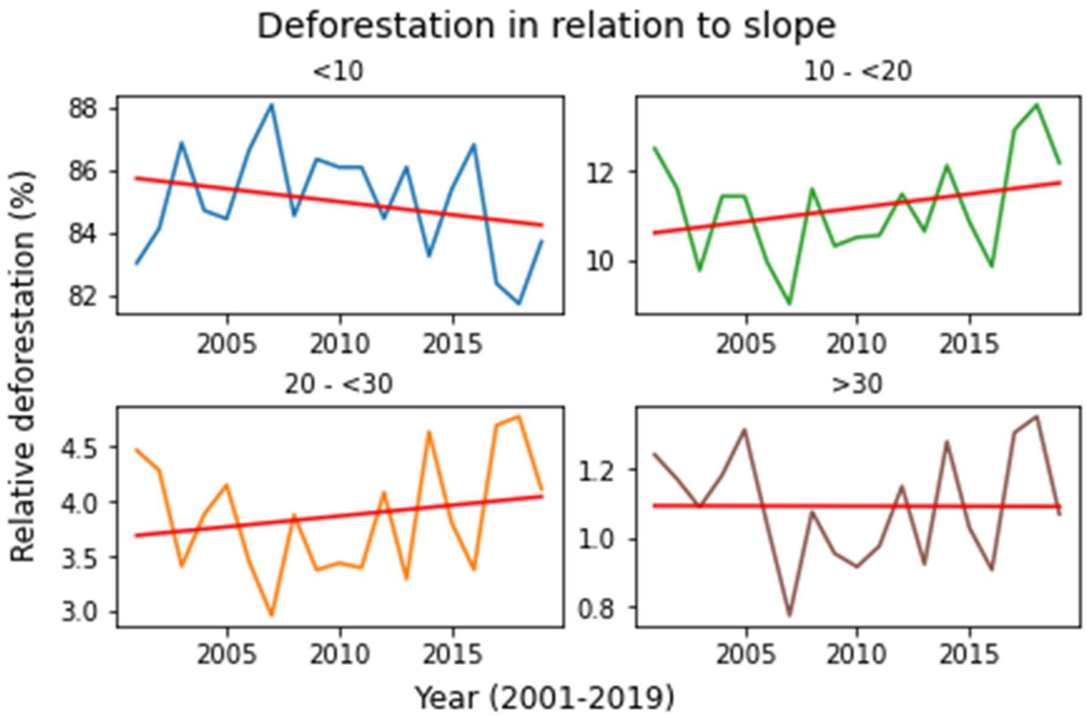

Figure 2. Graphs indicating relative deforestation within different slope classes between the period of 2001-2019.

While the regression line in the different categories can be seen to increase or decrease (with >30% being an exception), these results are not reflected when looking at the r^2 of each category. As seen in table 3, the highest r-squared is 0.090 in the lowland category and $2.1 * 10^{-5}$ in the highlands. In addition, none of the slope categories yield a statistically significant value (*P*-value ≤ 0.05).

Variable		Total deforestation (2001-2019)		R-squared	*P*
	%	Area (km^2)	%		
Slope	<10	147 491	84.18	0.075	0.26
	10 – <20	19 206	10.96	0.090	0.21
	20 – <30	6 640	3.79	0.042	0.40
	>30	1 864	1.06	0.000021	0.99

Table 3. Total deforestation within different slope categories with statistical values describing the relationship between the rate of deforestation over the period between 2001 and 2019.

3.2 Elevation

Like the relationship between slope and deforestation, similar results can be seen within the elevation categories. In this case, the second and third category both experience a slight increase in areas deforested, the low-lying areas has a minor decrease while the highlands experience little no change in the regression line.

