Deforestation, Forest Degradation, Erosion and Communities' Perspectives in Southern Belize

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DEFORESTATION, FOREST DEGRADATION, EROSION AND COMMUNITIES’ PERSPECTIVES IN SOUTHERN BELIZE

Doctoral Thesis

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Abstract

In Belize, the lack of deforestation, forest degradation, socioeconomic and erosion data results in the inability of management organizations to make timely assessments and decisions for sustainable resource management in southern Belize. This study uses CLASlite algorithms, statistical analysis, social surveys and the Revised Universal Soil Loss Equation to identify erosion hotspots, drivers, measure, analyze and map deforestation, and forest degradation that occurred in southern Belize. In Toledo, land and institutional policy, distance to markets and lack of alternative livelihoods are the main drivers of deforestation and forest degradation. The results of the deforestation and forest degradation analysis indicate that in 2009-2011 and 2011-2012 the annual rates of deforestation were 0.75% (2,480 ha) and 1.17% (3,834 ha) respectively and the annual rates of forest degradation in 2009-2011 and 2011-2012 were 0.09% (307 ha) and 0.33% (1,110 ha) respectively. Moreover, along the Belize-Guatemala border, forest declined from 96.9% to 85.7% in Belize and from 83.15% to 31.52% in Guatemala. The Mann-Whitney U test identified significant differences between leaders and stakeholders regarding the ranking of challenges faced by management organizations in the Belize-Guatemala border, except for the lack of assessment and quantification of deforestation (LD, SH: 18.67, 23.25, U = 148, p > .05). Finally, in Toledo’s Rio Grande watershed erosion hotspots were located in the upper-mid reaches of the watershed near the communities of Crique Jute, Naluum Ca, San Pedro Columbia and San Miguel. The Mann-Whitney U test identified significant difference in the ranking of erosion drivers (cattle ranching, logging, and clearing of slopes) between communities. This research provides significant information on the drivers, deforestation, forest degradation and erosion that will aid stakeholders to garner community support, develop and implement sustainable management practices in southern Belize.
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Chapter I

1. Introduction

In Central America, domesticated, as well as non-domesticated lands are under increasing pressure because of increasing population and demands for services and products from a fixed natural resources base, increasing use of marginal lands, and scarce resources, and intensification of agriculture on existing cultivated and pasture lands (Farrow & Winograd, 2001). According to FAO, forest cover change during 2000-2010 in Central America and South American countries was estimated at 1.2% and 0.5% annual rates respectively, compared to 0.49% annual rate in Africa, 0.19% in Asia and the Pacific region, 0.03% in North America, and 0.09% in Europe (Portillo, Quintero et al. 2012). Latin America, consequently, is an example of a particular region experiencing large-scale land use land cover change (LUCC) (Zeledon & Kelly, 2009). The conversion of forestland to cropland, grazing land, and settlements has often resulted in erosion which in turn leads to soil degradation and nutrient losses (An et al., 2008).

In Belize, forest cover and deforestation data indicated that deforestation rate between 1980 and 2010 was approximately 25,000 acres / year (0.6%) (Cherrington et al., 2010). In order to safeguard its natural resources Belize has established a series of protected areas. Historically, protected areas (PAs) in Belize were designated primarily for exploitation of timber resources, scenic value and wildlife protection. Rarely were protected areas designated for ecological or scientific purposes, though the latter purpose is becoming more common (Young & Horwich, 2007). The total national territory that is under some form of protection is 26.22% of which 9.3% is strictly for conservation management purposes (Meerman, 2005). Although protected areas (PAs), by definition, are established for biodiversity conservation rather than for climate change mitigation, they play an important role in carbon sequestration (Damnyag et al., 2013). However, forested land in Belize, inside and outside protected areas,
are being threatened by several drivers of deforestation and forest degradation, ranging from subsistence agriculture to global demand for exotic timber species. In Belize, deforestation and forest degradation have been linked to habitat fragmentation, loss of biodiversity and soil erosion (Kay & Avella 2010; Fabro & Rancharan, 2011).

The southern part of Belize is of particular interest as it is one of the regions suffering from deforestation and forest degradation, trans-boundary deforestation and soil erosion. In southern Belize deforestation and forest degradation, trans-boundary deforestation and soil erosion are occurring as a result of changes in land use practices, illegal trans-boundary incursions, rapid population growth, immigration and unsustainable agricultural practices. Land-use practices have provided societies with a variety of benefits, including increased food production, but often also come with trade-offs in terms of loss of biodiversity and alteration of hydrology and water quality, among others (Farley et al., 2012). The further degradation of natural resources in southern Belize will have major effects not only on the environment but also will impact the economy, food security and public health of the communities living in the region. Information regarding deforestation, forest degradation, erosion and community perspectives are necessary for monitoring, evaluating, protecting and planning; thus, the availability of this data is crucial for effective management.

Given the widespread ecological and environmental problems in southern Belize this study integrated communities’ knowledge and CLASlite’s semi-automated remote sensing algorithms to generate vital deforestation and forest degradation information of Toledo; utilized multi-temporal deforestation rates and spatial metrics to improve the historic knowledge-base regarding deforestation along the Belize-Guatemala border and utilized the Revised Universal Soil Loss Equation (RUSLE) and surveys to identify erosion vulnerable areas and communities’ perspectives regarding erosion in Toledo’s Rio Grande Watershed. This study provides scientifically sound information that can be used to understand and respond effectively to the environmental and ecological problems occurring in southern
Description of Chapters

Chapter II

In this chapter we analyzed the deforestation and forest degradation that occurred in Toledo inside and outside protected areas and forest ecosystems as result of an increase of anthropogenic activity in 2010-2012. We also identified the drivers of deforestation and forest degradation based on social surveys and determined if the perspectives of communities within 2 km from a protected area are significantly different from those of communities more than 2 km of a protected area regarding deforestation and forest degradation drivers. The study of deforestation but most importantly forest degradation in Toledo provides an understanding of where, when and why this phenomenon is occurring. Identifying and quantifying deforestation and forest degradation in Toledo is important as this information is needed to design and implement forest management strategies. In Toledo several studies have assess deforestation but, often, information on forest degradation and local communities’ knowledge or socio-economic factors are rarely included. Forest degradation data is not only important at the local level but also at the international level, especially, in the context of the Reduction of Emissions from Deforestation and Forest Degradation (REDD+). The investigation of Toledo’s communities’ perspectives regarding deforestation and forest degradation is very important as the majority of the communities in this region depend on subsistence agriculture and forest products. The separation of the communities in Toledo into two categories in order to identify differences in perspectives is important in order to determine which communities might pose a higher threat to protected areas. The identification of where communities’ perspectives differ is helpful to better understand why this difference might exist. The multi-disciplinary approach of this chapter in integrating communities’ knowledge and CLASlite’s semi-automated remote sensing algorithms will
help develop robust and successful forest management scheme to address the deforestation and forest degradation phenomenon in Toledo.

Chapter III

In this chapter we analyze deforestation along the Belize-Guatemala border and utilize spatial metrics to study the spatial characteristics of deforested patches. We also surveyed communities buffering the Maya Mountain Massif and key stakeholders within the protected areas management community in Belize to better understand their perspective regarding deforestation along the border. The buffering communities’ and key stakeholder perspectives regarding deforestation along the Belize-Guatemala border were compare using statistical analysis to determine if they differ. In order to understand the dynamics of the deforestation occurring along the Belize-Guatemala border we combined multi-temporal deforestation rates and spatial metrics. The muti-temporal deforestation analysis conducted in this study aid in answering the following questions: Where is deforestation occurring? Which areas are being impacted the most? Are the deforested patched temporary or permanent? And are the strategies being implemented effective? The answers to these questions are important to assist managing organizations in the area to better plan and implement deforestation abetment strategies. Moreover, studying the spatial characteristics of the deforested patches is essential to determine if the patches sizes are getting smaller or bigger, if the patches are changing shape, if the patches are increasing or decreasing and if the patches are focused in one location or dispersed throughout the study area. The information generated by analyzing the deforested patch spatial characteristics provided information regarding land use changes and human behavior which is useful in assessing deforestation in the study site. It is necessary to understand where the buffering communities and key stakeholders’ perspectives concur and differ in order to develop strategies to strengthen collaborative efforts to address deforestation. In order to address the deforestation problem in the area it is important to understand the
dynamics of deforestation but most importantly establish national and bi-national collaborations, which include partnerships with NGOs, Governments and community organizations.

Chapter IV

The main objective of this chapter is to identify erosion vulnerable areas and to assess the difference of perspective between communities near (NEH) and far (FEH) from erosion hotspots on the drivers and underlying causes of erosion. The hotspots in the study area were identified using the Revised Universal Soil Loss Equation (RUSLE). Identifying soil erosion vulnerable areas is crucial as it allows stakeholders to identify areas that need immediate intervention to reduce soil degradation. This is important, especially, in Belize where resources are limited; thus, resources need to be used efficiently and effectively where they are needed the most. Once erosion hotspots were established communities in the Rio Grande watershed were divided into two categories: (NEH) if communities were found within 2 km from a hotspot otherwise as (FEH). In order to assess the differences of perspective between communities near (NEH) and far (FEH) from erosion hotspots on the drivers and underlying causes of erosion statistical analysis was conducted. Understanding the differences of perspectives on the drivers of erosion between NEH & FEH communities is important in order to garner support from community members to implement erosion prevention techniques. In the Rio Grande watershed differences in socio-economic and demographics circumstances exist; this differences need to be taken into consideration as they have important implications in the development of effective land management strategies in Rio Grande watershed. Better understanding the socio-economic characteristics and perceptions of community members can aid in developing broadly acceptable erosion mitigation strategies. The identification of the drivers and underlying causes of erosion highlight the need to incorporate all relevant stakeholders in the development of mitigation strategies in the
Chapter V

In this chapter we concluded the findings in each of the previous sections of this research and discuss their importance in terms of management and conservation in southern Belize.
Chapter II

2. CLASlite Algorithms and Social Surveys to Assess and Identify Deforestation and Forest Degradation in Toledo’s Protected Areas and Forest Ecosystems, Belize

2.1. Introduction

Remote sensing studies have measured deforestation and forest change but very few have measured forest degradation given that, forest degradation is more complex to assess from satellite imagery, and rates of forest degradation and fragmentation are also difficult to obtain (Panta et al., 2008; Houghton, 2012). The monitoring and assessment of forest degradation has become very important over the past few years especially in the context of the Reduction of Emissions from Deforestation and Forest Degradation (REDD+). Information on the extent and level of forest degradation is required to support reporting obligations under international conventions, to design and implement forest-related policies and as input to potential payment mechanisms and incentive schemes (Miettinen et al., 2014; Sulla-Menashe et al., 2014). Even though remote sensing studies, to some degree, have successfully assessed the extent and level of forest degradation, but information on local communities’ knowledge or socioeconomic factors is rarely included (Damnyag et al., 2013). The integration of local communities’ knowledge with forest degradation data will help develop robust and successful forest management scheme to address the deforestation and forest degradation phenomenon. Deforestation and forest degradation in developing countries are a leading cause of climate change, arguably the most serious global environmental problem (Blackman, 2013). With deforestation in the tropics accounting for upwards of 20% of global CO₂ emissions, mitigation efforts against global climate change must include
considerations to reduce tropical deforestation and forest degradation (DeVries et al., 2015).

Belize is the country in Central America with the highest relative forest cover. Protected areas in Belize have been effective in safeguarding the nation’s forests; as such protected areas encompass the bulk of forested areas in Belize. Historically, protected areas (PAs) in Belize were designated primarily for exploitation of timber resources, scenic value and wildlife protection. Rarely were protected areas designated for ecological or scientific purposes, though the latter purpose is becoming more common (Young & Horwich, 2007.). The total national territory that is under some form of protection is 26.22% of which 9.3% is strictly for conservation management purposes (Meerman, 2005). Although protected areas (PAs), by definition, are established for biodiversity conservation rather than for climate change mitigation, they play an important role in carbon sequestration (Damnyag et al., 2013). However, forested land in Belize, inside and outside protected areas, are being threatened by several drivers of deforestation and forest degradation, ranging from subsistence agriculture to global demand for exotic timber species. Forest cover and deforestation data indicate that Belize’s deforestation rate between 1980 and 2010 was approximately 0.6% per year (Cherrington et al., 2010). In Belize, deforestation and forest degradation have been linked to habitat fragmentation, loss of biodiversity and soil erosion (Kay & Avella, 2010; Fabro & Rancharan, 2011).

From 2010-2012 the southernmost district of Belize, Toledo, had increasing pressures on forested lands from anthropogenic activities, that included an intensification of deforestation and forest degradation from varying drivers (logging, road construction and agriculture) Toledo’s forests were intensively harvested of its rosewood (Dalbergia stevensonii), primarily for export to Asian markets. The uncontrolled and illegal logging of rosewood harvest inside and outside protected areas during 2010-2012 was so intense that the government of Belize had to implement a moratorium on legally permitted exports of rosewood lumber in August 2012 (Ya’axché, 2013). Additionally, in 2011 the construction of
the Jalacte highway started which will connect Belize to Guatemala and will pass through several Maya villages in the Toledo district. A study conducted, by (Chomitz & Gray, 1996) in southern Belize determined that road construction lower the costs of migration, land access, and land clearing for subsistence farmers. The new highway will create conditions that are conducive to increase deforestation and forest degradation in southern Belize. New diversions of land uses have impacts on the livelihoods of the rural Maya within this area. Historically, the livelihoods of the rural Maya in Toledo are based on long-term fallow subsistence agriculture, supplemental household income from harvest of non-timber forest products and external work as laborers (Binford, 2007).

Over time forest degradation associated with selective logging, road construction, extraction of non-timber forest products and agriculture will limit the forest’s ability to provide environmental services and the extracted resources themselves (Robinson et al., 2008). If deforestation and forest degradation continue unabated in Toledo, the impact may be irreversible, not only at the environment level but on the livelihood of the Mayan communities as well. Therefore, the timely identification of deforestation and most importantly forest degradation at various spatial and temporal scales can provide useful information for planning and sustainable management of forests (Panta et al., 2008).

This study aims to utilize CLASlite algorithms to measure, analyze and map, not only deforestation, but most importantly forest degradation that occurred in Toledo’s ecosystems and protected area as a result of the increased anthropogenic activity reported in 2010-2012. In addition to this, the study attempts to identify the main drivers of deforestation and forest degradation based on social surveys conducted in households within 2 km and more than 2 km from protected areas. This study integrates communities’ knowledge and CLASlite’s semi-automated remote sensing algorithms to generate vital deforestation and forest degradation information that is necessary to address the current and arising deforestation and forest degradation problem in Toledo.
2.2. Study Area

Toledo is the hub of Belize’s Mayan population, descendants of the ancient Mayan civilization that flourished throughout substantial parts of Mexico and Central America hundreds of years prior to European arrival in the Western Hemisphere (Anaya, 1998). The landscapes in Toledo slopes upwards from the sea westwards to 792 meters above sea level and is dissected into two distinct inhabited regions: the Maya Mountains and foothills and the coastal plain and floodplains (Marcotte, 2003). Belize has a total of 94 legally recognized protected areas of which 16 are designated as forest reserves for extractive purposes (Meerman, 2005). 51.6% of Toledo’s territory is under some form of protection of which 21.6% are strictly for conservation management purposes (Fig.1).

Figure 1. Surveyed communities and protected areas.
The population in Toledo in 2009 comprised of 5.5% Creole, 3.9% Garifuna, 69.4% Maya, 12.1% Mestizo and 9.1% other (Halcrow Group Limited, Decision Economics, Penny Hope Ross et al., 2010). The poverty assessment in the country indicates that Toledo is the district that has the highest percentage of household poverty of 37.5% (Halcrow Group Limited, Decision Economics, Penny Hope Ross et al., 2010).

The rural communities in Toledo depend on subsistence agriculture and forest resources. However, rapid population growth among the Maya, together with increase in immigration from neighboring countries, has resulted in the expansion in acreage of traditional Milpa (slash and burn) for the cultivation of maize for household use and rice as a cash crop (Chomitz & Gray, 1996). This recent intensification may be leading to deforestation and forest degradation. Furthermore, logging concessions granted by the Government of Belize of almost 202,343 ha and areas ceded for oil exploration and development purposes of approximately 303,199 ha (Schaaf et al., 1999) affect the rural parts of Toledo which are inhabited primarily by Maya people (Anaya, 1998).

Several studies have reported that deforestation rates are lower in protected areas than non-protected area (Wallace et al., 2003; Dalia & Christensen, 2008; Cherrington et al., 2010). However, global demand for timber (rosewood), an increase in anthropogenic activity in 2010-2012 along with weak enforcement resulted in illegal logging and encroachment in Toledo’s protected areas.

