MAPPING FOREST COVER IN COSTA RICA: A COMPARATIVE CASE STUDY FOR THE LA AMISTAD-CARIBE CONSERVATION AREA

by

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ABSTRACT

This study is intended to offer insights on forest cover trends in Costa Rica, aiming to improve monitoring mechanisms and to conduct a spatially detailed forest cover assessment in the future. Using very high spatial resolution aerial orthophotos and an object-based classification method I create a land use/ land cover map that encompasses small scale forest cover (< 3ha) for La Amistad-Caribe Conservation Area (ACLA-C) located in the Northern Atlantic region of Costa Rica, for the year 2005. Next, in order to assess the potential effects of mapping land cover at different spatial scales, I compare the resulting classification with the Costa Rican official national forest cover assessment for the year 2005 created from Landsat 7 ETM+ imagery. Results from my classification indicate a highly heterogeneous landscape in the northern region of ACLA-C characterised by fragmented forest, agroforestry, tree plantations, and pastures. Even though the results reveal a low divergence between my baseline map and the national forest classification in terms of total forest area, they also reveal 3,100 ha of unmapped forest below 3 ha and an underestimation of the deforestation class by 98 percent by the official cover assessment within ACLA-C. This study emphasizes the importance of integrating small scale land use change in forest cover assessments to more accurately estimate rates and areas of deforestation, forest fragmentation and forest cover.

CHAPTER I: INTRODUCTION

Tropical forests provide important ecosystem services such as climate regulation, nutrient cycling, primary productivity, erosion control, as well as cultural services such as recreational, educational, and spiritual values to society (Parrota et al. 2012). In response to the transformation and degradation of tropical rain forests, governments and organizations have developed strategies to conserve biodiversity and sustain livelihoods through socioeconomic, legal, and political actions in these tropical regions (Koellner et al. 2008). In Costa Rica, for example, since the establishment the Payment for Environmental Services (PES) program in the 1990s, land use practices have substantially changed throughout the country (de Camino et al. 2000). Sánchez-Azofeifa et al. (2003) determined that PES provides incentives to decrease deforestation rates and promote reforestation. However, land use /land cover studies in Costa Rica and other tropical countries based on remote sensing are generally carried out with multispectral satellite imagery with “low” spatial resolution (Blaschke 2010). Therefore the land cover maps based on coarse spatial resolution satellite imagery (e.g. Landsat 5 TM, SPOT, MODIS) and pixel based classification methods might overestimate or underestimate certain types of land use types (e.g. agroforestry, palm forests, forest), which in turn could affect the allocation of PES or other conservation incentives (e.g. REDD+) . As Sasaki and Putz (2009) state, there is a need for global policies to consider events of small scale deforestation.

Currently, remote sensing, such as satellite imagery and aerial photography, is being applied to investigate a wide range of ecological processes at different spatial scales. While a pixel based classification method using satellite imagery can offer accurate estimates of ecological processes, such as the determination of forest successional stages of a tropical dry forest (Arroyo-Mora et al. 2005a), it can also obscure the detection of small scale land use changes (Sánchez-Azofeifa et al. 2003). The utility of satellite imagery in pixel based classification methods in forest cover assessments is limited because there are factors that can affect its ability to detect small scale deforestation (Townshend et al. 1991). For example, Asner et al. (2005) showed current estimates of tropical forest transformation are conservatives because small-scale deforestation and low-intensity logging are often not included in these assessments.

Through the interpretation of aerial photography, remote sensing has the potential to be an effective tool in mapping land use/land cover and assessing small-scale forest cover changes.

This research is intended to offer insights on forest cover trends in Costa Rica, aiming to improve monitoring mechanisms and conduct more spatially detailed forest cover assessment in the future. Consequently, the main objective of my research is a land use/land cover map that encompasses small-scale forest cover (< 3 ha) for La Amistad-Caribe Conservation Area (ACLA-C) located in the Northern Atlantic of Costa Rica, for the year 2005. A second objective of my research is the development and application of a methodology for using very high spatial resolution aerial orthophotos and object oriented classification in order to obtain the land use/land cover map. Finally, in order to assess potential effects of mapping at different spatial scales (Lam and Quattrochi 1992), the resulting classification is compared with the Costa Rican official national forest cover assessments for the year 2005 created from Landsat 7 ETM+ imagery (FONAFIFO, 2005).

The completion of this study will emphasise the importance of integrating small scale land use in forest cover assessments to more accurately estimate areas of deforestation, forest fragmentation and forest cover. Chapter II presents a literature review providing a framework on the importance, degradation, and mitigation of tropical rainforests, on land cover/ land use dynamics in Costa Rica, and remote sensing applications in monitoring natural resources such as forest cover. Chapters III and IV present the methodology and results from my data analysis, respectively. Chapter V presents the discussion of the results and addresses the advantages and shortcomings of my study as well as an insight into the importance of my study in the PES framework.

CHAPTER II: LITERATURE REVIEW

2.1. Tropical Forests: Importance, Degradation and Mitigation

Tropical rainforests, covering 1101.6 million ha, play an important role in the global carbon cycle and provide many ecosystem services (FAO 2010). According to Pan et al. (2011), 55% of global forest carbon stocks are stored in tropical rain forests. Furthermore, tropical rainforests play an important role in nutrient cycling, soil formation, and primary productivity (MA 2005). Tropical rainforests also provide services such as soil erosion control and climate regulation (Parrota et al. 2012). As well, they provide food, timber, and medicine to society as well as spiritual values and cultural services such as recreation, ecotourism, educational (Parrota et al. 2012). Furthermore, Daily and Ehrlich (1992) highlight the importance of tropical rainforests in climate system regulation, atmospheric composition, and to the Earth's life-support system. Climate system is composed of the atmosphere, hydrosphere, lithosphere, and biosphere systems that regulate the Earth’s climate (NWS 2004).

In the past decades, deforestation and degradation of tropical rainforest has been have become the main thread for the long-term subsistence and stability of these ecosystems. In the 1990s, around 16 million ha of tropical rainforests were lost due to anthropogenic or natural causes (FAO 2010). As well, FAO (2010) reports a net forest loss rate of 80 million ha per year between 2000 and 2005. Asner et al. (2009) showed that, between 2000 and 2005, there was a 1.4% loss of global humid tropical forest due to deforestation and forest degradation. Vaughan et al. (1998) estimates that 76,000 to 92,000 km^2 of tropical forests are cleared and 100,000 km^2 are being altered every year due to human activities such as agriculture practices and timber extraction.

Human activities are the direct drivers of deforestation and forest degradation (Geist and Lambin 2002; Kissinger et al. 2012). According to Geist and Lambin (2002), the primary cause of deforestation and forest degradation are infrastructure extension, agriculture expansion, wood extraction, pre-disposing environment factors such as land characteristics (e.g. soil quality), biophysical drivers such as drought and fire, and social trigger events such as economic shocks. For instance, agriculture is responsible for two thirds of the total deforested area in Latin America (Kissinger et al. 2012). Timber extraction and logging activities are responsible for more than 70% of total forest degradation in Latin America and (sub)tropical Asia (Kissinger et al. 2012). Furthermore, Geist and Lambin (2002) denotes that deforestation and forest degradation is also triggered by underlying drivers of deforestation such as demographic, economic, technological, policy and institutional, and cultural factors. Kissinger et al. (2012) found that these drivers "act at multiple scales: international (markets, commodity prices), national (population growth, domestic markets, national policies, governance), and local circumstances (subsistence, poverty)" (pg 5). More specifically, deforestation and forest degradation are the result of changes in how people use land due to the change of social, economic, and political drivers through time (Calvo-Alvarado et al. 2009).

In response to tropical rainforests deforestation and degradation governments, organisations, and individuals have developed strategies to conserve biodiversity and sustain livelihoods through socioeconomic, legal, and political action. To slow the deforestation of tropical forests, global and national strategies have been implemented such as the Tropical Forestry Action Plan by the FAO, the World Bank, the United Nations Development Programme and the World Resources Institute since the 1985s (Myers 1992). In 2008, the United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries (REDD) was created to encourage the participating countries to reduce emissions from deforestation and forest degradation, to sustainably manage forests, and enhance forest carbon stocks (Arcidiacono-Bársony et al. 2011). At the local level, implementing payment for environmental services (PES) mechanisms can be a way to achieve development goals and natural resource conservation, especially in low-income regions (Locatelli et al. 2008). Fletcher and Breitling (2012) denote that PES has become an increasingly popular mechanism for financing conservation of natural resources in recent years. For example, Australia, Mexico, and Costa Rica are countries with regulatory systems of payments for ecosystem services (Sanchez-Azofeifa et al. 2007).

2.2. Land Cover/Land Use Dynamics and PES in Costa Rica

Since the 1950s, the main land use changes in Costa Rica have been the transformation of forests to pastures and farm land for cattle ranching (Lutz and Daly 1991) as well as the expansion of agriculture for cash crop plantations, logging, urban expansion, and infrastructure development Busch et al. (2000). Sánchez-Azofeifa et al. (2001) show that since 1970 the land use/land cover change has been driven by crop expansion and cattle production. Prior to the 1980s, Costa Rica experienced the highest deforestation rates in the world. Deforestation and forest fragmentation rates in the 1970s and 1980s were estimated to range from a rate of 30,000 ha to 50,000 ha per year (de Camino et al. 2000). Busch et al. (2000) found that pasture land area doubled while forested area decreased by 50% in Costa Rica between 1961 and 1989. Starting with the 1980s, deforestation rates had decreased significantly due to the introduction of Structural Adjustment Programs (SAPs) by the World Bank and Costa Rican policies that promoted reforestation and forest management throughout the country (de Camino et al. 2000). To promote reforestation and forest management the Costa Rican government established policies such as the Soft Credits for reforestation in 1983 and Forest Payment Title in 1986 which seeks to provide an equal distribution of resources for forest activities (de Camino et al. 2000).

Furthermore, since the establishment of the Payment for Environmental Services (PES) program in the 1990s (part of the Forest Law No. 7575) land use practices have continued to change in Costa Rica (de Camino et al. 2000). Since 1997, 12% of the national territory has been enrolled in the program (Arriagada and Pattanayak 2009). By 2004, 230,000 ha were under contract in the Costa Rican PSA program (Engel et al. 2009). A national forest cover assessment using Landsat data from 1986 to 1997 revealed that deforestation at a national scale slowed down to a rate of about 1% per year (FONAFIFO 1998 as cited by Busch et al., 2000). Furthermore, a study done by the World Bank on deforestation patterns in Costa Rica revealed that by 1993 deforestation had decreased from approximately 30,000 ha per year in the 1980s to approximately 5000 hectares per year in 1993 (Lutz et al. 1993). Using census data combined with remote sensing data on land use in Costa Rica, Arriagada and Pattanayak (2009) found that PES have a significant contribution to forest transition and observed an increase in forest gain between 1998 and 2004. Moreover, Arroyo-Mora et al. (2005b) looked at the social dynamics of forest deforestation and restoration in Guanacaste from 1960 to 2005, on how structural drivers shape patterns of forest-cover change and how Costa Rican conservation policies promoted forest restoration. Their study reveals that forest regrowth can be attributed to not only conservation policies but also to a shift from agricultural practices towards tourism in the Guanacaste region.

Even though the main objective of PES main is to reduce deforestation, there is limited empirical research linking land use decisions, ecosystem protection and restoration to PES programs in Costa Rica (Arriagada and Pattanayak 2009; Sierra and Russman 2006). Estimates of PES are dependent upon differences between baseline and mitigation scenarios and on deforestation rates before and after the implementation of a project (Busch et al. 2000). Sierra and Russman (2006) examined the efficiency of programs supporting the conservation of forest resources and services through direct payments to land owners (PES) in Osa Peninsula, Costa Rica. Their results indicate that payments have limited immediate effects on forest conservation in the region because they are achieved through land use decisions affecting non-forest land cover. Sanchez-Azofeifa et al. (2007) evaluated the intention, implementation, and impact of Costa Rica's PSA on deforestation with the use of remote sensing and econometrics and found low deforestation rates between 1997 and 2000. The study also revealed that only 7.7% of PSA payments were located within 1 km of all deforestation fronts.

Multiple studies have focused on forest cover change and deforestation across Costa Rica; however most of the studies are based on data with a map unit of three hectares disregarding all changes in forest cover at a finer scale. For instance, Sánchez-Azofeifa et al. (2001) estimated forest cover in Costa Rica using Landsat 5 TM satellite between 1986 and 1991 finding a deforestation rate of 4.2% per year and an increase in forest fragmentation between 1986 and 1991.

Veldkamp and Fresco (1997) conducted a more complex land use/land cover for 1973 and 1984 revealing an intensification of urbanisation of the Central Valley and an expansion of arable land and pasture in remote areas across Costa Rica during the study period. Furthermore, Kleinn et al. (2002) gathered 54 studies to study forest/non-forest cover in Costa Rica revealing a variation in forest cover assessments between 1940 and 1998. The authors found a homogeneous variation in forest cover assessments between 1940 and 1990. During the 1990 – 1998 period they found that while more forest cover studies were published, there is more variability in the estimates; as well they do not form a continuous trend with the 1940 – 1990 estimates (15 percent higher). In summary, the complex historical, political and social aspects of land use land cover in Costa Rica, present a challenge to determine baseline maps and analyze the potential impacts of conservation policies like PES or even define priority areas for its deployment.

2.3. Remote Sensing Application

Remote sensing (e.g., satellite imagery and aerial photography) is used as a tool to map and monitor natural resources. It supplies data over multiple temporal and spatial scales thereby playing an important role in providing indicators of environmental conditions and ecological processes (Cohen and Goward 2004). Kerr and Ostrovsky (2003) state that remote sensing has the capability to provide data for the interpretation of multiple ecological processes such as studying landscape characteristics and their biophysical properties as well as detecting land cover changed caused by natural or human events. Studies have used remote sensing in analysing changes in landscape spatial structure (Lambin and Strahler 1994), mapped land cover/land use change (Lambin and Ehrlich 1996), assess biodiversity (Nagendra 2001), measure drought (Boyd et al. 2006), and predicting terrestrial net primary productivity (Field et al. 1995). Moreover, remote sensing provides a way to increase the sampled area size and improve the statistical sampling design when conducting forest inventories (Clark et al. 2004). As well, it has been noted throughout the literature that a cost efficient accuracy assessment of land cover changes in tropical environments requires remote sensing technology (Subak 2000). Foody (2003) considers satellite remote sensing as the only cost-effective and feasible means of monitoring land cover change such as deforestation.

A common source of remote sensed data used on a large scale to monitor ecological processes is satellite imagery. Satellite imagery can provide information on the state and temporal dynamics of ecosystems, such as spatial patterns, and ecological models such as habitat assessments and socioeconomic studies. For instance, Souza et al. (2005) used satellite imagery to assess forest canopy damaged as a result of selective logging and forest fires in the Sinop region, in the Southern Brazilian Amazon. Furthermore, Myneni et al. (2007) studied phenological patterns in leaf area of Amazon rainforests revealing seasonal variation in green leaf area using satellite imagery. Morton et al. (2005) also applies satellite imagery to assess deforestation locations and deforestation dynamics occurring annually in the Amazon, Brazil. As well, Clark et al. (2004) demonstrated in a study conducted at the La Selva Biological station in Costa Rica that satellite data, at 1 meter and 4 meters resolution, can successfully be used to study the structure, function, and distribution of tropical forests at small spatial scales.