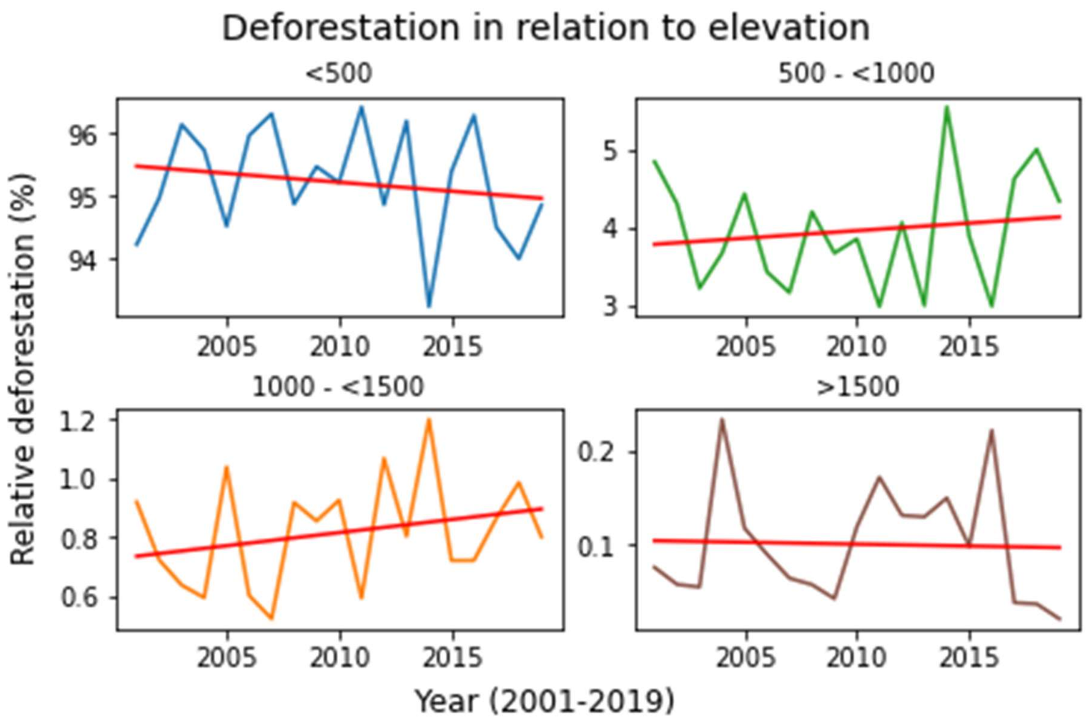

Figure 3. Graphs indicating relative deforestation within different elevation classes between the period of 2001-2019.

A notable difference between the slope and elevation is the distribution of area within both parameters, while the first category in slope contained about 84% of all values, in elevation this number is much higher, with only 5% of the area distributed in the other three categories. At last, it is critical to mention that none of the results calculated are statistically significant.

Variable		**Total deforestation (2001-2019)**		**R-squared**	***P***
	m	Area (km^2)	%		
Elevation	<500	170 998	95.14	0.032	0.46
	500 – <1000	7 059	3.93	0.022	0.55
	1000 – <1500	1 487	0.83	0.073	0.26
	>1500	196	0.11	0.001	0.88

Table 4. Total deforestation within different elevation categories with statistical values describing the relationship between the rate of deforestation over the period between 2001 and 2019.

4. Discussion & conclusion

This paper sought out to analyze the relationship between deforestation and terrain parameters, namely slope and elevation, on the island of Borneo. Anthropogenic deforestation is a major problem for the island of Borneo, with over 170,000 square kilometers of forest being cleared in the period from 2001 to 2019. Most of this conversion to non-forest state has occurred in the defined lowland classes, slope lower than 10% and elevation below 500 meters, with each category containing 84% and 95% of total area deforested. In addition, once a simple regression had been calculated, a negative trend was detected along the aforementioned lowland classes, meaning that deforestation has been decreasing in comparison with the other categories. On the other hand, a positive trend was established in the second and third categories where deforestation has been gradually increasing. Therefore, the relationship between the terrain parameters and deforestation indicate that extensive clearing of lowland forests causes a drive towards less accessible terrain.

The results seen in this paper are comparable to similar studies focusing on the correlation between slope and deforestation, e.g., Sandel and Svenning (2013); Gayen and Saha (2018), which both concluded a correlation between deforestation rates and slope. Furthermore, comparable results are seen with elevation, e.g., Bhattarai et al. (2009); Linkie et al. (2004); Bax et al. (2016), with the latter concluding "…that areas at lower altitudes are more prone to deforestation threats such as farming and logging".

