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Land use change in four landscapes in the Peruvian Amazon

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1 Introduction

This paper analyzes temporal changes in land cover composition in four multi-village landscapes dominated by smallholder agriculture in the Peruvian Amazon. The objective of this study was to use Earth Observation data and remote sensing methods to characterize and compare historical patterns of land cover change at these locations between 1987 and 2017. The research was part of a broader project examining migration patterns and their impact on forests and forest livelihoods in Peru, and therefore this land cover change analysis will be used with other data gathered on migration and related socioeconomic characteristics of residents in selected village sites to understand the connection between changes in forest cover and demographic and socioeconomic changes.

In this report, we briefly summarize the overarching project and the rationale for this particular study. We then introduce the methodology used to define landscape sites and to analyze land use at these sites. The core of this paper will present the results of that analysis to highlight key observations and patterns. After the Results section, we discuss comparisons between these landscapes and implications of the patterns observed. The last section of the paper offers our conclusions.

2 Background

In response to expanding deforestation in the Amazon, the Peruvian government committed to stopping deforestation of primary forest within its territory by 2021 (MINAM 2016). In recent decades, deforestation in Peru has averaged approximately 125,300 ha per year, peaking in 2014 with an estimated loss of 177,586 ha of forest cover, and with total forest loss estimated at 2,130,122 ha between 2001 and 2017 (MINAM n.d.). Effecting these deforestation trends will depend on having a better understanding of deforestation patterns and the behavior underlying them.

Deforestation in Peru is the result of a complex interplay of factors, including infrastructural development, policy incentives for land occupation and rural production along with demographic changes and migration patterns (Ravikumar et al. 2017). Much debate has focused on the influence of smallholder migrants and swidden agriculture (Watters 1971; Dourojeanni 1987; Brack Egg 1997), but such narratives oversimplify local dynamics (Porro et al. 2015; Ravikumar et al. 2017; Bennett et al. 2018; Menton and Cronkleton 2019). While the influx of migrants to the Amazon is a factor contributing to deforestation, push and pull factors such as policies and road construction underlie these demographic shifts (Limachi et al. 2006). In fact, multiple authors have emphasized the tendency of road construction to facilitate land invasion and subsequently deforestation (Rudel and Roper 1997; Mäki et al. 2001; Alvarez and Naughton-Treves 2003; Dourojeanni 2006; Southworth et al. 2011). In Ucayali, recent deforestation hotspots have been concentrated along roads and linked to oil palm plantations (Finer and Mamani 2018). Because patterns of deforestation associated with demographic changes, policy and infrastructural development vary widely across the Peruvian Amazon, a more nuanced understanding is needed to link deforestation to localized behavior to better inform policymaking.

This paper reports results from a study that used remote sensing techniques to create a time series of classified images of forested landscapes in the central Peruvian Amazon. The landscapes analyzed are defined as discrete zones around groups of contiguous villages roughly approximating areas of influence of residents of these smallholder communities. By fusing Landsat multispectral data with radar data, we were able to distinguish different land cover classes such as closed-canopy forest, secondary forest, oil palm and agricultural land. These classifications enabled us to quantify changes in the landscape over time.

3 Study areas

This study examines four multi-village landscapes in the Peruvian Amazon to observe and compare local patterns of land use change over time within and between each of these landscapes. The landscapes were purposefully selected to only include areas occupied by smallholder farmers, avoiding locations dominated by large enterprises or absentee owners, and to represent both remote areas accessible only by river and more accessible areas near roads with better transportation infrastructure.[1] Each landscape consisted of four villages, located in close proximity to each another. In all cases and prior to including a site, the project team received consent from community leaders to facilitate field visits and resident interviews during other phases of the study. To denominate the four landscapes, we used either the names of the local district or watershed where the villages are located. These sites were: 1) the Tournavista landscape, 2) the Neshuya landscape, 3) the Abujao landscape and 4) the Pisqui landscape. To ensure anonymity, we will not name the specific villages that participated in the project. The goal of this analysis was to examine local patterns of land use near the villages in each landscape. Since the Peruvian government does not define administrative boundaries around rural villages, we defined a 5 km radius from a central point in each village as a buffer, with the four combined buffer zones forming the landscape. The 5 km buffer provided a consistent guide for defining landscapes and avoided bias in the selection of areas for comparison. The buffers are assumed to cover a large portion of lands managed by village residents and so served as proxies for each village's areas of influence. However, because the distances between villages and their configuration varied in each landscape, some buffer zones overlapped while others were dispersed and had noncontinuous buffers. As a result, the size of landscapes varied (Figure 1).

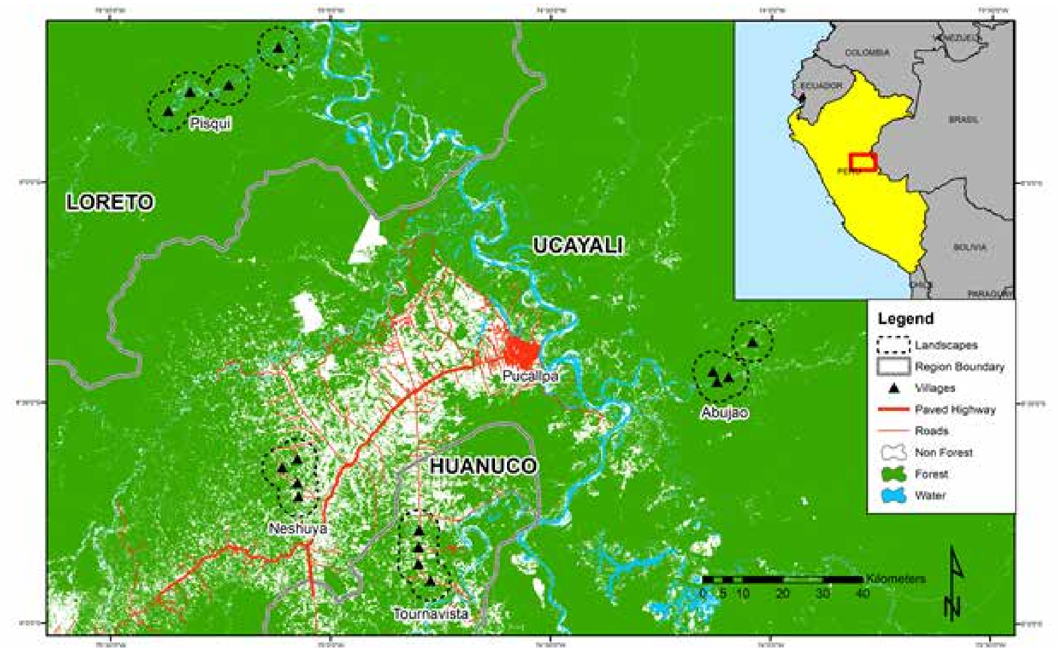

Figure 1. Study area. The four multi-village landscapes in Ucayali, Loreto and Huánuco.

1 Two of the landscapes include villages where our project partner, the German Cooperation, implemented by GIZ, through its ProAmbiente programme, had worked previously (Neshuya and Pisqui).

Table 1. Size of the buffer zones used for the four landscapes considered in the analysis.

Landscape	Area (ha)
Tournavista	21,045
Neshuya	19,8145
Abujao	21,060
Pisqui	30,058

3.1 Landscape descriptions

Tournavista landscape: The selected villages in this landscape are situated along the road stretching between the settlement of Campoverde on the Federico Basadre Highway (officially PE-18C) south to the town of Tournavista. The landscape is located in the Honoria and Tournavista Districts of the Puerto Inca Province. It is named Tournavista due to its proximity to the town with the same name. The road was first opened by a company called LeTourneau after it received a concession for nearly 400,000 ha from the government in 1954 (Eidt 1962) to settle colonists. Later, the government reallocated much of the area to a large parastatal enterprise to produce cattle. During the Fujimori presidency in the 1990s, this enterprise was privatized. According to key informants, the company that purchased that land did not occupy all of the area, which appeared unused and was targeted for settlement by families looking for land to homestead. Some of the original settlers were employees of the company and claimed that managers had encouraged them to settle the land to better control areas along the road. Later, more settlers arrived and formed new communities. For more than a decade, the private company has attempted to dislodge the settlers and reclaim land but so far has been unsuccessful. Due to overlapping claims, it has been difficult for settlers in these villages to acquire formal land title.

Neshuya landscape: This landscape is located in the district with the same name within Ucayali's Padre Abad Province. It includes secondary roads extending north from the Federico Basadre Highway at kilometer 72, west of the regional capital Pucallpa. The first settlements in this landscape began in the early 1980s. At that time, employees from a timber company working in the area decided to stay in the forest after the logging season ended to set up homesteads and cultivate coca. Subsequently, they invited family and friends to accompany them and the villages began to grow. The timber company attempted to expel these families, but was unsuccessful. Reportedly, this was a period of violent unrest so there was little state presence in the area, which allowed the communities to expand. In the 1990s, drug eradication initiatives entered the region and the government introduced crop substitution programs to end coca production. These programs improved roads and introduced incentives for commercial crops such as cacao. The last of the four villages settled in this landscape was formed during this period to take advantage of these incentives.

Abujao landscape: This landscape is located about 50 km east of the Ucayali capital Pucallpa, within the watershed of the Abujao River. The Abujao River is a tributary of the Ucayali River within the Calleria District of Coronel Portillo Province. The Abujao River and its tributary the Shesha River provide the main access to the four villages in this landscape. The area has a long history of settlement dating from the 19th century rubber boom and earlier, with villages shifting with the shifting course of the rivers. Among current residents, the oldest arrived in 1959 with the current villages being formally founded in the 1970s and 1980s. Due to rural violence caused by armed conflicts between guerilla groups and the military during the mid-1980s and mid-1990s, the rural population fled to urban centers and some villages were completely depopulated. Only in the past 10 to 15 years have families returned to their homesteads along with a growing population of new arrivals.

Pisqui landscape: This landscape is located approximately 100 km northwest of Pucallpa just over the regional boundary between the Ucayali and Loreto Regions in the Contamana District of Loreto's

Ucayali Province. The landscape's name comes from the Pisqui River that constitutes the primary access to the four communities. Village residents are from the Shipibo indigenous group. Three of the communities were originally recognized by the government in the 1950s and were granted communal titles in the 1970s. The government recognized the remaining community in 1991 but its title is pending. Unlike the villages in the other three landscapes (which are composed mostly of mestizo families with individual parcels), the Shipibo communities received communal titles over their lands. However, residents farm small individual plots around the villages.

4 Methods

4.1 Input data

This analysis used 39 Earth Observation data scenes from the satellites of Landsat 5, 7 and 8 with pixel values representing ground reflectance at the 2.0 level of processing (Table 2, Appendix A). The Landsat program offers satellite data for free and available images allowed analysis over three decades, a duration sufficient to track patterns of land cover change. The Landsat data ensured inputs with consistent spatial resolution and radiometric characteristics across the entire time series. Landsat's 30 m spatial resolution is suitable for classifying land cover and tracking change in land cover over time. In addition, its 16-day temporal resolution facilitated the selection of images with suitable cloud cover and atmospheric conditions to allow for classification.

Downloaded data were used to build mosaics at two- or three-year intervals between 1987 and 2017. The images were selected to correspond with the dry season (August–September) for each target year to ensure good quality information unobscured by cloud cover or atmospheric interference. The high cloud cover over the study area did not permit the building of annual mosaics due to the lack of suitable images. For each reference year, the best quality images coming from the same year or the immediately previous or following year were downloaded. Data from more than one year were needed to ensure the derivation of a cloud-free mosaic covering the entire study area.