Even though satellite imagery can be used for many ecological applications, its use in pixel based classification methods for forest cover assessments at small scales (below 10 ha) might be limited because there are factors that can affect the ability of the methodology to detect small-scale changes (e.g. Landsat studies). For example, Asner et al. (2005) showed current estimates of tropical forest degradation are conservative as small-scale deforestation and low-intensity logging are not included in the assessments. The same author found that selective logging doubles the total amount of forest degradation caused by human activities; however it might go unnoticed if coarse scale imagery along with pixel based classification is used. Furthermore, Foody (2003) observed a 50 to 70% underestimation of the rate of deforestation derived from satellite imagery analysis due to coarse spatial resolution. Clark et al. (2004) found that commonly used space-borne sensors in ecological studies cannot distinguish older secondary growth or selectively logged forest without extensive fieldwork. Asner et al. (2009) showed that deforestation and forest regrowth can be difficult to accurately monitor using satellite imagery (NOAA AVHRR data) because it is difficult to detect vegetation at a fine scale. A study carried by Sánchez-Azofeifa et al. (2003) showed Landsat TM has limitations when observing small encroachments, illegal deforestation, and illegal mining. Furthermore, Mumby et al. (1999) also reveals that the application of pixel based classification on satellite imagery for tropical coastal resources assessment and management is inadequate for fine detail mapping. Satellite imagery, such as Rapideye and Landsat, is a powerful tool for mapping ecological processes but has limitations when assessing small-scale changes leading to inaccurate results. New sensors with high spectral resolution (e.g. WorldView 2) might be a potential solution; however the price is still high to carry out large-scale studies. Chambers et al. (2007) denote little research about the spatial extent and intensity of selective logging in tropical forests and how forest disturbances are yet not fully detectable using satellite imagery.

Remote sensing through high- resolution aerial photography interpretation can offer accurate forest inventories and represents an effective tool in monitoring natural vegetation cover and land use (Morgan et al. 2010). Interpretation of aerial photography is considered a standard tool for mapping and monitoring at a detailed scale due to high spatial details (Morgan et al. 2010). Clark et al. (2004) use aerial photography to map small-scale forest characteristics such as tree canopy. In addition, aerial photography is considered a tool that can provide the long-term spatial data of landscape change (prior to the 1970s) (Morgan et al. 2010). For example, Mas et al. (2004) used aerial photography from 1968 to 1986, with an average date of 1976, along with satellite imagery (Landsat 5 TM for the year 1993 and Landsat 7 ETM+ for the year 2000) to create a national multidate spatial database of land use/ land cover in Mexico up to the year 2000.

A major advantage of high-resolution aerial photography or of high resolution satellite imagery is that object-oriented classification can be applied for the photo-interpretation of different thematic classes. This method then, relies on a computer semi-automatic process that can include user expertize. In an object-based classification method neighbouring pixel with similar characteristics are grouped and classified together (Walter 2004). The Tropical Ecosystem Environment Observation by Satellite project of the European Commission's Join Research Centre used an object-based methodology for tropical forest cover classification and change assessment with an accuracy of 91 % across Brazil between 1900 and 2010 (Rasi et al. 2013). Other studies have demonstrated that object based classification methods can successfully monitor shrub vegetation changes (Laliberte et al. 2004), map thaw lakes and drained thaw lake basins (Frohn et al. 2005), as well as measure and monitor agriculture land use (Jensen et al. 2006). Taking all these factors into consideration, aerial photography interpretation combined with objected based classification methods can be powerful tools in monitoring and assessing small scale changes in land cover/land use. An object based classification method that looks at image characteristics such as colour, texture, and shape provides an advantage over pixel based classification method for accurate estimates of small scale changes in forest assessments.

CHAPTER III: METHODOLOGY

To create a land use/land cover map for ACLA-C, object oriented classification and interpretation of colour digital aerial photographs for the year 2005, with a spatial resolution of 50 cm, was applied. Semi-automatic photo-interpretation can be used as a tool to create land use/land cover baseline map and forest cover assessment at a small scale due to its ability to map fine-scale landscape features (Cots- Folch et al. 2007; Morgan et al. 2010). The following methodology section includes a description of the study area, pre-processing steps, segmentation, classification, and analytical steps, while Figure 3.1 shows summarizes these steps in a flow chart.

3.1. Study area

La Amistad-Caribe Conservation Area (ACLA-C), one of the eleven conservation areas in Costa Rica is located in the southeast on the Caribbean Sea coast characterised by flat and mountainous areas (Figure 3.2). ACLA-C is located between 82°33' - 83°40' W and 10°18'- 9°04'N and covers 620,967 hectares of land (12% of the country) and 26,386 marine hectares (SINAC 2005). Thirty-three percent of the land area of ACLA-C is a conservation area named the *Amistad Caribe Conservation Area.* According to SINAC (2005), forest represents 72% of ACLA-C's total protected area. ACLA-C includes two forest reserves (Rio Pacuare Forest Reserve and Pacuare Matina Forest Reserve), two protected areas (Cuenca Rio Siquirres Protected Zone and Cuenca Rio Banano Protected Zone), two national parks (Barbilla National Park and Cahuita National Park), one international park (La Amistad Biosphere Reserve), three wildlife refuges (Limoncito Wildlife Refuge, Gandoca Manzanillo Wildlife Refuge, and Aviarios del Caribe Wildlife Refuge), one biological reserve (Hitoy Cerere Biological Reserve), and one wetland zone (Lacustrino Bonilla-Bonillita Wetlands) (Figure 3.3).

The study area's landscape encompasses the cantons territories of Siquirres, Matina, Limon, and Talamanca, parts of the Turrialba and Cartago cantons and the Talamanca Cordillera mountain range. The Talamanca Cordillera is characterised by both high biodiversity and steep topogragy (WWF and Hogan, 2012). Further, ACLA-C includes the Atlantic lowlands, which are largely made up of the Isthmian-Atlantic moist forest (WWF and Hogan, 2012). The study area is characterised by a humid to wet climate regime with up to 10 rainy months per year (Van Laake and Sánchez-Azofeifa 2004)

Outside the protected areas ACLA-C is a mosaic of different land uses such forest, forest plantations, banana and pineapple plantations (Veldkamp et al. 1992), and crops such as rice and maize (Gotz Schroth 2004). The main urban areas within ACLA-C are Limon, Matina, and Siquirres. In this study the agroforestry class was used to characterise land areas covered by forest fragments intertwined with secondary forest, pastures and crop fields. Since the 1990s, agroforestry has been expanding from silvopastoral systems and trees associated with coffee and cacao plantations during the 1970s and 1980s to more complex systems such as plantation crop combinations, improved fallows, alley cropping, home gardens, and multi-purpose trees in crop lands (Brenes 2004). In the Talamanca region of Costa Rica, Deheuvels et al. (2012) documented the presence of complex agroforestry systems composed of high structural and functional plant diversity. Furthermore, Gotz Schroth (2004) identified cocoa agroforests in the Talamanca region made up of forest fragments, small plantations of banana and plantain, rice and maize fields, and pastures with individual cocoa plots averaging less than 2 hectares.

3.2. Pre-processing Step: Subsets creation

Orthorectified, colour aerial photograph mosaics (jpg2000 format), with a spatial resolution of 50 cm, were clipped to the conservation area boundaries layer of ACLA-C using ArcMap 10.0. As well, 1:50 000 cartographic sheets located inside the study area were divided into subsets and clipped to the boundaries of ACLA-C. The next step was creating multiple subsets for each cartographic sheet inside the study area and clipping the aerial photographs to them. The subsets were created based on two rules, which aimed to standardize clip characteristics: minimal number of clips and equal area of land. This step is important as it facilitated the segmentation and classification processes given each cartographic sheet has a large file size (approximately 5GB). A total of 23 cartographic sheets were divided into 90 subsets (Figure 3.4).

To create the subsets the following steps where followed: firstly, each cartographic sheet was divided into 1 to 8 subdivisions depending on its size and location in regards to the conservation area (i.e. located on the boundaries vs. in the middle of the conservation area) adding up to 90 subsets. Table 3.1 shows the number of subdivisions created for each cartographic sheet in the study area. The subsets were labelled with letters from a(1) to h(8) depending on the number of subsets established for a specific cartographic sheet. Figure 3.5 shows an example of how the Matina cartographic sheet was divided into six equal subsets delineating the subsets' boundaries within the cartographic sheet. The following naming convention was used in the analysis: *firstlettersofthecartographicsheet_1letterofsubdivion_processtep.* For example, the first subset of the Matina cartographic sheet was saved as a vector file (*.shp) under the name of "*mati_1a*".

The next step was to convert the subsets vectors created previously into rasters. Given the size of each aerial photograph mosaic (approximately 5GB), creating rasters of the subsets and clipping them with the aerial photos was more time efficient than using the vector version. The rasters created were then used to clip the aerial photographs. The new subset aerial photos were saved under the established convention name and the respective subset letter in a GeoTIFF format, maintaining their projection and coordinate information for their analysis in eCognition 8.0. The final pre-processing step was to exclude protected areas as this study aims to create a land cover/ land use map outside these areas.

3.3. Segmentation Process

The second step in creating the land cover/land use map of the study area was the segmentation of each orthophoto subset. A multi-resolution segmentation, bottom-up segmentation process was run in eCognition incorporating user-defined colour and scale parameters to maximize precision of polygons delineating land cover uses (Trimble 2011). Bottom-up segmentation is defined as the process that assembles objects/pixels to create larger objects (Trimble 2011). The multi-resolution segmentation consequently merges pixels or existing image objects based on colour, scale, and compactness parameters (Trimble 2011). A user defined colour, based on a standard deviation of the Blue, Green, and Red bands, of 0.2 was used as it was determined after multiple trials to be the best parameter value to maximize the precision of the polygons. As well, after multiple trials a scale of 70 was considered to be the best parameter that maximizes the precision of the segmentation. The scale parameter determines the maximum allowed heterogeneity for the resulting image objects; therefore by modifying the value in the scale parameter, the size of the image objects can be varied (Trimble 2011). The last segmentation parameter used was a compactness factor of 0.5. The compactness criterion is used to determine the relative weighting against smoothness of the object (Trimble 2011). Figure 3.6 shows an example of how a subset within the Parismina cartographic sheet was segmented into polygons. After the segmentation was completed, the resulting layers were exported in a vector format as a backup.

3.4. Classification process

After the segmentation process was applied, the classification methodology was followed (Trimble 2011). Fifteen classes were established based on expert criteria for each photo subset. The classes created for the land cover/ land use classification were: forest, agroforestry, tree plantations, crops, pastures, deforestation, wetlands, bare soil, urban, river bank, protected areas, water, clouds, shadows, and no data. Table 3.2 shows the description and criteria of the classes mentioned above. As well, Appendix A shows an image for each of the land cover/land use classes as a visual example of their interpretation.

The objects of each photo subset were manually assigned to what class they belong. As well, classification rules were created when it was possible to shorten the time allocated towards the classification process. For the no data class a rule based on brightness was used. In some photo subsets the no data was displayed in white, while in others in black. For the no data displayed in white the following rule was given to execute: "Classify polygons with Brightness higher than 230 as no data". For the no data displayed in black the following rule was created: "Classify polygons with Brightness less than 5 as no data". The two rules were used in the "Assign Class" process which is the most simple classification algorithm that uses threshold condition to determine whether an image object belongs to a class or not (Trimble 2011). As well, the Crust Green Ratio (CGR) index was used on photo subsets as an arithmetic feature for the forest class rule on subsets where forest was predominant. For example, the rule, "CGR greater than 0.387 is forest" was used with the "Assign Class" tool from the eCognition rule set. The CGR is a ratio equation between the Green, Blue, and Red bands and it is equal to the mean of the green band divide by the sum of the green, blue, and red mean bands (Trimble Navigation, 2010). Figure 3.7 shows an example of a land area classified as belonging to the agroforestry class.

Next, a class related rule was created to classify remaining small-unclassified polygons along the borders of already classified ones. The "Relation to borders" tool, a Class-Related feature tool, was used for assigning those unclassified polygons to their corresponding classes. After multiple trials it was established that a 'relation to neighbour object border' of equal to and greater than 0.5 classifies the small remaining unclassified objects around the classes created in the study. After each subset was classified, the land cover/land use classification was exported as a shapefile. The final step towards creating a land cover/ land use baseline map was to refine the classification to ensure its accuracy. Manual refinement was performed on each photo subset to certify there were no misclassified polygons. When misclassified polygons were found, the manual classification tool was used to reclassify them to the correct class. Next, the "Merge region" rule set was applied to each subset to reduce the number of polygons in each class. The final classified subsets were then exported as a shapefile. Figure 3.8 shows a classification sample of a subset within the Parismina cartographic sheet.

3.5. Land Cover/Land use Analysis

The final steps of the classification involved the merging of subsets back to the cartographic sheet level and performing the statistical analysis of the land cover/land use map. To do so, subsets belonging to the same cartographic sheet were merged using the ArcMap 10.1 "Merge" tool. For visual purposes the datasets were merged together resulting in a classification covering the entire study area. The polygons of the new classification dataset could not be dissolved by class because of overlapping polygons and artefacts resulting from the creation of the subsets. Therefore, I analyzed the classification by cartographic sheet and used the "Summary statistics" tool from ArcMap toolsets to summarize the areas per class.

Finally, in order to discuss potential implications for Environmental Services Payments related to forest cover between high and low spatial resolution classifications, I compared my results from the orthophotos to the official classification for the year 2005 for the same area (FONAFIFO, 2005). The forest cover area and percentage of the total surface area inside each cartographic sheet was calculated for both my classification and the official national assessment.

The percentage of forest cover per cartographic sheet were divided into four forest cover percentage categories: between 0 and 25 percent forest cover, between 25 and 50 percent forest cover, between 50 and 75 percent forest cover, and between 75 and 100 percent forest cover. I then compared the forest cover percentages between the two classifications to assess potential differences. A spatial comparison could not be performed because the two classifications do not align spatially in ArcMap 10.1.

Table 3.1 Number of subsets created for each cartographic sheet inside ACLA-C.

Cartographic Sheet	Number of Subsets
Amubri	5
Baribilla	5
Bonilla	6
Cabagra	1
Cahuita	5
Chirripo	4
Durika	4
Estrella	6
Guacimo	1
Kamuk	3
Matama	5
Matina	6
Moin	3
Parismina	4
Pittier	1
Rio Banano	6
San-Andres	3
Siola	6
Sixaola	4
Sukut	4
Telire	6
Tucurrique	2

Table 3.2. Classes used in the object based classification for the land use/land cover baseline map of ACLA-C.