Like the study from Bax et al., agriculture is a major source of deforestation in Borneo. This is reflected by a recent report from the World Wide Fund for Nature (Pacheco et al., 2021) which identified five primary and secondary causes of forest loss, of which three can be considered agricultural in nature: tree plantations, large-scale oil palm plantations and smallholder farming. In line with the hypothesis, the increase in deforestation at higher altitudes and steeper slopes might be explained due to an increase of forest to agriculture conversion. Both large-scale oil palm plantations and smallholder farms (often consisting of oil palms as well) are effective at altitudes as far as 1500 meters and slopes up to 46% (Pirker et al., 2016), being closely linked with the classifications used in this research. In addition, a study conducted by Gaveau et al. (2018), concluded that plantations (88% oil palm; 12% pulpwood) have expanded by over 170% since 2000. However, two other common crops grown by smallholders are rubber and rice, both of which are unable to grow at high altitudes or steep slopes, with rubber being unable to grow at heights greater than 600 meters and slopes of 30% (Ahmed et al., 2017) and rice being most productive at elevation below 375 meters (Islam et al., 2018). In short, agriculture is likely a major cause of deforestation and driver towards less accessible terrain, nonetheless, differences between crop growing conditions make the data inconclusive to reliably name agriculture as the single source.

For this reason, the results should be taken into account when considering how to prevent deforestation and forest degradation. Oil palm plantations have rapidly expanded since 2000 and are effective at heights similar to classifications used within this research (1500 meters), hence, it is recommended to consider and research sustainable plantations. A recent study conducted by Gatti and Velichevskaya (2020) claims that current certification does not suffice as production of sustainable palm oil is occurring on deforested habitat of large mammals and stating "…every area that was a forest just "yesterday", and is logged "today", can become a sustainable plantation "tomorrow or the day after…". As a result, the implementation of stricter certification for sustainable produced palm oil is recommended. One such recommendation made by van Houten and de Koning (2018) is to "…include smallholders in the palm oil supply chain and enhance their certification. This could significantly enhance their productivity and thus overall production". Ensuring inclusion of smallholders within the certification process might reduce illegal forest clearing and prevent deforestation on new frontiers.

Another implication our results have been shown is that local deforestation hotspots are more likely to appear at altitudes between 500 and 1500 meter and sloping regions of 10-30%. This terrain is likely to make it more difficult for agricultural expansion or illegal logging to occur, at the same time, organizations with the aim of preventing deforestation face the same obstacle, often with less financial means available. Thus, it might be necessary to limit expansion of agriculture in these regions to protect existing forests. Be aware that restriction of oil palm plantations might require financial compensation for local citizens as plantations can have an economic benefit of $227 million (Naidoo et al., 2009).

The reliability of the results was impacted by lack of statistical significance, making it near impossible to draw decisive conclusions on the relationship between deforestation and terrain parameters. It should be noted that a trend line is visible within the data but because of high variance in the relative deforestation data no significant value can be calculated. In addition, concerns have been raised over the classification of slope and elevation categories as both categories have arbitrary intervals. During the research the intervals were chosen to be similar to other literature, but no scientific classification exists. As a consequence, results could be significantly different when different ranges are chosen, for example <10%, 10-20%, >30% compared to <5%, 5-10% and >10%. Moreover, results for the fourth category (>30% and >1500m) showed little change over the selected time period, likely because of inaccessible terrain and low quantity of pixels covering these ranges. For example, only 0.4% of the whole study area was located at an elevation greater than 1500 meter.

Future studies should take into account that the classification intervals need to be adjusted, preferably with smaller intervals. This would allow greater distinction between different forest types and accompanying tree species as altitude is of major importance to both tree diversity and distribution (Slik et al., 2009). Depending on the processing power, this approach could be better improved even further when the relationship is compared on a pixel-by-pixel basis. Using this method would completely remove the obstacle of categories skewing or influencing the data. However, processing power was a major issue for this paper and two parameters would require greater server capacity. At last, for future studies it might be beneficial to expand the spatial scale to include other major deforestation frontiers such as New Guinea, the Peruvian Amazon and Gran Chaco (Pacheco et al., 2021). This would allow greater testing of the hypothesis and yield more conclusive results, aiding future policy development concerning deforestation trends.

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