In addition, our analysis used radar data from the Advanced Land Observing Satellite (ALOS) housing the Phased Array type L-band Synthetic Aperture Radar (PALSAR) owned by the Japanese Aerospace Exploration Agency for the years the data were available: 2017, 2015, 2010 and 2007 (see Table 2). ALOS-PALSAR provides back-scatter data that can improve the discrimination between different land covers, especially oil palm plantations and forests (Gutiérrez-Vélez and DeFries 2013). Two images of PALSAR data were acquired for each year, for eight images in total. The 2007 PALSAR data were applied to the image from 2005, the year that oil palm started expanding significantly, to enhance the distinction between oil palm and other vegetative covers. This set an accurate baseline for oil palm that year to improve the quality of the temporal filter. Since PALSAR data were available for 2010 and 2015, there was no need to include a different year's PALSAR data for 2013 since the temporal filter corrected most inaccuracies that year.

Additional data used included an elevation band derived from a digital elevation model (Shuttle Radar Topography Mission, SRTM) (NASA JPL 2013) and a wetland map from NASA's Distributed Active Archive Center for Biogeochemical Dynamics (Hess et al. 2015). The wetland map represents wetland extent, vegetation type and dual-season flooding state of the entire lowland Amazon basin. The two data files improved the discrimination of land cover types by classifying areas by their suitability for cultivation. For example, oil palm is unlikely to be cultivated in flooded areas because it does not to grow well in such areas. See Table 2 for data used in each year.

Table 2. Data used in image classification.

Year of Image	Landsat	ALOS-PALSAR	Additional Data
2017	Landsat 8	2017	SRTM/Wetland
2015	Landsat 8	2015	SRTM/Wetland
2013	Landsat 8	N/A	SRTM/Wetland
2010	Landsat 5	2010	SRTM/Wetland
2007	Landsat 5	2007	SRTM/Wetland
2005	Landsat 5	2007	SRTM/Wetland
2002	Landsat 5	N/A	SRTM/Wetland
2000	Landsat 5	N/A	SRTM/Wetland
1997	Landsat 5	N/A	SRTM/Wetland
1995	Landsat 5	N/A	SRTM/Wetland
1993	Landsat 5	N/A	SRTM/Wetland
1991	Landsat 5	N/A	SRTM/Wetland
1987	Landsat 5	N/A	SRTM/Wetland

The 2015 image classification algorithm was calibrated using 677 training polygons drawn to represent the 15 most salient land cover types observed at the selected resolution: young oil palm, adolescent oil palm, mature oil palm, secondary forest, closed-canopy forest, flooded forest, lake, river, algae, urban, bare ground, sandbanks, pasture, old burn scars and recent burn scars. The training polygons were defined through visual interpretation of typical land cover types using high-resolution imagery from Google Earth and by interpreting false-color composites from Landsat bands of the normalized images to infer distinct land covers. False composites display the electromagnetic response of different features in the landscape in different regions of the electromagnetic spectrum as semi-transparencies in red, green and blue colors. This causes certain features to become more apparent in the landscape and therefore facilitates the discrimination between land cover classes. For example, burn scars become very obvious visually when certain segments of infrared radiation are set to display as red.

4.2 Data pre-processing

The radiometric normalization of the input Landsat scenes used for the analysis ensured a radiometrically consistent signal for any given land cover type throughout a given time period by attenuating any spectral differences caused by factors such as atmospheric composition and sun illumination geometry. (Differing light and atmospheric circumstances can result in satellite sensors recording different values for equal land covers unless corrected by radiometric normalization.)
The radiometric consistency of the land cover mosaics built for every reference year allowed for the application of the Random Forest algorithm (Breiman 2001) calibrated in 2015 to the classification of land covers in all years considered in this analysis.

4.3 Land cover classification

The Random Forest classification algorithm was used to classify land cover (Breiman 2001).
Random Forest is an ensemble machine learning algorithm that builds multiple decision trees for data classification. Each decision tree produces successive nodes that divide the data into subgroups that best discriminate the membership of pixels to each one of the categories to be classified. The threshold for the subdivision of pixels in each node is produced based on the best value among a randomly selected subset of input variables that maximizes the purity of the resulting subgroups in terms of class membership. Each subgroup is successively subdivided into smaller subgroups until a given change in purity with respect to the previous node is achieved. Random Forest builds several decision trees and

assigns to each pixel the class classified for the majority of the trees. Random Forest has been used successfully for land cover classification in the study region (Gutiérrez-Vélez and DeFries 2013).

The data supplied to the algorithm consisted of five reflectance bands from the Landsat satellites. We did not include band 1 from Landsat 8 because that layer is not available for previous missions. We also used the Horizontal-Horizontal (HH) and Horizontal-Vertical (HV) bands from ALOS-PALSAR and the Normalized Difference Vegetation Index (NDVI), calculated from the Landsat data. NDVI provides a measure of variations of vegetation greenness, or vegetation health.

After classification, the 15 original classes collected with the training data described above were merged into six final classes: oil palm, secondary forest, closed-canopy forest, agricultural land, water and unvegetated land (see Table 3 for more detail).

Table 3. Land cover classification.

Original classification	Classification after merging
Young oil palm	Oil palm
Adolescent oil palm	
Mature oil palm	
Secondary forest	Secondary forest
Closed-canopy forest	Closed-canopy forest
Flooded forest	
Lake	Water
River	
Algae	
Urban	Unvegetated
Bare ground	
Sandbanks	
Pasture	Agricultural land
Old burn scars	
New burn scars	

The combined classes provided sufficient accuracy to discriminate between land cover types.

- **Closed-canopy forest** refers to flooded and unflooded forests with a closed-canopy. In addition, this category may include areas that could be classified as ‘secondary forest’ using other measures. For example, forests have regrown sufficiently to be indistinguishable spectrally and texturally from closed-canopy forest. Therefore, areas classified as primary forests in a given year might include some that were formerly classified as secondary forest, even though there could be important ecological differences.
- **Secondary forest** refers to all tree-dominated areas where crowns do no not form a closed-canopy. These include deforested patches undergoing initial stages of regrowth, agricultural fallows or areas recently or periodically subjected to selective logging, fires, flooding or other disturbances. Riverine floodplain forests and most agroforestry systems including tree-dominated home gardens and shaded perennial cultivations such as cacao are also expected to be classified as secondary forests. One exception is oil palm, which is classified as an independent class, as it is distinguishable with radar data.
- **Agricultural land** includes areas of pastures or annual crops and those with recent and old burn scars. Most burnings in the study area occurred in pasture areas that quickly reverted into the previous pasture condition.
- **Unvegetated land** includes bare ground, urban areas and sand banks.
- **Oil palm** corresponds to the combination of young, adolescent and adult oil palm.

4.4 Data post-processing

Two post-classification filters were applied to the images to reduce the incidence of misclassified pixels. A majority filter was applied that compares each pixel's land cover classification with the classification of neighboring pixels in a 3×3 pixel window. The pixel's value is converted to the value of the majority of the eight surrounding pixels if the pixel under consideration has a different value. This was useful for eliminating the 'salt and pepper' effect that is common in classification maps derived from remote sensing. In addition, a temporal filter was applied to each image that converted pixels whose classification implied an impossible transition. For example, if a pixel was classified as agriculture in 2013, but as forest in 2010 and 2015, then the 2013 pixel was reclassified as forest.

4.5 Land cover time series

We calculated land cover areas in each landscape per year by counting the number of pixels in each land cover class. Each pixel represents an area of 900 m^2. We used the extract function from the raster library written for the R programming environment (R Core Team 2017) to calculate surface area in each class. Once this calculation was completed for each year in the time series, we compared temporal changes in the proportion of each land cover type in the villages.

4.6 Accuracy assessment

The accuracy of the resulting land cover maps was calculated by comparing the land cover classification calibrated for 2015 using the Random Forest algorithm with that of other years. This process used a classified map for 2010 as the test year based on validation polygons collected in 2010 to ground-truth land cover classifications (Gutiérrez-Vélez et al. 2011). Classified pixels in the 2015 map were compared with the same land cover in the validation polygons; if they matched, the classified pixel was considered 'true' and if not it was considered a false detection. True and false detections were used to calculate overall user's accuracy (i.e. how accurately the map compares with the field) and producer's accuracy (i.e. how accurately the field appears on the map).

The accuracy assessment judged the capacity of the maps to quantify trends in land cover change. The overall accuracy of the image was good but did improve with the addition of PALSAR data. The image with PALSAR data had an accuracy level of 91.4%, while without PALSAR data the overall accuracy fell to 89.7%. The inclusion of PALSAR data mostly improved the accuracy in the classification of secondary forests. Pixels within the oil palm and secondary forest polygons were the land cover types with the lowest accuracy when using Landsat data only. Secondary forest suffered the most without PALSAR data, with its producer's accuracy dropping 14%. Oil palm dropped by approximately 1% (Figure 2). Given these accuracy assessment results, there is a high level of confidence in the depiction of land cover across the time series considered in this study.

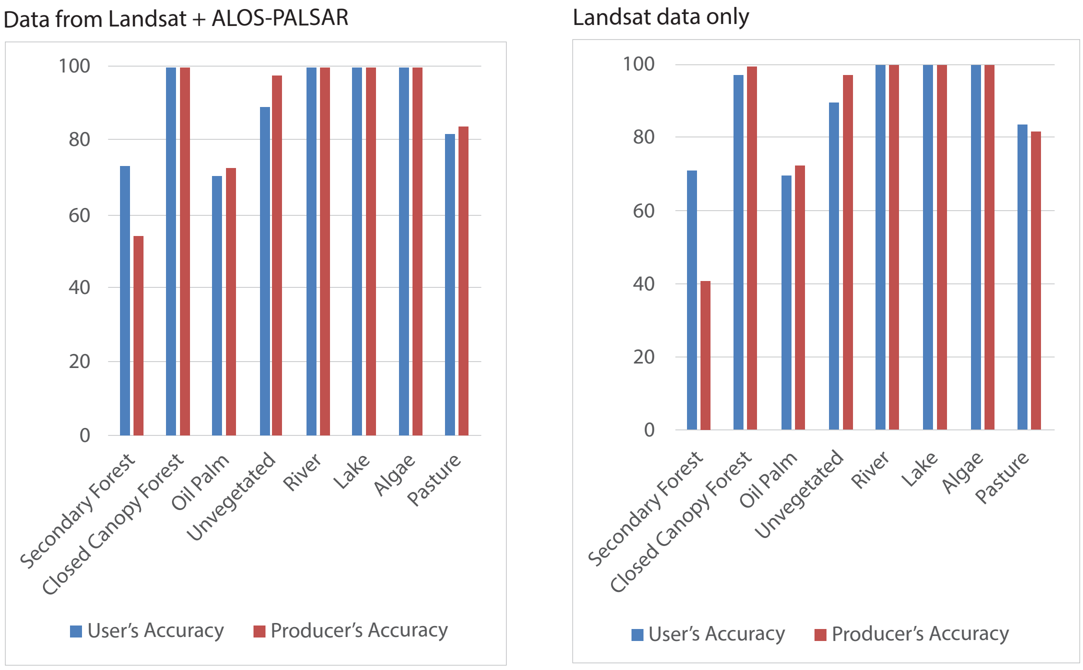

Figure 2. User's and producer's accuracy for 2010 validations using both Landsat and ALOS-PALSAR data (left) and Landsat data only (right).

5 Results

In this section we describe observed land cover changes in each landscape during the study period.

5.1 Tournavista

The Tournavista landscape covers an area of 21,045 ha. At the start of the study period, this landscape had already undergone significant forest loss. In general, the landscape was relatively stable during the 1990s. However, starting in 2002, the area experienced significant forest loss as agricultural lands and secondary forest expanded.