Class	Description
Forest	Land areas "spanning more than 0.5 hectares with trees higher than 5 meters of more than 10 percent, or trees able to reach these thresholds *in situ*" (FAO, 2010). Mixed forest and palm forest included.
Agroforestry	Land areas covered by forest patches intertwined with secondary forest (less than 0.5 ha), pasture, and various crop fields (Gotz Schroth 2004).
Tree plantations	Land areas covered by tree plantations.
Crops	Land areas covered by agricultural activities, small and large scale.
Pasture	Land area covered by grass and single trees.
Deforestation	Land area characterized by clear cutting and traces of logging residue (Paine and Kiser 2012).
Wetlands	Land areas covered by marshes, swamps, ponds, and/or mangroves.
Bare soil	Land areas with exposed soil and agricultural land not being used at the time aerial photographs were taken.
Urban	Land cover by cities, roads, and any human construction.
River bank	Land areas characterised as exposed soil, coastal land, or sand in close proximity to rivers/streams.
Protected Areas	Land area declared as protected area located inside ACLA-C.
Water	Land areas characterized as rivers and lakes
Clouds	Cloud cover
Shadows	Any type of shadow artefact
No data	Unclassifiable regions, non-photographed areas

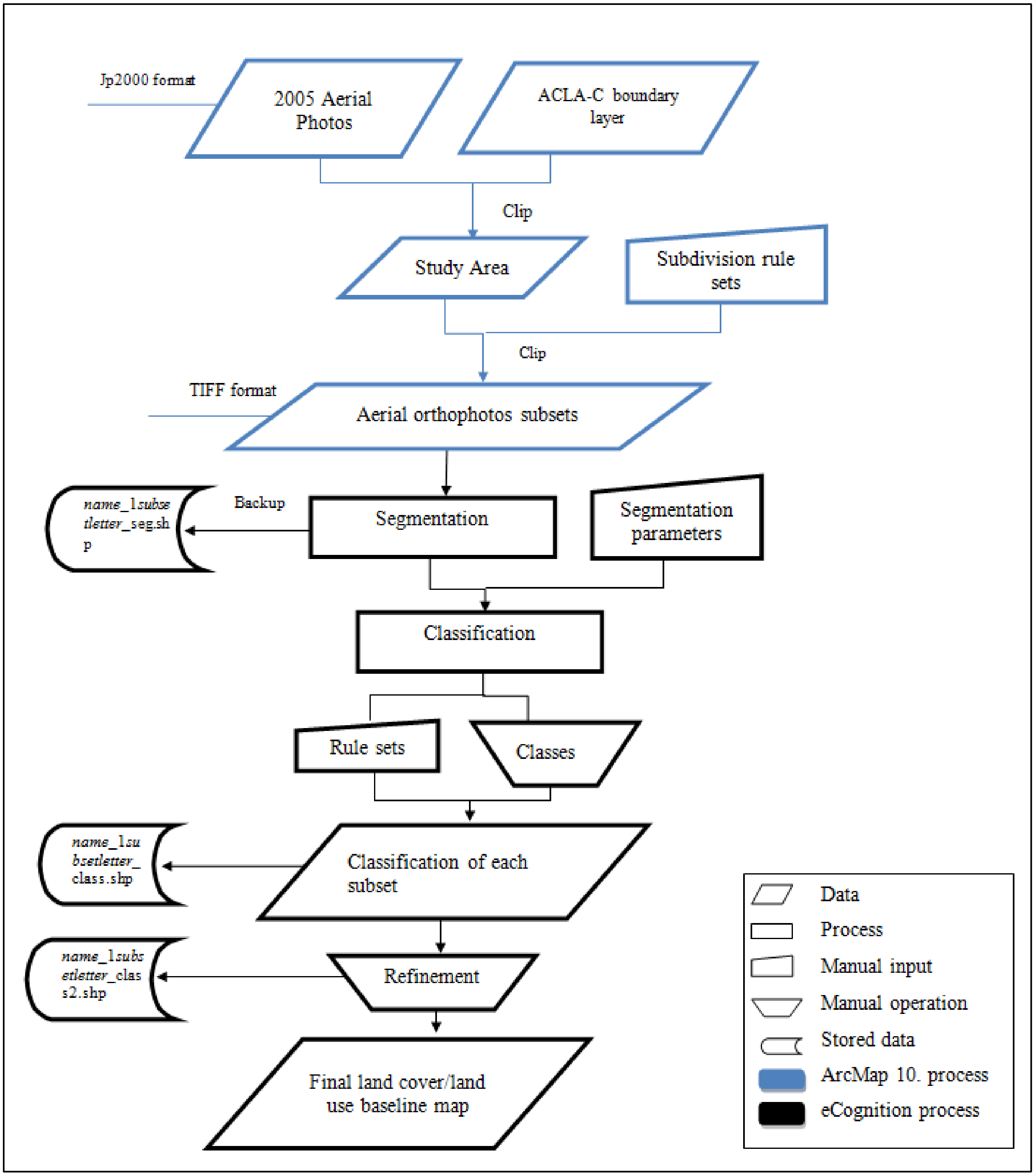


Figure 3.1. Main steps of the semi-automatic photo interpretation process.

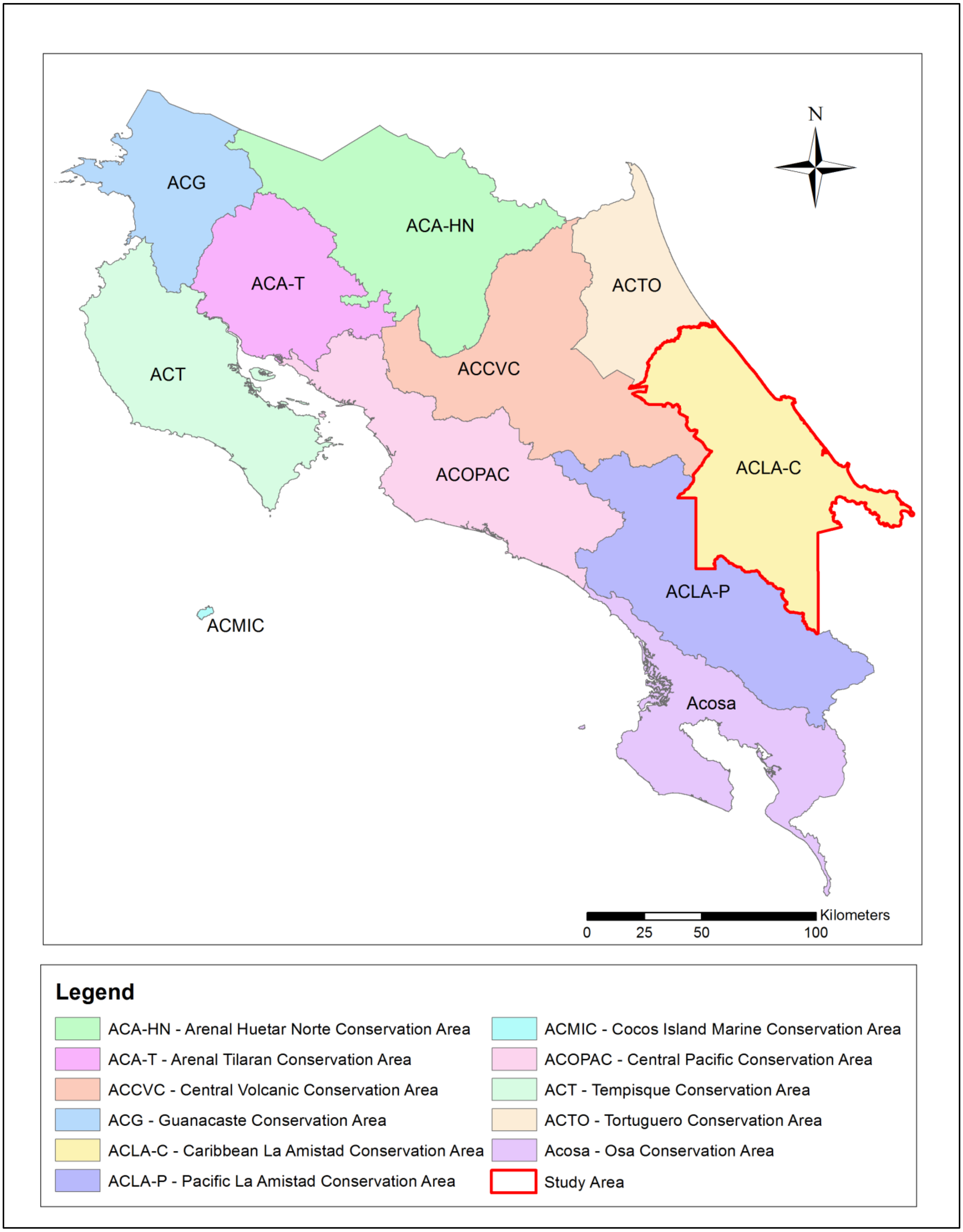


Figure 3.2. Conservation Areas in Costa Rica and study area location. Source: SINAC 2008.

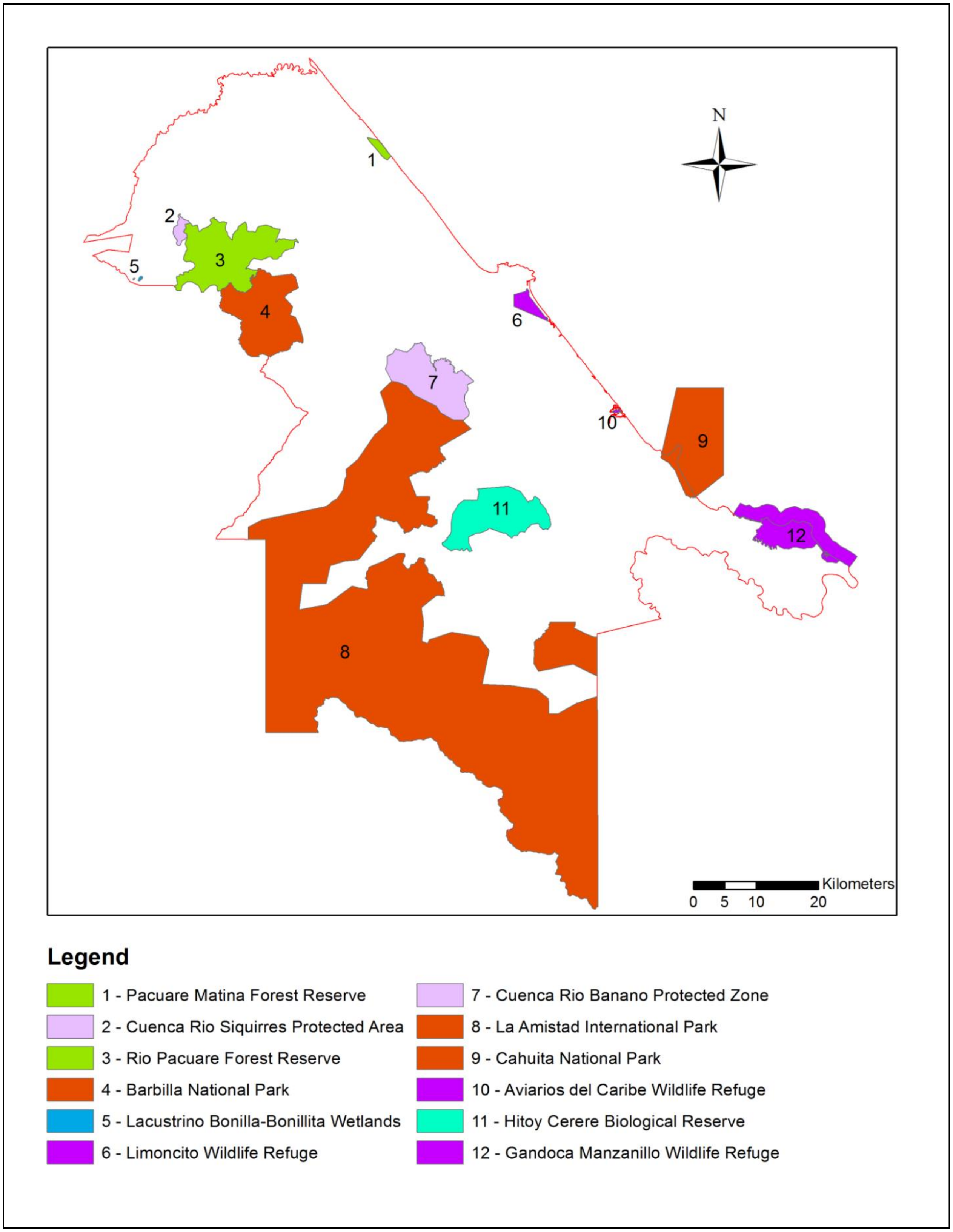


Figure 3.3. Protected areas located inside ACLA-C. Source: SINAC 2008.

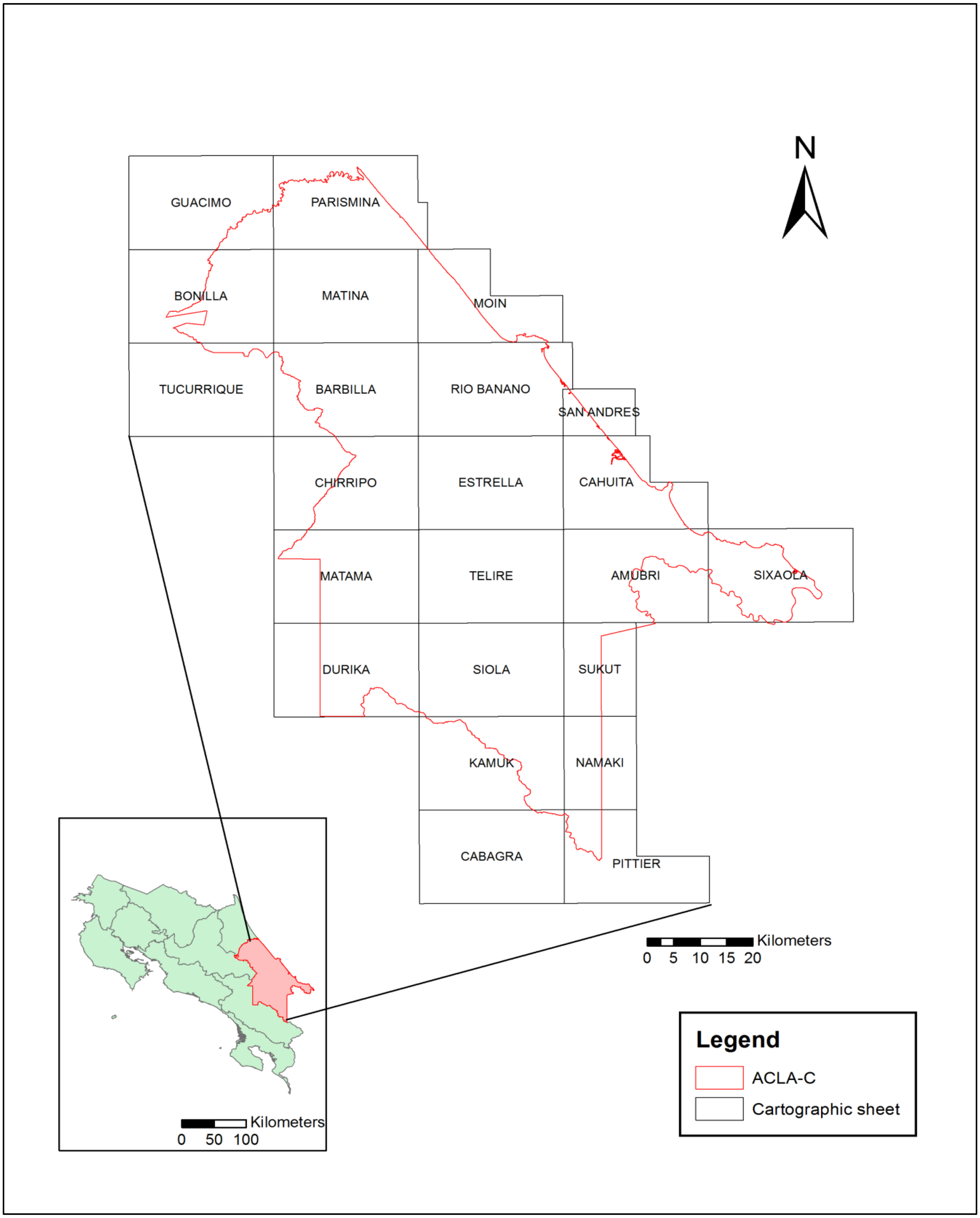


Figure 3.4. Cartographic sheets of ACLA-C used to create the land use/land cover baseline map.