2.3. Materials and Methods

2.3.1. Communities sampling approach and survey design

A multi-stage sampling approach was implemented to select the surveyed communities. The community’s shapefile was obtained from (http://biological-diversity.info/GIS.htm) and used to extract the communities found in the Toledo district. The total numbers of
communities located in the Toledo district were 62 according to the data provided by the National Association of Village Councils in Belize (NAVCO); however, the Statistical Institute of Belize (SIB), which provided the 2010 population Census data, does not follow the list of communities maintained by NAVCO. As a result, for this study only communities that were common to both NAVCO and SIB were selected. From the 62 communities 44 were common. The 44 communities were classified into two categories based on a buffer analysis that was conducted in ArcGIS: communities that were less than two kilometers from a protected area (CL2K) and communities that were more than two kilometers from a protected area (CM2K). The 2 km threshold to distinguish the two categories was selected because communities found within 2 km have easier access to protected areas, relative to those communities further away and are engaged in subsistence agriculture in lands buffering protected areas. From the 44 communities 15 were within 2 kilometers from a protected area and 29 were more than two kilometers from a protected area. Three communities from each category were then randomly selected using the random point generation tool in ArcGIS and 25 random household surveys were conducted in each community. From the 6 communities selected Trio, San Pedro Colombia and Conejo Creek ($f=75$) were classified as CL2K and San Pablo, San Marcos and Santa Ana ($f=75$) were classified as CM2K. The 3 communities surveyed within the 2 km buffer from a protected area represented 20% of the communities and the 3 communities surveyed beyond the 2 km buffer from a protected area represented 10.3% of the communities. The 6 communities surveyed represent 13.6% of the total communities. A literature review was conducted to identify the drivers of deforestation and forest degradation in the study area (Wyman & Stein, 2010; Saqui et al., 2011). A list of drivers was then generated and discussed in focus groups in four different communities. Based on the result of these two activities a closed-ended survey was designed, prepared and administered to households in the 6 communities in March, 2015. The survey data were analyzed using Statistical Package for Social Sciences (SPSS). Chi square goodness of fit test
was conducted to determine significant attitude difference on the drivers of deforestation and forest degradation between CL2K and CM2K communities. The Chi square goodness of fit is given by (Diener-West, 2008).

\[ c^2 = \sum_{i=1}^{k} \left( \frac{(O_i - E_i)^2}{E_i} \right) \]  

(1)

The degrees of freedom are:

\[(r-1)(c-1)\]

r = # of rows

c = # of columns

O\_i = the observation frequency in the i\textsuperscript{th} cell of the table

E\_i = the expected frequency in the i\textsuperscript{th} cell of the table

The strength of association was determined by Phi and Cramer’s V. The measure of association, Phi, is a measure which adjusts the chi square statistics by the sample size. Phi is defined as

\[ \phi = \sqrt{\frac{x^2}{n}} \]  

(2)

Phi squared is also used as a measure of association, and phi squared is defined as (Leaaffre et. al, 2009)

\[ \phi^2 = \frac{x^2}{n} \]  

(3)

In order to calculate these measures, the chi square statistic for the table is first
determined.

We also used Cramer’s V to measure association, which is defined by (Leaaffre et. al, 2009)

\[ V = \sqrt{\frac{\varphi^2}{\tau}} = \sqrt{\frac{x^2}{nt}} \]  

(4)

By using the information concerning the dimensions of the table, Cramer’s V corrects for the problem that measure of association for tables of different dimension which may be difficult to compare directly. Cramer’s V equals 0 when there is no association and values closer to 1 indicating strong association.

Households ranked the 12 main drivers of deforestation and forest degradation identified in the study area from 1 (being the least important) and 12 (being the most important).

2.3.2. Image processing and classification

Forest change and disturbance were mapped from Landsat satellite imagery (Table 1), available from USGS (http://www.usgs.gov/), by utilizing CLASlite’s semi-automated algorithms (http://claslite.carnegiescience.edu/en/about/software.html). Forest, non-forest and forest degradation layers were derived by the CLASlite processing stream. In this study deforestation is referred to as the sum of all forested areas transitioning to non-forested areas and forest disturbances are referred to as forest degradation. The deforestation and forest degradation data layers for 2009-2011 and 2011-2012 were overlaid with the 2010 protected areas and the 2011 Belize Ecosystems map layers in ArcGIS, to determine the temporal and spatial distribution of deforestation and forest degradation in protected areas and ecosystem types. The 2011 Belize Ecosystems map is an update from the 2001 and 2004 Belize
Ecosystems map produced by Meerman and Sabido in 2001, which was developed by using Landsat imagery and ground truthing data consisting of 125 vegetation plots (Meerman et al., 2010). The land cover categories, in the ecosystem map, use the UNESCO Classification code. The English names of the Ecosystems are linked to a unique UNESCO classification code. For Belize the English names have been adopted slightly but are essentially interchangeable for all Ecosystems identified as part of the Central America Ecosystem Mapping Project (Meerman & Sabido, 2001). In this study “area of agriculture use” refers to areas used by the rural Maya in Toledo. This area is under a long-term fallow subsistence agriculture system (Binford, 2007). Traditionally, this fallow period lasted between 10 and 12 years, so soil had enough time to regain fertility (Ruscalleda, 2012).

2.3.3. Filling the Gaps of Landsat 7 ETM+ images

The scan-line corrector (SLC) of the Landsat 7 Enhanced Thematic Mapper Plus (ETM+) sensor failed in 2003, resulting in about 22% of the pixels per scene not being scanned (Chen et al., 2011). The data gaps in the Landsat 7 ETM+ images for April 14, 2009 and April 22, 2012 were filled by utilizing the Gapes Filling for Landsat 7 SLC-Off Images software developed by the Center for Space and Remote Sensing Research (CSRSR). The software uses a procedure that detects changed pixels by using correlation coefficient when changes occur between filled and working images. If the correlation coefficient is higher that the threshold, stage 1 fills the gapped pixels otherwise gapped pixels are filled by stage 2 (Canto, 2011).

<table>
<thead>
<tr>
<th>Imagery</th>
<th>Satellite</th>
<th>Spatial Resolution</th>
<th>Path</th>
<th>Row</th>
<th>Date</th>
</tr>
</thead>
<tbody>
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<td>2006,</td>
<td>Landsat-7</td>
<td>30 m</td>
<td>19</td>
<td>49</td>
<td>March 21, 2006 (working II)</td>
</tr>
<tr>
<td>2009,</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>April 14, 2009 (Filled)</td>
</tr>
</tbody>
</table>
2.3.4. Pre-Processing and Processing of Satellite imagery

The pre-processing stage for satellite images consisted of the conversion of Digital Numbers (DNs) of initial pixels into surface reflectance (Kolios & Stylios, 2013) and the removal of irrelevant data, image noise and acquisition errors (e.g. water bodies and clouds) (Coppin et al., 2004). The pre-processing and processing of imagery was done by utilizing automated CLASlite algorithms which took the raw Landsat imagery and produce forest cover, deforestation and disturbance layers. CLASlite’s processing stream consists of the following steps: (1) radiometric calibration and atmospheric correction of satellite data; (2) cloud, water and shadow masking; (3) decomposition of image pixels into fractional surface covers (sub-pixel analysis). Step 3 is the most important process in CLASlite, which uses a sub-model referred to as the AutoMCU (Automated Monte Carlo Unmixing). This sub-model provides quantitative analysis of the percentage or fractional cover of Photosynthetic Vegetation (PV), Non-photosynthetic Vegetation (NPV) and Bare Substrate (S). The method uses three spectral endmember libraries, PV, NPV and S, to decompose each image pixel using the following linear equation (Asner et al., 2009):

\[
\rho(\lambda)_{\text{pixel}} = \Sigma [C_e \cdot \rho(\lambda)_e] + \varepsilon = [C_{pv} \cdot \rho(\lambda)_{pv} + C_{npv} \cdot \rho(\lambda)_{npv} + C_{substrate} \cdot \rho(\lambda)_{substrate}] + \varepsilon \quad (5)
\]

Where \(\rho(\lambda)_e\) is the reflectance of each land-cover endmember (e) at wavelength \(\lambda\) and \(\varepsilon\) is an error term. Solving for each sub-pixel cover fraction (\(C_e\)) requires that the satellite

<table>
<thead>
<tr>
<th>Year</th>
<th>Satellite</th>
<th>Resolution</th>
<th>Year</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010</td>
<td>Landsat-5</td>
<td>30 m</td>
<td>January 11, 2010 (Working I)</td>
<td></td>
</tr>
<tr>
<td>2011</td>
<td>Landsat-5</td>
<td>30 m</td>
<td>March 27, 2011</td>
<td></td>
</tr>
<tr>
<td>2011</td>
<td>Landsat-7</td>
<td>30 m</td>
<td>November 30, 2011 (Working II)</td>
<td></td>
</tr>
<tr>
<td>2012</td>
<td></td>
<td></td>
<td>March 21, 2012 (Working I)</td>
<td></td>
</tr>
<tr>
<td>2012</td>
<td></td>
<td></td>
<td>April 22, 2012 (Filled)</td>
<td></td>
</tr>
</tbody>
</table>
observations \( \rho(\lambda)_{\text{pixel}} \) contain sufficient spectral information to solve a set of linear equations, each of the form in equation (5) but at different wavelengths \( \lambda \) (Asner et al., 2009). The result of this step is a fractional cover output image with 7 bands. Fractional cover estimates are then standardized using sub-pixel cover data called Vegetation Continuous Fields (VCF) from MODIS. This step is followed by step 4 and 5 which classify the imagery into forest cover, deforestation and forest disturbance. Forest and non-forest cover in CLASlite are derived by a decision tree which defines forest as pixels where the photosynthetic vegetation cover is \( \geq 80 \) and where bare substrate cover fraction is \( < 20 \) and non-forest as pixels where the photosynthetic vegetation cover is \( < 80 \) or where the bare substrate cover fraction is \( > 20 \). In multi-image analysis CLASlite is capable of detecting forest loss (deforestation), gain (secondary regrowth) or degradation (areas of persistent forest disturbance). Equations 6 and 7 are used by CLASlite to detect deforestation and forest disturbance (Asner et al., 2009).

Deforestation \hfill (6)

\[
(PV_0 > 60\%) \text{ AND} \\
((-100\% < PV_1-PV_0 < -40\%) \text{ AND} (NPV_1-NPV_0 > 4\%)) \text{ OR} \\
((NPV_0 < 30\% \text{ and } S_0 < 15\%) \text{ AND} (PV_1 < 80\% \text{ and } NPV_1 > 20\% \text{ and } S_1 > 0\%)) \text{ AND} \\
(PV_1-PV_0 < -9\% \text{ and } NPV_1-NPV_0 > 15\% \text{ and } S_1-S_0 > -99.9\%))
\]

Forest disturbance \hfill (7)

\[
(PV_1-PV_0 > -40\%) \text{ AND} \\
(PV_0 > 80\% \text{ and } NPV_0 < 25\% \text{ and } S_0 < 15\%) \text{ AND} \\
(PV_1 < 85\% \text{ and } NPV_1 > 15\% \text{ and } S_1 < 7\%) \text{ AND} \\
((PV_1-PV_0 < -6\% \text{ and } 7\% < NPV_1-NPV_0 < 14\% \text{ and } S_1-S_0 > -1\%)) \text{ OR} \\
(PV_1-PV_0 < -7\% \text{ and } NPV_1-NPV_0 > 13\% \text{ and } S_1-S_0 < -1\%))
\]
PV = photosynthetic vegetation
NPV = non-photosynthetic vegetation
S = bare substrate
Subscripts 0 and 1 = changes from one year to the next

2.3.5. Post-Processing

Post-processing was performed on the outputs of CLASlite’s image classification. The cover layers generated by CLASlite for 2009, 2011 and 2012 were vectorized in ArcGIS and the forested, non-forested, water and cloud areas for each layer were calculated. The water polygons were reclassified as non-forest and the cloud polygons for 2009, 2011 and 2012 were reclassified as forest if the area appeared as forest in 2011, 2012 and 2013 respectively, otherwise as non-forest. In the case of mixed polygons, polygons containing clouds and forest, the polygon was split into its respective categories and reclassified according to the criterion aforementioned. The layers were reclassified into the following classes:
1: Forest
2: Non-Forest
CLASlite algorithms are capable of detecting deforestation and forest degradation of 0.1 ha from Landsat imagery (Asner et al., 2009); thus, all areas that were less than 0.1 ha were eliminated from the deforestation and disturbance layers. The area covered by clouds in the study area in the 2009, 2011 and 2012 datasets was 0.99%, 0.03% and 0.82% respectively.

2.3.6. Accuracy Assessment

For this study 300 random points for each year were used to develop error matrices, from which statistical measures of map accuracy (i.e. Kappa statistics, overall-accuracy, producer’s and user’s accuracy) were computed (Were et al., 2013) (Table 2-4 ).
Table 2: Error matrix for the 2009 forest cover map.

<table>
<thead>
<tr>
<th>Class</th>
<th>Forest</th>
<th>Non-forest</th>
<th>Total</th>
<th>Commission %</th>
<th>Omission %</th>
<th>User Acc %</th>
<th>Producer Acc %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>219</td>
<td>14</td>
<td>233</td>
<td>6.01</td>
<td>3.95</td>
<td>93.99</td>
<td>96.05</td>
</tr>
<tr>
<td>Non-forest</td>
<td>9</td>
<td>58</td>
<td>67</td>
<td>13.43</td>
<td>19.44</td>
<td>86.57</td>
<td>80.56</td>
</tr>
<tr>
<td>Total</td>
<td>228</td>
<td>72</td>
<td>300</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Overall Accuracy = (277/300)  92.33%
Kappa Coefficient = 78%

Table 3: Error Matrix for the 2011 forest cover map.

<table>
<thead>
<tr>
<th>Class</th>
<th>Forest</th>
<th>Non-forest</th>
<th>Total</th>
<th>Commission %</th>
<th>Omission%</th>
<th>User Acc %</th>
<th>Producer Acc %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>200</td>
<td>41</td>
<td>241</td>
<td>17.01</td>
<td>0.99</td>
<td>82.99</td>
<td>99.01</td>
</tr>
<tr>
<td>Non-forest</td>
<td>2</td>
<td>57</td>
<td>59</td>
<td>3.39</td>
<td>41.84</td>
<td>96.61</td>
<td>58.16</td>
</tr>
<tr>
<td>Total</td>
<td>202</td>
<td>98</td>
<td>300</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Overall Accuracy = (257/300)  85.67%
Kappa Coefficient = 64%

Table 4: Error matrix for the 2012 forest cover map.

<table>
<thead>
<tr>
<th>Class</th>
<th>Forest</th>
<th>Non-forest</th>
<th>Total</th>
<th>Commission %</th>
<th>Omission%</th>
<th>User Acc %</th>
<th>Producer Acc %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>188</td>
<td>43</td>
<td>231</td>
<td>18.61</td>
<td>2.59</td>
<td>81.39</td>
<td>97.41</td>
</tr>
<tr>
<td>Non-forest</td>
<td>5</td>
<td>63</td>
<td>68</td>
<td>7.39</td>
<td>41.2</td>
<td>92.65</td>
<td>58.80</td>
</tr>
<tr>
<td>Total</td>
<td>193</td>
<td>107</td>
<td>300</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Overall Accuracy = (251/300)  83.67%
Kappa Coefficient = 61%

The overall accuracies and user accuracies in this study exceed the USGS’s suggested threshold of 80% which is “commonly considered acceptable” and Kappa Coefficient statistics exceeding 60% show “substantial agreement” (Cherrington et al., 2010).

The 300 random points for each dataset in this study were generated in ENVI. The random points were generated in order to avoid bias selection of known forested or non-forested areas in the study site. The values of forest and non-forest for these points were derived from a visual interpretation of higher resolution imagery available on Google Earth, the 2011 Belize Ecosystems Map, and the radiometric calibrated, atmospheric corrected and
pan sharpen (Gram-Schmidt Pan Sharpening) multispectral composites of Landsat’s band 1,2,3,4,5 and 6 for 2009 and 2012 datasets.

2.4. Results

2.4.1. Socio-economic characteristics

From the 150 surveys that were conducted 78% of respondents between the ages of 29 to 50 participate in the study. Of all the respondents 76% were males, which are usually the head of the household. The rural communities in Toledo are inhabited mainly by Maya which are engaged in subsistence agriculture. From those interviewed 81% were of Maya Q’eqchi ethnicity of whom 77% were farmers. The main crops that the households depend on are beans, corn and rice. From the respondents 60% had a salary of 1-100 BZ dollars per week and 77% only had primary school education. The majority of the respondents (61%) considered themselves unemployed.

2.4.2. Perception of the drivers of deforestation and forest degradation

The communities ranked land policy and institutional factors, with the exception of Conejo Creek, as the main driver of deforestation and forest degradation (Fig. 2). The holistic analysis of the data revealed that 14%, 13% and 12% of the households ranked land and institutional policy, distance to markets and lack of alternative livelihoods respectively, as the main drivers of deforestation and forest degradation. It is important to note that only 2% and 5% of the households ranked agriculture and road construction as the main drivers of deforestation respectively.
2.4.3. **Land policy and institutional factors**

In terms of land policy and institutional factors the analysis indicated that there are significant differences (Cramer’s $V= 0.562$, $p < 0.001$) between CL2K and CM2K on whether the government recognizes and respects the community’s communal property rights. Of the households near protected areas and households far from protected areas 61.3% and 77.3% respectively agreed that government recognizes and respects the community’s communal property rights. This difference between the two categories is attributed to the fact that areas under protection are considered communal land by CL2K communities but due to the protection status, communities have restricted access and use. Furthermore, 84% and 60% of the households in CL2K and CM2K communities respectively agreed that all community members have the same rights to access forest resources in communal land. Households in CL2K (68%) and CM2K (73%) agreed that clearing the land gives the community member...
ownership rights to the land, which is supported by national law. This outdated government policy promotes deforestation and forest degradation because prospective owners sometimes clear the land just to retain ownership (Young, 2008).