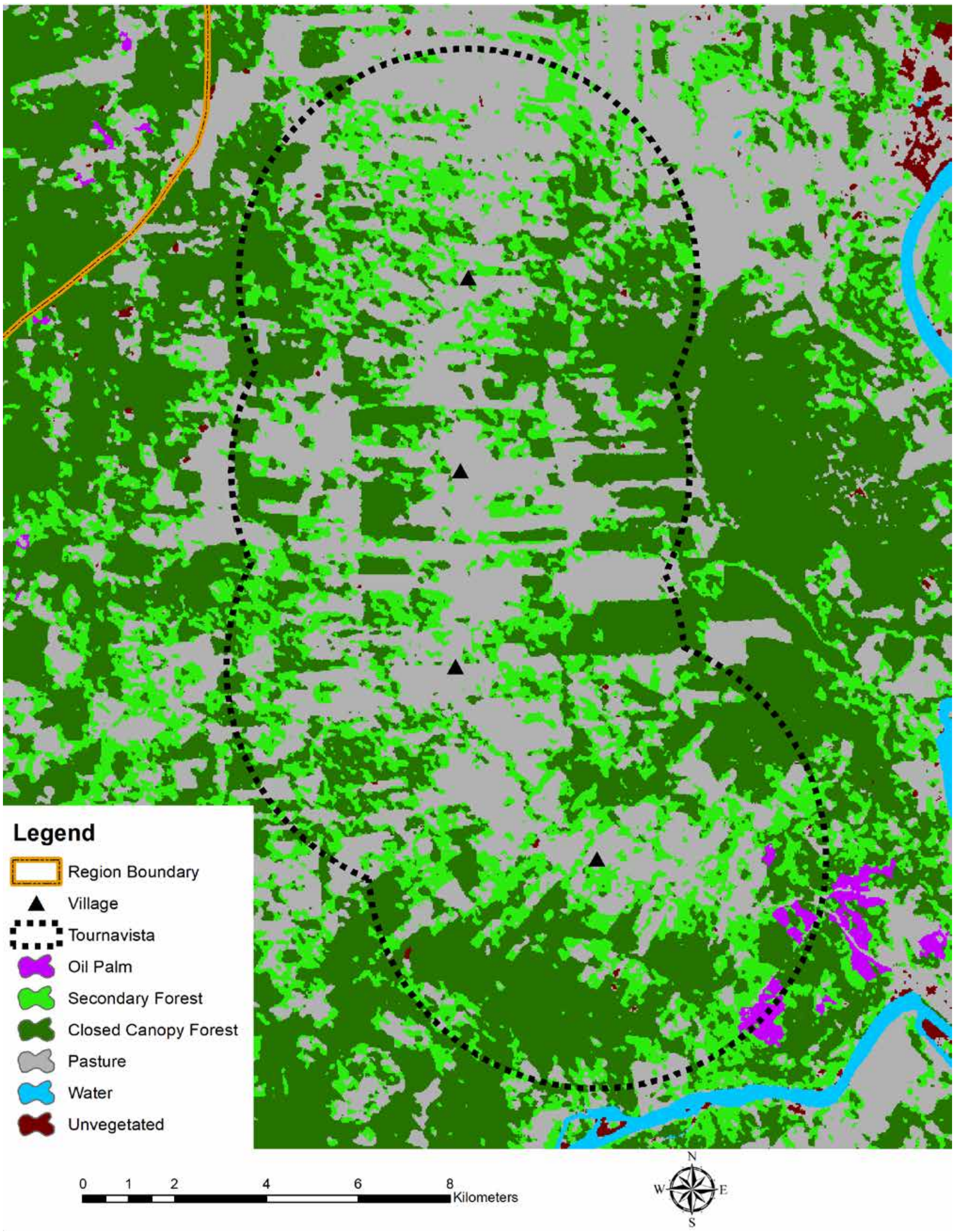

Figure 3. Tournavista landscape

Closed-canopy forest cover reduced substantially during the study period, from 11,065 ha (53% of the landscape) in 1987 to 7651 ha (36% of the landscape) by 2017 (Figure 4). The loss of closed-canopy forest was not a linear process. Although there was an initial drop in forest area between 1987 and 1991, closed-

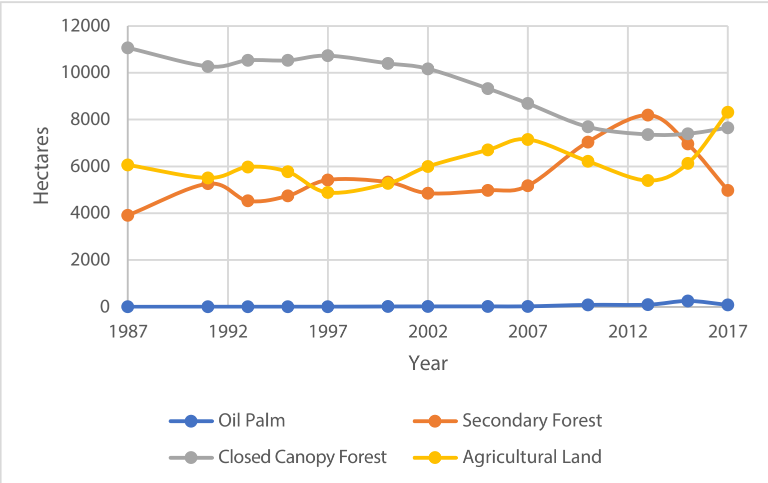

Figure 4. Land cover change in Tournavista.

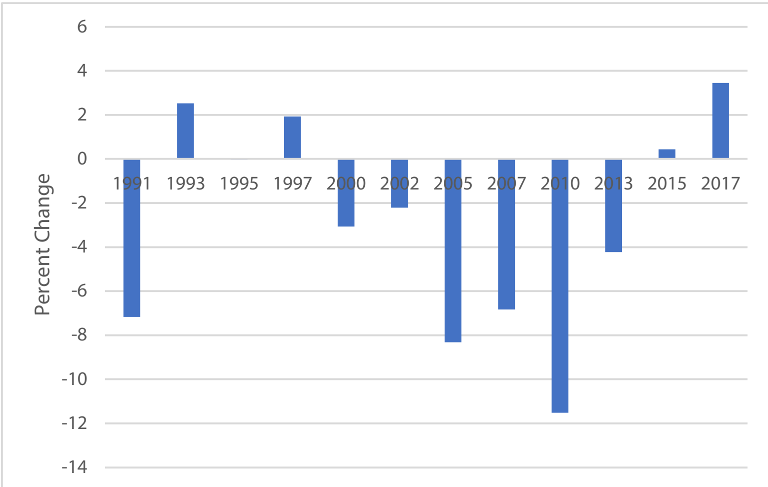

Figure 5. Percent change on previous year in closed-canopy forest cover, Tournavista.

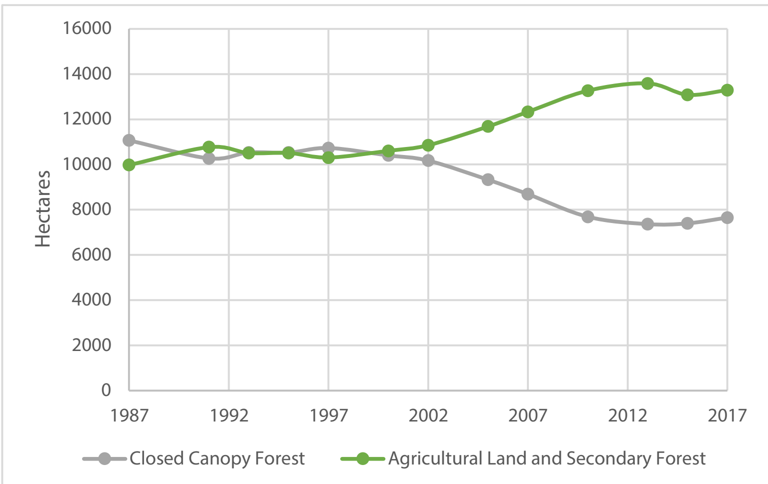

Figure 6. Closed-canopy forest versus agricultural land and secondary forest combined, Tournavista.

canopy forest cover remained relatively stable between 1991 and 2002. After 2002, however, there was a sharp decrease in closed-canopy forest cover until 2013. In this period, the forest area dropped from 10,171 ha to 7363 ha, representing a 27.6% decrease. Figure 5 illustrates how the intervals with greatest percentage loss of closed-canopy forest were between 2002 and 2013. In 2017, at the end of the period analyzed, there was a small increase in closed-canopy forest cover, breaking with the decade-long trend of loss.

Agriculture was the second most common land use at the start of the study period, covering 6064 ha, or 29% of the Tournavista landscape in 1987. After a slight decline in 1997, when agriculture dropped to its lowest point (23% of the landscape), agricultural land surged across the landscape up to 7154 ha in 2007, followed by a decline until 2013, before then surging back up to 8313 ha by 2017, to become the predominant land cover that year (covering approximately 40% of the landscape).

Secondary forest initially covered 3913 ha in 1987, or 19% of the landscape. From 1991 until 2007, secondary forest cover oscillated around 5000 ha (Figure 4). However, after that point, secondary

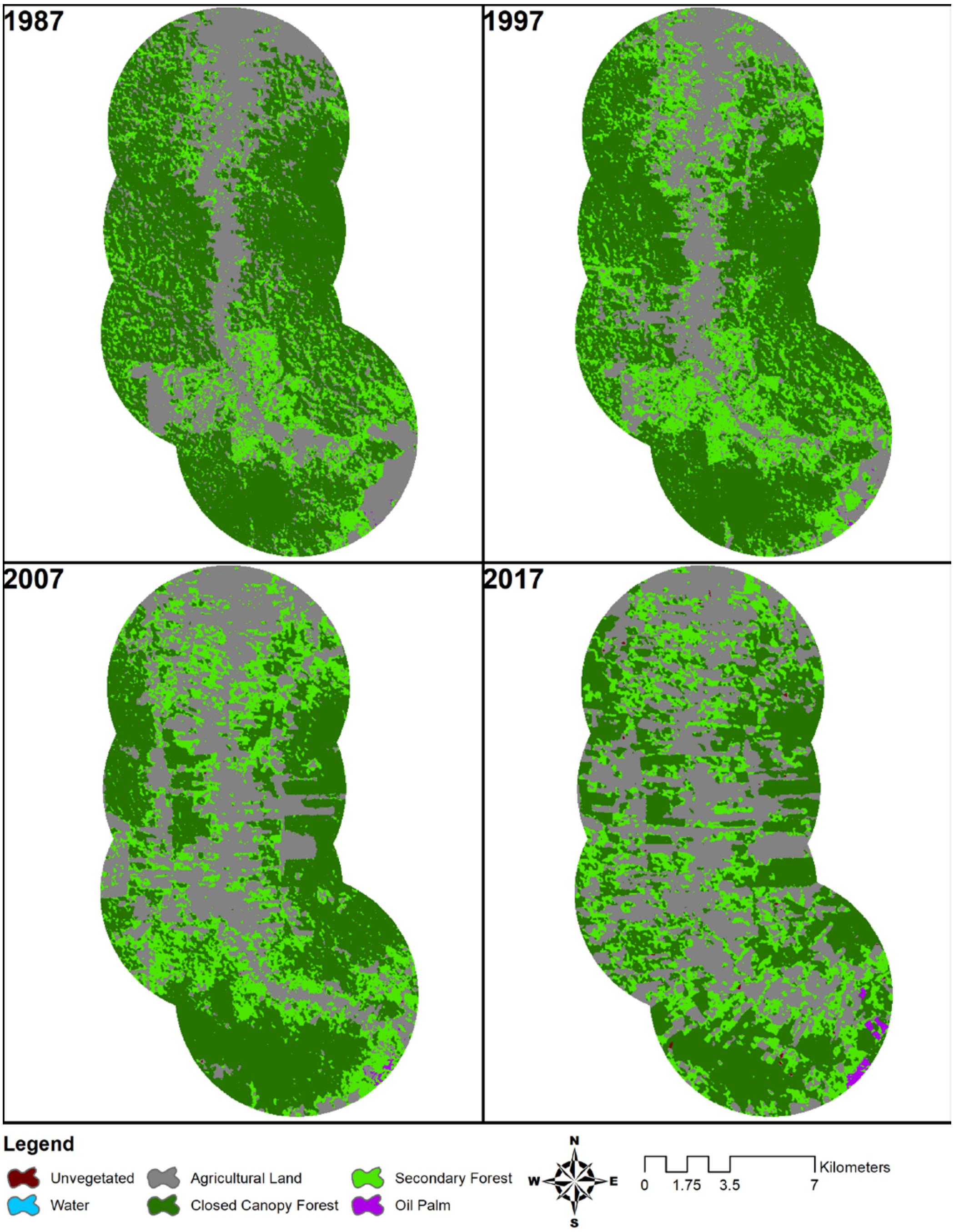

Figure 7. Tournavista landscape change. Top left: 1987; Top right: 1997; Bottom left: 2007; Bottom right: 2017.

forest rapidly expanded to 8192 ha by 2013 to become the most common land use, covering 39% of the landscape. After 2017, the area of secondary forest dropped back to 4976 ha.