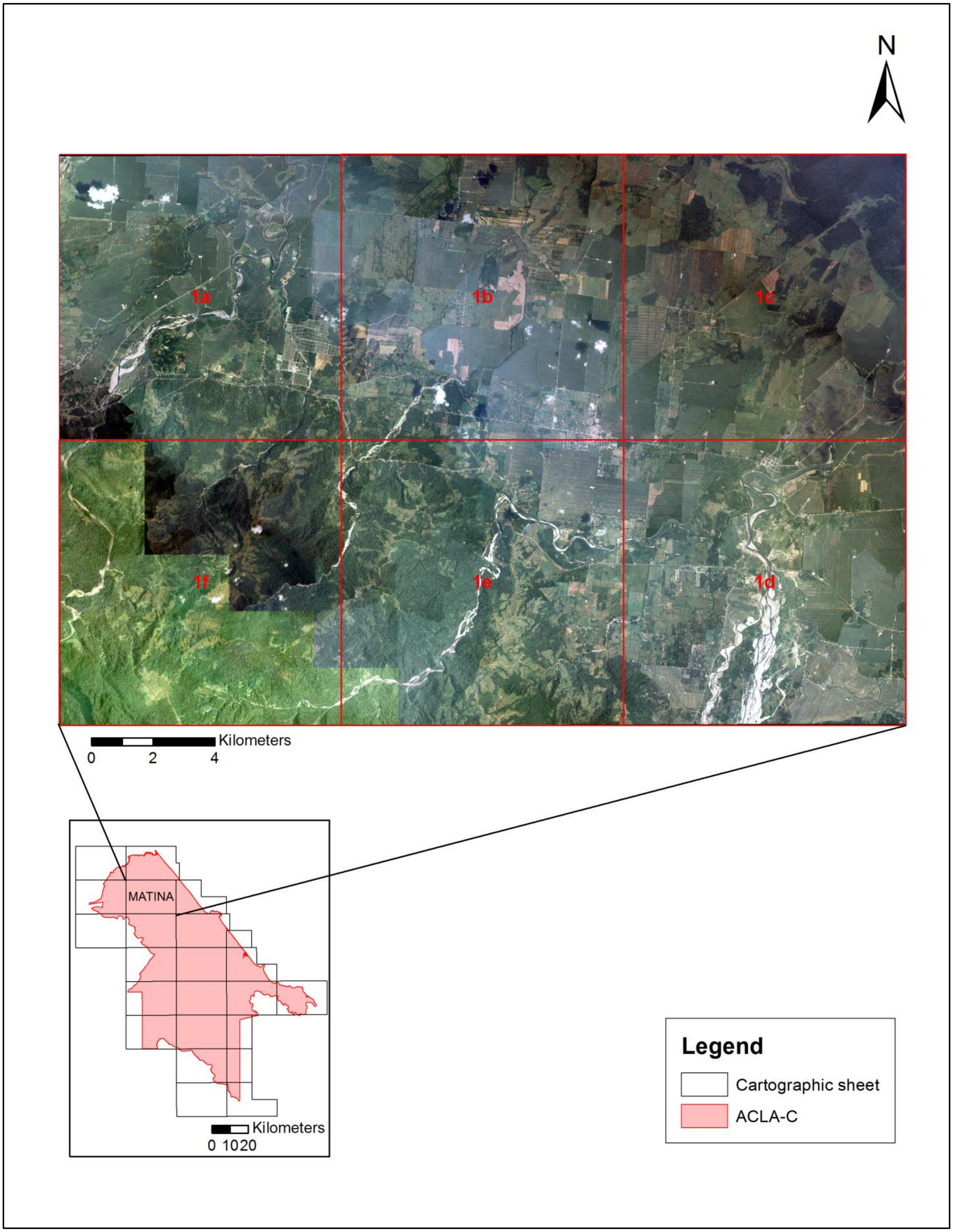


Figure 3.5. Subsets created for the Matina cartographic sheet.

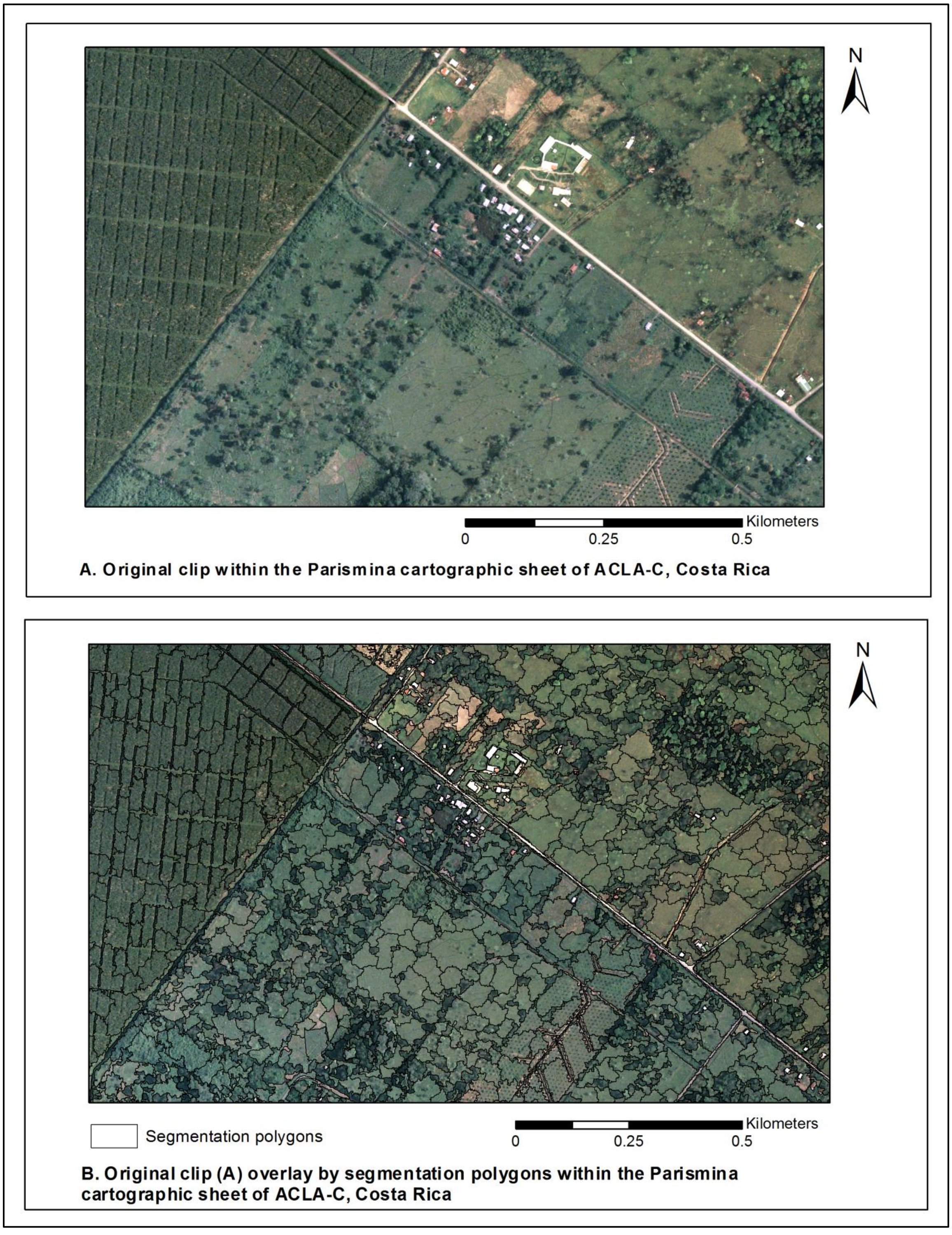


Figure 3.6. Example of the segmentation process for one of the Parismina's orthophoto subsets. a) Original clip within the Parismina cartographic sheet. b) Original clip (A) overlain by segmentation polygons within the Parismina cartographic sheet.

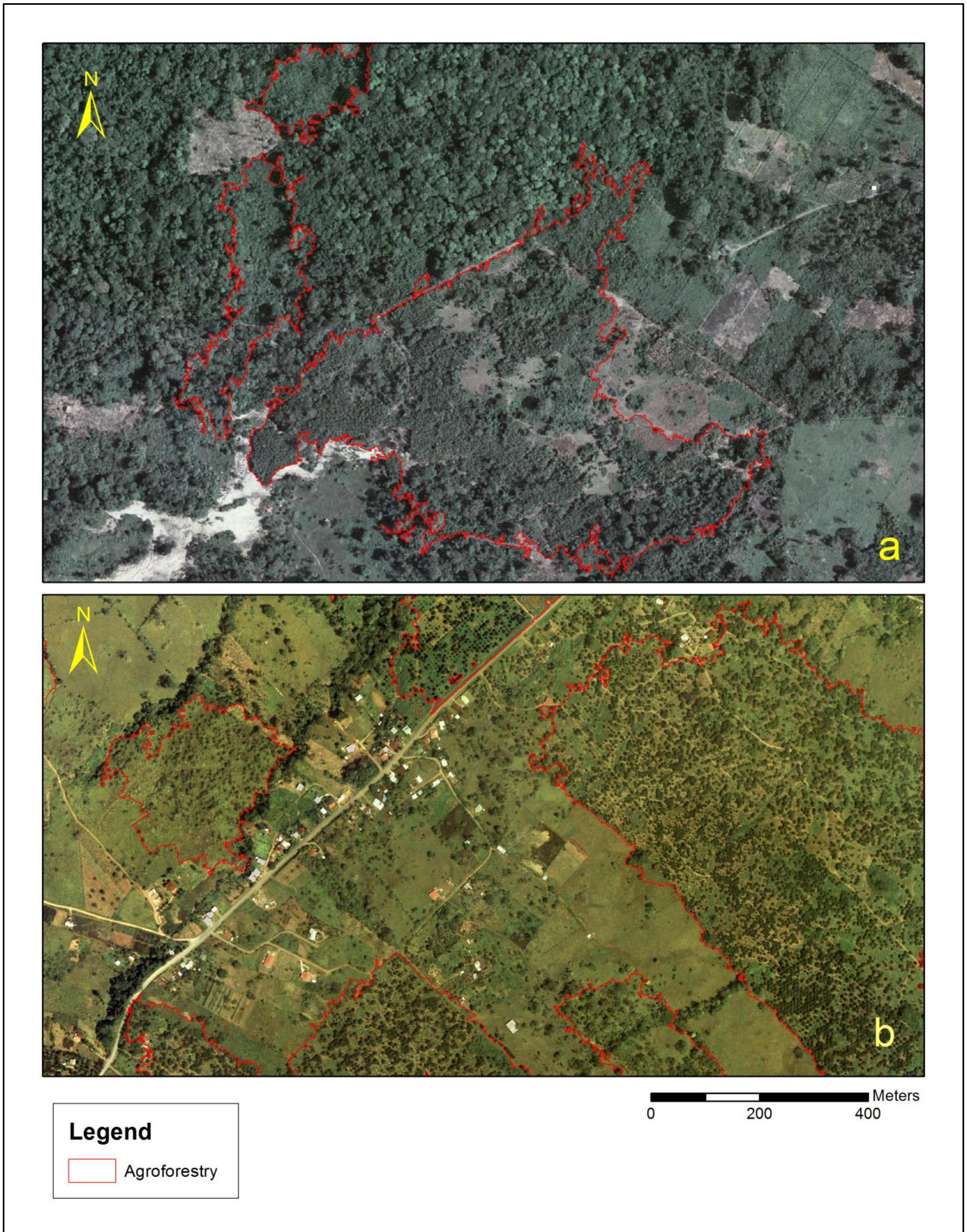


Figure 3.7. Example of land use classified as agroforestry inside the Amubri (**a**) and Bonilla (**b**) cartographic sheets.

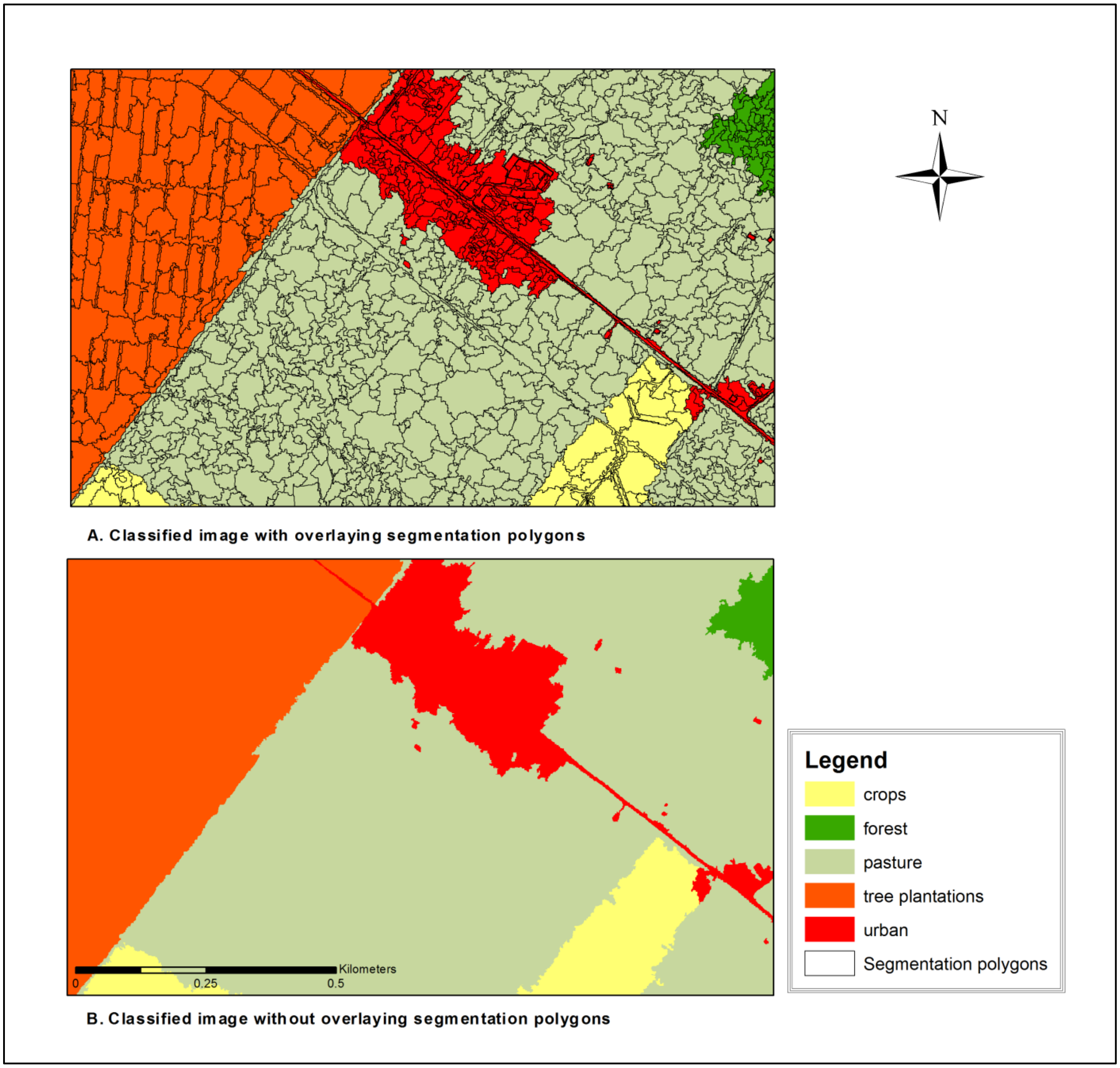


Figure 3.8. Example of the object based classification process with overlaying segmentation polygons (**A**) and without overlaying segmentation polygons (**B**) within one of the Parismina cartographic sheet.