2.4.4. Distance to markets and soil quality

In the Toledo district there are many remote Mayan communities that have limited access to markets. The road conditions, primarily those near protected areas, are poor; thus, public transport is limited, resulting in limited accessibility to markets. The analysis indicated that there is a significant difference on the need to access markets to sell products (Cramer’s V= 0.231, p < 0.05) between CL2K and CM2K communities. Of households near protected areas and far from protected areas 80% and 69% respectively agreed that they need access to markets. Moreover, 45% and 32% of the households in CL2K and CM2K communities agreed respectively that if road conditions and public transportation improve they will increase agriculture production (Cramer’s V= 0.315, p < 0.01). Households that are far from protected areas are less remote; thus, they enjoy better roads and market accessibility. If road conditions were to improve the analysis shows that overall agriculture productivity of households in both categories would increase. The increase of agriculture productivity under the current conditions will result in deforestation and forest degradation. Currently, there are very few farmers in the communities that are knowledgeable of and are implementing sustainable agricultural methods. In terms of agriculture techniques and support, 86% and 97% of households agreed that the main agricultural technique used is slash and burn, and that farmers cannot get technical agricultural support from the relevant agencies respectively. Slash and burn especially in areas of higher elevation results in soil erosion, which in turn causes soil degradation. Households in CL2K and in CM2K communities 77% and 51% respectively agreed that the soil quality has decreased as a result of soil erosion and
unsustainable agricultural practices (Cramer’s V= 0.278, p < 0.01). CL2K communities are more vulnerable to erosion and soil degradation because of poor soil conditions, higher elevations and unsustainable agricultural practices. Households in CL2K communities 71% agreed that farmers in their community farm on marginally fertile soils compared to 29% of households in CM2K communities (Cramer’s V= 0.434, p < 0.001). Soil degradation in CL2K communities is resulting in a decrease in agriculture yields; thus, 69% of households agreed that there is a need to use more land, of which 61% agreed that more forest must be cleared in order to access fertile soils. On the other hand, 94% of households agreed that farmers are willing to learn and adopt sustainable agriculture techniques.

2.4.5. Lack of alternative livelihoods and logging

The dependency of Toledo’s communities on subsistence agriculture with limited alternative livelihoods is one of the main drivers of deforestation and forest degradation. For many of the communities in the Toledo district, the alternative to agriculture is selective logging. From the households surveyed 62.7% agreed that selective logging is a common practice. The results regarding selective logging as a common practice in the communities indicate that there is a significant difference (Cramer’s V= 0.211, p < 0.05) between CL2K and CM2K, with households near protected areas agreeing of having higher levels of selective logging. Selective logging has been linked to habitat fragmentation, biodiversity loss and forest degradation; thus, unsustainable levels of selective logging pose a threat to protected areas. In 2010-2012 there was an increase of selective logging in the Toledo district, which was driven by an increase of Rosewood demand from Asia. Households near protected areas (76%) and far from protected areas (60%) agreed that before 2010 logging was mostly done for local use (Cramer’s V= 0.202, p < 0.05). However, 69.3% and 21.3% of households near protected areas and households far from protected areas respectively agreed that logging
was mostly done for commercial purposes in 2010-2012 (Cramer’s V= 0.499, p < 0.001). Rosewood extraction in Toledo was occurring outside as well as inside of protected areas. There was also a significant difference (Cramer’s V= 0.214, p < 0.05) between CL2K and CM2K households when asked if illegal activities increased dramatically in 2010-2012. During the rosewood “bonanza” communities reported that it was members from other communities that were illegally harvesting rosewood in their communal land. The results indicate that there was a significant difference (Cramer’s V= 0.279, p < 0.01) between CL2K and CM2K regarding illegal logging by other community members, with CL2K communities agreeing of having higher illegal logging activities in 2010-2012. Rosewood stocks are higher around and inside protected areas; thus, attracting community members from other communities to log in these areas. The results from the surveys coincide with the increase in forest disturbance that was detected in 2011-2012 from the satellite imagery analysis (Fig. 3).

2.4.6. Extent of deforestation and forest degradation in ecosystems and protected areas from satellite imagery analysis

The annual rate of deforestation and forest disturbance for this study were calculated by utilizing the Puyravaud equation (Puyravaud, 2003).

\[ r = \frac{1}{t_2 - t_1} \ln \frac{A_2}{A_1} \]  

(8)

\( r = \text{rate of forest change} \)

\( A_1 = \text{Forest cover at time } t_1 \)

\( A_2 = \text{Forest cover at time } t_2 \)

The results show that for the period 2009-2011 the annual rate of deforestation was
0.75% (2,480 ha) and the annual rate of forest degradation was 0.09% (307 ha). For the period of 2011-2012 the annual rate of deforestation was 1.17% (3,834 ha) and forest degradation was 0.33% (1,110 ha) (Fig. 4).

From the results it can be depicted that there was an increase of deforestation and forest degradation in 2011-2012 (Fig. 3). The total forest in 2009-2011 was 78.37% and non-forest was 21.63% and in 2011-2012 forest was 77.06% and non-forest was 22.94% (Fig. 4).
Figure 4. Toledo's deforestation and forest degradation 2009-2011-2012.

The deforestation and forest degradation analysis in protected and unprotected areas show that in 2009-2011 out of the 613 ha of degradation 75.71% occurred in areas that are unprotected and 24.29% occurred in protected area of which 17.36% occurred in National Parks. In 2011-2012 out of the 1,110 ha of degradation 65.41% occurred in areas that are unprotected and 34.59% occurred in protected areas of which 28.95% occurred in Forest Reserves (Fig. 5). The results depict that there was an increase of forest degradation in protected areas in 2011-2012.

Figure 5. Forest degradation in protected and unprotected areas.
Moreover, in 2009-2011 out of the 4,959 ha of deforestation 90.66% occurred in areas that are unprotected and 5.60% occurred in Forest Reserves. In 2011-2012 out of the 3,834 ha of deforestation 76.03% occurred in areas that are unprotected and 14.04% occurred in Forest Reserves (Fig. 6). In 2009-2011 only 9.34% of forest loss occurred inside protected areas in comparison to 2011-2012 were 23.97% of forest loss occurred inside protected areas (Fig. 3).

![Figure 6. Deforestation in protected and unprotected areas.](image)

In 2012 it was reported that commercially viable standing stock of rosewood (*Dalbergia stevensonii*) in Toledo had been assessed at approximately 142,091 m$^3$, after a decrease of around 13% over three years 2010-2012 (Belize, 2013). The deforestation and the forest degradation analysis in ecosystems show that in 2011-2012 out of the 3,834 ha of deforestation 52.89% occurred in areas of Agricultural use and 25.28% occurred in Lowland broad-leaved wet forest.
Furthermore, in 2011-2012 out of the 1,110 ha of degradation 42.62% occurred in areas of Agricultural use, 30.38% occurred in Lowland broad-leaved wet forest and 19.39% occurred in Sub-montane broad-leaved wet forest (Fig. 7). The forest degradation detected in 2011-2012 are consistent with the habitat distribution of *Dalbergia stevensonii* which is known to be found in broadleaf evergreen swamp forests and has a restricted distribution, mainly concentrated in the Toledo district, between latitudes 16-17° N (Belize, 2013). This species occurs in fairly large patches within its habitat (Chudnoff, 1984) and has been reported as a dominant component of the forest types in Belize in which it occurs. The patch and dominant characteristics of this species allowed CLASlite algorithms to identify the “hotspots” of where forest degradation occurred as a result of the uncontrolled extraction of this species during 2010-2012.

In addition, to the ban of rosewood exports by the government of Belize, *Dalbergia stevensonii* was also listed on CITES Appendix II at the 2013 Conference of the Parties in
Bangkok, Thailand (Belize, 2013). It is important for agencies managing protected areas in Belize to increase their knowledge on forest monitoring techniques and global demand trend of species in order to effectively plan and implement strategies to address activities that can lead to deforestation and forest degradation.

2.5. Discussion

In Belize, the free availability of Landsat images have resulted in the local (DiFiore 2002; Ek 2004; Penn et al. 2004) and national (White et al., 1996; Meerman & Sabido, 2001; Meerman et al., 2010) assessments of deforestation and forest cover change. Although, these assessments have provided useful information that is used for sustainable forest planning and management, they often lack forest degradation and communities’ knowledge information which is crucial to detect, assess, plan and implement sustainable forest management strategies in areas that are more vulnerable to deforestation and forest degradation. Forest degradation data is often omitted due to the methodologies that are used during pre-processing, image classification and post-processing of satellite imagery. For instance the majority of forest assessment studies in Belize used a supervised whole pixel classification approach. Although whole pixel classification is useful for land cover mapping it has limitations that CLASlite improves upon. Specifically, it is difficult to produce consistent results with whole pixel classification as a result of the judgments made by the user during mapping, which introduces inherent subjectivity. Moreover, forest degradation often occurs at the sub-pixel level, which is not detected by whole pixel classification, since each pixel can only be designated one land cover class. Other global automated land cover and change detection datasets have been introduced in Belize; nevertheless, these automated datasets often do not detect forest degradation. For instance, in the Hansen et al. (2013), High-Resolution Global Maps of 21st-Century Forest Cover Change, forest degradation that
did not lead to a non-forest state was not included in the change characterization. Furthermore, Reimer et al. (2015) found that the Hansen et al. (2013) approach uses the greenest NDVI, provided by Google Earth Engine, for image or pixel-scale mosaicking, which severely reduced the amount of apparent forest cover lost over time, and in some regions it vastly over-estimated forest recovery. Moreover, global automated datasets may include blurry and noisy input data especially in regions affected by clouds. On the other hand, CLASlite improves upon these limitations and most importantly is able to detect forest degradation, which often occurs at a subpixel level, by using the AutoMCU. The semi-automated CLASlite method provides an easier, fast and more effective way to map deforestation and forest degradation.

2.5.1. Social Surveys and satellite imagery analyses

The social surveys that were conducted on the perceived drivers of deforestation and forest degradation provide very important information for conservation purposes. Of importance are the strong significant differences that exist between CL2K and CM2K communities regarding property rights (Cramer’s V= 0.562, p < 0.001), selective logging (Cramer’s V= 0.499, p < 0.001) and soil quality (Cramer’s V= 0.434, p < 0.001). Communal land used by communities far from protected areas seems to be well established as opposed to communities near protected areas. It is very crucial that communities located near protected areas to have a sense of ownership of their communal land and perceive that their ownership rights are being respected. The conflict that exists between communal property land rights and protected areas needs to be resolved. Otherwise, the uncertainties of the Mayan communities’ communal land property rights will likely lead to an increase in deforestation and significant forest degradation inside protected areas. The overall literature supports the idea that secure tenure title and control over land resources are linked to sustainable forest
management and improved economic opportunities (Wyman & Stein, 2010); thus, the Mayan communities communal land property rights should be clearly defined and established, failure to do so will lead to environmental degradation.

Before 2010, selective logging was not a problem since the majority of the communities conducted this activity for local use. As the demand for exotic timber species increases in global markets, selective logging is being done more and more for commercial purposes to satisfy the increasing demand. As a result forested land, mainly those in protected areas have come under threat. This concept is reinforced by the satellite imagery analysis results generated by this study. The analysis revealed that the majority of deforestation and forest degradation for the period of 2009-2011-2012 occurred in areas that are not protected. This study results correlate with the study conducted by Amor and Christensen (2008) where they found that protected areas are acting as barriers to forest lost. Even though, protected areas have been effective to protect against deforestation, this study shows that protected areas are not so effective in the mitigation of forest degradation caused by uncontrolled and illegal activities. In mid-2010-2012, the Toledo forest was under pressures as a result of global rosewood demand leading to an increase of uncontrolled and illegal activities. Belize reported exports of a total of 1,377.87 m$^3$ from February to July 2012 after the rosewood moratorium was issued, but according to the General Administration of Customs of the People's Republic of China, China has imported 3,400 m$^3$ of rosewood from Belize in the same period of time (Belize, 2013), which is reinforced by the increase in disturbance inside protected areas detected in the imagery analysis in 2011-2012. Illegal activities in Belize’s protected areas are difficult to monitor, ascertain and address because these usually occur in remote areas and the managing organizations that are responsible for protecting the forest usually lack the economic resources to effectively address this problem. Therefore, new approaches, economic incentives and monitoring systems are needed to monitor and address illegal incursion in protected areas. In order to address the lack of economic resources some
organizations (Friends for Conservation and Development and Program for Belize) are already venturing in carbon sequestrtion, for the purpose of participating in the REDD+ scheme. Although REDD+ strategy promises immediate financial incentive, at a global level REDD+ remains a politically volatile issue, with debates raging about whether it will meet its primary goal of reducing global carbon emissions and whether it will support or undermine local livelihoods and well-being (Caplow et al., 2011). Furthermore, at a national level Belize still has limited capacity for forest inventories and carbon pool reporting (Romijn et al., 2012), weak institutional and legal frameworks (Young, 2008) and lack of infrastructure and technical capacity that might prevent it to carry REDD+ project objectives. Albeit these limitations Belize should continue to pursue opportunities in the context of REDD+ schemes. In the meantime Belize needs to urgently adopt or develop alternative schemes to effectively reduce deforestation and forest degradation in Toledo.

Studies that have been conducted in Toledo suggest that road construction and agriculture are the main drivers of deforestation (Kongsager & Corbera, 2015; Chomitz & Gray, 1996). However, the results of this study indicate that communities in the Toledo district do not perceive agriculture and road construction as the main drivers of deforestation. This can be attributed to the fact that for decades the communities in the Toledo district have been engage and depend on subsistence agriculture as their main livelihood (Binford, 2007; Emch, 2005); thus, agriculture is not perceived as a threat. Even though the majority of the households did not rank agriculture directly as the main driver of deforestation and forest degradation communities are concerned about the loss of soil fertility and the need to utilize more land, which leads to deforestation. Albeit this concerns the communities lack sustainable agriculture knowledge, lack technical support from relevant agencies and have poor economic conditions. Ranking agriculture as the main drivers of deforestation might increase pressure to establish more sustainable farming systems, which will require communities to investment in these systems that they can’t afford (Moore, 2007). Regarding
roads it is important to note that the majority of the communities in the Toledo district are remote and road conditions are very bad; ranking roads as the main driver of deforestation might prevent the improvement and construction of roads that are need to access markets. This notion is supported by the results of the survey where communities agreed that if roads were to improve they will increase agriculture productivity. However, communities view the lack of alternative livelihoods as a threat since other than agriculture community members are involve in selective logging, which resulted in forest degradation due to the increased demand of Rosewood in 2010-2012. The need to develop alternative livelihoods in the region is seen as primordial by communities as agricultural lands become less fertile. Due to the poor economic conditions and dependency on subsistence agriculture in the study area is unlikely that the communities will be able to address the problem themselves, which highlights the need for collaboration between communities and relevant agencies to develop alternative livelihoods. Understanding the difference between communities' perspectives and expert knowledge regarding the main drivers of deforestation and forest degradation in the study area are essential if any program is to be planned, develop and executed to address deforestation and forest degradation.

The lack of knowledge and lack of assistance from the relevant agencies leave the communities no other alternative than to use their traditional agricultural practices and to clear more forested land in order to access fertile soils. The proximity of these communities to protected areas makes them a priority; thus, environmental problems need to be addressed as soon as possible. As soils deteriorate and fertile soil becomes scarce, communities will start encroaching in protected areas. This phenomenon can already be observed from the satellite imagery analysis where forest disturbance is more pronounced in the periphery of protected areas. It can also be observed from the deforestation and forest degradation that occurred in protected areas during 2010-2011 that the majority occurred in forest reserves. Forest reserves in Belize, are rich in forest resources but are less regulated. Consequently,
these areas have become more vulnerable to illegal activities. These areas are solely managed by the Belize Forest Department, which has very limited human and economic resources. The government should encourage the co-management of forest reserves through forest management committees representing all stakeholder groups; a scheme that has proven to be successful in Belize for community based organizations such as Ya’axche and SATIM. The results of this study are significant for conservation planning in Belize. This study shows that as anthropogenic activities increase and new challenges emerge, the traditional protected areas system in place will be ineffective in mitigating deforestation and forest degradation. The forest management organizations will need to integrate new affordable emerging remote sensing technologies and methodologies, and cost-effective stakeholder-based programs in order to assess, monitor, plan and implement forest conservation programs to address deforestation and forest degradation.
Chapter III

3. Using Spatial Metrics and Surveys for the Assessment of Trans-boundary Deforestation in Protected Areas of the Maya Mountain Massif: Belize - Guatemala Border

3.1. Introduction

Literature attributes significant merits to trans-boundary protected areas, such as socio-economic development, the promotion of cooperation and peace and conservation (Trillo-Santamaría & Paül, 2016). However, in most of the developing world forests outside and within trans-boundary areas are been threatened by complex, interconnected drivers such as agricultural expansion and forest degradation (Tejada et al., 2016). These drivers may be hard to control, especially, in trans-boundary areas because they might originate in the other country where environmental laws, enforcement capabilities and socio-economic pressures differ (McCallum et al., 2015). Thus, it is urgent to identify strategies that balance trade-offs between human needs and ecosystems integrity in tropical forests of developing countries (Brandt et al., 2016).

The Belizean-Guatemalan trans-boundary protected area system presents unique management challenges for both nations. Deforestation along the Belize-Guatemala border has been a persistent issue for the past 30 years and continues today. Deforestation is caused by complex, interconnected socio-economic problems on both sides of the border. In Guatemala, population growth, economic development and agricultural expansion have depleted most of the forest in the Montanas Mayas Biosphere Reserve (MMBR). Local organizations have teamed with government through CONAP to provide protected areas management in the Guatemalan border area. However, their efforts have not been able to stop...
illicit extraction activities. In Belize, a lack of population along the border, the relative remoteness of the area and insufficient resource allocation to management has left Belize’s protected areas vulnerable to trans-boundary incursions. These incursions from Guatemala into Belize have resulted in deforestation, environmental degradation, illegal natural resource extraction and agricultural settlements. Because the border area of Belize is largely unpopulated and remote, natural resource protection enforcement is very challenging. Therefore, natural resources in Belize have been left largely unguarded despite their financial, ecological and aesthetic values. In order to understand the dynamics of the deforestation process, stakeholders’ perspectives and generate historical deforestation rates along the Belize-Guatemala border it is necessary to undertake a multi-disciplinary approach and incorporate multi-temporal deforestation rates, surveys and spatial metrics.