Combining agricultural land and secondary forest, we observe that the cumulative area changed from 9977 ha in 1987 to 13,290 ha in 2017, going from 47% to 63% of the total landscape area at the end of the time period. However, this transition did not take place over the entire period. From 1987 through to 2000, land use was relatively stable in the landscape. Secondary forest and agricultural land oscillated in gains and losses, each mirroring the other (Figure 4). This suggests that swidden agriculture was occurring on land previously claimed for this purpose, with little to no expansion deeper into closed-canopy forest, which varied little during this period. However, the surge in agricultural land use from 2000 through to 2007 accompanied the most rapid loss of closed-canopy forest, while the expansion of agricultural land from 2013 accompanied the loss of recently gained secondary forest. This is apparent when the combined effects of secondary and agricultural land are compared with closed-canopy (Figure 6). The two trends were relatively stable until 2000, when closed-canopy forest cover was reduced and the combined classes increased until 2013 when the two trends stabilized again.

Oil palm constituted a marginal class in Tournavista during the entire time series. It never expanded beyond a peak of 85 ha or 0.04% of the landscape in 2010. (See Figure 7 for a visualization of land cover change over time.)

5.2 Neshuya

The Neshuya landscape covers 19,814 ha. This landscape did not show much variation or intervention in land cover at the start of the study period. However, Neshuya later experienced major change due to the loss of closed-canopy forest, which was apparently displaced by agricultural expansion.

Agricultural land cover stood at 492 ha in 1987, just under 3% of the landscape area. However, after 1991, agricultural expansion accelerated. In 1993, agricultural land cover had almost tripled to cover an area of 1345 ha, and by 2015, agricultural land cover reached 6495 ha, representing 33% of the Neshuya landscape (Figure 9).

Secondary forest stood at only 477 ha at the start of the study period, but exhibited continuous growth over the time series from 1991 through 2015, when it reached a maximum extent of 3593 ha or 18% of the area. The growth of secondary forest then plateaued until 2015, before falling to 2691 ha in 2017.

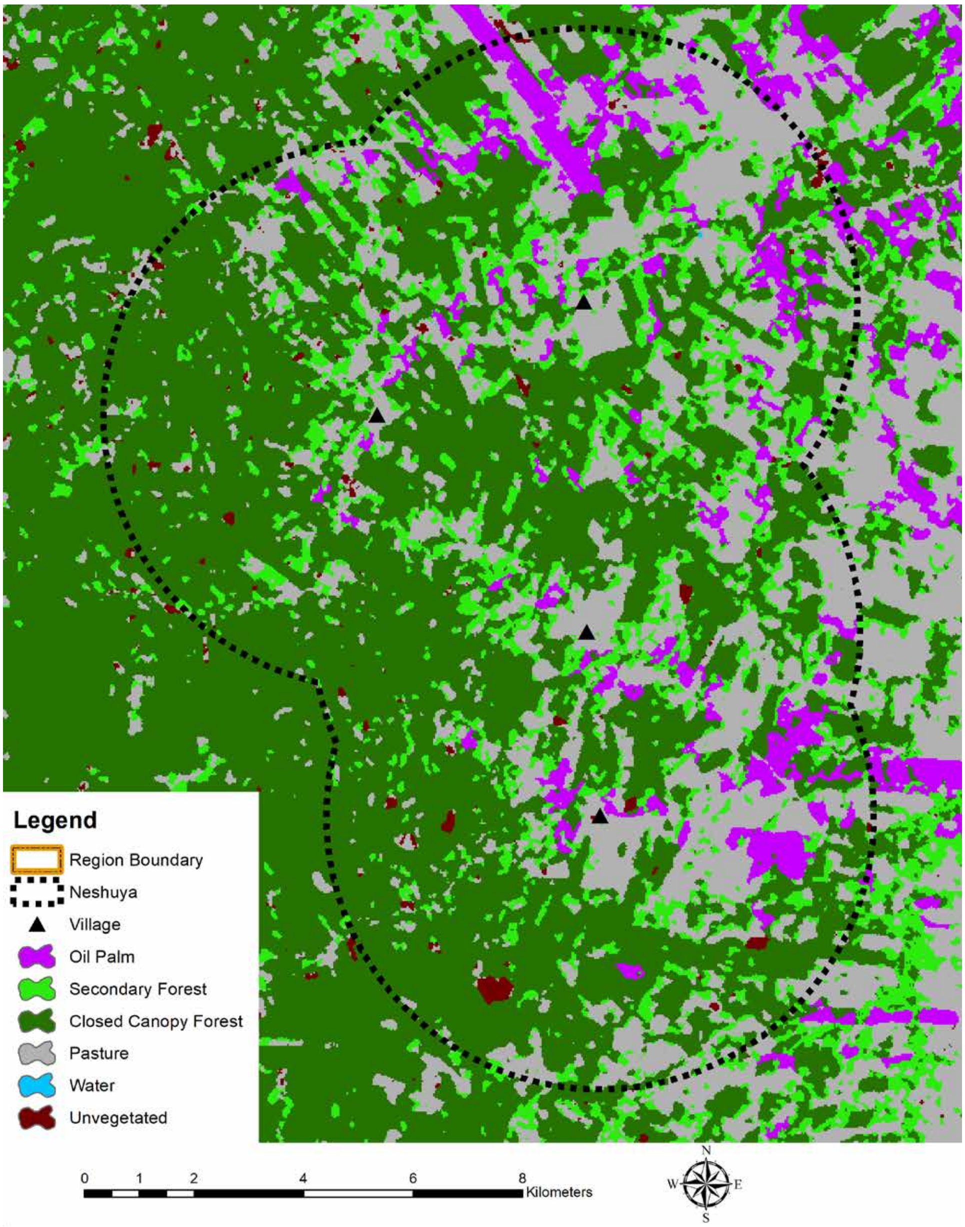

Figure 8. Neshuya landscape.

The cyclical pattern of increasing and decreasing agricultural land and secondary forest observed in Tournavista was not present here. Agricultural land cover was greater than secondary forest cover throughout the time series. Both classes had approximately the same area in 1987 and 1993. The two classes expanded until 2015 at which point their growth reached its maximum.

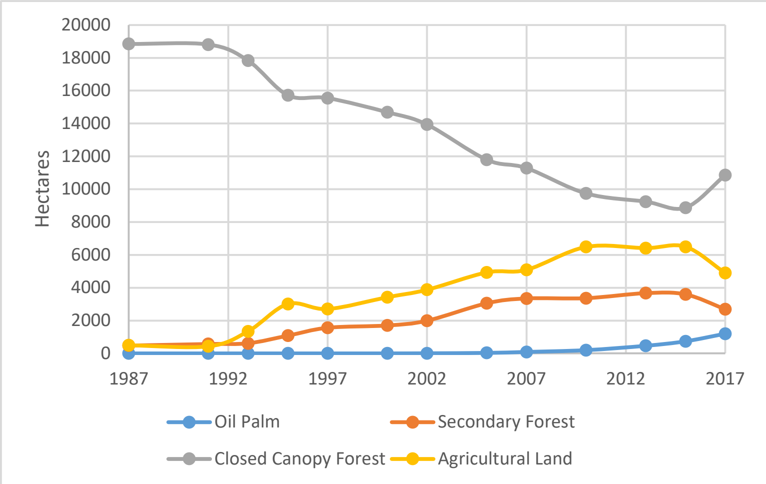

Figure 9. Land cover change in Neshuya

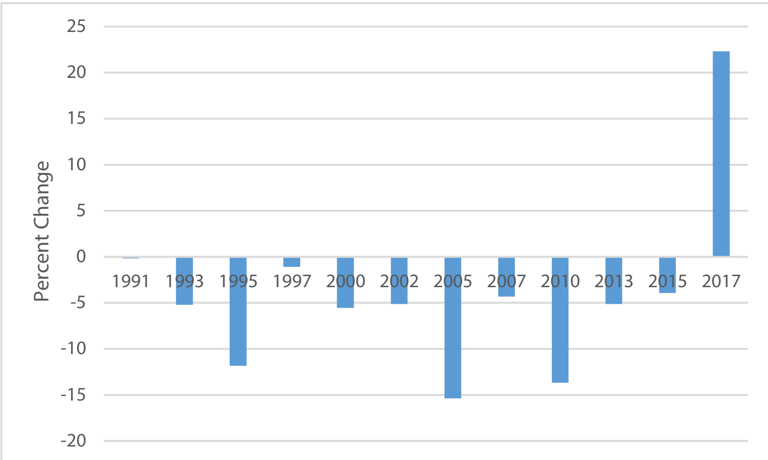

Figure 10. Percent change on previous year in closed-canopy forest cover in Neshuya.

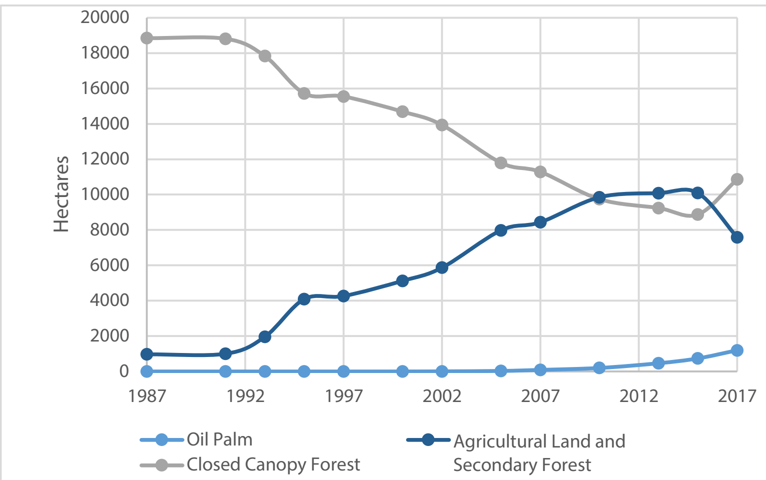

Figure 11. Closed-canopy forest versus agricultural land and secondary combined, and oil palm; Neshuya

Closed-canopy forest initially covered 18,844 ha (95% of the total landscape) in 1987. While this forest cover was relatively stable until 1991, it dropped precipitously to only 8878 ha in 2015, representing a drop of 52.8% from 1991. In 2017, for the first time in the period studied, closed-canopy forest experienced some recovery, expanding back to 10,860 ha, an increase from 2015 levels. Figure 10 illustrates that, with the exception of one interval in the mid-1990s, the intervals with the greatest forest loss occurred between 2002 and 2010.