CHAPTER IV: RESULTS

4.1. Land Cover/ Land Use Baseline Map Analysis

The land cover/land use baseline map of the ACLA-C conservation area reveals that the forest class is the most predominant land cover with a total area of 2441.9 km^2 (or 60.9% of the total land cover outside protected areas) (Table 4.1). Results show closed forest cover increases in density visually as moving towards protected areas (Figure 4.1). The northern part of the study area, encompassing the Guacimo, Parismina, Bonilla, Matina, and Moin cartographic sheets, have a highly heterogeneous landscape characterised by fragmented forest, agroforestry, pasture, and tree plantations (Figure 4.1 and Figure 4.2). Furthermore, the results reveal that forest below 3 ha (0.03 km^2) covers 31.1 km^2 and is predominant in the same region, the Bonilla cartographic sheet (Figure 4. 3). The second most predominant land use/land cover type is pasture with a total surface area of 710.1 km^2 followed by tree plantations covering a total surface of 343.6 km^2 (Table 4.1).

The classification results show that agroforestry, covering 197.1 km^2, has a high density not only in the northernwest region but as well in the southeastern parts of ACLA-C within the Bonilla, Sixaola, and Amubri cartographic sheets (Figure 4.4). Figure 4.4 shows that agroforestry, within the Amubri cartographic sheet, is in close proximity to forest; while agroforestry inside the Bonilla and Sixaola cartographic sheets is in proximity to urban land use and low forest cover. Furthermore, results reveal a deforestation of 4.5 km2 with a high density of 25% located within the Amubri cartographic sheet (Figure 4.5). The classification also reveals that urban land use covers a total surface are of 74.2 km^2 of ACLA-C (Table 4.1). The smallest land cover type revealed by the results is wetlands with a total surface area of 2.17 km^2 (Table 4.1). As well, other classes such as bare soil, clouds, crops, shadows, river bank, water, and no data encompass 233.1 km^2 (Table 4.1).

4.2. Comparison with the 2005 Official National Forest Cover Assessment of Costa Rica

The official national forest cover assessment of ACLA-C reveals 56.3 km^2 (5630 ha) more than the forest cover assessed in this study. The comparison between the two classifications shows 31.1 km^2 (3100 ha) of forest cover below 3 ha unmapped by the official forest cover assessment. The official national forest cover assessment reveals two deforestation land patches with a total surface area of 0.06 km^2 (6.33 ha) and a mean of 0.03 km^2 (3.16 ha) located in proximity of the La Amistad International Park (Figure 4.6). In comparison, my study results reveal 1035 deforestation patches, spread out throughout the study area, with a total land area of 4.48 km^2 (447.6 ha), a mean area of 0.004 km^2 (0.4 ha), and a range of 0.27 km^2 (27 ha). This results in a 98 percent (or 4.42 km^2) underestimation of deforestation by the official forest cover assessment.

The comparison between the forest cover percentage of the study and the official classification reveals that fifteen of the eighteen cartographic sheets within ACLA-C have the same forest cover percentage resulting in a low divergence in terms of forest area. Differences in forest cover percentage are seen within the Guacimo, Tucurrique, and Estrella cartographic sheets. Results show that Guacimo has a forest cover between 0 and 25 percent, while the official forest cover assessment shows a forest cover between 25 and 50 percent. As well, Tucurrique has forest cover between 25 and 50 percent according to my classification results and a forest cover between 0 and 25 percent according to the official forest cover assessment. In the case of Estrella, my classification results show a forest cover between 50 and 75 percent while the official forest cover assessment shows a 75 to 100 forest cover percentage.

Table 4.1. Area (km^2) and percentage (%) of the land cover/ land use classification results by class of ACLA-C, Costa Rica for the year 2005

Class	Area (km^2)	Percentage (%)
Wetlands	2.17	0.1
Deforestation	4.48	0.1
Bare soil	7.98	0.2
Clouds	14.69	0.4
Crops	21.18	0.5
Shadows	23.01	0.6
River bank	41.26	1.0
Water	42.08	1.1
Urban	74.19	1.9
No data	82.87	2.1
Agroforestry	197.05	4.9
Tree plantation	343.64	8.6
Pasture	710.13	17.7
Forest	2441.90	60.9
Total	4006.66	100.0

Table 4.2. Categories of forest cover percentage (%) within cartographic sheets of this study classification results and the official national forest cover assessments for the year 2005 of ACLAC-C, Costa Rica.

Forest cover percentage category	Study forest cover assessment	Official forest cover assessment
0 to 25 % forest cover	Guacimo	Tucurrique
25 to 50 % forest cover	Matina, Parismina, Bonilla, Tucurrique, Moin	Matina, Parismina, Guacimo, Bonilla, Moin
50 to 75 % forest cover	Sixaola, San Andres, Cahuita, Rio Banano, Amubri, Estrella	Sixaola, San Andres, Cahuita, Rio Banano, Amubri
75 to 100% forest cover	Sukut, Barbilla, Telire, Chirripo, Matama, Siola	Sukut, Barbilla, Telire, Chirripo, Matama, Siola, Estrella

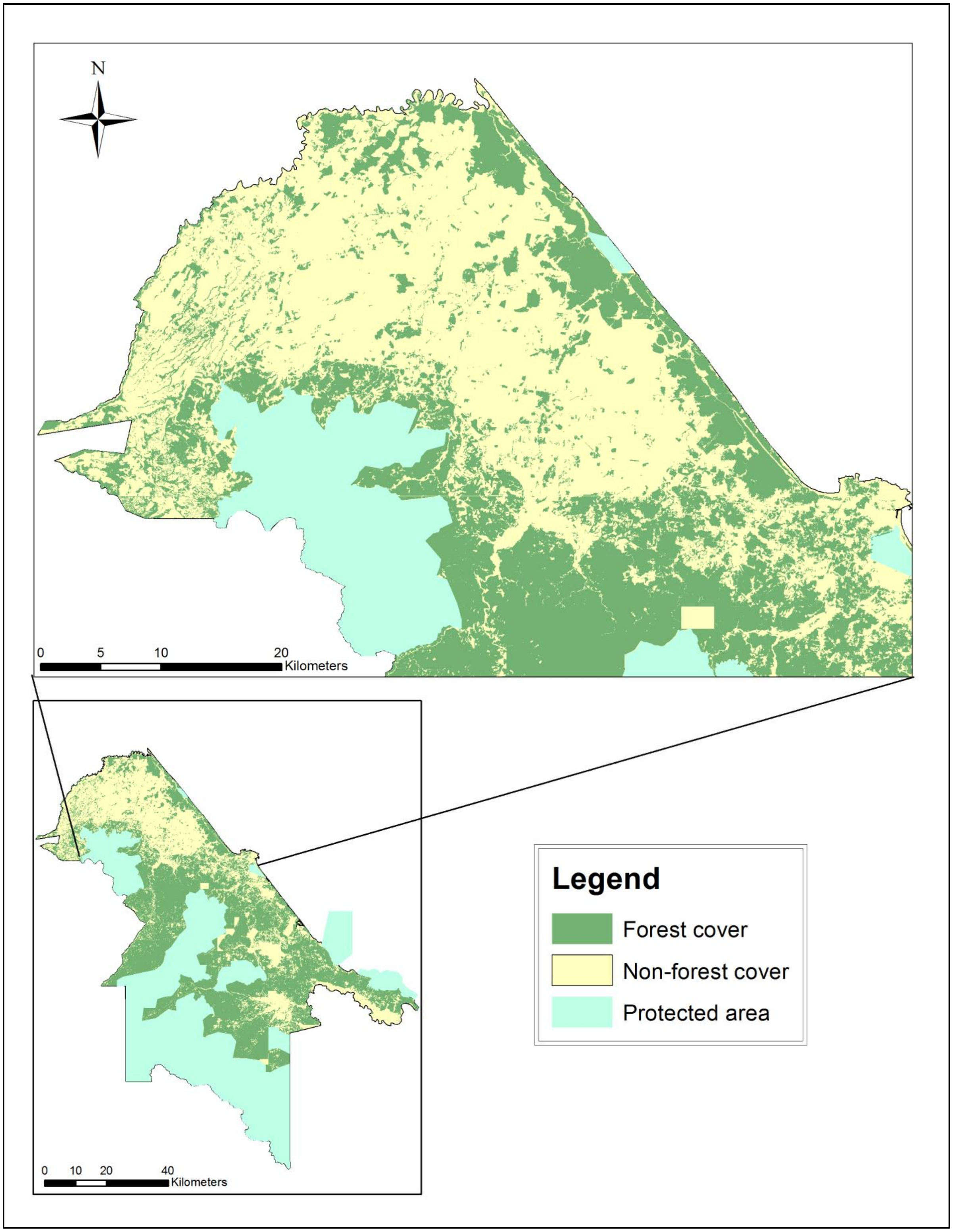


Figure 4.1. Region with the lowest forest cover density within ACLA-C for the year 2005. (Note: no data was included in the non-forest cover on the map).

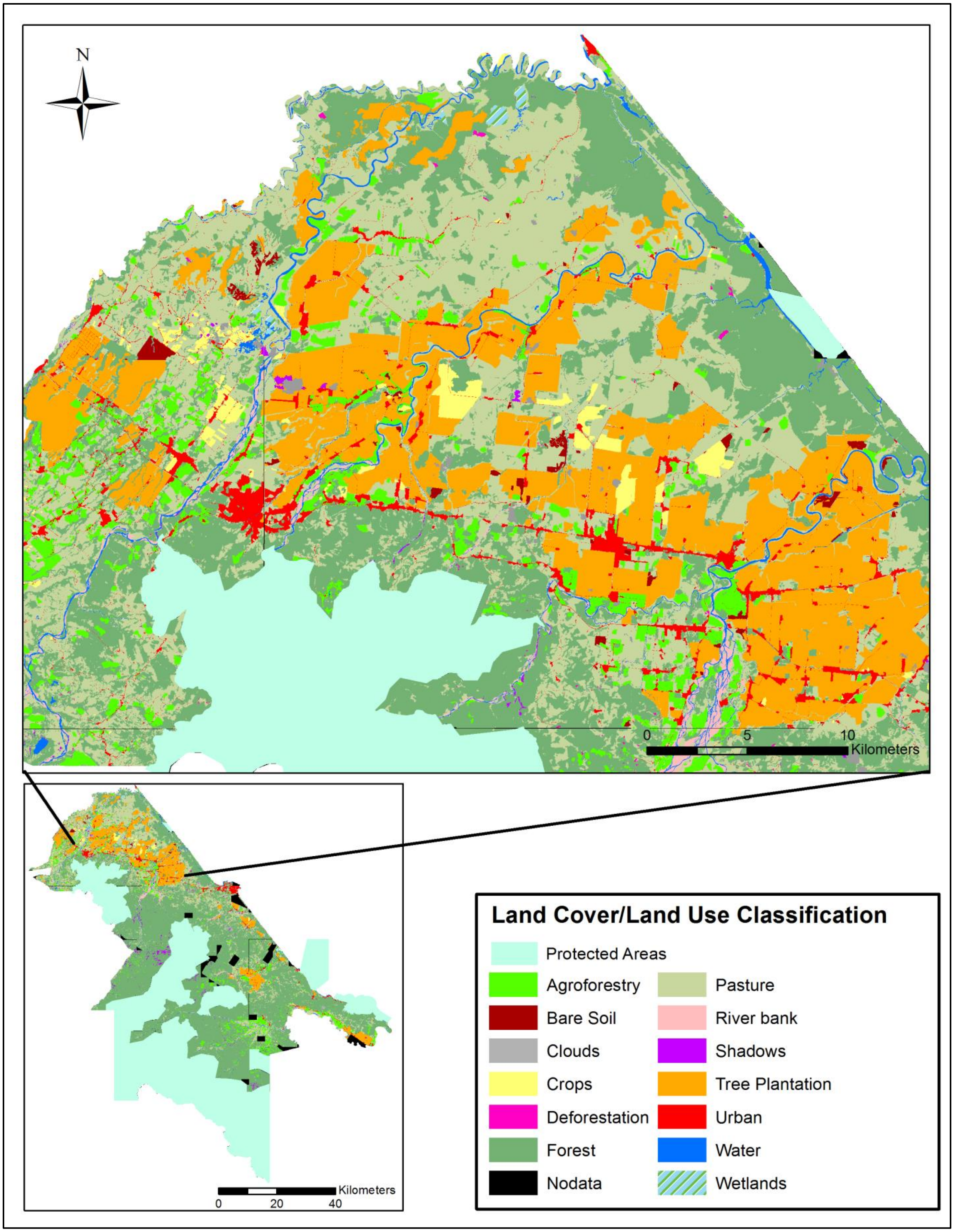


Figure 4.2. Region with the most predominant tree plantation land use within ACLA-C for the year 2005.

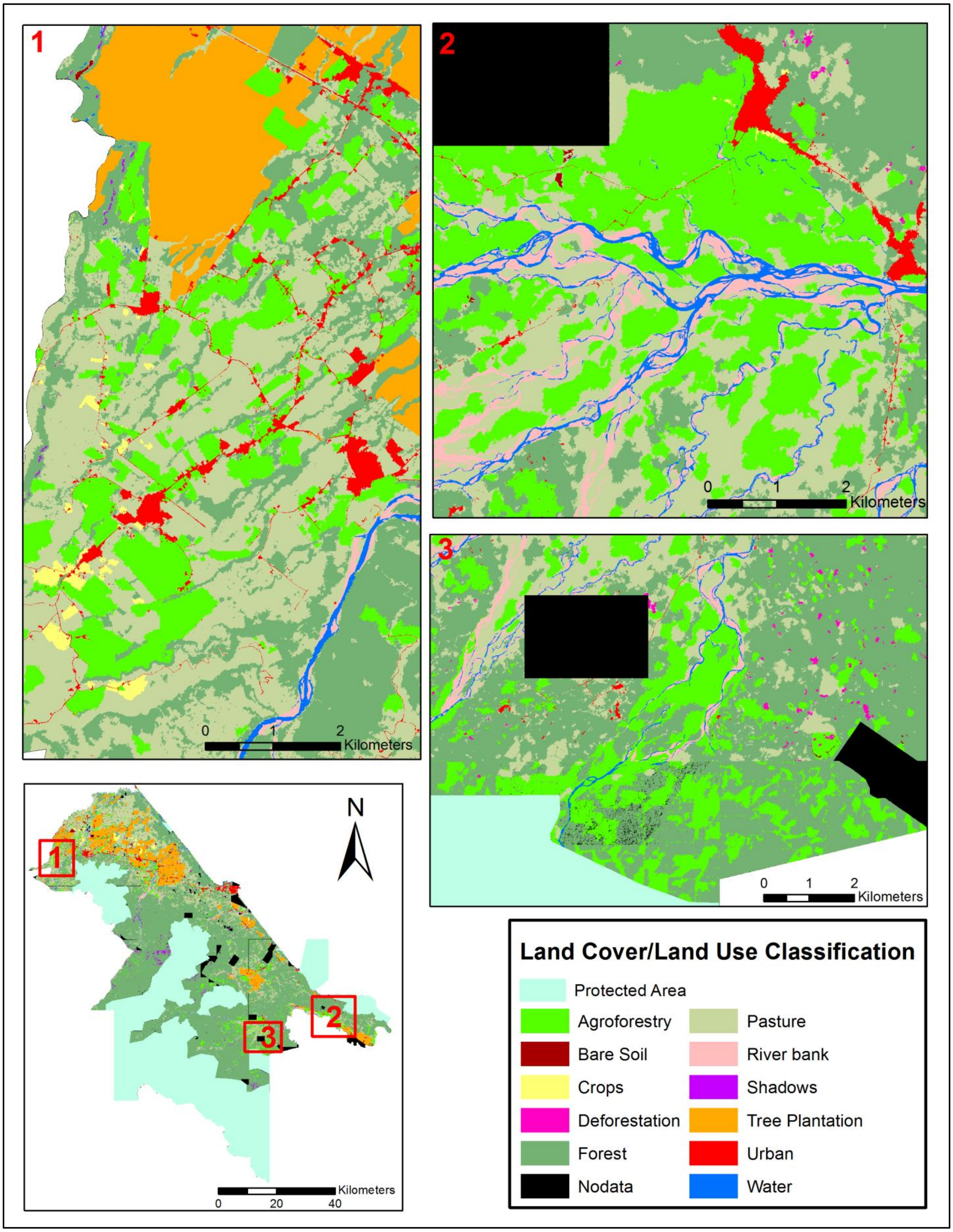


Figure 4.3. Regions with the most predominant agroforestry land use within ACLA-C for the year 2005: (1) Bonilla (2) Sixaola (3) Amubri.