Spatial metrics are algorithms that measure spatial characteristics of class patches, landscape patches, or entire landscape mosaics (Zaragozí et al., 2012). Spatial metrics have been used to plan strategically for environmental management, to quantify ecological processes, to measure and monitor landscape change, and to study the effects of society on landscape and examine habitat fragmentation (Bailey et al., 2007; Zhou & Li, 2015). Information derived from spatial metrics can describe the structure and pattern of a landscape, lending information about socio-economic circumstances (Tang et al., 2008). And also spatial metrics ability to quantify changes in class patch characteristics as a result of land use changes and human behavior can be useful in assessing a landscape process; such as deforestation (Jiao et al., 2012).

This issue of illegal trans-boundary incursions is exacerbated by surging demand for resources in Guatemala, insufficient enforcement on both sides of the border and lack of bi-national collaboration. Research and advocacy has again largely been left to NGOs on both sides of the border, which to their credit, work very hard and effectively with few resources. Organizations are under pressure to quantify deforestation along the border, and to make the
case to their respective governments and the world for more enforcement resource allocation. Through this research we seek to improve the historic knowledge-base regarding deforestation along the Belize-Guatemala border utilizing multi-temporal deforestation rates and spatial metrics. Also, this analysis is supplemented with data generated by surveys of key stakeholders within the protected areas management community in Belize to better understand their perspective regarding deforestation along the border. The information provided by this research should aid managing organizations in their continued efforts to implement effective deforestation mitigation strategies along the border.

3.2. Study Site

The study site includes an 81 km long by 12 km wide section of the Belize-Guatemalan “Western Border”. The study area width includes 6 km each way into both Belize and Guatemala. The study sight in Guatemala is part of the Montana Maya Biosphere Reserve (MMBR), which has been heavily deforested over the past 30 years. The study site on the Belizean side includes several protected areas within the Maya Mountain Massif (MMM) which has no permanent Belizean settlements and has been less impacted by human activity over the past 30 years.

The study area lies within UTM Zone 16 in southwestern Belize and northeastern Guatemala and shares a border with Petén, Guatemala. The Guatemalan section of the study area includes a section of the Chiquibul-Montanas Mayas Biosphere Reserve (CMMBR). The Belizean section of the study area includes several protected areas including Vaca Forest Reserve (VFR), Chiquibul National Park (CNP), Caracol Archeological Reserve (CAR) and Columbia River Forest Reserve (CRFR); all comprising part of a greater system called the Maya Mountain Massif (MMM) (Fig. 8). The ecosystem types found in the study area are mostly variants of tropical broadleaved forests, and aquatic ecosystems. Geologically, the
study area was formed by geological uplifting and consists of sandstone, granite, limestone, and volcanic rock (Meerman & Salas, 2008). The MMM contains steep slopes with a maximum elevation of 1,124 meters above sea level.

![Figure 8. Study Site: Belize-Guatemala border.](image)

Historically, the study area’s remote locale provided a buffer against over-exploitation; but since the mid-nineties settlements along the border and incursions from Guatemalans have significantly degraded biological and cultural resources (UNEP, 2011). Guatemalan communities buffering the Belize-Guatemala border have created a complex trail system to
conduct subsistence agriculture and access resources inside the protected areas within the MMM (Meerman & Salas, 2008). Conversely, access into the MMM from Belize is limited due to absence of roads and trails. Population growth, climate change, poverty and degraded lands continue to cause environmental quality decline within the study area.

3.3. Background

Over the previous decades, many tropical countries have established protected areas to safeguard their natural resources (Chiaravalloti et al., 2015; Morales-Hidalgo et al., 2015). In Belize, protected areas account for 36% of national territory (Meerman & Cherrington, 2005), the highest percentage in the region. Guatemala’s protected areas account for 27% of Guatemala’s national territory (Nature Conservancy, 2016). As Belize and Guatemala’s economies and populations grow at annual rates of 2.7% and 2% (World Bank, 2016), demand for land and natural resources continues to increase. This pressure, coupled with simultaneous threats from climate change, poverty, and environmental decline strains Belize’s protected areas (Young and Horwich, 2008). Protected areas managers have long engaged local communities adjacent to protected areas in order to achieve conservation objectives (Buta et al., 2014; Pietrzyk-Kaszyńska et al., 2012). However, adjacent communities’ attitudes towards protected areas depend on a number of complex factors pertaining to access and resources rights which may govern losses and gains in their livelihood (Kelboro & Stellmacher, 2015). These factors coupled with socio-economic, policy, institutional frameworks and political differences between Belize and Guatemala make bi-national cooperation and co-management challenging.

Over the past 20 years, a host of studies attributed the increase of deforestation in Petén, Guatemala to internal Guatemalan migration, local population growth, landlessness, poverty, depletion of forest resources and unsustainable agricultural practices (Shriar, 2014). There is
a clear timeline correlation between internal Guatemalan migration, population growth in Petén, and deforestation in Belize-Guatemala border area. According to Shriar (2014) in 1970, 70–80% of Petén was densely forested. By the late 1990s, half of it had been cleared. This study’s results support the deforestation timelines proposed by Carr (2009) and Brooks (2002), which indicate escalating deforestation in the late nineties and aughts. Much of this timing can be explained by socio-economic circumstances and political events in Guatemala that have encouraged internal migration and agricultural expansion.

The increasing deforestation during the 1990s, particularly in Petén, was caused by a wave of internal migration, from more populated regions of Guatemala to Petén. There were several causes for this human migration. First, Petén has always been Guatemala’s last great frontier and policy developed in the 1990s sought to exploit Petén for its natural resources and farmland. The 1980s had been an economic lost decade for the region, and poverty in Guatemala was widespread. In 1994, the government of Guatemala gave armed conflict refugees land in Petén as part of the retribution process. Many Guatemalans took advantage of new agricultural land availability and relocated their families to this new frontier where land was available for purchase.

The 1990s and 2000s in Petén was a period of rapid agricultural expansion, economic development and population growth. Land owners in Petén were under pressure to produce cheaply; resulting in rapid agricultural expansion, depletion of natural resources and intensive water use. Economic development continued to attract migrants despite increasing land prices. As land became scarcer and prices increased, the landless population grew. A generation later, massive landlessness and resulting poverty pushed many peasants into protected areas in search of timber, construction material, food, and anything of value such as xate, wildlife and archeological artifacts. All of this activity accelerated in the 1990s and 2000s, spilling over into protected areas (Ovando, 2008). This study seeks to retrace the resulting deforestation history by analyzing satellite images of the study area throughout this socially tumultuous
period.

3.4. Methodology

This study covers a time span of 23 years from 1991 to 2014 divided by 7 time steps (1991, 1995, 1999, 2003, 2007, 2012, and 2014). Landsat 5 Thematic Mapper and Landsat 7 Enhance Thematic Mapper imagery were used from 1991 to 1999 and from 2003 to 2014. The satellite image bands obtained from the United States Geological Survey global archives were stacked and a mosaic was created for each time step (Fig. 9). Next, we digitized the 81 km Belize-Guatemalan MMM border and created a 6 km buffer on each side. Then we used the buffer to clip the study site from the Landsat mosaics. The study site datasets were then re-processed and classified by CLASlite algorithms. The algorithms classified forest as pixels where the photosynthetic vegetation cover was $\geq 80$ and where bare substrate cover fraction was $< 20$. The algorithms classified non-forest as pixels where the photosynthetic vegetation cover was $< 80$ or where the bare substrate cover fraction was $> 20$ (Asner et al., 2009).

3.4.1. Filling the Gaps of Landsat 7 ETM+ image

The scan-line corrector (SLC) for the ETM+ sensor on board Landsat 7 failed permanently on May 31, 2003, resulting in data gaps which comprise approximately 22% pixels of the image (Chen et al., 2011). To compensate for this loss required filling the mosaics with other images of similar dates. We generated the filled mosaics for 2007, 2012 and 2014 by utilizing two other Landsat 7 ETM + images (Table 5).
Table 5: Landsat scenes used in the forest cover and change analysis

<table>
<thead>
<tr>
<th>Mosaic</th>
<th>Satellite Spatial Resolution</th>
<th>Path</th>
<th>Rows</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>1991</td>
<td>Landsat-5 30 m</td>
<td>19</td>
<td>48, 49</td>
<td>3/20/1991</td>
</tr>
<tr>
<td>1995</td>
<td>Landsat-5 30 m</td>
<td>19</td>
<td>48, 49</td>
<td>2/27/1995</td>
</tr>
<tr>
<td>1999</td>
<td>Landsat-5 30 m</td>
<td>19</td>
<td>48, 49</td>
<td>4/27/1999</td>
</tr>
<tr>
<td>2003</td>
<td>Landsat-7 30 m</td>
<td>19</td>
<td>48, 49</td>
<td>4/30/2003</td>
</tr>
<tr>
<td>2003</td>
<td>Landsat-7 30 m</td>
<td>19</td>
<td>48, 49</td>
<td>4/30/2003 (working II)</td>
</tr>
<tr>
<td>2006</td>
<td>Landsat-7 30 m</td>
<td>19</td>
<td>48, 49</td>
<td>3/21/2006 (working I)</td>
</tr>
<tr>
<td>2007</td>
<td>Landsat-7 30 m</td>
<td>19</td>
<td>48, 49</td>
<td>4/25/2007 (Filled)</td>
</tr>
<tr>
<td>2010</td>
<td>Landsat-7 30 m</td>
<td>19</td>
<td>48, 49</td>
<td>1/11/2010 (working II)</td>
</tr>
<tr>
<td>2012</td>
<td>Landsat-7 30 m</td>
<td>19</td>
<td>48, 49</td>
<td>5/08/2012 (working I)</td>
</tr>
<tr>
<td>2012</td>
<td>Landsat-7 30 m</td>
<td>19</td>
<td>48, 49</td>
<td>3/21/2012 (Filled)</td>
</tr>
<tr>
<td>2014</td>
<td>Landsat-7 30 m</td>
<td>19</td>
<td>48, 49</td>
<td>2/23/2014 (working II)</td>
</tr>
<tr>
<td>2014</td>
<td>Landsat-7 30 m</td>
<td>19</td>
<td>48, 49</td>
<td>12/24/2014 (working I)</td>
</tr>
<tr>
<td>2014</td>
<td>Landsat-7 30 m</td>
<td>19</td>
<td>48, 49</td>
<td>4/28/2014 (Filled)</td>
</tr>
</tbody>
</table>

3.4.2. Pre-processing, Classification and Post-Processing of Satellite Imagery

We used CLASlite algorithms to convert the Landsat images from raw digital number format (DN) to forest cover and forest change maps (Reimer et al., 2015). We then conducted post-processing on the outputs of CLASlite. Post-processing consisted of 4 steps. First, we vectorized the forest cover and forest change datasets generated by CLASlite algorithms. We removed areas in each dataset that were less than 1 hectare. Second, we reclassified the datasets into three classes: a) non-forest, b) cloud, and c) forest; water was classified as no-forest. Third, we reclassified cloud pixels in each dataset into forest or non-forest based on a visual analysis conducted on images before and after the classified dataset. Last, we reclassified the datasets into two classes 1: Forest and 2: Non-Forest. Then we converted the datasets to ENVI classification raster layers and conducted change statistics for the 7 time-steps.

3.4.3. Comparison with other work
In most of the developing world, the absence of extensive groundtruth data hinders the accuracy assessment of historic cover change results. However, in order to verify cover change results in the absence of groundtruth data, Reimer et al. (2015) compared their results with existing studies’ results. In our study, we verify our results by comparing them with the only deforestation dataset results available to us for the study region, Deforestation in Belize 1980-2010 (Cherrington et al., 2010).

3.4.4. Estimation of deforestation rates

We calculated forest cover and deforestation rates in the study site using the standardized approach proposed by Puyravaud (2003) and modified by Remere et al. (2015).

\[
\text{Deforestation rate yr}^{-1} = \frac{1}{\text{time A}_2 - \text{time A}_1} \times \log(\frac{A_2}{A_1}) \times 100
\]  

\( A_1 \) = Forest Area at beginning of time step  
\( A_2 \) = Forest Area at end of time step  
\( \text{time A}_1 \) = Year and day count as digit number of beginning of time step  
\( \text{time A}_2 \) = Year and day count as digit number of end of time step

We used the resulting deforestation rates to compare deforestation in Belize and Guatemala and Belize’s protected areas during the study period.

3.4.5. Spatial Metrics

For this study, we used class level metrics to characterize the deforestation patches that occurred in the study site for the 6 sub-time steps. The selection of metrics invariably depends on the objectives of the research (Aguilera et al., 2011). For this study, we selected
and calculated six metrics with the help of Patch Analyst run in an ArcGIS platform (Table 6). Patch Analyst has been widely used in characterizing, monitoring, modeling, and assessing landscape pattern and structure (Liu et al., 2016). We used the spatial metrics indices or average indices in order to compare deforested patches spatial structure complexity, irregularity, size, number and change tendency between the sub-time steps to better understand the dynamic changes of deforested patches as a result of interventions to curb deforestation.

Table 6: Class level metrics indices to characterize the deforestation patches.

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Name</th>
<th>Description</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>NumP</td>
<td>Number of patches</td>
<td>Estimates the number of patches in class types.</td>
<td>Aggregation</td>
</tr>
<tr>
<td>MPS</td>
<td>Mean patch size</td>
<td>MPS measures the average patch area in class types.</td>
<td>Area</td>
</tr>
<tr>
<td>MedPS</td>
<td>Median patch size</td>
<td>Equals the area value of the patch representing the 50th percentile in a class type.</td>
<td>Area</td>
</tr>
<tr>
<td>PSCoV</td>
<td>Patch size coefficient of variation</td>
<td>Is the coefficient of variation of patches for a certain class type.</td>
<td>Area</td>
</tr>
<tr>
<td>AWMSI</td>
<td>Area-weighted mean shape index</td>
<td>Is equal to 1 when all patches are circular (for polygons) or square (for rasters (grids)) and it increases with increasing patch shape irregularity. AWMSI equals the sum of each patch's perimeter, divided by the square root of patch area (in hectares) for each class (when analyzing by class) or for all patches (when analyzing by landscape), and adjusted for circular standard (for polygons), or square standard (for rasters (grids)), divided by the number of patches.</td>
<td>Shape</td>
</tr>
<tr>
<td>AWMPFD</td>
<td>Mean patch fractal dimension</td>
<td>Is the same as mean patch fractal dimension with the addition of individual patch area weighting applied to each patch. Because larger patches tend to be more complex than smaller patches, this has the effect of determining patch complexity independent of its size. The unit of measure is the same as mean patch fractal dimension.</td>
<td>Shape</td>
</tr>
</tbody>
</table>

* Adopted from McGarigal and Marks, 1994 and McGarigal and Marks, 1995
3.4.6. Communities sampling approach, survey preparation and data analysis

For this study, expert and local knowledge and literature were used to identify the social and environmental issues regarding deforestation in the study site. The social and environmental issues identified were then used to prepare a survey which was administered to community leaders and stakeholders from January-March 2016. A two tier sampling approach was conducted. ArcGIS was used to build the 4 km buffer around the MMM in which 24 communities resided. Visits were done to these communities to conduct a one on one interview/survey. 45 MMM stakeholders were selected including researchers, NGO representatives, or governmental employees. The 45 stakeholders selected were contacted via email and were asked to answer the survey and returned it to the researchers. From the stakeholders that were contacted 20 responded.

Radar charts were created to illustrate the average rankings of drivers, underlying causes, impacts, barriers to bi-national collaboration and solutions by leaders and stakeholders. The survey data were analyzed using Statistical Package for Social Sciences (SPSS). The Chi square goodness of fit test was conducted to determine significant attitude differences between the leaders (f = 24) and stakeholders (f = 16). The questions targeting deforestation issues along the border were ranked on a likert scale of 1-3, with 1 being disagree and 3 being agree and yes and no, with 1 being yes and 2 being no. The strength of association was determined by Phi and Cramer’s V. Questions targeting challenges faced by protected areas organizations were ranked on a likert scale of 1-5, with 1 being the least important and 5 being the most important. The Mann-Whitney U test was used to determine if there was a significant difference in the ranking of challenges by leaders and stakeholders. The Mann-Whitney U test consider two samples $X_1, \ldots, X_n$ and $Y_1, \ldots, Y_n$ from two possible different populations, with underlying distribution functions $L$ and $S$, respectively in order to test.
H$_0$: $L = S$ vs.

HA: $L(x) \geq S(x)$ $\forall x$, with strict inequality for at least one $x$ (i.e., stochastic ordering), in this case we used the Mann-Whitney U test, which is given by (John & Priebe, 2007).

\[ \frac{1}{mn} \sum_{i=1}^{n} \sum_{j=1}^{m} I(X_i \leq Y_j) \]  \hspace{1cm} (10)

Here $I(.)$ is the indicator function. Let $L_n(x) = \frac{1}{n} \sum_{i=1}^{n} I(X_i \leq x)$ and $S_n(x) = \frac{1}{n} \sum_{j=1}^{m} I(X_j \leq x)$ be the empirical function corresponding to $L$ and $S$, respectively (John & Priebe, 2007).