By combining agricultural and secondary forest land cover types, it is apparent the expansion of these land uses closely mirrors the loss of closed-canopy forests in the Neshuya landscape (Figure 10). Together, agricultural land and secondary forest covered only 5% of the landscape in 1987. By 2015, these classes covered 51% of the landscape, with agricultural land cover at 6495 ha and secondary forest at 3593 ha. The same year, closed-canopy forests covered only 44% of the area. In 2017, the combined agriculture–

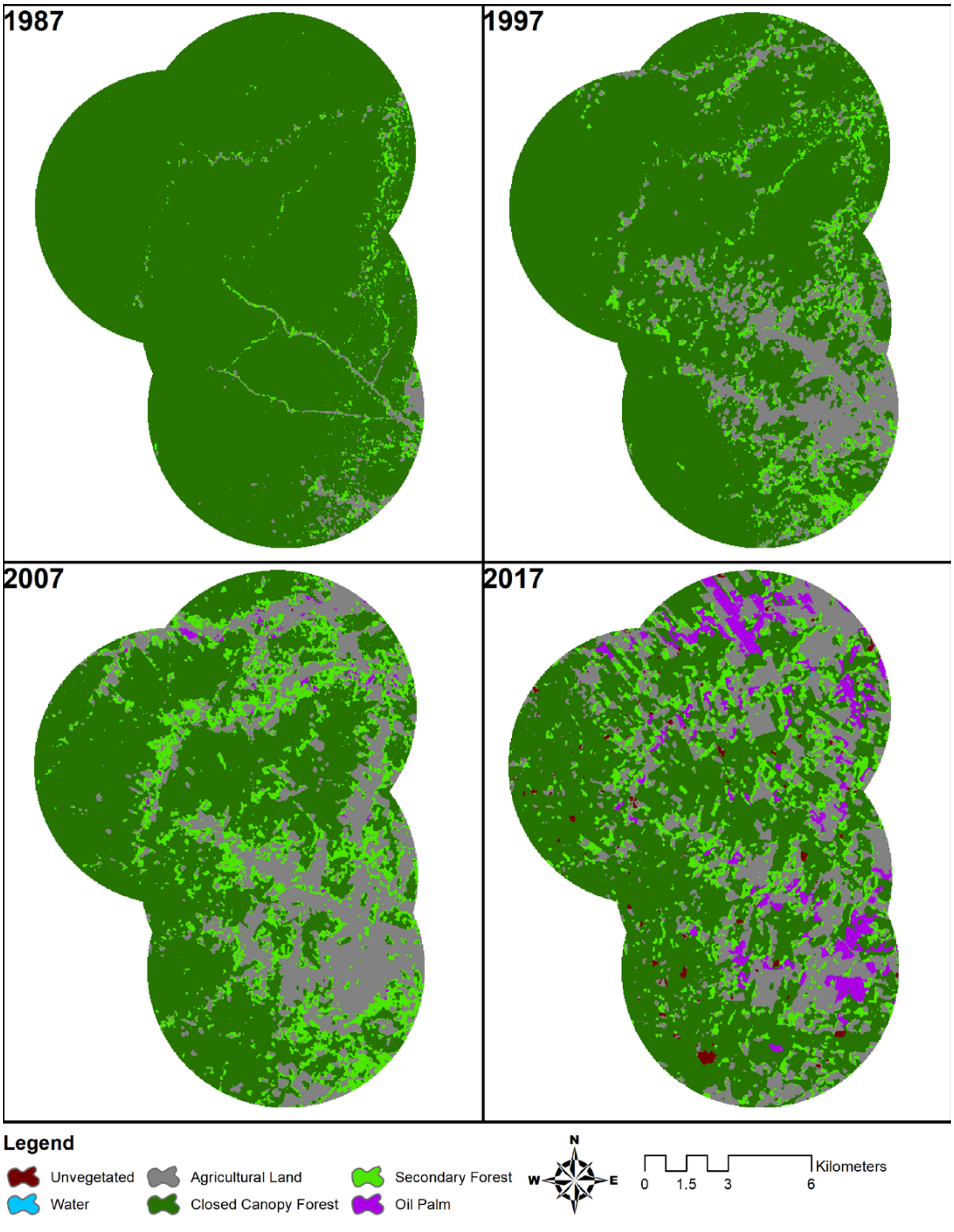

Figure 12. Neshuya landscape change. Top left: 1987; Top right: 1997; Bottom left: 2007; Bottom right: 2017.

secondary forest class had fallen back to just 38% of the area, with agricultural land at 4897 ha, and secondary forest at 2691 ha. Closed-canopy forest, on the other hand, recovered its predominance in 2017, covering 55% of the landscape.

Unlike the other three landscapes, Neshuya exhibited a significant growth of oil palm. Oil palm was first observed in 2000 and covered just 1 ha. Subsequently, the area of oil palm nearly doubled each year observed after its appearance in the landscape. By 2017, oil palm covered 1200 ha. The emergence of oil palm corresponded with the maximum growth of agricultural land/secondary forest. (See Figure 12 for a visualization of land cover change over time.)

5.3 Abujao

The Abujao landscape covers 21,060 ha and had a high percentage of forest cover at the start of the study. This land cover was relatively stable throughout the study period. Indeed, unlike the first two landscapes, Abujao exhibited a modest trend of closed-canopy forest expansion over the course of the period studied. Initially, secondary forest also covered significant portion of the landscape, usually in floodplains flanking the main rivers. Results indicate secondary forest cover declined gradually over the course of the study. Agricultural land cover had a relatively small footprint and declined throughout the study period.

Closed-canopy forest comprised 72% of the landscape in 1987. Initially, closed-canopy forest cover fell during the first interval, measured at 15,194 ha in 1987 and 14,576 ha in 1991, the low point for this land use class during the study period. Closed-canopy forest had rebounded by 1993, and throughout the 1990s it remained relatively stable. After 2002, closed-canopy forests expanded every year through 2013, and reached the maximum extent in 2017, increasing to 17,741 ha or 84% of the landscape. Overall, closed-canopy forest grew over the time series, from 15,194 ha in 1987 to 17,741 ha in 2017 (see Figures 14 and 15).

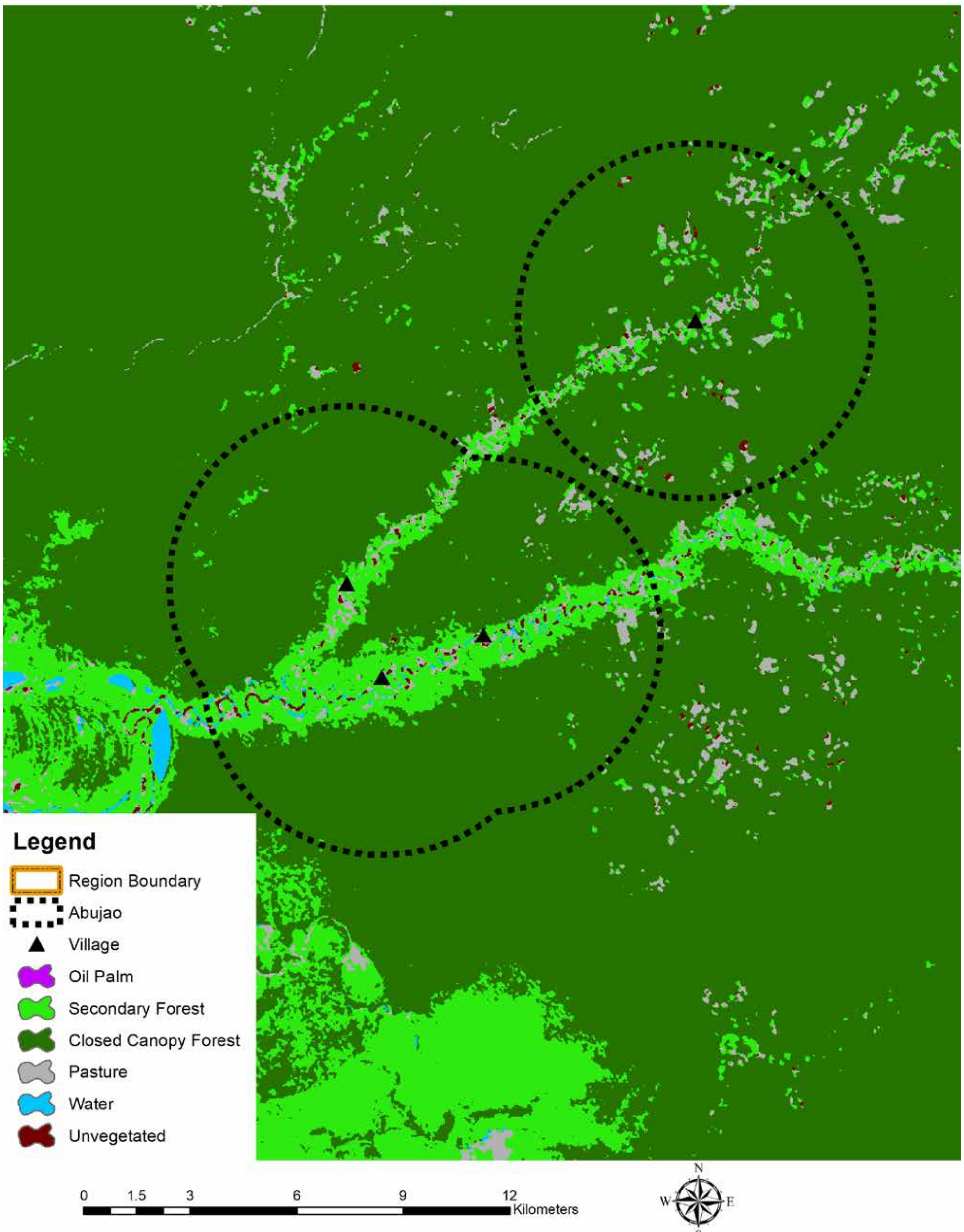

Figure 13. Abujao landscape.

Agricultural land cover was marginal throughout the period studied, averaging only 4% of the landscape and peaked early, in 1991 at 6%, covering an area of 1226 ha at that high point. Following that peak,

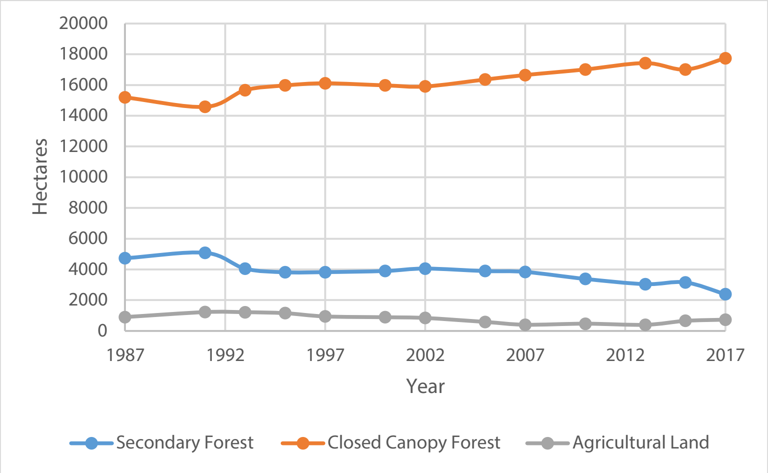

Figure 14. Land cover change in Abujao.

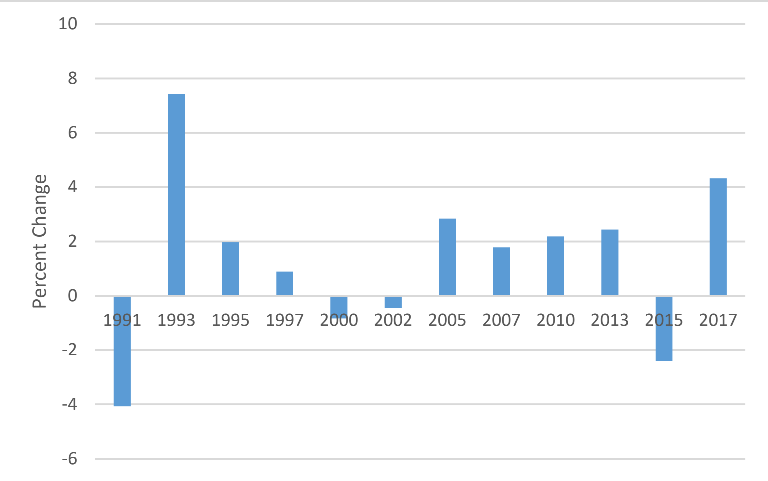

Figure 15. Percent change on previous year in closed-canopy forest cover in Abujao.