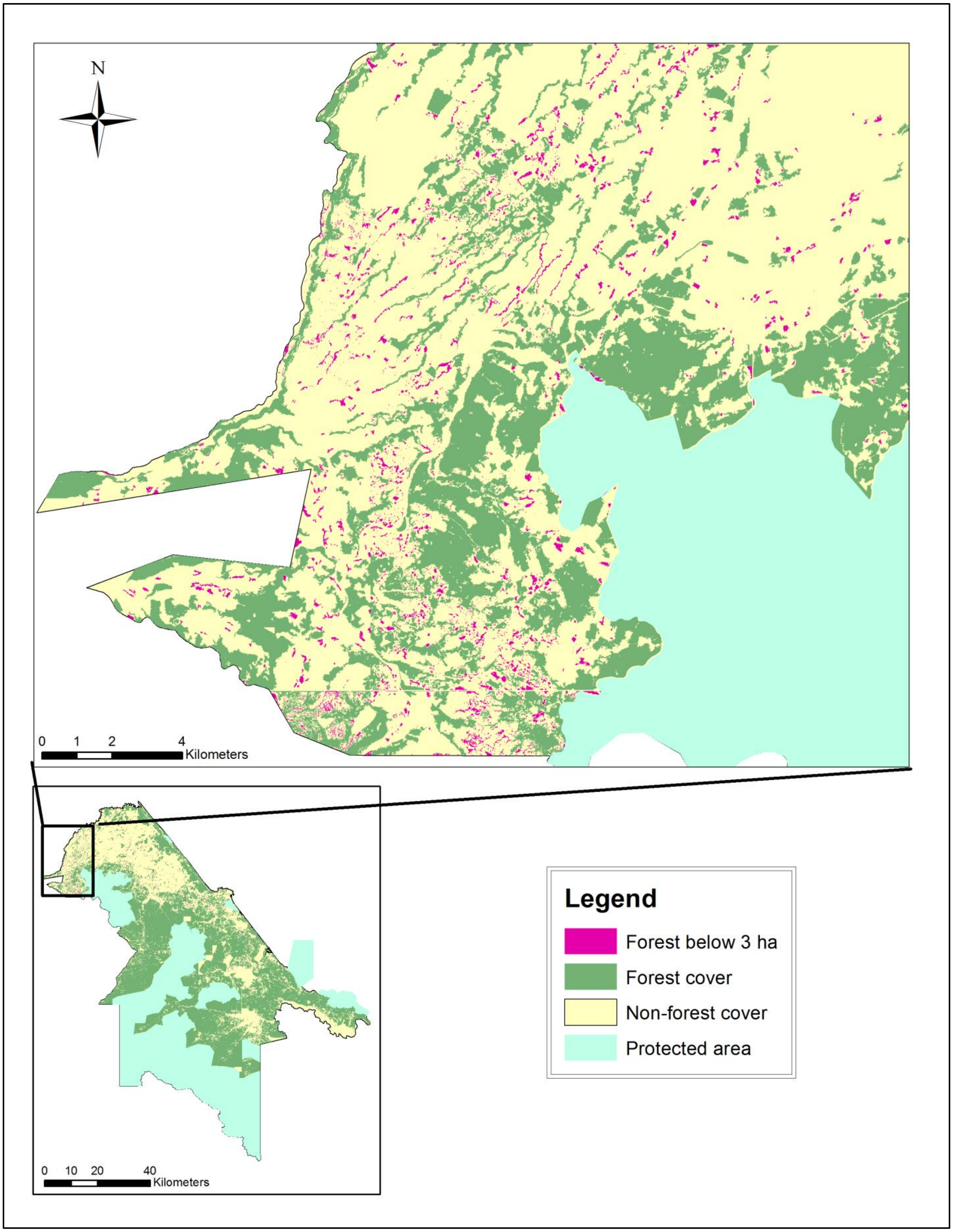


Figure 4.4. Region of ACLA-C with the greatest area of forest in patches below 3 ha for the year 2005. (Note: no data class was included in the non-forest cover class).

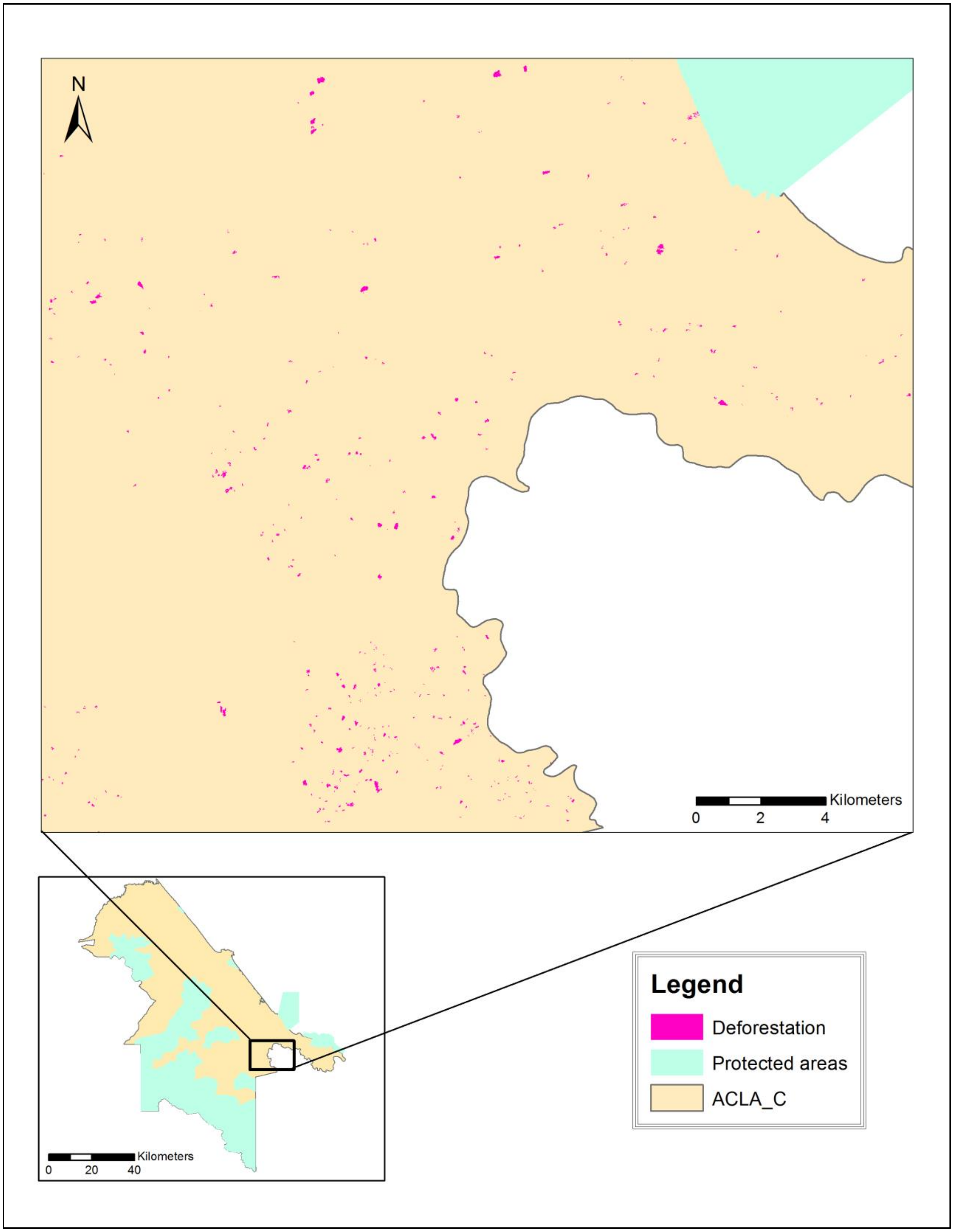


Figure 4.5. Deforestation assessed by my 2005 land use/land cover baseline map using semi-automatic photo interpretation of ACLA-C.

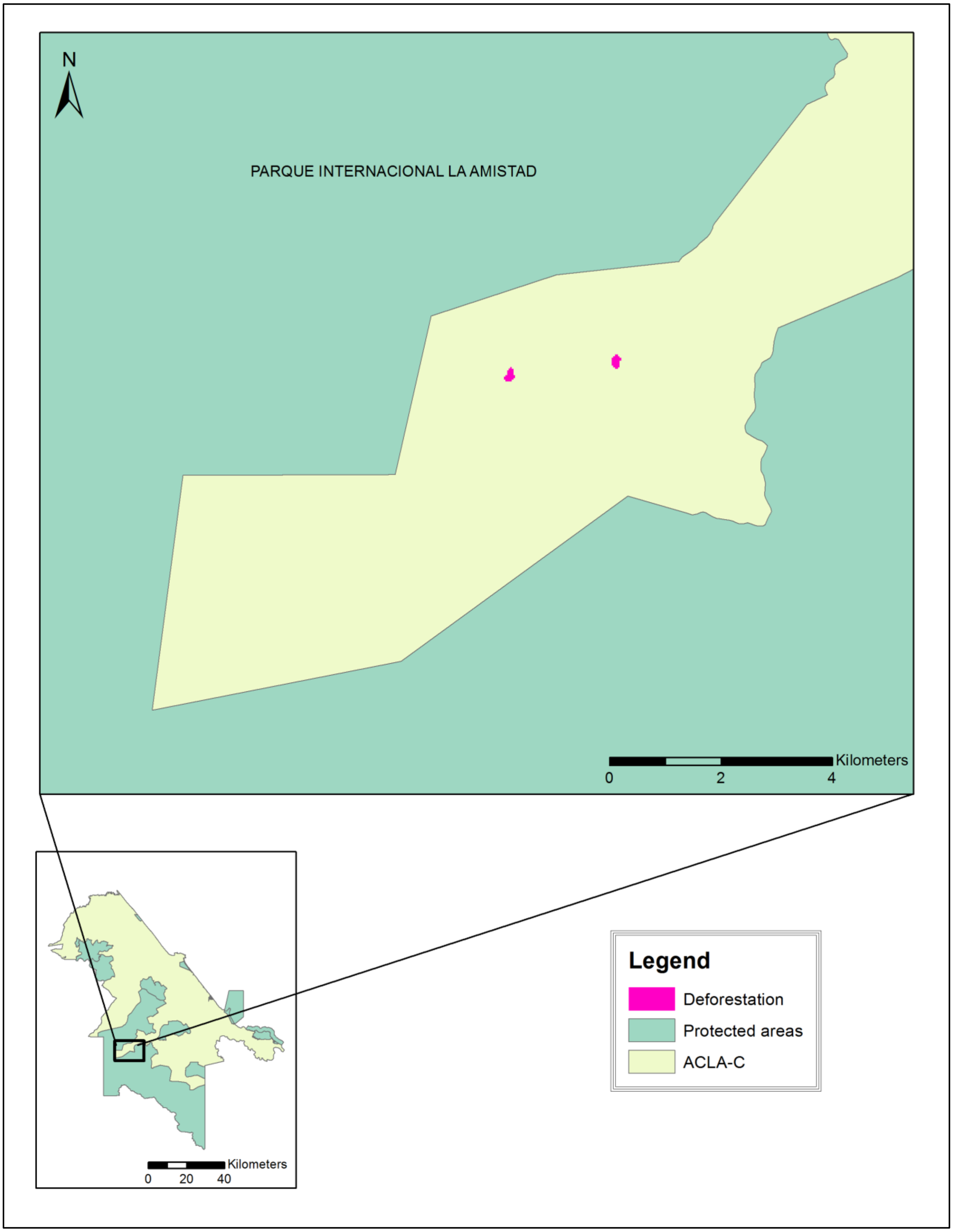


Figure 4.6. Deforestation reported by the 2005 official national forest cover assessment inside ACLA-C.

CHAPTER V: DISCUSSION

This study focuses on a novel classification for the ACLA-C region in Costa Rica. The methodology used in this study includes semi-automatic classification (Walter 2004) of very high spatial resolution aerial orthophotos from the year 2005. Results reveal a forest cover of 60.9 % of the ACLA-C region outside protected areas with closed forest being more predominant in proximity of protected areas. Sánchez-Azofeifa et al. (2001) attribute the high percentage of forest cover in the Limon province partly due to the presence of the large tracks of forest in Talamanca and Tortuguero regions characterised by high slopes that limit access and potential for exploitation.

Furthermore, my results reveal a 31 km^2 (3100 ha) of forest cover below 3 ha, while the official classification, using coarse spatial resolution satellite imagery, did not map forest below 3 ha. For instance, Sánchez-Azofeifa et al. (2001) used satellite imagery (Landsat 5TM) to study forest fragmentation in Costa Rica at a minimum mapping unit of 3ha. These unmapped fragmented forests with a surface area below 3ha can be more susceptible to deforestation. According to Sánchez-Azofeifa et al. (2001) forest patches with a surface area between 0.03 km^2 and 1 km^2 experience a higher deforestation rate in comparison with forest patches greater than 1 km^2. Furthermore, the authors argue that small and isolated forest patches are susceptible to loss of both genetic and species diversity. To the extent of my knowledge no studies were found that take into consideration forest cover below 3 ha in Costa Rica for official maps prior to 2005. A nation-wide study was carried by Kleinn et al. (2001) consisting of a pilot forestry based on low intensity inventory and aerial photo interpretation, however the northern and Atlantic regions were not covered because of a lack of aerial photo data (Arroyo pers. Comm.).

The official national forest cover assessment underestimated the deforestation class by 4.5 km^2 (447.6 ha), or 98 percent of the deforestation found within ACLA-C by the baseline map classification. It can be argued that the underestimation of deforestation can be associated with the coarse spatial resolution of the satellite imagery or the minimum mapping unit established by these studies (Cohen and Goward 2004) in the official forest cover assessment. This reasoning goes along with Asner et al. (2009) argument that global sensors such as Landsat often miss details of forest loss occurring at patches smaller than 25 ha.