The statistic (1) which may also be written as

\[ \int_{-\infty}^{\infty} L_n(x) dS_m(x) \]  \hspace{1cm} (11)

Is an empirical estimate of the function.

\[ \int_{-\infty}^{\infty} L(x) dS(x) \]  \hspace{1cm} (12)

The classical Mann-Whitney statistic is robust, in the sense that it is distribution free.

### 3.5. Results

Figure 10 depicts the expanding of deforestation in Guatemala, which ultimately extended across the border into Belize’s protected areas. The results illustrate that in 1991, there were three deforested “hotspots” in Guatemala and only one in the northernmost part of the Belize’s Vaca Forest Reserve. In 1991-1995 slight expansion occurred with the emergence of small deforested area in the center region in Guatemala. However, in the period of 1995-1999, existing deforested areas in Guatemala and Belize expanded and new deforested areas emerged in Guatemala and Belize’s protected areas (CAR, CNP and CRFR). From 1999-2003, deforested areas expanded especially in the southernmost region in Belize’s
Columbia River Forest Reserve and Guatemala. However, in 2003-2007, deforestation expanded vertically connecting northern and central deforested areas in Guatemala (Fig. 10). From 2007-2012, new deforestation remained relatively stagnant, with expansion occurring nearby deforested areas on both sides of the border. Then once again in 2012-2014, new deforested areas appeared in the Vaca Forest Reserve, Caracol Archeological Reserve and Chiquibul National Park.

Figure 10. Deforestation along the Belize-Guatemala border 1991-2014.

3.5.1. Comparison with other work

Figure 11 compares the results of the accumulated deforestation between 1980 and 2004 in Belize. The datasets used to do this comparison cover different study periods (1980-2010 & 1991-2014); however, there is an overlap of the study periods 1991-2004. The 1980-2010
study dataset is the most comprehensive national deforestation study that has been conducted in Belize.

![Figure 11. Accumulated deforestation comparison, Deforestation in Belize 1980-2010 and Maya Mountain Massif 1991-2014](image)

Both datasets show great similarity especially in years where the time-steps are only one year apart as is the case of 1994 & 1995, 1999 & 2000 and 2003 & 2004.

### 3.5.2. Belize and Guatemala deforestation rates

In Belize in 1991 the forest covered was 96.9% of the study area. By 2014 forest cover declined to 85.7% (Table 7). The results suggest that the highest forest cover loss occurred from 1995-1999 (-0.65%) and 1999-2003 (-0.59). The highest deforestation rates occurred from 2012-2014 (-1.04%) and 1995-1999 (-0.65%). The lowest forest loss and deforestation rate occurred from 1991-1995 (664.2ha or -0.36%).
Table 7: Forest cover and deforestation rates in Belize and Guatemala 1991-2014.

<table>
<thead>
<tr>
<th>Time A₁</th>
<th>Time A₂</th>
<th>Forest Cover A₁ (ha) BZ</th>
<th>Forest Cover A₂ (ha) BZ</th>
<th>Forest Cover A₁ (ha) Gua</th>
<th>Forest Cover A₂ (ha) Gua</th>
<th>Deforestation BZ (ha)</th>
<th>Deforestation Gua (ha)</th>
<th>Def rate yr⁻¹ BZ (%)</th>
<th>Def rate yr⁻¹ Gua (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1991.22</td>
<td>1995.16</td>
<td>47118.6</td>
<td>46454.4</td>
<td>40883.7</td>
<td>37738.6</td>
<td>664.2</td>
<td>3145.1</td>
<td>-0.36</td>
<td>-2.03</td>
</tr>
<tr>
<td>1995.16</td>
<td>1999.32</td>
<td>46454.4</td>
<td>45214.8</td>
<td>37738.6</td>
<td>29424.4</td>
<td>1239.6</td>
<td>8314.2</td>
<td>-0.65</td>
<td>-5.98</td>
</tr>
<tr>
<td>1999.32</td>
<td>2003.33</td>
<td>45214.8</td>
<td>44184.7</td>
<td>29424.4</td>
<td>25148.5</td>
<td>1030.1</td>
<td>4275.9</td>
<td>-0.57</td>
<td>-3.92</td>
</tr>
<tr>
<td>2003.33</td>
<td>2007.32</td>
<td>44184.7</td>
<td>43423.9</td>
<td>25148.5</td>
<td>20370.4</td>
<td>760.8</td>
<td>4778.1</td>
<td>-0.44</td>
<td>-5.28</td>
</tr>
<tr>
<td>2007.32</td>
<td>2012.22</td>
<td>43423.9</td>
<td>42604</td>
<td>20370.4</td>
<td>17880.9</td>
<td>819.9</td>
<td>2489.5</td>
<td>-0.39</td>
<td>-2.66</td>
</tr>
<tr>
<td>2012.22</td>
<td>2014.33</td>
<td>42604</td>
<td>41680.3</td>
<td>17880.9</td>
<td>15496.5</td>
<td>923.7</td>
<td>2384.4</td>
<td>-1.04</td>
<td>-6.78</td>
</tr>
</tbody>
</table>

In Guatemala in 1991, forest covered was 83.15% of the study area. By 2014, forest cover decreased to 31.52% (Table 7). Results indicate the highest forest loss occurred from 1995-1999 (-5.98%) and 2003-2007 (-5.28%). The highest deforestation rates occurred from 2012-2014 (-6.78%) and 1995-1999 (-5.98%). 1991-1995 incurred the lowest deforestation rate at -2.03% or 3,145.1 ha.

3.5.3. Deforestation rates in Belize’s protected areas

Between 1991 and 2014, forest cover declined in protected areas: VFR 97.88% to 87.62%, CNP 99.36% to 91.12%, CAR 99.47% to 78.10% and CRFR 89.22% to 78.38% respectively (Fig. 12). The period 2012-2014 had the highest annual deforestation rates for: VFR (-1.11%), CNP (-1.31%) and CAR (-1.98%). The highest annual deforestation rate in CRFR occurred in 1999-2003 (-0.86%). On the other hand, the lowest deforestation rate in VFR and CNP occurred in 1999-2003, -.12% and -.3% respectively.
And the lowest deforestation rate in CAR and CRFR occurred in 2007-2012, -0.69% and -0.15% respectively. The highest average deforestation rate in the study period occurred in CAR -1.13% compared to the lowest -0.33%, which occurred in CRFR (Table 8).

Table 8: Forest Cover and deforestation rates in Belize’s protected areas 1991-2014.

<table>
<thead>
<tr>
<th>Study Period</th>
<th>Def_VFR (ha)</th>
<th>Def_CNP (ha)</th>
<th>Def_CAR (ha)</th>
<th>Def_CRFR (ha)</th>
<th>Def rate yr-1VFR</th>
<th>Def rate yr-1CNP</th>
<th>Def rate yr-1CAR</th>
<th>Def rate yr-1CRFR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1991-1995</td>
<td>48.01</td>
<td>268.90</td>
<td>202.05</td>
<td>128.10</td>
<td>-0.15</td>
<td>-0.38</td>
<td>-0.78</td>
<td>-0.23</td>
</tr>
<tr>
<td>1995-1999</td>
<td>341.21</td>
<td>420.20</td>
<td>281.37</td>
<td>171.10</td>
<td>-1.05</td>
<td>-0.57</td>
<td>-1.07</td>
<td>-0.29</td>
</tr>
<tr>
<td>1999-2003</td>
<td>35.88</td>
<td>211.80</td>
<td>281.30</td>
<td>472.00</td>
<td>-0.12</td>
<td>-0.3</td>
<td>-1.17</td>
<td>-0.86</td>
</tr>
<tr>
<td>2003-2007</td>
<td>190.52</td>
<td>217.20</td>
<td>254.67</td>
<td>96.50</td>
<td>-0.63</td>
<td>-0.32</td>
<td>-1.11</td>
<td>-0.18</td>
</tr>
<tr>
<td>2007-2012</td>
<td>195.96</td>
<td>327.90</td>
<td>186.18</td>
<td>95.10</td>
<td>-0.54</td>
<td>-0.4</td>
<td>-0.69</td>
<td>-0.15</td>
</tr>
<tr>
<td>2012-2014</td>
<td>167.67</td>
<td>454.00</td>
<td>222.28</td>
<td>70.90</td>
<td>-1.11</td>
<td>-1.31</td>
<td>-1.98</td>
<td>-0.26</td>
</tr>
</tbody>
</table>

3.5.4. Spatial metrics characteristics of Belize and Guatemala deforested patches

The analysis of deforested patches using spatial metrics in Belize and Guatemala reveal the dynamic changes of patches’ characteristics: mean patch size (MPS); patch size
coefficient of variation (PSCoV); number of patches (NumP); area weighted mean patch fractal dimension (AWMPFD) and area weighted mean shape index (AWMSI). The results of the spatial metrics indices suggest that patch characteristic variations exist between Belize and Guatemala in the same and between different time periods (Table 9).

<table>
<thead>
<tr>
<th>Study Period</th>
<th>AWMSI_Gua</th>
<th>AWMPFD_Gua</th>
<th>MPS_Gua</th>
<th>NumP_Gua</th>
<th>PSCoV_Gua</th>
<th>AWMSI_BZ</th>
<th>AWMPFD_BZ</th>
<th>MPS_BZ</th>
<th>NumP_BZ</th>
<th>PSCoV_BZ</th>
</tr>
</thead>
<tbody>
<tr>
<td>1991-1995</td>
<td>2.31</td>
<td>1.35</td>
<td>4.47</td>
<td>703.00</td>
<td>258.14</td>
<td>1.86</td>
<td>1.34</td>
<td>3.09</td>
<td>215.00</td>
<td>135.70</td>
</tr>
<tr>
<td>1995-1999</td>
<td>5.87</td>
<td>1.40</td>
<td>9.13</td>
<td>911.00</td>
<td>640.88</td>
<td>2.45</td>
<td>1.36</td>
<td>4.59</td>
<td>271.00</td>
<td>193.69</td>
</tr>
<tr>
<td>1999-2003</td>
<td>2.80</td>
<td>1.37</td>
<td>5.45</td>
<td>785.00</td>
<td>208.76</td>
<td>2.20</td>
<td>1.34</td>
<td>4.91</td>
<td>210.00</td>
<td>212.26</td>
</tr>
<tr>
<td>2003-2007</td>
<td>4.13</td>
<td>1.39</td>
<td>6.92</td>
<td>690.00</td>
<td>420.93</td>
<td>2.30</td>
<td>1.36</td>
<td>4.11</td>
<td>185.00</td>
<td>211.66</td>
</tr>
<tr>
<td>2007-2012</td>
<td>2.04</td>
<td>1.34</td>
<td>4.55</td>
<td>547.00</td>
<td>154.85</td>
<td>1.83</td>
<td>1.32</td>
<td>4.46</td>
<td>184.00</td>
<td>153.68</td>
</tr>
<tr>
<td>2012-2014</td>
<td>2.33</td>
<td>1.36</td>
<td>4.07</td>
<td>586.00</td>
<td>182.60</td>
<td>1.98</td>
<td>1.34</td>
<td>4.18</td>
<td>221.00</td>
<td>119.85</td>
</tr>
</tbody>
</table>

The results indicate that AWMSI_Gua and AWMSI_BZ range from 2.04-5.87 and 1.83-2.45. AWMPFD_Gua and AWMPFD_BZ ranged from 1.34-1.4 and 1.32-1.36. In both countries, the highest (AWMSI and AWMPFD) and Lowest (AWMSI and AWMPFD) occurred in 1995-1999 and in 2007-2012. Although, MPS_Gua range was higher than MPS_BZ on average during the study period MPS were 5.8 ha and 4.2 ha respectively. On average, the number of patches in Guatemala were 489 times higher than the number of patches in Belize. The lowest difference between NumP_Gua and NumP_BZ occurred between 2007-2014. The average PSCoV_Gau and PSCoV_BZ during the study period was 311.03 and 171.14.

3.5.5. Spatial metrics characteristics of Belize’s protected areas deforested patches

The analyses of deforested patches in Belize’s protected areas depict differences in deforested patch characteristics among protected areas in the same and between different study periods (Fig. 13).
Figure 13. Spatial metrics characteristics of Belize’s protected areas deforested patches.

The results indicate that on average the highest AWMSI occurred in CNP (1.99) and CAR (2.34) respectively. AWMPFD ranged from 1.32-1.38 in VFR, 1.32-1.36 in CNP, 1.32-1.36 in CAR and 1.33-1.35 in CRFR. On average during the study period, the MPS was higher in CAR (6.81 ha) and CRFR (4.01 ha). The number of patches was greater in Chiquibul
National Park (82) followed by Vaca Forest Reserve (58.33). The greatest number of patches occurred in CNP in 1991-1995 (103) and 2012-2014 (100). The graph illustrates that, throughout the study period, the patches in CNP and CAR followed a similar trend; with the exception for 2012-2014 when there was a sudden increase in patches in CNP. Between 1991-1995, protected areas in the study site had the following number of patches and mean patch size (MPS): VFR 31 patches, 1.55 ha/mps; CNP 103 patches, 2.61 ha/mps; CAR 53 patches, 3.81 ha/mps; and CRFR 26 patches, 4.27 ha/mps. Conversely, in 2012-2014 the number of patches and mean patch size were: VFR 64 patches, 2.62 ha/mps; CNP 100 patches, 4.54 ha/mps, CAR 33 patches, 6.74 ha/mps and CRFR 26 patches, 3.66 ha/mps. During the study period, on average, the highest PSCoV occurred in CNP and CAR.

3.5.6. Leaders and Stakeholders perspectives on deforestation along the Belize - Guatemala border

All 24 leaders completed the survey. Of the 45 requests for participation via e-mail, 20 respondents completed the survey, of these 20 surveys, 4 were discarded because less than 50% of questions were answered. The average overall major underlying cause, driver, impact, barrier to bi-national collaboration and solution identified from the data analysis were: demand for agricultural products and exotic species; agriculture; habitat fragmentation; claim of Guatemala over Belize and bi-national collaboration between organizations and governments respectively (Fig. 14).
Figure 14. Average rankings of drivers, underlying causes, impacts, barriers to bi-national collaboration and solutions by leaders and stakeholders.

The Mann–Whitney U test identified significant differences between Leaders and Stakeholders in the ranking of underlying causes, drivers, impacts and solutions (Table 10). No significant differences were found between community leaders and stakeholders regarding barriers to bi-national collaboration. The overall minimum or the maximum ranking that a respondent gave to the two underlying causes that were significantly different between the leaders and stakeholders ranged from 1-6 or 2-6. The overall mean of the respondents for agriculture was 5.38.

Table 10: Ranking of underlying causes, drivers, impacts and solutions by leaders and stakeholders.

<table>
<thead>
<tr>
<th>Challenges</th>
<th>Number of respondents</th>
<th>Mean</th>
<th>Mann-Whitney U test Leaders (LD) and Stakeholders (SH)</th>
<th>P- Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Underlying Causes)</td>
<td>40</td>
<td>4.58</td>
<td>LD, SH: 26.58, 11.38,</td>
<td>p &lt; .001</td>
</tr>
<tr>
<td>Demand for agricultural products and Exotic species</td>
<td>U = 46</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The Mann-Whitney U test identified significant differences between leaders and stakeholders regarding the ranking of challenges faced by management organizations in the MMM, except for the lack of assessment and quantification of deforestation (Table 11).

### Table 11: Ranking of perceived challenges faced by protected areas management organizations in the MMM.

<table>
<thead>
<tr>
<th>Challenges</th>
<th>Number of respondents</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Mann-Whitney U test Leaders (LD) and Stakeholders (SH)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(Mean rank, U, p-value)</td>
</tr>
<tr>
<td>Lack of financial resources</td>
<td>40</td>
<td>1</td>
<td>5</td>
<td>4.03</td>
<td>LD, SH: 15.10, 28.59, U = 62.5, p &lt; .001</td>
</tr>
<tr>
<td>Lack of personnel and capacity</td>
<td>40</td>
<td>1</td>
<td>5</td>
<td>4</td>
<td>LD, SH: 16.5, 26.5, U = 96, p &lt; .05</td>
</tr>
<tr>
<td>Lack of assessment and quantification of deforestation</td>
<td>40</td>
<td>1</td>
<td>5</td>
<td>3.25</td>
<td>LD, SH: 18.67, 23.25, U = 148, p &gt; .05</td>
</tr>
<tr>
<td>Lack of coordination among managing organizations</td>
<td>40</td>
<td>1</td>
<td>5</td>
<td>4.20</td>
<td>LD, SH: 24, 15.25, U =108, p &lt; 0.05</td>
</tr>
</tbody>
</table>
Leaders (95%) and Stakeholders (87%) agreed that incursions along the border are the main threat to conservation in the MMM protected areas. 70% of leaders and 94% of stakeholders agreed that deforestation along the border is increasing. Only 16% of leaders and 12% of stakeholders agreed that programs implemented to address the deforestation issue along the border have been successful. When asked if surrounding Belizean buffer communities participate in the planning and implementation of protected areas management plan, 46% of the leaders answered yes compared to 57% of the stakeholders. However, only 17% of the leaders said that their community co-manages a protected area. Leaders (62%) and stakeholders (87%) disagreed that it is possible to stop illegal deforestation along the borders without bi-national cooperation. When asked if it is possible for buffer Guatemalan communities along the border to be included in the planning and executing strategies to address deforestation, 62% of leaders answered no compared to 12% of stakeholders (Cramer’s V=.496, p < 0.05).