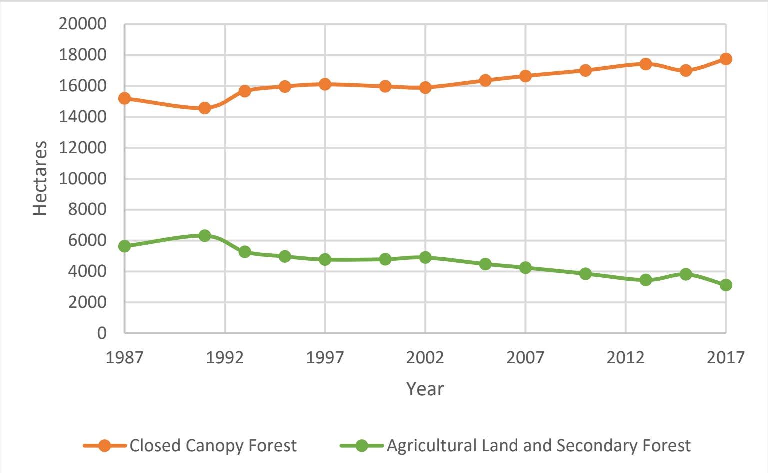

Figure 16. Closed-canopy forest versus agricultural land and secondary forest combined, Abujao.

agricultural land cover exhibited losses between 1993 and 2013, dropping to 399 ha. After 2013, agriculture land use started to experience a recovery with a slight positive trend expanding up to 733 ha in 2017 (Figure 14).

The trajectory of secondary forest mirrored that of closed-canopy forest, exhibiting a decrease throughout the time series. This negative correlation suggests an overall land cover pattern dominated by forest regrowth. Secondary forest initially increased from 4730 ha to 5084 ha during the period from 1987–1991. Subsequently, the trend was otherwise down across the time series, with the final observation at 2389 ha in 2017, approximately 11% of the area (Figure 14).

The combined effects of agricultural land and secondary forest do not differ significantly from secondary forest dynamics in this landscape (Figure 16) due to the relatively small areas covered by agriculture throughout the period studied. The combined classes stood at 5632 ha in 1987 and fell to 3123 ha in 2017. (See Figure 17 for a visualization of land cover change over time.)

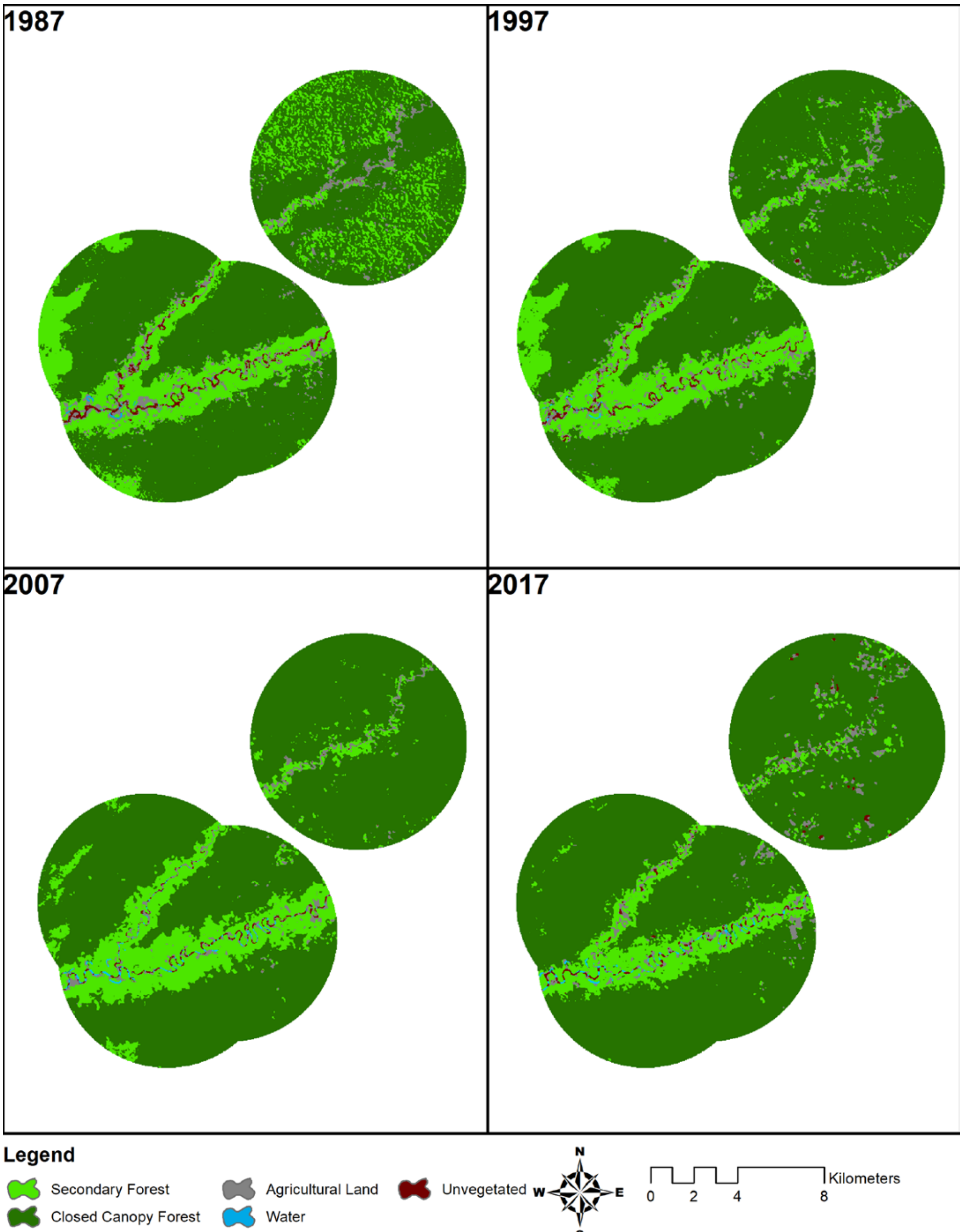

Figure 17. Abujao landscape change. Top left: 1987; Top right: 1997; Bottom left: 2007; Bottom right: 2017.

5.4 Pisqui

The 30,058 ha Pisqui landscape was dominated by a combination of closed-canopy forest and secondary forest throughout the period studied. Most of the secondary forest was concentrated on the broad floodplains flanking the Pisqui River. The footprint of agricultural land use was relatively small and remained stable throughout the study period.

In 1987, closed-canopy forest covered 15,834 ha, and secondary forest was 12,133 ha, representing 52.7% and 40.4% of the landscape, respectively. While the two land use classes oscillated throughout the time series, sometimes changing places, the pattern indicated relative stability. Closed-canopy forest averaged 49% of the landscape area, peaking at 54% in 2017, while the average secondary forest coverage was 44%, peaking at 49% in 2015.

Agricultural land cover initially stood at 645 ha in 1987 and only increased to 700 ha by 2017, averaging about 2% of the landscape area throughout the time series. Agricultural land use never rose above 4%

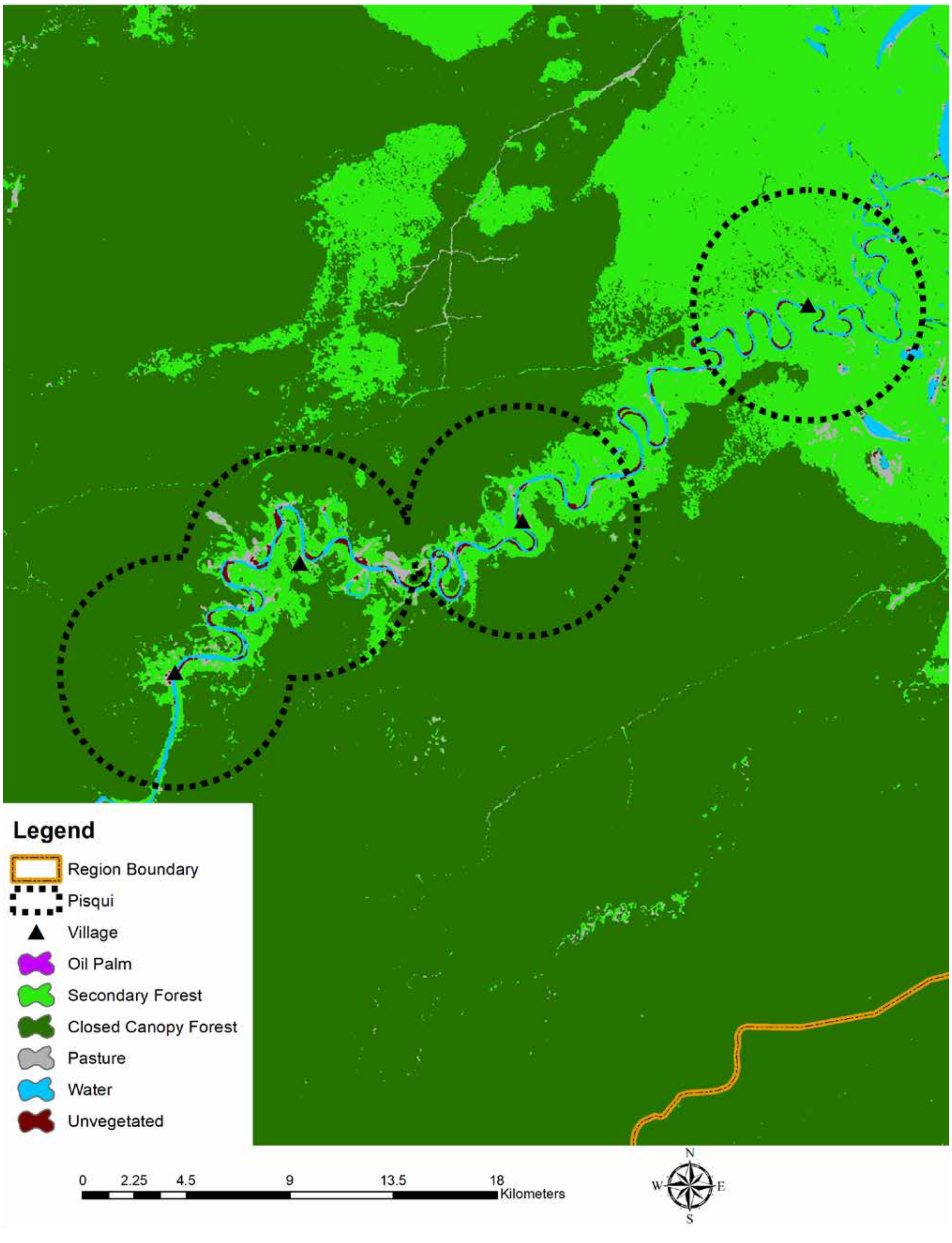

Figure 18. Pisqui landscape.

of the entire landscape area and only reached that level once, in 1995 (see Figures 19 and 20). Closed canopy forest was relatively stable over the entire time series, with minor fluctuations throughout. The only exception is the final year of observation that saw a 19% growth of closed canopy cover.