Results show that the Northern region of ACLA-C (Figure 4.3) is characterised by a heterogeneous landscape such as fragmented forest, agroforestry, tree plantations, and pasture. Sánchez-Azofeifa et al. (2001) found that the expansion of pastures for cattle production poses a threat to remaining closed forest fragments in the Limon province, Costa Rica. According to Sanchez-Azofeifa (2000), pasture area in Limon was expanding at a rate of 7 percent between 1973 and 1984, as well forest covered 60% of the province in 1991. Given the 7% expansion rate, it would be expected that by 2005 forest cover would decrease to 51%. In comparison, my study found a forest cover of approximately 55 % in the Limon province for the year 2005. The higher than expected forest cover percentage indicates that PES is effective in the region at reducing deforestation rates. As well, high deforestation and habitat fragmentation in the Atlantic region of Costa Rica is attributed to the intensification and expansion of agricultural cash crops such as banana and pineapple (Sánchez-Azofeifa et al. 1999; Veldkamp et al. 1992). Sánchez-Azofeifa et al. (2003) found that throughout Costa Rica as the distance from national parks and biological reserves increases so does the deforestation rate. More specifically, their study reveals that between 1986 and 1992 national parks on the Atlantic slopes are experiencing higher deforestation than those on the Pacific slopes, especially the Cahuita National Park, located inside the study area, and Tortuguero and Braulio Carrillo National Parks located outside ACLA-C. Van Laake and Sánchez-Azofeifa (2004) also identified hot spots of deforestation with a minimum mapping unit of 3 ha in the province of Limon between 1986 and 1997. Their studied reveals that the main drivers of deforestation during the study period were banana plantations, cattle farming, and commercial production of palm heart (*Bactris gasipaes* Kunth). More specifically their study shows that Siquirres experienced a deforestation rate of 44.8 percent between 1986 and 1997 due to advances in technology, which allowed areas of lesser agricultural capacity to be used for commercial banana production. The study further reveals that the Talamanca region experienced a lower deforestation rate of 13.2 percent but still underwent a rapid conversion of banana cultivation between 1986 and 1997. My study found the most forest cover (approximately 1010 km^2 out of 2198 km^2) and approximately 31 percent of deforestation (approximately 1.4 km^2 out of 4.5 km^2) in the same region for the year 2005. The Talamanca region's forest cover will become even more susceptible to deforestation if cash crops plantations continue to expand in the future.

Based on the comparison between the land use/land cover baseline map and the official national forest cover assessment potential implications for the PES framework in the study area are discussed. This study offers a more detailed understanding of land cover/ land use at a small scale. Including forest cover below 3 ha provides potential insights to improve land policy development and land management. According to the Forest Development Plan for Costa Rica, an estimated 30 percent of the registered raw material for the wood industry comes from non-forest land (MINAE et al. 2001 as cited by Kleinn et al. (2005)). As a result, the forest sector must take into consideration these forest regions as a serious forest resource and make them part of the forest inventory as they can serve as environmental services and have a high economic value at the same time (Kleinn et al. 2005). Given that PES implementation have slowed deforestation rates in Costa Rica since their establishment, future PES policies would be more efficient if they focus on degraded areas characterised by fragmented forest (Arriagada and Pattanayak 2009; Lutz et al. 1993; Sanchez-Azofeifa et al. 2007). Van Laake and Sánchez-Azofeifa (2004) suggests that identifying regions with high deforestation rates can be important in directing scarce resources to regions that need the most attention. As well, PES can focus on areas with high-density forest cover remaining to avoid further forest loss in the future. As the results of the land cover/land use map reveal, the highest deforestation is located in areas still covered by closed forest. As Van Laake and Sánchez-Azofeifa (2004) argue, regions with lower deforestation rates and still covered by closed forests can be prime candidates for remedial action allowing both economic development of the area and a sustainable ecological framework.

Furthermore, inaccurate forest cover assessments can lead to ineffective carbon sequestration estimations within the PES and other programs (e.g. REDD+). Busch et al. (2000) highlighted the need for an accurate baseline forest cover map in order to better assess deforestation pressures in Costa Rica. Their study reveals errors in forecasting carbon sequestration as a result of an overestimation of forest cover assessments before and after PES implementation. The more precise the forest cover estimation, the greater is the estimation of carbon sequestration (Busch et al. 2000). As Kalacska et al. (2008) state, errors in forest cover baseline estimates have implications for PES and can lead to unrealistic values for carbon stocks. Therefore, the 3100 ha of forest below 3ha disagreement between my classification and the official national forest cover assessment might have a significant impact in calculating carbon sequestration estimations.

My study used an object based classification method as a means to map land cover/ land use at a small scale. Studies have showed that object-based classification methods improve accuracy in monitoring natural resources. Duveiller et al. (2008) used an object based classification approach to delineate and efficiently classify land cover and estimate deforestation at regional, national, and landscape levels of the Congo River for the years 1990 and 2000. As well, Cleve et al. (2008)'s study on urban expansion reveals that object based methods provide high accurate land cover/land use classifications, while Laliberte et al. (2004) used object based classification methods in mapping shrub encroachment from 1937 to 2003 in southern New Mexico.

An accuracy analysis was not performed for this study due to the lack of ground truth data and time constraint factors. For further analysis an accuracy assessment can be performed using a spatial accuracy consisting of series of several classification overlays and their boundaries created by different interpretations of the same ground area using a systematic dot grid (Paine and Kiser 2012).

Shortcomings were encountered during the process of creating the land cover/ land use baseline map of ACLA-C for the year 2005. The pre-processing step, where the aerial photographs were divided into subsets, was time consuming but necessary as the aerial orthophotos were large (5GB). As well, even though the subsets had a lower file size (approximately 2GB) the segmentation of each subset was still time consuming taking up to 45 minutes. The refinement of the classification was as well time consuming as the aerial photographs used in the study have only 3 bands (Red, Blue, and Green) which made it difficult for the software to distinguish between the forest, pasture, and agroforestry classes characterised by similar colour and texture information. Moreover, creating subsets caused some problems in the final stage of the analysis resulting in topology errors caused by overlapping polygons between cartographic sheets. As a result, a continuous area of the entire land cover/ land use could not be calculated. However, this problem was address by analyzing the data at the cartographic sheet level. Given the spatial resolution of 50 cm, the high-quality of the orthophotos posed little problems in terms of variations in colour, illumination, and contrast within a mosaic. Polygons assigned to the wrong class due to variations in colour, illumination, and contrast, were refined manually.

CHAPTER VI: CONCLUSION

By applying a semi-automatic classification of very high spatial resolution aerial orthophotos for the year 2005 to map land cover/land use of the ACLA-C region in Costa Rica, I was able to measure small-scale forest cover (below 3 ha) present in the study area as well as deforestation patterns, without the need of multi temporal datasets (Blaschke 2010) . In comparison with the 2005 official national forest cover assessment of Costa Rica, it seems both studies capture the highly heterogeneous landscape in the northern region of ACLA-C characterised by fragmented forest, agroforestry, tree plantations, and pastures. In addition, both studies show a low divergence in terms of forest area. However, my results reveal 3100 ha of forest below 3ha is not mapped by the official forest cover assessment. More important, fragmented forest below 3 ha might be more susceptible to deforestation due to pressure caused by tree plantations, crops and cattle grazing occurring in the same areas. For instance the official cover assessment underestimates the deforestation class by 98% within ACLA-C. The results of this study emphasise the importance of integrating small scale land use change in forest cover assessments to more accurately estimate rates and areas of deforestation, forest fragmentation and forest cover. Furthermore, the ability to map forest cover below 3 ha might have potential implications within programs like the Costa Rican PES or other future programs where detailed land use/ land cover mapping is key. Further analysis comparing the spatial location of forest and non-forest classes (agroforestry, tree plantations) between both classifications is recommended for better understanding differences in the classifications.

REFERENCES

Arcidiacono-Bársony, C., Ciais, P., Viovy, N., & Vuichard, N. (2011). REDD Mitigation. *Procedia Environmental Sciences, 6*, 50-59

Arriagada, R.A., & Pattanayak, S.K. (2009). Payments for environmental services and their impact on forest transition in Costa Rica. In

Arroyo-Mora, J.P., Sánchez-Azofeifa, G.A., Kalacska, M.E.R., Rivard, B., Calvo-Alvarado, J.C., & Janzen, D.H. (2005a). Secondary Forest Detection in a Neotropical Dry Forest Landscape Using Landsat 7 ETM+ and IKONOS Imagery1. *Biotropica*, *37*, 497-507

Arroyo-Mora, J.P., Sanchez-Azofeifa, G.A., Rivard, B., Calvo, J.C., & Janzen, D.H. (2005b). Dynamics in landscape structure and composition for the Chorotega region, Costa Rica from 1960 to 2000. *Agriculture Ecosystems & Environment, 106*, 27-39

Asner, G.P., Knapp, D.E., Broadbent, E.N., Oliveira, P.J.C., Keller, M., & Silva, J.N. (2005). Selective Logging in the Brazilian Amazon. *Science, 310*, 480-482

Asner, G.P., Rudel, T.K., Aide, T.M., Defries, R., & Emerson, R. (2009). A Contemporary Assessment of Change in Humid Tropical Forests.

. *Conservation Biology*, *23*, 1386-1395

Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, *65*, 2-16

Boyd, D.S., Foody, G.M., & Phipps, P.C. (2006). Dynamics of ENSO drought events on Sabah rainforests observed by NOAA AVHRR. *International Journal of Remote Sensing*, *27*, 2197-2219

Brenes, A.R. (2004). A Review of the Agroforestry Systems of Costa Rica. *Journal of Sustainable Forestry*, *21*, 97-119

Busch, C., Sathaye, J.A., & Sanchez-Azofeifa, G.A. (2000). Estimating the greenhouse gas benefits of forestry projects: a Costa Rican case study. *Lawrence Berkeley National Laboratory–Report*

Calvo-Alvarado, J., McLennan, B., Sánchez-Azofeifa, A., & Garvin, T. (2009). Deforestation and forest restoration in Guanacaste, Costa Rica: Putting conservation policies in context. *Forest Ecology and Management*, *258*, 931-940

Chambers, J.Q., Asner, G.P., Morton, D.C., Anderson, L.O., Saatchi, S.S., Espirito-Santo, F.D., Palace, M., & Souza, C., Jr. (2007). Regional ecosystem structure and function: ecological insights from remote sensing of tropical forests. *Trends Ecol Evol, 22*, 414-423

Clark, D.B., Read, J.M., Clark, M.L., Cruz, A.M., Dotti, M.F., & Clark, D.A. (2004). Application of 1-M and 4-M resolution satellite data to ecological studies of tropical rain forests. *Ecological Applications, 14*, 61-74

Cleve, C., Kelly, M., Kearns, F.R., & Moritz, M. (2008). Classification of the wildland–urban interface: A comparison of pixel- and object-based classifications using high-resolution aerial photography. *Computers, Environment and Urban Systems, 32*, 317-326

Cohen, W.B., & Goward, S.N. (2004). Landsat's role in ecological applications of remote sensing. *BioScience, 54*, 535-545

Cots-Folch, R., Aitkenhead, M.J., & Martínez-Casasnovas, J.A. (2007). Mapping land cover from detailed aerial photography data using textural and neural network analysis. *International Journal of Remote Sensing, 28*, 1625-1642

Daily, G.C., & Ehrlich, P.R. (1992). Population, Sustainability, and Earth's Carrying Capacity. *BioScience, 42*, 761-771

de Camino, R., Segura, O., Arias, L.G., & Perez, I. (2000). Costa Rica: Forest Strategy and the Evolution of Land Use. In, *Evaluation Country Case Study Series*. Washington, D. C. : Operations Evaluation Department of the World Bank, The World Bank

Deheuvels, O., Avelino, J., Somarriba, E., & Malezieux, E. (2012). Vegetation structure and productivity in cocoa-based agroforestry systems in Talamanca, Costa Rica. *Agriculture Ecosystems & Environment, 149*, 181-188

Duveiller, G., Defourny, P., Desclee, B., & Mayaux, P. (2008). Deforestation in Central Africa: Estimates at regional, national and landscape levels by advanced processing of systematically-distributed Landsat extracts. *Remote Sensing of Environment, 112*, 1969-1981

Engel, S., Wünscher, T., & Wunder, S. (2009). Increasing the efficiency of forest conservation: The case of payments for environmental services in Costa Rica. *Avoided deforestation: Prospects for mitigating climate change. Oxford, Routledge*, 314-328

FAO (2010). Global Forest Resources Assessment In: Food and Agriculture Organisation

Field, C.B., Randerson, J.T., & Malmstrom, C.M. (1995). Global Net Primary Production - Combining Ecology and Remote-Sensing. *Remote Sensing of Environment, 51*, 74-88

Fletcher, R., & Breitling, J. (2012). Market mechanism or subsidy in disguise? Governing payment for environmental services in Costa Rica. *Geoforum, 43*, 402-411

Foody, G.M. (2003). Remote sensing of tropical forest environments: Towards the monitoring of environmental resources for sustainable development. *International Journal of Remote Sensing, 24*, 4035-4046

Frohn, R.C., Hinkel, K.M., & Eisner, W.R. (2005). Satellite remote sensing classification of thaw lakes and drained thaw lake basins on the North Slope of Alaska. *Remote Sensing of Environment, 97*, 116-126

Geist, H.J., & Lambin, E.F. (2002). Proximate Causes and Underlying Driving Forces of Tropical Deforestation. *BioScience, 52*, 143-150

Gotz Schroth, G.A.B.d.F., Celia A. Harvey, Claude Gascon, Heraldo L. Vasconcelos, and Anne-Marie N. Izac (2004). Agroforestry and Biodiversity Conservation in Tropical Landscapes In G.A.B.d.F. Gotz Schroth, Celia A. Harvey, Claude Gascon, Heraldo L. Vasconcelos, and Anne-Marie N. Izac (Ed.) (p. 537): Island Press

Jensen, J.R., Garcia-Quijano, M., Hadley, B., Im, J., Wang, Z., Nel, A.L., Teixeira, E., & Davis, B.A. (2006). Remote Sensing Agricultural Crop Type for Sustainable Development in South Africa. *Geocarto International, 21*, 5-18

Kalacska, M., Sanchez-Azofeifa, G.A., Rivard, B., Calvo-Alvarado, J.C., & Quesada, M. (2008). Baseline assessment for environmental services payments from satellite imagery: A case study from Costa Rica and Mexico. *Journal of Environmental Management, 88*, 348-359

Kerr, J.T., & Ostrovsky, M. (2003). From space to species: ecological applications for remote sensing. *Trends in Ecology & Evolution, 18*, 299-305

Kissinger, G., Herold, M., & De Sy, V. (2012). Drivers of deforestation and forest degradation: a synthesis report for REDD+ policymakers. *Lexeme Consulting, Vancouver, Canada*

Kleinn, C., Corrales, L., & Morales, D. (2002). Forest area in Costa Rica: a comparative study of tropical forest cover estimates over time. *Environmental Monitoring and Assessment, 73*, 17-40

Kleinn, C., Ramirez, C., Chaves, G., & Lobo, S. (2001). Pilot forest inventory in Costa Rica for the Global Forest Survey In: Food and Agriculture Organisation of the United Nations

Kleinn, C., Ramírez, C., Holmgren, P., Valverde, S.L., & Chavez, G. (2005). A national forest resources assessment for Costa Rica based on low intensity sampling. *Forest Ecology and Management, 210*, 9-23

Koellner, T., Sell, J., Gähwiler, M., & Scholz, R.W. (2008). Assessment of the management of organizations supplying ecosystem services from tropical forests. *Global Environmental Change, 18*, 746-757

Laliberte, A.S., Rango, A., Havstad, K.M., Paris, J.F., Beck, R.F., McNeely, R., & Gonzalez, A.L. (2004). Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. *Remote Sensing of Environment, 93*, 198-210

Lam, N.S.-N., & Quattrochi, D.A. (1992). On the issues of Scare, Resolution, and Fractal Analysis in the Mapping Sciences. *Professional Geographer, 44*, 88-98

Lambin, E.F., & Ehrlich, D. (1996). The surface temperature-vegetation index space for land cover and land-cover change analysis. *International Journal of Remote Sensing, 17*, 463-487

Lambin, E.F., & Strahler, A.H. (1994). Indicators of Land-Cover Change for Change-Vector Analysis in Multitemporal Space at Coarse Spatial Scales. *International Journal of Remote Sensing, 15*, 2099-2119

Locatelli, B., Rojas, V., & Salinas, Z. (2008). Impacts of payments for environmental services on local development in northern Costa Rica: A fuzzy multi-criteria analysis. *Forest Policy and Economics, 10*, 275-285

Lutz, E., & Daly, H. (1991). Incentives, regulations, and sustainable land use in Costa Rica. *Environmental and Resource Economics, 1*, 179-194

Lutz, E., Vedova, M., Martínez, H., San Román, L., Vázquez, R., Alvarado, A., Merino, L., Celis, R., & Huising, J. (1993). *Interdisciplinary fact-finding on current deforestation in Costa Rica*. World Bank, Environment Department

MA (2005). MA Conceptual Framework. In, *Millennium Ecosystem Assessment. Ecosystems and Human Well-being: Policy Responses*. Washington DC: Island Press.