3.6. Discussion

The multi-disciplinary approach undertaken by this study illustrates the deforestation dynamics in Belize’s protected areas and the differences in perception between community leaders and stakeholders. Understanding the dynamic of deforestation is important in order to allocate resources, which are limited, to areas that are being affected the most. Moreover, the findings of the study highlight the perceptual differences between LD and SH, which need to be addressed if collaboration is to be established. The findings have important implications for the development of effective deforestation strategies along the Belize-Guatemala border. Moreover, the identification of the underlying causes, drivers, impacts and barriers to bi-national collaboration highlight the need to incorporate all stakeholders, both national and bi-national, in the development of mitigation strategies. Understanding the difference
between leader’s perspectives and stakeholder knowledge is essential if any program is to successfully mitigate the deforestation problem.

The lowest deforestation rates in Belize and Guatemala occurred in 1991-1995 and 2007-2012 and the highest deforestation rates occurred in 1995-1999 and 2012-2014. The results suggest that while the lowest deforestation rate in Guatemala and Belize was observed in 1991-1995, the highest recorded deforestation rate in Belize and Guatemala occurred directly after this period from 1995-1999. The same pattern was observed in 2007-2012 (low deforestation) followed by 2012-2014 (high deforestation). This suggests that as Guatemala’s resources became more depleted, extraction increasingly spilled over into Belize. The highest deforestation rate that occurred in Guatemala in 2012-2014 also exerted highest deforestation rate in Caracol, Vaca and Chiquibul. The difference in deforestation rate in Columbia River Forest Reserve might be because it is buffered to the west by Guatemalan communities and to the north by Belizean communities; thus, influencing deforestation rate dynamics in comparison to Guatemala. Differences in deforestation rates between Guatemala and Belize’s protected areas are likely due to decrease of deforestation rate in Guatemala, vertical expansion of deforestation in Guatemala and increased monitoring along the Belize-Guatemala border by Belize’s NGOs.

The protected areas that have been mostly impacted by the increased deforestation by illegal incursions are CAR and CRFR. Increased deforestation in both protected areas is likely due to the accessibility and proximity of Guatemalan communities, which depend on subsistence agriculture and forest resources for their food supply and economic livelihoods. Friends for Conservation and Development (FCD) has recognized eleven Guatemalan buffer communities that depend on agriculture for their subsistence, which are increasingly farming within the Chiquibul National Park (Meerman & Salas 2008; Arevalo, 2011). Furthermore, Weishampel et al. (2012) suggested that most of the deforested areas in Caracol continued to be used for agriculture or pastureland; thus, forest was not permitted to
In 2007 in an effort to address illegal deforestation, key NGOs in Belize increased monitoring along the Belize-Guatemala border. Also in 2007, the Belize Defense Force started the destruction of illegal crop fields inside Belize’s MMM (Friends for Conservation and Development, 2007). The deforestation rate and the spatial metrics results indicate that these strategies have been somewhat effective in some protected areas to curb deforestation. For instance, compared to the average deforestation rate from 1991-2007, the deforestation rate results of 2007-2012 period indicate that the increased monitoring and destruction of illegal fields might have been linked to a decrease in deforestation rates in Caracol (-0.69%), Vaca (-0.54%) and Columbia (-0.15%). It is important to note that in Caracol and Columbia, the 2007-2012 period had the lowest deforestation rate. However, for the same period, an increase in deforestation rate occurred in Chiquibul (-0.40%).

Likewise, compared to the average spatial metrics indices results from 1991-2007, the indices results of 2007-2012 period indicate a decrease in MPS and NumP in Caracol and Columbia. On the other hand, in Chiquibul and Vaca MPS increased and NumP decreased. As Gkyer (2013) indicated that if MPS and NumP value decrease it is understood that fragmentation decrease in the field. From the spatial metrics indices, it can be concluded that in Caracol and Colombia fragmentation decreased in 2007-2012, since both MPS and NumP decreased. While in CNP and VFR the increase in MPS and the decrease of NumP make it difficult to conclusively state that fragmentation decreased. However, it can be stated that in CNP and VFR aggregation occurred where NumP declined producing an increase in MPS (Aguilera et al., 2011). The results of deforestation rates and spatial metrics indices indicated that while monitoring and destruction of fields might have been effective in 2007-2012, there is an indication that displacement of deforestation from the other protected areas to Chiquibul might have occurred. The Chiquibul shares a larger border area with Guatemala, which is buffered by several Guatemalan communities and is less accessible from Belize; making it
vulnerable to displaced deforestation. Moreover, according to Derric Chen Chiquibul is also experiencing displaced deforestation within its boundaries (News5, 2015). Overall, a comparison of the deforestation rates and spatial metrics indices (NumP and MPS) of 1991-1995 and 2012-2014 demonstrated that fragmentation and deforestation are increasing in protected areas. These results are further supported by the perspectives of leaders and stakeholders which agreed that deforestation along the border is increasing. A comparison between the highest deforestation rate and lowest deforestation rate periods indicated that AWMSI and AWMPFD increased during the highest deforestation rate period and decreased during the lowest deforestation period in protected areas. This is as a result of the nature of deforestation that is occurring in the area, slash and burn, which created complex deforested patches during expansion. Deforested patches, in the study area, witnessed compaction during low deforestation rates, which involves the formation of rounded patches and elongation during high deforestation rates.

Amidst the decrease of deforestation rate in 2007-2012, the deforestation rate in Belize’s protected areas increased dramatically in 2012-2014. This increase can be attributed directly to increased deforestation rate in Guatemala, especially along the border. By 1991-2012, only fragmented patches of forest remained within the Guatemalan study area. With the forest that once served as a buffer for Belize gone, and given the limited monitoring capabilities by managing organizations in Belize, deforestation inside Belize’s MMM during 2012-2014 increased. This is an indication that although the increased monitoring and destruction of crops are having an impact in curbing deforestation, more work is needed.

The multi-temporal geospatial data analysis results of this study are further supported by the survey results. Leaders and stakeholders agreed that deforestation is increasing and that current mitigation strategies are not halting the problem. The ranking of underlying causes, drivers, impacts, and solutions by leaders and stakeholders revealed significant difference. For instance, the ranking of underlying causes revealed that while community leaders
perceived the demand for agricultural products and exotic species as the main cause of deforestation along the border, leaders perceived poverty as the main cause. Both leaders and stakeholders ranked agriculture as the main driver of deforestation; however, stakeholders ranked agriculture higher. Also, there were significant differences in the ranking of impacts, where leaders ranked habitat fragmentation higher than stakeholders and stakeholders ranked pollution of surface water higher than leaders. The ranking of pollution of surface water as the lowest impact by community leaders have important implication since communities in the study area depend on surface waters as a source of drinking, washing, and irrigation. It is necessary to develop awareness of the impacts that deforestation is having on surface water within communities as they are the ones that are directly impacted. Interestingly, there were no significant differences regarding barriers to bi-national collaboration. However, concerning solutions there were many significant differences between leaders and stakeholders. In one hand, leaders ranked enforcement and the creation of stricter laws and regulations addressing illegal incursions higher than stakeholders and on the other, stakeholders ranked involvement of buffer communities in the planning and implementing of strategies to address deforestation higher than leaders. This indicates that community leaders perceive their roll in addressing the problem as less important. However, as the majority of these communities depend on subsistence agriculture and forest products (Binford, 2007), it is important for them to assume a central role in in the development and implementation of programs addressing deforestation along the border. Additionally, the lack of coordination among managing organizations was seen as the major challenge. The differences regarding the ranking of challenges between leaders and stakeholders indicated the little involvement that buffer communities have with managing organizations, which is further supported by the low number of communities co-managing protected areas. The involvement of buffer communities, both in Guatemala and Belize, in planning and implementing deforestation strategies was regarded as crucial to address deforestation by stakeholders. Both leaders and
stakeholders supported the strengthening of bi-national collaborations between organizations and governments. However, leaders were significantly less optimistic than stakeholders about the involvement of Guatemalan buffer communities in planning and executing strategies to address deforestation along the MMM.

Spatial Metrics are sensitive to scale, spatial resolution and spatial extent (Frohn & Hao, 2006). Therefore variation in results is expected. In order to compare the results between the 6 sub-time steps, the same scale and spatial resolution, a spatial extent and classification process was used. Lechner et al. (2013) suggest that comparisons of spatial metric values between landscapes using the same methods are likely to remain consistent. Ideally, extensive ground truth data would be used to conduct the accuracy assessment of the data sets. However, due to security and remoteness, extensive ground data for the study site is lacking. Therefore, in order to overcome this hurdle we compared the results of this study with the only deforestation dataset available to us from the study region; Deforestation in Belize, 1980-2010. While the two datasets cover different study periods, 1980-2010 and 1991-2014, it was possible to compare and quantify the results of this study. Although there were some differences between the two datasets in terms of accumulated deforestation, after 24 years the accumulated outputs differed by only 8%, 1980-2004.
Chapter IV


4.1. Introduction

Soil erosion is common in much of the world, and is particularly devastating in developing countries that struggle to replace eroded soils and nutrients (Naqvi et al., 2015). In tropical countries, soil erosion is often associated with agriculture. Erosion reduces soil fertility and causes serious environmental problems, threatening agricultural productivity, and water quality (Prasannakumar et al., 2012; Ferreira et al., 2015; Xu et al., 2015). Loss in economic productivity will result in long mounting long-term costs, both financial and environmental. Like many small developing countries, agriculture is an important part of Belize’s economy (13% GDP), provides food security and food price insulation (Barrientos & Soria, 2014). Clearly it is in Belize’s best short and long-term economic and strategic interest to maintain agricultural productivity; however, little is done to prevent soil erosion and mitigate the flow of agricultural runoff into waterways.

Agricultural runoff often contains sediment, fertilizer and pesticides. While regulations exist to protect 20 meters of land along watershed banks, these laws are rarely enforced. Logging and agricultural incursions threaten riparian forests and degrade fresh water quality resulting in increased pollution and sedimentation. Greater downstream sediment deposits decrease flood-plains’ capacity to store water and mitigate flooding (Palmer et al., 2014). Increased nutrient load from fertilizer runoff disturbs fragile aquatic and marine ecosystems (Yuan et al., 2015). According to Lapointe et al. (2010), in the Caribbean region, pollution
from land-based sources is considered one of the most important threats to the marine environment. Increased algae and turbidity cause rapid decline in coral productivity and growth, and disruptions within the marine food web. Massive coral die-offs are associated with agricultural pollution and degraded fresh water quality (Wu, 2015). The broad impacts of soil erosion extend beyond ecological and environmental degradation. The economic costs include loss in agriculture & fisheries productivity, decreased tourism opportunities, increased cost of water purification and degraded public health. Farmers, manufacturers and the general population depend on fresh water for their production systems. The general population uses fresh water systems for drinking, washing and bathing. Clearly the total ecological, environmental and economic value provided by ecosystems exceeds the short term costs of targeted erosion mitigation enforcement. This study aims to provide information to better understand the spatial and social drivers of erosion, and assist in developing mitigation strategies.

Over the past decades, the Revised Universal Soil Loss Equation (RUSLE) has been widely applied to predict soil losses (Ji et al., 2014, Tanyaş et al., 2015). The RUSLE provides a convenient tool for soil loss evaluation by considering rainfall, topography, conservation support practice, soil, and vegetation (Zhou et al., 2008). Although the RUSLE model can be used to determine the spatial distribution of erosion hotspots, little is known about the perceptions of communities adjacent or far from erosion hotspots. Given the undocumented communities’ perception, worldwide acceptance, application and relatively simple parameterization of the RUSLE model, this study employs a mixed method approach, combining spatial analysis and social surveys, to generate spatial, quantitative and qualitative information about erosion. Knowing the socio-economic characteristics that influence the perceived implementation of soil erosion measures, stakeholders will have a better understanding of the land management practices and land use history of communities (Avakoudjo et al., 2011). The perception of these erosion drivers is important because, to
garner support and behavior requires an understanding of the target audience’s perception and attitudes toward erosion. By introducing this mixed approach, this study seeks to address a specific knowledge gap with the aim to improve stakeholder understanding and engage in more effective dialogue toward erosion mitigation.

In the Rio Grande watershed of Belize, steep slopes, high rainfall conditions and unsustainable anthropogenic practices are exacerbating soil erosion. Soil erosion has major economic and environmental implications resulting in declining agricultural productivity and increasing water pollution. Communities depend on the watershed as a source of drinking water, for washing, and for irrigation; particularly in San Pedro Columbia and San Miguel (McLoughlin, 2010). Therefore, degradation of this watershed has major impacts not only on the ecology, economy, food security and public health of the communities living within its boundaries, but also on the coastal zone ecosystems (Chicas & Omine, 2015). Soil erosion can be attributed to deforestation and other land cover conversions. These include farming on marginal lands, farming on steep slopes, fire, growth and expansion of human settlements, invasive species, overgrazing of livestock, logging and surface mining (Meerman & Cherrington, 2005). Very little is known about Rio Grande’s spatial distribution of erosion hotspots and communities perception of erosion. Given the widespread ecological and economic impacts of erosion in this watershed, this study aims to identify erosion vulnerable areas (hotspots) and to assess, utilizing statistical analysis, the difference of perspective between communities near (NEH) and far (FEH) from erosion hotspots on the drivers and underlying causes of erosion. Identifying erosion vulnerable areas, drivers, underlying causes and the perception of communities will assist stakeholders to promote community-based problem identification, planning, and implementation of efficient and effective soil erosion conservation measures in watershed systems throughout the world.
4.2. Study Area

In 2009, the population in Toledo, the District comprising the study area, was comprised of 5.5% Creole, 3.9% Garifuna, 69.4% Maya, 12.1% Mestizo and 9.1% other (Halcrow Group Limited, 2010). A recent poverty assessment of Belize indicates that Toledo is the poorest district in Belize (Halcrow Group Limited, 2010). The climate of this region is characterized by two seasons; rainy and dry with average annual rainfall of approximately 4,000 mm. Within the study area there are both low-lying and mountainous areas which rise to 1070 meters (Meerman & Sabido, 2001). The headwaters of the Rio Grande watershed emerge in the Maya Mountains and are protected by the Bladen Nature Reserve and the Columbia River Forest Reserve. The lower reaches of the watershed partially flow within the Maya Mountain Marine Corridor, and discharge into the Port Honduras Marine Reserve. The Rio Grande watershed consists of three geomorphological areas: Volcanic material and karstic limestone in the upper reaches; flat alluvial plain in the middle reaches; and limestone in its lower reaches (Chicas & Omine, 2015). The river drops through sinkholes and emerges out of springs as it makes its way through the underground limestone cave systems; meandering through indigenous Mayan communities, and on to coastal Creole communities before discharging into the sea (McLoughlin, 2010). The Milpa slash-and-burn agricultural system is sustained in response to local conditions and provides the Kekchi and Mopan Maya of the region with food and material resources (Emch et al., 2005).
Accessibility of the communities in the upper-mid reaches of the watershed is often determined by the weather and road conditions (Fig. 15). Major roads are rarely maintained and impassible during the rainy season. Tracks or footpaths are used by community members to access agricultural fields.

4.3. Methodology

4.3.1. Geospatial data analysis and the Revised Universal Soil Loss Equation

The RUSLE model was utilized to identify erosion hotspots and calculate the average soil loss in the Rio Grande watershed in 2001 and 2011 (t ha\(^{-1}\) yr\(^{-1}\)) (Eq. 13 & Fig. 16) (Chicas
\[ A = R \times K \times L \times S \times C \times P \]  \hspace{1cm} (13)

A = annual average soil erosion expected on field slope (t ha\(^{-1}\) yr\(^{-1}\))

R = Rainfall-runoff erosivity factor, function of storm energy and intensity (MJ mm ha\(^{-1}\) h\(^{-1}\) yr\(^{-1}\))

K = Soil erodibility factor, a measure of the soil properties (t ha h ha\(^{-1}\) MJ\(^{-1}\) mm\(^{-1}\))

L = Slope length factor

S = Slope steepness factor

C = Cover-management factor, a measure of the land use

P = Support practice factors, a measure of best management practice
In this study, forest was defined as a pixel with photosynthetic vegetation cover ≥ 80 and where the bare substrate cover fraction was < 20. Non-forest was identified as pixels where the photosynthetic vegetation cover was < 80 or where the bare substrate cover fraction was > 20 (Asner et al., 2009). For this study a Digital Elevation Model (DEM) of 90 meters resolution was obtained from (http://www.earthexplorer.usgs.gov). The main tributaries of Rio Grande were digitized from high resolution satellite imagery available in Google Earth to hydrologically correct the DEM. The DEM was then used to derive the slope, aspect, drainage network, flow accumulation and slope gradient. From which the slope length factor (L) and the slope steepness factor (S) were calculated. The L and S factor values were calculated using the Hydrotools in ArcGIS spatial analyst. Equation 14-16 (Foster et al., 1977) and equation 17 (Desmet and Govers, 1996) were used to calculate the L factor and equation 18 (McCool et al., 1987) was used to calculate the S factor.

\[ L = \left( \frac{\lambda}{22.13} \right)^m \]  

\[ L = \text{slope length factor} \]
\[ \lambda = \text{slope length (m)} \]
\[ m = \text{slope length exponent} \]

\[ M = \frac{f}{(1 + f)} \]  

\[ M = \text{slope length exponent} \]
\[ f = \text{fournier’s index} \]
\[ F = \frac{\sin \beta / 0.0896}{3(\sin \beta)^{0.8} + 0.56} \]  
(16)

\[ F = \text{fourier's index} \]

\[ \beta = \text{slope (deg)} \]

\[ L_{(i,j)} = \frac{(A_{(i,j)} + D^2)^{m+1} - A_{(i,j)}^{m+1}}{x^m. D^{m+2}. (22.13)^m} \]  
(17)

\[ A_{(i,j)} = \text{contributing area at the inlet of a grid cell with coordinates (i,j)} \]

\[ D^2 = \text{the grid cell size (m)} \]

\[ x = \text{correction factor} \]

\[ L_{(i,j)} = \text{slope length factor the grid cell with coordinate (i,j)} \]

\[ m = \text{slope length exponent} \]

\[ S_{(i,j)} = \begin{cases} 
10.8 \sin \beta_{(i,j)} + 0.05 & \text{if } \tan \beta_{(i,j)} < 0.09 \\
16.8 \sin \beta_{(i,j)} - 0.5 & \text{if } \tan \beta_{(i,j)} < 0.09 
\end{cases} \]  
(18)

\[ S_{(i,j)} = \text{slope factor with coordinates (i,j)} \]

\[ \beta_{(i,j)} = \text{slope (deg) with coordinates (i,j)} \]

\[ L \] is the slope length factor which is the ratio of soil loss from the field slope length to soil loss from a 22.1 m length under the same conditions; \[ S \] is the slope steepness factor which is the ratio of soil loss from the field slope gradient to soil loss from a 9% slope under the same conditions (Alkharabsheh et al., 2013).