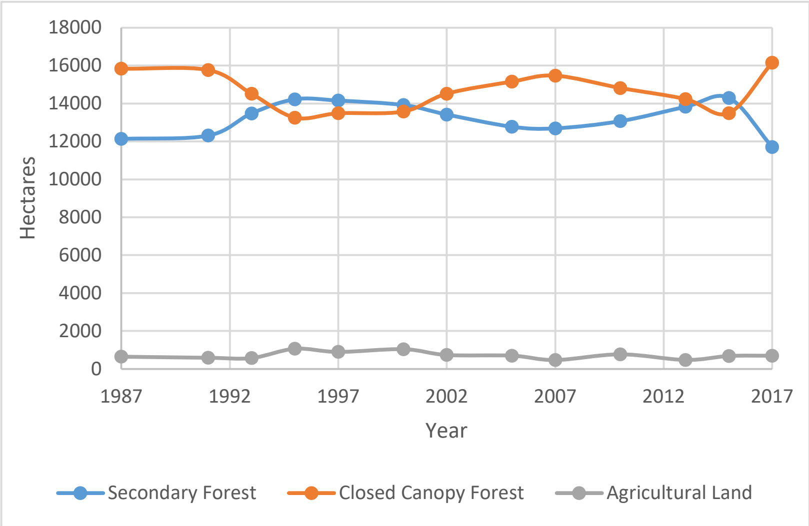

Figure 19. Land cover change in Pisqui.

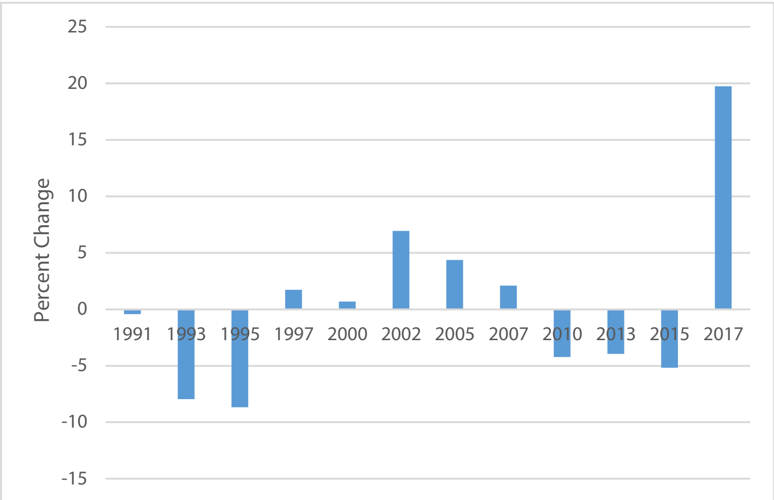

Figure 20. Percent closed-canopy forest change in Pisqui.

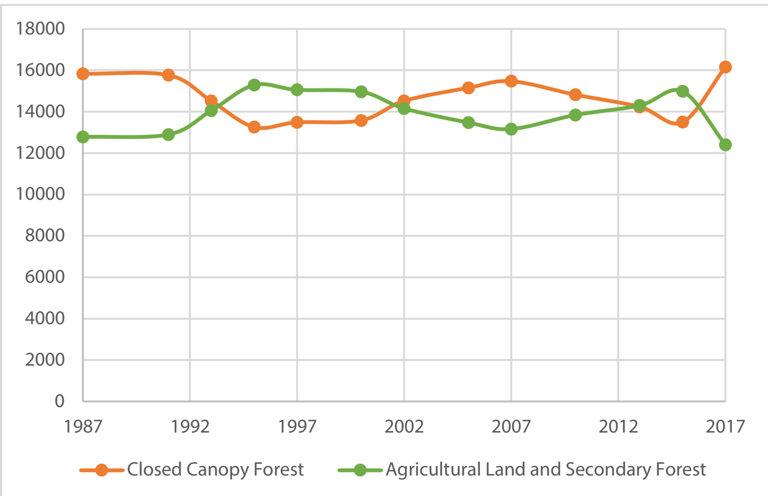

Figure 21. Closed-canopy forest versus agricultural land and secondary combined, Pisqui.

A cyclical pattern of closed-canopy forest gain and loss was coupled with secondary loss and gain across the entire time series in Pisqui. The combined effects of agricultural land and secondary forest do not differ significantly from secondary forest dynamics in this landscape (Figure 21). This is largely due to the relatively small areas covered by agricultural land use throughout the study period. (See Figure 22 for a visualization of land cover change over time.)

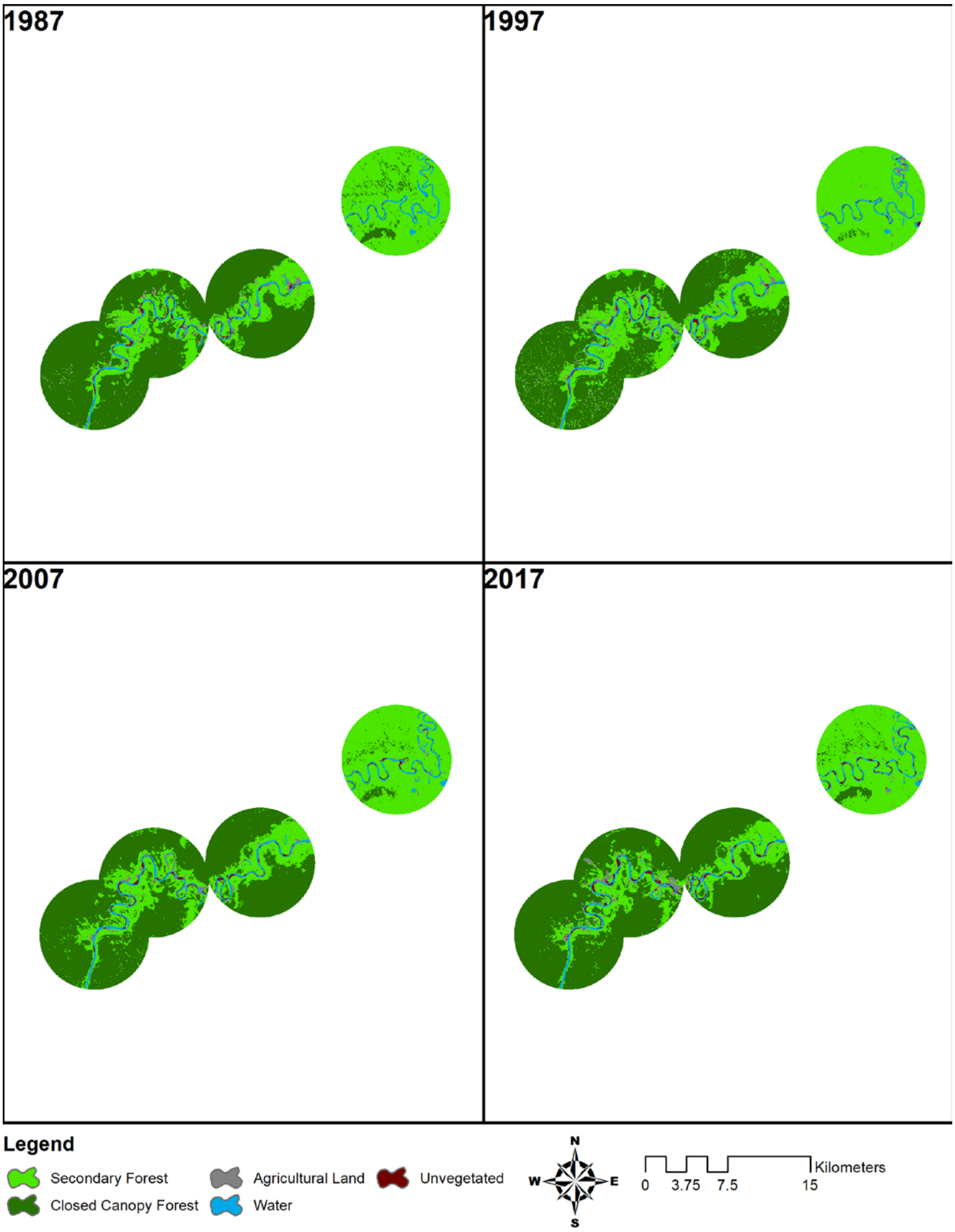

Figure 22. Pisqui landscape change. Top left: 1987; Top right: 1997; Bottom left: 2007; Bottom right: 2017.

6 Discussion

This research defined buffer zones around selected villages to demarcate finite landscapes that could be used to compare localized patterns of land use change. These landscapes served as proxies for the area of influence of settlements that share similar histories, ecological conditions and levels of governmental support and services. As such, the patterns of change observed in these landscapes should provide an additional foundation for analyzing and debating the factors that contribute to land use change and, more specifically, deforestation in the Amazon. There are several trends or patterns that are particularly noteworthy.

6.1 Clear variation in land cover change between accessible sites and inaccessible sites

The study was designed with purposefully selected smallholder landscapes that exhibited distinct realities in terms of access: less remote landscapes accessible by road (Tournavista and Neshuya), and remote landscapes accessible only by river (Abujao and Pisqui). As a result, it is not surprising that the observed patterns of land use change reflect this dichotomy. In general terms, land use in the accessible landscapes experienced more volatile anthropogenic change, while the inaccessible areas were more stable during the interval studies, with minimal anthropogenic impact.

There was greater deforestation in the accessible sites of Tournavista and Neshuya. While this pattern was apparent from the outset, this study allowed us to examine how this pattern unfolded. Both sites experienced dramatic losses of closed-canopy forest over the past two or three decades, although the pattern varied. In the 1980s, the Tournavista landscape was already heavily altered given the early history of road construction by large enterprises in the area. However, in Neshuya, initially the land cover pattern was very similar to the river sites with extensive tree cover. In fact, residents of one of the villages had actually entered the area via a tributary of the Aguaytía River, as other forms of access were difficult in the 1980s. In both of the accessible landscape sites, deforestation exhibited a fishbone-like pattern spreading from road networks, suggesting a strong link between accessibility and deforestation. Conversely, the inaccessible sites experienced relatively stable forest cover, both in terms of closed-canopy forest and secondary forest. In fact, our results are consistent with the narrative from Abujao residents who reported that the landscape had been largely abandoned during the violence of the 1990s. Analysis of the Landsat images indicated that agricultural land cleared at the outset of the study decreased after 1995 until 2015, while secondary forest transitioned into closed-canopy across the time series, resulting in a small expansion of closed-canopy forest classification.

6.2 Increased agricultural expansion in accessible sites compared with inaccessible sites

Agricultural expansion was a key factor in land use change in the two accessible landscapes. The agricultural land use class in Tournavista and Neshuya averaged 29% and 19%, respectively, of the landscape over the time series. In Tournavista, agriculture was always present, never going below 23% and increasing to as much as 40% of the landscape. However, in Neshuya, agricultural land was almost absent at the start, covering only 2% initially before increasing to 33% of the landscape in 2015. Conversely, agricultural land was relatively stable at both river sites across the time series, with relatively small fluctuations from year to year, averaging 4% in the Abujao and 2% in the Pisqui landscapes. These minor fluctuations had no significant impact on the dynamics of either landscape. This suggests that the agriculture at these sites is predominantly small-scale swidden, largely for subsistence. Furthermore, fields tended to be concentrated along rivers, utilizing floodplains for cultivation after flooding events. It is apparent, that the fluctuations in closed-canopy and secondary forest observed at the Pisqui and the Abujao sites are not driven by expanding agricultural practices.

6.3 Secondary forest variation between riverine sites and road sites

Secondary and closed-canopy forests dominated the landscapes of riverine sites and were not greatly affected by land use change associated with agriculture. Secondary forest cover in Pisqui oscillated with closed-canopy forest. This pattern may be due to riparian dynamics in the floodplains of these sites. In the Abujao landscape, following abandonment during the 1990s, most agricultural land transitioned into secondary forests and some secondary fallows matured to a closed-canopy state.