Mas, J.-F., Velázquez, A., Díaz-Gallegos, J.R., Mayorga-Saucedo, R., Alcántara, C., Bocco, G., Castro, R., Fernández, T., & Pérez-Vega, A. (2004). Assessing land use/cover changes: a nationwide multidate spatial database for Mexico. *International Journal of Applied Earth Observation and Geoinformation, 5*, 249-261

Morgan, J.L., Gergel, S.E., & Coops, N.C. (2010). Aerial Photography: A Rapidly Evolving Tool for Ecological Management. *BioScience, 60*, 47-59

Morton, D.C., DeFries, R.S., Shimabukuro, Y.E., Anderson, L.O., Del Bon Espírito-Santo, F., Hansen, M., & Carroll, M. (2005). Rapid assessment of annual deforestation in the Brazilian Amazon using MODIS data. *Earth Interactions, 9*, 1-22

Mumby, P.J., Green, E.P., Edwards, A.J., & Clark, C.D. (1999). The cost-effectiveness of remote sensing for tropical coastal resources assessment and management. *Journal of Environmental Management, 55*, 157-166

Myers, N. (1992). Tropical forests: The policy challenge. *Environmentalist, 12*, 15-27

Myneni, R.B., Yang, W., Nemani, R.R., Huete, A.R., Dickinson, R.E., Knyazikhin, Y., Didan, K., Fu, R., Negron Juarez, R.I., Saatchi, S.S., Hashimoto, H., Ichii, K., Shabanov, N.V., Tan, B., Ratana, P., Privette, J.L., Morisette, J.T., Vermote, E.F., Roy, D.P., Wolfe, R.E., Friedl, M.A., Running, S.W., Votava, P., El-Saleous, N., Devadiga, S., Su, Y., & Salomonson, V.V. (2007). Large seasonal swings in leaf area of Amazon rainforests. *Proc Natl Acad Sci U S A, 104*, 4820-4823

Nagendra, H. (2001). Using remote sensing to assess biodiversity. *International Journal of Remote Sensing, 22*, 2377-2400

NWS (2004). Climate Glossary. In: Center for Weather and Climate Prediction

Paine, D.P., & Kiser, J.D. (2012). *Aerial photography and image interpretation*. Wiley

Pan, Y., Birdsey, R.A., Fang, J., Houghton, R., Kauppi, P.E., Kurz, W.A., Phillips, O.L., Shvidenko, A., Lewis, S.L., Canadell, J.G., Ciais, P., Jackson, R.B., Pacala, S.W., McGuire, A.D., Piao, S., Rautiainen, A., Sitch, S., & Hayes, D. (2011). A large and persistent carbon sink in the world's forests. *Science*, *333*, 988-993

Parrota, J.A., Wildburger, C., & Mansourianm, S. (2012). Understanding Relationship between Biodiversity,Carbon, Forests, and People: The Key to Achieving REDD++ Objectives: A Global Assessment Report. In. Vienna: Global Forest Expert Panel on Biodiversity, Forest Management, and REDD++

Rasi, R., Beuchle, R., Bodart, C., Vollmar, M., Seliger, R., & Achard, F. (2013). Automatic Updating of an Object-Based Tropical Forest Cover Classification and Change Assessment. *Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of, 6*, 66-73

Sanchez-Azofeifa, G.A. (2000). Chapter 16 - Land Use and Cover Change in Costa Rica: A Geographic Perspective. In A.S.H. Charles, P. Carlos Leon, C.L.P. Gregoire LeclercA2 - Charles A.S. Hall, & L. Gregoire (Eds.), *Quantifying Sustainable Development* (pp. 473-501). San Diego: Academic Press

Sánchez-Azofeifa, G.A., Daily, G.C., Pfaff, A.S.P., & Busch, C. (2003). Integrity and isolation of Costa Rica's national parks and biological reserves: examining the dynamics of land-cover change. *Biological Conservation, 109*, 123-135

Sánchez-Azofeifa, G.A., Harriss, R.C., & Skole, D.L. (2001). Deforestation in Costa Rica: A Quantitative Analysis Using Remote Sensing Imagery1. *Biotropica*, *33*, 378-384

Sanchez-Azofeifa, G.A., Pfaff, A., Robalino, J.A., & Boomhower, J.P. (2007). Costa Rica's payment for environmental services program: intention, implementation, and impact. *Conserv Biol*, *21*, 1165-1173

Sánchez-Azofeifa, G.A., Quesada-Mateo, C., Gonzalez-Quesada, P., Dayanandan, S., & Bawa, K.S. (1999). Protected Areas and Conservation of Biodiversity in the Tropics. *Conservation Biology, 13*, 407-411

Sasaki, N., & Putz, F.E. (2009). Critical need for new definitions of “forest” and “forest degradation” in global climate change agreements. *Conservation Letters, 2*, 226-232

Sierra, R., & Russman, E. (2006). On the efficiency of environmental service payments: A forest conservation assessment in the Osa Peninsula, Costa Rica. *Ecological Economics, 59*, 131-141

SINAC (2005). Costa Rica National Parks. In

Souza, C.M., Roberts, D.A., & Cochrane, M.A. (2005). Combining spectral and spatial information to map canopy damage from selective logging and forest fires. *Remote Sensing of Environment, 98*, 329-343

Subak, S. (2000). Forest protection and reforestation in Costa Rica: Evaluation of a clean development mechanism prototype. *Environmental Management, 26*, 283-297

Townshend, J., Justice, C., Li, W., Gurney, C., & Mcmanus, J. (1991). Global Land Cover Classification by Remote-Sensing - Present Capabilities and Future Possibilities. *Remote Sensing of Environment, 35*, 243-255

Trimble (2011). eCognition Developer 6.64.1 User Guide. In: Trimble: Munchen, Germany.

Van Laake, P.E., & Sánchez-Azofeifa, G.A. (2004). Focus on deforestation: zooming in on hot spots in highly fragmented ecosystems in Costa Rica. *Agriculture, Ecosystems & Environment, 102*, 3-15

Vaughan, C., Fallas, J., & McCoy, M. (1998). Conservation mapping in Costa Rica. In B.G. Savitsky, & T.E.L. Jr (Eds.), *GIS Methodology for Developing Conservation Strategies: Topical Forest Recovery and Wildlife Managementin Costa Rica* (pp. 3-13). New York: Columbia University Press

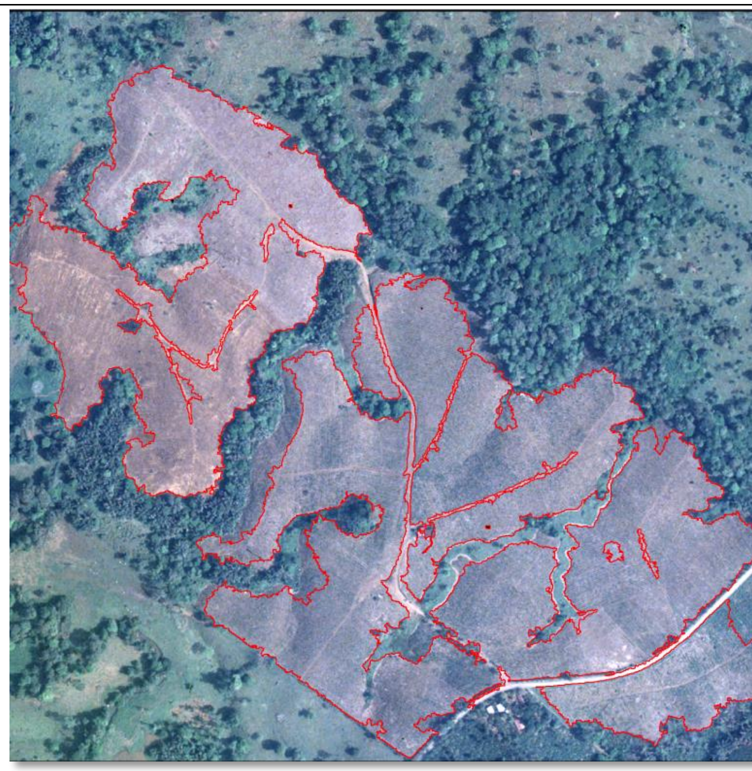
Veldkamp, A., & Fresco, L.O. (1997). Reconstructing land use drivers and their spatial scale dependence for Costa Rica (1973 and 1984). *Agricultural Systems, 55*, 19-43

Veldkamp, E., Weitz, A.M., Staritsky, I.G., & Huising, E.J. (1992). Deforestation trends in the Atlantic Zone of Costa Rica: A case study. *Land Degradation & Development, 3,* 71-84

Walter, V. (2004). Object-based classification of remote sensing data for change detection. *ISPRS Journal of Photogrammetry and Remote Sensing, 58*, 225-238

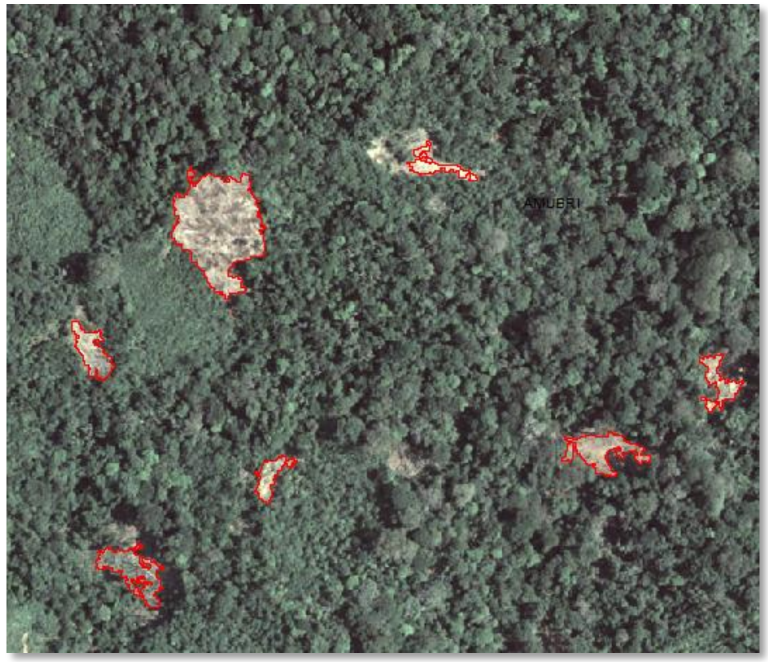
APPENDIX A

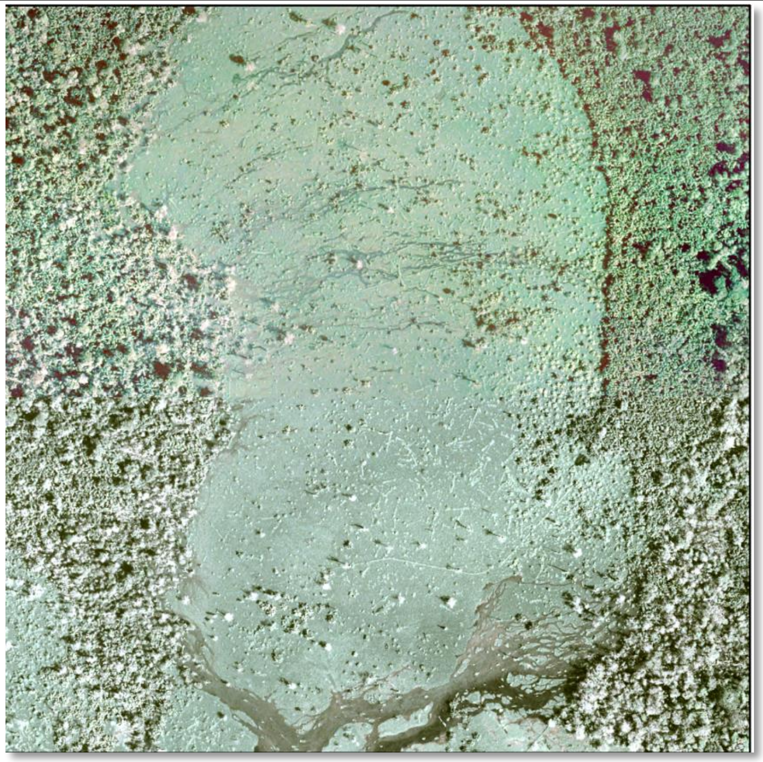
Table showing examples of visual interpretation of the main classes used in the land use /land cover classification.

Classification classes[1]	Thematic description
Agroforestry Land areas covered by forest patches (below 0.5 ha) intertwined with secondary forest, pasture, and various crop fields (Gotz Schroth 2004).	
Bare soil[2] Land areas with exposed soil and agricultural land not being used at the time aerial photographs were taken	

Crops[2] Land areas covered by agricultural activities, small and large scale	
Forest Land areas "spanning more than 0.5 hectares with trees higher than 5 meters of more than 10 percent, or trees able to reach these thresholds *in situ*" (FAO 2010). Mixed forest and natural palm forest included.	

Pasture Land area covered by grass and single trees	
Tree plantations Land areas covered by tree plantations	

Deforestation Land area cover characterized by clear cutting and traces of logging residue (Paine and Kiser 2012).	
Urban Land cover by cities, roads, and any human construction	

Wetlands Land areas covered by marshes, swamps, and ponds.	

[1]clouds, no data, shadows, river bank, and water classes not included in the table
[2]class outlined in red

APPENDIX B

Figure showing the land use/ land cover baseline map of ACLA-C for the year 2005.