The cover management factor (C factor) which is the ratio of soil loss from an area with specified cover and management to soil loss from an identical area in tilled continuous fallow (Alkharabsheh et al., 2013) was calculated from Landsat satellite imagery which were downloaded from (http://www.earthexplorer.usgs.gov) (Table 12).
The satellite imagery was atmospherically corrected and the normalized difference vegetation index (NDVI) was calculated. The NDVI was derived using equation 19 and the C factor was derived using equation 20 (Alexakis et al., 2013).

\[
NDVI = \frac{NIR - RED}{NIR + RED} \tag{19}
\]

\[
NDVI = \text{normalize difference vegetation index}
\]

\[
NIR = \text{near infrared band}
\]

\[
RED = \text{red band}
\]

\[
C = \exp\left(-a \frac{NDVI}{(b - NDVI)}\right) \tag{20}
\]

\[
C = \text{cover management factor}
\]

\[
NDVI = \text{normalize difference vegetation index}
\]

\[
a \text{ & } b = \text{unitless parameters that determine the shape of the curve relating to NDVI and C factor}
\]

According to Alexakis et al. (2013) an a-value of 1 and a b-value of 2 seem to give reasonable results. For this study the value of b was the highest NDVI values for the respective satellite imagery, which gave reasonable results.

Satellite imagery for 2001 and 2011 were used to calculate forest cover using Claslite
algorithms (Asner et al., 2009). The ecosystem maps for 2001 and 2011, which were acquired from (www.biodiversity.bz/), were used to classify the forest cover into the respective land uses. The land use cover maps for 2001 and 2011 were then overlaid with the C factor layers of 2001 and 2011 respectively and the mean C factor was calculated for each land use type (Table 13).

Table 13: Land Use and mean C factor for 2001 and 2011

<table>
<thead>
<tr>
<th>Land Use</th>
<th>C factor 2001</th>
<th>C factor 2011</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lowland Broad-leaved wet forest</td>
<td>0.007</td>
<td>0.007</td>
</tr>
<tr>
<td>Lowland pine forest</td>
<td>0.008</td>
<td>0.009</td>
</tr>
<tr>
<td>Mangrove and littoral forest</td>
<td>0.36</td>
<td>0.37</td>
</tr>
<tr>
<td>No-forest</td>
<td>0.058</td>
<td>0.084</td>
</tr>
<tr>
<td>Shrub land</td>
<td>0.008</td>
<td>0.008</td>
</tr>
<tr>
<td>Submontane broad-leaved wet forest</td>
<td>0.004</td>
<td>0.003</td>
</tr>
<tr>
<td>Wetland</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Urban</td>
<td>0.10</td>
<td>0.13</td>
</tr>
</tbody>
</table>

The rainfall erosivity factor ($R$ factor) is computed as a product of the total storm energy and the maximum 30-min intensity, summed over the storms occurring through the year (Thattai, 2003). Since rainfall data is limited in the study area, the monthly precipitation derived from a 1 km resolution global raster precipitation data set called WorldClim2 was used to calculate the $R$ factor. Monthly precipitation data were summed to produce annual rainfall estimates. The data set was then re-sampled to 90 meters resolution and equation 21 was used to calculate the $R$ factor (Burke, 2006).

$$R = 3786.6 + 1.5679 \times (P) - 1.9809 \times (E)$$ (21)
R = megajoule*mm per hectare
P = precipitation in mm
E = elevation in meters

The soil erodibility factor (K factor) which is the soil loss rate per erosion index unit for a specified soil as measured on a standard plot (22.1 m in length of uniform 9% slope in continuous clean tilled fallow) (Alkharabsheh et al., 2013), was obtained from the Soil and Terrain Database for Latin America and the Caribbean (http://www.isric.org/projects/soter-latin-america-and-caribbean-soterlac).

A value of 1 was used for the land management practices (P factor) which is the ratio of soil loss with a support practice such as contouring, strip cropping, or terracing to soil loss with straight row farming up and down the slope (Alkharabsheh et al., 2013). The value of 1 was used because very few farmers use support practices in the Rio Grande watershed.

The inherent erosion vulnerability in the Rio Grande watershed was calculated from equation 22 (Burke & Sugg, 2006). This equation accounts for slope, soil erodibility and rainfall-runoff erosivity, but omits land cover type. The R and K parameters used in this equation are the same as those used in the RUSLE equation, with the exception of Slope (S), which was calculated from a 90 meter resolution DEM.

\[
\text{Vulnerability} = R \times K \times S^{0.6}
\]  
(22)

\begin{align*}
R &= \text{Rainfall-runoff erosivity factor} \\
K &= \text{Soil erodibility factor} \\
S &= \text{Slope (in degrees)}
\end{align*}

The RUSLE and the inherent vulnerability models were run in an ArcGIS platform in
order to determine inherent erosion vulnerability and erosion hotspots in 2001 and 2011 in the Rio Grande watershed.

4.3.2. Community sampling approach, survey preparation and data analysis

For this study, soil erosion hotspots were classified as areas with an annual soil loss more than 201 ton/ha/yr, based on the RUSLE model results. A three tier sampling approach was implemented to select the communities and households in the Rio Grande watershed to be surveyed. A buffer analysis was conducted to classify the fourteen communities found in the Rio Grande watershed into two categories: communities that were more than two kilometers from an erosion hotspot (FEH) and communities that were less than two kilometers from an erosion hotspot (NEH). FEH communities included Silver Creek, Big Falls, Jacinto Ville, Forest Home, San Marcos, Yemeri Grove, Eldridgeville, Wilson Road and Cattle Landing. NEH communities included Naluum Ca, Crique Jute, San Migue, San Pedro Colombia and Hicatee. The random point generation tool in ArcGIS was used to select four communities from each category and 25 random household surveys were conducted in each selected community; with the exception of Naluum Ca where the entire community was surveyed as it only consists of 11 households. The 186 sampled households represent 20.1% of the total households in the 8 communities (Statistical Institute of Belize, 2010). The focus group approach was employed to discuss erosion drivers with community members. The drivers and underlying causes identified by members and researchers were then used to prepare surveys. These surveys were administered to households in the 8 communities in May 2015.

The resulting survey data sets were analyzed using Statistical Package for Social Sciences (SPSS). The Chi square goodness of fit test was utilized to determine significant attitude differences regarding the underlying causes of erosion between the two community categories; FEH (f=100) and NEH (f=86). The questions targeting underlying causes were ranked on a likert scale of 1-3, with 1 being disagree and 3 being agree. The strength of
The association was determined by Phi and Cramer’s V. The questions targeting the main drivers of erosion were ranked on a Likert scale of 1–5, with 1 being strongly disagree and 5 being strongly agree. The Mann-Whitney U test was used to determine whether there was a significant difference in the ranking of the erosion drivers between FEH and NEH communities.

The 186 households were asked if erosion prevention techniques were being implemented in their communities (No = 0 and Yes = 1). Responses were controlled by ethnicity: (Maya Mopan = 0, Maya Kekchi = 1, Mestizo = 2, Creole = 3 and Other = 4); Distance from erosion hotspots (NEH = 0, FEH = 1); Gender (Male = 0, Female = 1); Employment (Unemployed = 0, Employed = 1 and Self-employed = 2); Education (0 = None, Primary School = 1, Secondary School = 2 and College < = 3); and Age (18-28 = 0, 29-39 = 1, 40-50 = 2 and 51 < = 3). Logistic regression model was then used to determine the importance of the above mentioned variables regarding the implementation of erosion prevention techniques. The logistic regression function models the probability response as a function of a set of predictor variables $X = [X_1, X_2, \ldots, X_p]^T$ and regression coefficients $\beta = [\beta_0, \beta_1, \ldots, \beta_p]^T$ as given by (Kumar, 2014).

$$P = \frac{e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p}}$$  \hspace{1cm} (23)

$P =$ the probability of perceived erosion implementation measures

$E(Y) =$ the expected value of the dependent variable $Y$

$\beta_0 =$ constant to be estimated

$\beta_i =$ the coefficient to be estimated for each explanatory variable $X$

This logistic function (Eq. (23)) can be transformed (Eq. (24)) into a linear function (Eq.
(25)) which is called logit or logistic transformation:

\[
\text{logit}(p) = \frac{\log_e \left( \frac{p}{1-p} \right)}{(24)}
\]

\[
\text{logit}(p) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p
\]

(25)

The diagnostic tests that were used to validate the logistic regression model were Goodness of fit (Hosmer and Lemeshow test), Multicollinearity test (correlation matrix) and Cook’s distance (influential cases). The model was utilized to model the communities’ perceptions regarding whether erosion prevention techniques were applied or not; and to improve understanding on the socio-economic characteristics that influence a households’ perception on the implementation of erosion prevention techniques.

4.4. Results

Spatial analysis utilizing the RUSLE model indicated that erosion vulnerable areas were concentrated in the upper-mid reaches of the Rio Grande watershed. Social surveys indicated a widespread belief that the main drivers of erosion were cattle ranching, logging, fires, agriculture and clearing of slopes. The Mann-Whitney U test indicated that there were significant differences in the ranking of these erosion drivers between communities NEH and FEH communities. The logistic regression model suggests that ethnicity, gender, employment and distance from erosion hotspots were significant indicators of the perceived implementation of erosion prevention techniques.

4.4.1. Soil loss and erosion hotspots
Erosion was categorized into 3 classes based on the results of the RUSLE model: Low (1-50 ton/ha/yr.), high (51-200 ton/ha/yr.) and severe (201 < ton/ha/yr.). The inherent erosion vulnerability map shows that in the absence of land cover, the upper-reaches of the Rio Grand watershed have severe erosion vulnerability; and the mid-reaches to lower-reaches have high erosion vulnerability (Fig. 17). The severe erosion vulnerability areas are due to steep slopes, high soil erodability properties, and high precipitation.

![Rio Grande Watershed Inherent Erosion Vulnerability](image1)

![Rio Grande Watershed Land Cover Change 2001-2011](image2)

**Figure 17.** Rio Grande watershed inherent erosion and land cover change 2001-2011.

The maps generated from the 2001 RUSLE model illustrate that erosion hotspots were located in the upper-mid reaches of the watershed near the communities of Crique Jute, Naluum Ca, San Pedro Columbia and San Miguel (Fig. 17). The forest cover change analysis conducted using Claslite algorithms demonstrate that from 2001 to 2011 there was a decrease
of Lowland broad-leaved wet forest of 7.53 km$^2$, Shrubland of 4.66 km$^2$, and Wetland of 0.08 km$^2$ (Chicas & Omine, 2015). The maps generated from the 2011 RUSLE model suggest that the land cover changes between 2001 and 2011 resulted in the expansion of erosion hotspots and the emergence of a new hotspot in the upper reaches of the Rio Grande watershed (Fig. 18). The new erosion hotspot resulted from a land cover change from shrubland to no-forest in the upper reaches of the watershed.

![Figure 18. Rio Grande watershed 2001 and 2011 soil erosion.](image)

The maps generated in this study indicate that the majority of the erosion occurred within the agriculture use zone and the upper reaches of the watershed; which both have some areas with high and medium degradation potential (Meerman & Cherrington, 2005).

4.4.2. Communities’ socio-economic characteristics
Out of the 186 surveys conducted, the majority of participants were male Maya between 18-39 years with varying levels of education (Table 14.) There were distinct socio-economic variations between NEH and FEH communities; with education among the most pronounced variance. Of the households that had secondary education, 12% and 58% were NEH and FEH respectively. Moreover, NEH communities are poorer with 66% of individuals’ salaries of 0-100 BZ dollars per week compared to only 15% of communities FEH salaries within that range (Cramer’s V = .531, p < 0.001).

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value (NEH)</th>
<th>Value (FEH)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Male 66%, Female 34%</td>
<td>Male 73%, Female 27%</td>
</tr>
<tr>
<td>Ethnicity</td>
<td>Maya Mopan 42%, Maya Kekchi 53%, Mestizo 5%, Creole 0% Other 0%</td>
<td>Maya Mopan 10%, Maya Kekchi 32%, Mestizo 6%, Creole 27% Other 25%</td>
</tr>
<tr>
<td>Education</td>
<td>None 11%, Primary School 74%, Secondary Education 12%, Collage &lt; 3%</td>
<td>None 1%, Primary School 21%, Secondary Education 58%, Collage &lt; 20%</td>
</tr>
<tr>
<td>Salary (SBZ per/week)</td>
<td>1-100 (66%), 101-200 (21%), 201-300 (6%), 301&lt; (7%)</td>
<td>1-100 (15%), 101-200 (52%), 201-300 (22%), 301&lt; (11%)</td>
</tr>
<tr>
<td>Age</td>
<td>18-28 (26%), 29-39 (22%), 40-50 (22%), 51&lt; (30%)</td>
<td>18-28 (31%), 29-39 (45%), 40-50 (19%), 51&lt; (5%)</td>
</tr>
<tr>
<td>Employment</td>
<td>Unemployed 54%, Employed 9%, Self-employed 37%</td>
<td>Unemployed 26%, Employed 65%, Self-employed 9%</td>
</tr>
</tbody>
</table>

4.4.3. Communities’ perceptions of erosion drivers, underlying causes and effects

The causes and the impacts of erosion were identified from the focus group discussions and questionnaires (Fig. 19). Five main anthropogenic and three natural drivers of soil erosion were identified by focus group participants. The drivers of anthropogenic activities in the study site are outlined in figure 5. The identified underlying causes of soil erosion in the watershed are as a result of policy, institutional factors, demographics, economic circumstances and cultural influence.
Figure 19. Communities’ perspective on erosion drivers, underlying cause and effects.

4.4.4. Agriculture

NEH households were more likely (95%) than FEH households (33%) to agree that agriculture is very important to their community (Cramer’s V = .640, p < 0.001). Of the households NEH (49%) compared to FEH (11%) agreed that every year new forested land is slashed and burned for agricultural purposes (Cramer’s V = .643 p < .001). Only 26% of NEH and 43% of FEH households agreed that farmers in the community have access to agricultural technical support. Households NEH (91%) agreed that farmers are willing to learn and adopt erosion prevention measures.

4.4.5. Clearing of Slopes

Of the households NEH (62%) agreed that forested lands on slopes are cleared for planting in the rainy season. NEH (67%) and FEH (33%) households agreed that the
increased need for land is causing the farmers to clear forested lands higher on slopes for crop planting (Cramer’s V = .421, p < .001). The majority of the households were unaware of alternative soil conservation measures, other than mulching.

4.4.6. Logging

NEH (30%) and FEH (25%) households agreed that logging is very important to their community (Cramer’s V = .255, p < 0.005). When asked if logging companies are logging in their communal lands 9% of NEH and 65% of FEH households agreed. NEH (22%) and FEH (72%) households agreed that new feeder roads are created as a result of logging.

4.4.7. Cattle Ranching

NEH and FEH households agreed that ranching is very important to their community, 56% and 44% respectively. Of the households near erosion hotspots and far from erosion hotspots 60% and 30% respectively agreed that every year new forested land is cleared for cattle ranching (Cramer’s V = .311, p < .001). NEH (30%) and FEH (54%) households agreed that in the dry season cattle ranches have vegetation cover.

4.4.8. Fires

Households NEH and FEH agreed that forest fires commonly occur in the area, 43% and 69% respectively. NEH (61%) and FEH (20%) households agreed that fires destroys more forest than agriculture every year (Cramer’s V = .458, p < .001). Moreover, 69% of NEH and 53% of FEH households agreed that most forest fires are started from agriculture fires.

4.4.9. Mann-Whitney U test

The Mann-Whitney U test identified significant differences between NEH and FEH
communities’ erosion drivers ranking. FEH communities ranked cattle ranching and logging higher than NEH communities as the main drivers of soil erosion (NEH and FEH, mean = 79.02, 105.92, (U) = 3055, p < 0.001 and mean = 84.9, 100.90, (U) = 3560.5 p < 0.05) respectively. On the other hand, NEH communities ranked clearing and planting on slopes higher than FEH communities as the main driver of soil erosion (NEH and FEH, mean = 107.03, 81.86, (U) = 3136.5, p < 0.001). There was no significant ranking difference between the two community categories regarding agriculture and fires (Table 15).