In the accessible landscapes, the expansion of secondary forest and the oscillation in the area they covered suggests swidden fallows cycles that expanded into closed-canopy forest. The Tournavista site in particular exhibited a clear trend in anthropogenic secondary forest expansion. Agricultural land first expanded at the expense of closed-canopy forest, which was then followed by an expansion of secondary forest as agricultural land cover declined, before a final surge of agricultural land. This strongly suggests that closed-canopy forest was converted into swidden agriculture, but that this transitional process likely has ceased in Tournavista as swidden has focused on clearing secondary forest lands.

Closed-canopy forest was lost to secondary forest and agricultural land in Neshuya, suggesting that swidden practices replaced closed-canopy there. However, similarly to Tournavista, this transition appears to have possibly run its course. A new regime of land use practices may be emerging there with a shift to perennial agroforestry crops such as cacao; however, more study is needed to understand this new reality.

6.4 Closed-canopy forest recovery in the final year of study

It remains unclear whether there is a general explanation for the expansion of closed-canopy forest cover across the landscapes in 2017 compared with that found for 2015. In Abujao, there may be some transition of secondary forest to closed-canopy forest via successional processes. In Pisqui, this is likely the result of riparian dynamics. In Neshuya, where this expansion was most dramatic, this may be due to the maturing agroforestry systems classified as closed-canopy forest. Informants reported increased income from crops such as cacao, which may have lowered the incentive to clear land for swidden agriculture. This topic merits further study.

Future work must engage with smallholders to better understand how the introduction of perennial crops is influencing their land use decisions and production strategies.

7 Conclusion

This paper examined trends in land use change within four multi-village landscapes near Pucallpa, Peru: *Tournavista, Neshuya, Abujao* and *Pisqui*. The landscapes were purposefully selected to include areas of smallholder family farms that represented two extremes in terms of access: landscapes with accessible villages in areas with developed road networks and landscapes with remote villages in areas primarily accessed by river. Each landscape was defined by demarcating a 5 km buffer around the center of each village. Observations were made at two- or three-year intervals between 1987 and 2017, using Landsat images that were analyzed to classify the land cover into six categories: closed-canopy forest, secondary forest, agriculture, oil palm, water and unvegetated areas. Changes in land cover within the four landscapes were calculated across the time series.

Closed-canopy forest loss was observed across the time series in two road-accessible landscapes, Neshuya and Tournavista. However, in the river-accessible landscapes, Abujao and Pisqui, closed-canopy forest was notably stable over time. This contrast supports other research showing that forest loss is closely associated with the development of road infrastructure.

Decreases in closed-canopy forest over time in Neshuya and Tournavista ran parallel with increases in agricultural land cover and secondary forest in these landscapes. This suggests that agricultural expansion was prompting forest change and was likely related to improved infrastructure and other market conditions driving commercial agriculture. It may also be due to greater population density as roads opened up these landscapes for settlement.

Proximity to infrastructure that improves access such as roads is apparently a key driver of forest loss. Improved access creates opportunities for commercial agriculture and facilitates the influx of migrants and increased population density that contribute to changes in forest cover. Our studies of the drivers of deforestation should focus on the multiple factors influencing how and where infrastructure expands, as well as the policy and governance contexts that create conditions for infrastructural expansion. Such analysis could better inform conservation and development policies by considering the broader context in which land use change occurs.

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Appendix A. Datasets used in the analysis

Year	Path/Row	Landsat Scene Identifier	Acquisition Date	Cloud Cover (%)
2017	06/066	LC08006066_20170722	7/22/2017	
	07/066	LC08007066_20171001	10/01/2017	
	07/065	LC08007065_20170729	7/29/2017	
2015	06/066	LC08006066_20150818	8/18/2015	1.41
	07/066	LC08007066_20140822	8/22/2014	6.24
	07/065	LC08007065_20140907	9/7/2014	1.26
2013	06/066	LC08007066_20140907	9/7/2014	7.39
	07/066	LC08007065_20130819	8/19/2013	3.49
	07/065	LC08006066_20130727	7/27/2013	0.22
2010	06/066	LT05006066_20100516	5/16/2010	1
	07/066	LT05007066_20110814	8/14/2011	14
	07/065	LT05007065_20101014	10/14/2010	5
2007	06/066	LT05007066_20070702	7/2/2007	23
	07/066	LT05007065_20060528	5/28/2006	8
	07/065	LT0006066_20060825	8/25/2006	0
2005	06/066	LT05006066_20040803	8/3/2004	0
	07/066	LT05007066_20050829	8/29/2005	8
	07/065	LT05007065_20050728	7/28/2005	5
2002	06/066	LT05007066_20010802	8/2/2001	6
	07/066	LT05007065_20010802	8/2/2001	5
	07/065	LT05006066_20030716	7/16/2003	0
2000	06/066	LT05006066_20000707	7/7/2000	
	07/066	LT05007066_20000831	8/31/2000	
	07/065	LT05007065_20000831	8/31/2000	
1997	06/066	LT05007066_19970908	9/8/1997	10
	07/066	LT05007065_19980522	5/22/1998	7
	07/065	LT05006066_19980718	7/18/1998	1

Continued to next page

Continued

1995	06/066	LT05006066_19961016	10/16/1996	3
	07/066	LT05007066_19950919	9/19/1995	7
	07/065	LT05007065_19950919	9/19/1995	0
1993	06/066	LT05006066_19931008	10/8/1993	9
	07/066	LT05007065_19930711	7/11/1993	2
	07/065	LT05006066_19931008	10/8/1993	0
1991	06/066	LT05006066_19910816	8/16/1991	23
	07/066	LT05007066_19910807	8/7/1991	7
	07/065	LT05007065_19910807	8/7/1991	0
1987	06/066	LT05006066_19880722	7/22/1988	0
	07/066	LT05007066_19880729	7/29/1988	4
	07/065	LT05007065_19870812	8/12/1987	0
1985	06/066	LT05006066_19850714	7/14/1985	0
	07/066	LT05007066_19861113	11/13/1986	1
	07/065	LT05007065_19850806	8/6/1985	5

ALOS-PALSAR
Acquired from the Japanese Aerospace Exploration Agency (JAXA)
Accessed 8 May 2015. https://www.eorc.jaxa.jp/ALOS/en/index.htm
§ SAR processing algorithm: Sigma-SAR IMAGE (for strip processing) and Sigma-SAR MOSAIC (for mosaicking)
§ Data format: binary image file + header file
§ Resolution: approx. 25 m (original product)
Resampled to 30 m
Lee filter applied to reduce speckle effect
§ HH and HV bands
§ Acquired for all years available during study: 2017, 2015, 2010, 2007

SRTM
Acquired from USGS Earth Explorer
Accessed 8 May 2015. https://earthexplorer.usgs.gov/

Wetland Layer
Acquired from NASA's Distributed Active Archive Center for Biogeochemical Dynamics
Accessed from: https://daac.ornl.gov/LBA/guides/LC07_Amazon_Wetlands.html
Hess LL, Melack JM, Affonso AG, Barbosa CCF, Gastil-Buhl M and Novo EMLM. 2015. LBA-ECO LC-07 Wetland Extent, Vegetation, and Inundation: Lowland Amazon Basin. Oak Ridge, Tennessee, USA: ORNL DAAC.. Accessed 8 May 2015. http://dx.doi.org/10.3334/ORNLDAAC/1284

Appendix B. Landscape data

Table B1. Tournavista (ha).

Class	1987	1991	1993	1995	1997	2000	2002	2005	2007	2010	2013	2015	2017
Oil Palm	2.88	5.94	6.03	7.38	8.19	17.55	19.98	22.05	23.13	85.32	93.69	252.45	84.33
Secondary Forest	3912.75	5260.77	4530.6	4740.57	5422.05	5330.43	4856.94	4975.11	5174.46	7043.49	8191.71	6956.73	4976.19
Closed Canopy Forest	11065.05	10271.52	10530.81	10527.21	10729.8	10401.21	10171.44	9325.89	8689.05	7688.16	7363.44	7396.2	7651.44
Agricultural Land	6063.93	5506.38	5977.17	5769.45	4884.57	5274.45	5995.08	6705	7153.92	6219.36	5394.69	6126.3	8312.85
Unvegetated	0	0	0	0	0	20.97	1.17	16.56	4.05	8.28	1.08	312.93	19.8

Table B2. Neshuya (ha).

Class	1987	1991	1993	1995	1997	2000	2002	2005	2007	2010	2013	2015	2017
Oil Palm	0	0	0	0	0	1.08	7.83	31.05	90	199.53	465.75	738	1199.52
Secondary Forest	476.64	572.13	616.95	1082.61	1561.5	1702.44	1992.69	3051.45	3346.92	3364.56	3670.56	3593.25	2691.45
Closed Canopy Forest	18844.11	18810.54	17830.44	15720.66	15547.59	14687.64	13935.78	11795.22	11284.65	9742.14	9242.46	8878.41	10860.21
Agricultural Land	492.3	430.38	1345.23	3009.78	2703.6	3421.8	3875.94	4932.45	5089.86	6485.13	6414.12	6494.67	4897.17
Water	0	0	0	0	0	0	0	0	0	0	0.27	0	0.9
Unvegetated	0	0	20.43	0	0.36	0.09	0.81	2.88	1.62	21.69	13.05	108.72	163.8

Table B3. Abujao (ha).

Class	1987	1991	1993	1995	1997	2000	2002	2005	2007	2010	2013	2015	2017
Secondary Forest	4730.31	5083.65	4053.78	3816.36	3824.73	3899.07	4056.48	3893.58	3838.68	3382.47	3043.8	3156.39	2389.41
Closed Canopy Forest	15194.34	14575.68	15659.37	15967.8	16109.28	15974.19	15902.73	16354.98	16646.4	17010.09	17424	17005.95	17740.8
Agricultural Land	901.8	1225.53	1218.87	1154.88	943.47	889.83	842.4	585.54	403.65	470.79	399.78	655.56	733.41
Water	20.52	27.45	33.66	25.65	19.26	29.25	42.75	37.26	66.87	64.62	118.08	130.68	59.94
Unvegetated	212.31	146.97	93.6	94.59	162.54	266.94	214.92	187.92	103.68	131.31	73.62	110.7	135.72

Table B4. Pisqui (ha).

Class	1987	1991	1993	1995	1997	2000	2002	2005	2007	2010	2013	2015	2017
Secondary Forest	12132.72	12306.78	13478.13	14221.26	14155.2	13919.04	13418.55	12773.61	12689.1	13067.91	13824.72	14296.5	11706.12
Closed Canopy Forest	15833.7	15764.58	14512.77	13254.93	13484.25	13576.5	14518.17	15152.31	15470.55	14818.32	14232.69	13495.68	16157.97
Agricultural Land	646.56	590.13	575.64	1065.24	898.56	1042.65	736.65	701.64	471.69	771.75	475.65	683.55	700.11
Water	1157.58	1054.26	1040.04	1106.1	1189.35	1040.67	1115.1	1193.85	1143.36	1186.56	1236.78	1366.83	1070.37
Unvegetated	285.93	340.74	449.91	408.96	329.13	477.63	268.02	235.08	281.79	206.01	286.65	213.93	421.92

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This working paper uses remote sensing data and methods to characterize land cover change in four sites in the lowland Peruvian Amazon over a period of three decades (1987-2017). Multi-village landscapes were purposefully selected to include road accessible sites and others only accessible by river. Landscape analysis focused on buffers around the selected villages used to approximate the areas of influence of farmers in these communities. Deforestation in the Peruvian Amazon has been commonly attributed to agriculture expansion by smallholders. This belief falls short in acknowledging that the contribution of smallholder deforestation is mediated by others decisions around infrastructure development. In this analysis, road connected landscapes experienced greater loss of closed-canopy forest while closed-canopy forest remained mostly stable in the river sites over the thirty year study period. Results indicated that closed-canopy forest loss occurred in parallel with agricultural expansion at the road sites. The findings contribute to a more nuanced understanding of local land use dynamics and the role of regional infrastructure development as a driver of forest loss.

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