**Table 15: Ranking of perceived drivers of soil erosion among household in the Rio Grande watershed.**

<table>
<thead>
<tr>
<th>Erosion drivers</th>
<th>Number of respondents</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Mann-Whitney U test Communities mean rank, U, p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>186</td>
<td>1</td>
<td>5</td>
<td>3.10</td>
<td>NEH, FEH: 94.07, 93.01, U = 4251, p &gt; .05</td>
</tr>
<tr>
<td>Cattle ranching</td>
<td>186</td>
<td>1</td>
<td>5</td>
<td>3.09</td>
<td>NEH, FEH: 79.02, 105.95, U = 3055, p &lt; .001</td>
</tr>
<tr>
<td>Clearing of slopes</td>
<td>186</td>
<td>1</td>
<td>5</td>
<td>3.31</td>
<td>NEH, FEH: 107.03, 81.86, U = 3136.5, p &lt; .001</td>
</tr>
<tr>
<td>Logging</td>
<td>186</td>
<td>1</td>
<td>5</td>
<td>2.96</td>
<td>NEH, FEH: 84.9, 100.9, U = 3560.5, p &lt; 0.05</td>
</tr>
<tr>
<td>Fires</td>
<td>186</td>
<td>1</td>
<td>5</td>
<td>2.96</td>
<td>NEH, FEH: 92.62, 94.26, U = 4224.5, p &gt; .05</td>
</tr>
</tbody>
</table>

**4.4.10. Logistic Regression Model**

Model 1 results indicate that Ethnicity was highly significant in determining the perceived implementation of erosion prevention techniques (Wald = 17.950, df = 4, p < .001). The B coefficients for Maya Kekchi and Mestizo were significant and positive, indicating that the odds of perceived implementation of erosion prevention techniques were higher than those among the Maya Mopan. The odds ratios indicated that Maya Kekchi and Mestizo were
3.8 and 6.1 times more likely to perceive the implementation of erosion prevention techniques that Maya Mopan in the Rio Grande watershed. There was no significant difference between Maya Mopan, Creole and Other on the perceived implementation of erosion prevention techniques (Table 16).

Table 16: Socio-economic characteristics influence on the perceived implementation of erosion prevention techniques in the Rio Grande watershed.

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>SE</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.827</td>
<td>0.32</td>
</tr>
<tr>
<td>Ethnic group</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maya Que Chi</td>
<td>1.331</td>
<td>0.397</td>
</tr>
<tr>
<td>Mestizo</td>
<td>1.808</td>
<td>0.749</td>
</tr>
<tr>
<td>Creole</td>
<td>0.604</td>
<td>0.503</td>
</tr>
<tr>
<td>Other</td>
<td>-0.118</td>
<td>0.549</td>
</tr>
<tr>
<td>base= Maya Mopan</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FEH</td>
<td>1.335</td>
<td>0.491</td>
</tr>
<tr>
<td>base = NEH</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>-1.026</td>
<td>0.44</td>
</tr>
<tr>
<td>base= male</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed</td>
<td>1.075</td>
<td>0.498</td>
</tr>
<tr>
<td>Self-employed</td>
<td>1.089</td>
<td>0.491</td>
</tr>
<tr>
<td>base = unemployed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2LL</td>
<td>238.176</td>
<td></td>
</tr>
<tr>
<td>$X^2 = 19$, df $= 4$, $p &lt; .001$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nagelkerke $R^2$</td>
<td>13.20%</td>
<td></td>
</tr>
<tr>
<td>Hosmer &amp; Lemeshow test</td>
<td>$p =1.00$</td>
<td></td>
</tr>
<tr>
<td>Classification accuracy</td>
<td>65.1</td>
<td></td>
</tr>
</tbody>
</table>

In model 2, 5 more independent variables were controlled for; distance, gender, education, age, and employment. The results indicate that there was an increase in the
significance and overall Wald statistics for ethnicity (Wald = 28.153, df = 4, p < .001) (Table 16). The ratio for Maya Que Chi and Mestizo remained quite similar; 3.9 and 5.1. However, Mestizo was no longer significant. Instead, Other had a negative B coefficient, indicating less likelihood to perceive the implementation of erosion prevention techniques than other ethnicities.

The effect of distance was also highly significant and positive (Wald = 7.4, df = 1, p < .007), indicating that FEH communities were 3.8 times more likely to perceive the implementation of erosion prevention techniques than NEH communities. This was the case even after controlling for ethnicity, gender, education, age and employment.

Gender was also a significant indicator suggesting that women were less likely than men to perceive the implementation of erosion prevention techniques. Employment was also a significant indicator; suggesting that employed and self-employed were 2.9 and 3 times more likely than unemployed to perceive the implementation of erosion prevention techniques. Education and age were not significant.

4.4.11. Erosion Effects

NEH (63%) and FEH (75%) households believed they were affected by soil erosion. From the households near erosion hotspots and far from hotspots 79% and 82% respectively agreed that surface waters are being negatively affected by erosion in the Rio Grande watershed. When asked about their dependency of surface water for their household activities, 91% of NEH households and 70% of FEH households agreed to be dependent on surface water (Cramer’s V= .227, p < .001). Moreover, soil erosion is believed to irreversibly deteriorate soil quality resulting in decreased productivity. According to the results 57% of NEH and 43% of FEH households agreed that agricultural lands are less fertile as a result of erosion.
4.5. Discussion

This study illustrates the differences in socio-economic circumstance, demographics and perception of erosion that exists between NEH and FEH communities. The findings have important implications for the development of effective land management strategies in Rio Grande watershed. The results suggest that a diversity of perceptions must be addressed to garner buy-in from community members. Better understanding the socio-economic characteristics and perceptions of community members can aid in developing broadly acceptable erosion mitigation strategies. In order to address the current environmental and economic problems as a result of erosion, localized strategies based on the socio-economic findings need to be incorporated when developing a holistic watershed management plan. Moreover, the identification of the drivers and underlying causes of erosion highlight the need to incorporate all relevant stakeholders in the development of mitigation strategies in the area. Given that the underlying causes of erosion are not confined to the boundaries of the watershed, but extend beyond it.

Slash and burn agriculture in the Rio Grande watershed has been used by the Mayan people for many centuries. However, population growth and demand for agricultural products have resulted in the shortening of the fallow period (Simpson, 2010); rendering this method unsustainable. With shorter fallow periods and lack of erosion prevention techniques, soil fertility and structure are not maintained resulting in further erosion. Although, 67% of surveyed households agreed that agriculture on slopes is sustainable for a short period, forested lands on slopes are still being cleared for crop planting.

The erosion analysis conducted using the RUSLE model suggests that between 2001 to 2011, erosion hotspots remained largely in mid-upper reaches of the watershed. In 2011, a new erosion hotspot emerged as a result of landcover change. Landcover change and poor agricultural practices utilizing hillsides with little attempt to retain soil exacerbate the erosion
problem (Simpson, 2010). The land degradation analysis conducted by Meerman and Cherrington, (2005) suggests that land degradation in Belize is already widespread, which will be exacerbated by rapid population growth, increased use of substandard soils for agriculture, increased farming on steep slopes and increased input of fertilizers. The results of this study are similar to those cited by Tefera and Sterk, (2010) which associated high soil loss in Fincha’a watershed with an increase in the use of slopes for agriculture; this as a result of population growth and lack of sufficient soil-water conservation measures. On the other hand, due to easier access and flatter topography, commercial logging and cattle ranching are more prominent around FEH communities.

The results of the Mann-Whitney U test indicate that clearing of slopes (mean 3.31) and agriculture (mean 3.10) are perceived as the two most important drivers of soil erosion in the watershed. These results correlate with the RUSLE model results, which indicate that the majority of erosion is occurring within the agriculture use zone and the upper-reaches of the watershed. The concentration of erosion hotspots in the steeper upper-watershed is of interest as these lands are considered unsuitable for agriculture. However, population growth and increasing demand for agricultural products will continue to drive farmers into marginal lands.

The results indicate that 57% of NEH and 43% of FEH households agree that agricultural lands are less fertile as a result of erosion, suggesting positive identification of this cause and effect relationship. Furthermore, 91% of NEH and 70% of FEH households also strongly agree that they are dependent on surface water for their subsistence and livelihood. These beliefs suggest a broad recognition in the relationship between agricultural practices, erosion vulnerability, and water quality maintenance. NEH households consider themselves more dependent on agriculture and surface water than FEH households. This is to be expected since NEH households are more engaged in agriculture and draw their water directly from the river and streams. NEH communities are rural and isolated; therefore, they
lack the educational and economic resources enjoyed by FEH communities. All of these factors demonstrate the disparate attitudes and beliefs regarding erosion causes, prevalence, effects and control measures.

The results of the logistic regression model suggest that ethnicity, gender, distance, and employment were important predictors of perception concerning the implementation of erosion prevention techniques. Controlling for distance, gender and employment significantly improved the model’s ability to explain the variability in the outcome from 13% to 31%. As a result, the classification accuracy increased from 65% to 69%. FEH households were nearly 4 times more likely than NEH households to believe that erosion prevention measures were taking place. This is because FEH households have livelihoods other than agriculture and may assume that erosion prevention techniques are being implemented in their community and other communities. Women were significantly less likely than men to perceive the implementation of erosion prevention measures. This may be explained by gender roles, work distribution among families and communities in which men are more likely to farm than women. Employment too was a significant predictor of perceived erosion prevention. The employed or self-employed were 2-3 times more likely to believe that prevention measures were in place. This is likely due to the removed nature of their work in another economic sector or general unawareness of farming practices. Moreover, controlling for distance, gender, and employment changed the associations between ethnicity and the perceived implementation of erosion prevention techniques. The overall association between ethnicity and erosion prevention remained highly significant, but there was a change in significance for Mestizo (not significant) and Other (significant). Of importance, Mestizos living in the area were evenly distributed between NEH and FEH communities and Other lived in FEH communities. Even after controlling for distance, gender and employment, Maya Kekchi were still more likely than Maya Mopan to perceive the implementation of erosion prevention techniques. More data needs to be collected and analyzed to better understand the differences.
in perception that was highlighted by the study among ethnic groups, especially between Maya Mopan and Maya Kekchi, who largely depend on subsistence agriculture.

Local spatial data to calculate the K and R factors would have improved this study. This was more a limitation of the available data than the researchers’ use thereof. Also, the accuracy of average soil erosion per year can be improved with finer resolution data. Nevertheless, for the purpose of this study, the data generated by the RUSLE model was appropriate to identify hotspots. Even though the logistic regression model explained only 31% of the variability of the data, it provides insightful information regarding the socio-economic characteristics that might influence the implementation of soil erosion mitigation measures.

By integrating the RUSLE model and social surveys, this research provides improved information on the drivers, underlying causes, and spatial distribution of erosion vulnerable areas. This information can aid stakeholders in developing erosion mitigation approaches that will consider local community characteristics. Identifying soil erosion hotspots allows stakeholders to identify areas that need immediate intervention to reduce soil degradation. Understanding NEH & FEH communities’ disparate perspectives on the drivers of erosion aids in planning and execution of erosion mitigation measures. This study also highlights the need to implement cost-effective soil erosion prevention programs and to assess the loss of soil nutrients and agriculture productivity in the study site.

The erosion hotspots identified in the Rio Grande watershed will continue to expand if effective and feasible erosion mitigation measures aren’t implemented. At the moment, there is little effort to address the erosion problem. Communities that are especially in need of assistance are those located in the upper-mid reaches of the watershed. In this area, households are more dependent on agriculture, and the steep slopes are more vulnerable to erosion. Detailed studies are needed to assess erosion caused by land-use change. Some of which can emphasize processes and interactions involving socio-economic driving forces and
biophysical conditions (Travares et al., 2014). Furthermore, studies are needed to examine the viability of community-based erosion mitigation programs.

Soil erosion can be controlled by implementing small changes in agricultural practices and watershed management. One approach is using non-erosive ground cover types along watershed areas (Nunes et al., 2011). Clearing and planting of crops on slopes greater than 5° must be avoided. Contour planting patterns should be utilized in steppe terrain. Fallow crops should be used as ground cover and fields should be rotated to allow a recovery period. Fires are considered as one of the most widespread ecological disturbances of natural ecosystems that dramatically affect land cover dynamics at a variety of spatial and temporal scales as a result of the complete or partial removal of vegetation cover (Petropoulos et al., 2014); thus, farmers need to become aware of the ecological impacts of fires in the study site and trained to use slash and burn in a more responsible manner. Relevant agencies need to work with agricultural communities to reduce burning vegetation cover; especially in steep slopes and during the rainy season. Farmers need to become aware of cost-effective erosion prevention measures (mulching, contour farming, cover crop use) which will reduce soil erosion in vulnerable areas and improve soil conditions. Educational outreach to farmers and farmer-to-farmer education on soil conservation techniques will increase awareness of erosion mitigation measures. NGOs such as TIDE and Ya`axche can do community activities to raise local and broader awareness on the impacts of soil erosion. Ideally, more educated community members will encourage farmers to adopt erosion prevention techniques. In respect to logging, the government should implement erosion conservation measures in logging companies’ forest management plan and enforce illegal logging polices. Ranching in the area is relatively new compared to agriculture. Ranchers need to be educated about less destructive Silvopastoral Production Systems (SPS).
Chapter V

5. Overall Conclusions

This study generated important findings, which will be useful for management and conservation purposes, regarding several environmental problems that occurred in southern Belize which include: deforestation and forest disturbance in Toledo as a result of increased anthropogenic activities, trans-boundary deforestation along the Maya Mountain Massif, as a result of illegal incursions and erosion in Toledo’s Rio Grande watershed as a result of unsustainable agricultural practices.

The integration of satellite imagery analysis and social surveys to study deforestation and forest degradation in Toledo gave a new perspective on this problem. The information generated by this study on deforestation and forest degradation in Toledo will allow Belize’s non-government organizations and government organizations to better understand and effectively plan mitigation strategies. The sustainable management of forest resources in Toledo is of utmost importance because the Mayan communities depend on them. It is necessary for decision makers to clearly define land property rights of the Mayan communities. The identification of where conflicts between communal land and protected areas occur need to be conducted in conjunction with community consultations. Moreover, programs to develop new skills can be taught to community members to take advantage of the natural resources around them such as bird watching, tour guiding and added value to forest products. These alternative livelihoods will create meaningful jobs in the local communities; thus, reducing the dependence of communities on subsistence agriculture. The communities in Toledo have tremendous potential for the development of agro-forestry and silvo-pastoral systems, which need to be targeted by forest managing organizations. Agriculture will always be an essential livelihood for rural communities in Toledo.
Sustainable agricultural practices need to be taught to children in the last year of primary school and agricultural agencies should collaborate and provide incentives to farmers to learn, plan and implement sustainable agricultural practices. An incentive framework that Belize can adapt is the Payment for environmental services (PES) to reduce deforestation and forest degradation, which has been successfully adopted and executed in many Central American countries. The long-term sustainability of PES schemes crucially depends on how effective the incentive-based mechanism is at aligning stakeholders’ individual land-use decisions with the social benefits arising from conservation (Démurger and Pelletier, 2015). In the past, programs that have been implemented to reduce deforestation and forest degradation in Toledo have often failed due to the lack of sustainability and incentive-based frameworks within the programs. The inability to address the current and arising problems in Toledo will ultimately lead to irreversible social and environmental problems.

Moreover, the trans-boundary deforestation, in southern Belize, along the Belize-Guatemalan border, threatens the ecological integrity and diversity of protected areas inside the Maya Mountain Massif (MMM). The increase of deforestation will further aggravate the current environmental decline and further strain the already tense bi-national diplomatic relations. In this research, the use of a multidisciplinary approach, which incorporated spatial metrics, deforestation rates and surveys, provided important information on the perspectives, deforestation process and spatial characteristics of deforested patches along the MMM border. Although, this study has quantified the deforestation along the border, analysis of soil erosion, water quality degradation, and ecological impacts are lacking. In order to address the current situation, good collaborative networks need to be established between the border area stakeholders, and more resources need to be leveraged by both Belizean and Guatemalan authorities. National and bi-national collaborations need to be established which include partnerships with NGOs, Governments and community organizations. More binational research needs to be conducted to understand socioeconomic
dimensions of this problem, and to directly consider socio-economic challenges within management plans. Policy needs to be updated that will secure the area and provide legal guidelines for economic development. The results of this study will serve as a catalyst to establish national and binational collaboration and to garner support from the MMM stakeholders to effectively address the deforestation phenomenon.

Finally, understanding communities’ perspectives on the main drivers, underlying causes and effects of soil erosion in Toledo’s Rio Grande watershed is essential for planning, and developing and executing management strategies to reduce erosion. Even though the majority of the households interviewed are aware and concerned about the ecological impact of soil erosion and the loss of soil productivity, very little is being done to implement conservation measures. The lack of soil conservation knowledge, poor access to technical support, and poor economic status of the households in the upper-mid reaches of the watershed impede implementation of short and long term soil erosion conservation measures. Several studies have emphasized that soil conservation measures will gain more acceptance when capacities for learning and action are enhanced and the causes of soil erosion are addressed (Tefera & Sterk, 2010). Erosion mitigation plans need to account for socio-economic characteristics, communities’ perspectives and changing market demands.

This study highlight that the failure to integrate buffer communities coordinate among managing organizations and establish strong bi-national collaboration has resulted in continued ecological and environmental degradation in southern Belize. On the other hand, this research provides significant information on communities’ perspectives, drivers, underlying causes and erosion vulnerable areas that will aid stakeholders to garner community support and more efficiently and effectively develop and implement sustainable management practices. It is unlikely that the communities in southern Belize will be able to address the environmental problem themselves, which highlights the need for national and bi-national collaboration between communities, NGOs and GBOs.
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Appendix: Refereed Journals

Table of Contents


