Title

Beyond deforestation: Differences in long-term regrowth dynamics across land use regimes in southern Amazonia

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Abstract

The loss of tropical forests threatens a broad range of ecosystem services. Particularly, tropical deforestation is a major driver of biodiversity decline and substantial carbon emissions. Regrowth of secondary vegetation may help to restore habitat for many threatened species and improve ecosystem services that deteriorated due to deforestation. However, spatial-temporal patterns of regrowing secondary vegetation in the tropics remain weakly understood. We therefore analyze regrowth dynamics across two different land use systems in southern Amazonia: the extensive pastoralism in Pará and the capital-intensive agriculture in Mato Grosso. Both systems are connected by the BR-163 highway, which represents a major axis of deforestation and agricultural development in the Brazilian Amazon since decades. We used a 29 year time series of Landsat images to extract regrowth extent, duration, lag time between deforestation and regrowth, and frequency of regrowth cycles. Our results reached an overall accuracy of 89% and showed regrowth on up to 50% of the deforested area in Pará and a maximum of 25% in Mato Grosso. In both states, annual regrowth rates drastically dropped after 1996, which coincided with socio-economic transformations and drought events. The majority of regrowth was concentrated within 60m distance to forest edges and cleared again after an average of 5 years. Our approach bears great potential for mapping post deforestation regrowth dynamics within and beyond the Brazilian Amazon based on long-term and freely accessible remote sensing data collections, such as the Landsat and the forthcoming Sentinel-2 archives.

Keywords

Landsat, Time series, Secondary vegetation, Regrowth dynamics, Image compositing, Tropical forests

1. Introduction

Tropical forests exhibit the highest rates of forests converted to agricultural land globally (Hansen et al., 2013), rendering tropical deforestation one of the key processes driving climate change and global biodiversity loss (Lambin and Meyfroidt, 2011). At the same time, many tropical areas recover from initial forest removal (Grainger 2008) due to afforestation projects or abandonment of degraded lands (Silver et al., 2000; Aide and Grau, 2004). Furthermore, post deforestation land use systems in the tropics are often characterized by low land use intensity, due to unsuitable biophysical conditions and limited access to markets, finance, labor and machinery (Lambin et al., 2013). In such extensive land-use settings, regrowth is triggered by extended agricultural fallow periods or shifting cultivation (Fearnside, 2000). As a result, regrowth of secondary vegetation reached 10-22% of annual tropical deforestation rates in the 1990s and 2000s (FAO, 2000; Achard et al., 2002; Achard et al., 2010; Hansen et al., 2013) and provides essential ecosystem services, such as improved soil fertilization, water purification or soil erosion prevention (Aide and Grau, 2004; Cramer et al., 2008). So far, existing global estimates of secondary vegetation are restricted to secondary forests and give no indication on stand age which strongly limits biophysical interpretation (FAO, 2000; Achard et al., 2002; Achard et al., 2010; Hansen et al., 2013). Mapping secondary vegetation should therefore not rely on snapshots in time but include longer time periods, which would additionally allow to study the underlying regrowth process. The regrowth process not only depends on biophysical factors such as climate, soil type and seed availability, but is often influenced by the legacies of previous land use practices, which shaped local soil and water conditions (Zarin et al., 2001; Wandelli and Fearnside, 2015). Past and present land management determines regrowth duration, the lag time between deforestation and regrowth onset, the number of regrowth cycles in case of fallow periods and changes of spatial regrowth configuration over time. These attributes are essential to determine landscape structure (Batistella et al., 2003), to indicate local recovery potential (Zarin et al., 2001) and to differentiate active and fallow land use periods (Kuemmerle et al., 2013; Estel et al., 2015). Understanding such underlying drivers of regrowth is of major importance for evaluating past and

current land management and to balance ecosystem restoration on the one hand and land use intensification on the other hand.

One key area for monitoring regrowth dynamics are the deforestation frontiers in the Brazilian Amazon. Within the Brazilian Amazon, land use systems strongly differ between federal states, such as the extensive pasturelands in Pará and the intensively used agricultural lands in Mato Grosso (Coy and Klingler, 2014; Pacheco and Pocard-Chapuis, 2012). In both states, secondary vegetation plays a key role in land management as the federal law requires illegal deforested areas to be restored for improving soil fertility, carbon sequestration and biodiversity (Soares-Filho et al., 2014). A better understanding of regrowth processes can therefore aid in evaluating land management practices, strategies of law enforcement, and the influence of socio-economic development in this highly dynamic region.

Remote sensing plays a major role in characterizing secondary vegetation dynamics over large areas. Current datasets on the extent of secondary vegetation, like the Amazon-wide land use product TerraClass (INPE, 2015) or the global forest change dataset provided by Hansen et al. (2013), provide a good indication on the importance of secondary vegetation, but they do not capture its spatio-temporal regrowth dynamics over long time periods. With the opening of the Landsat archive, the longest record of consistent earth observation data became available free of charge (Wulder et al., 2008; Hansen and Loveland, 2012), which now allows for analyzing deep time series of Landsat data and long term regrowth processes. The challenge for time series analysis based on Landsat data involves reducing the effects of the atmosphere, topography, view angle and irregular image acquisitions with data gaps of months or even years (Song et al., 2001; Kovalskyy and Roy, 2013). Since atmospheric correction and cloud screening became operationalised (Masek et al., 2006; Zhu et al., 2012), compositing methods (Griffiths et al., 2013; Roy et al., 2014; White et al., 2014; Nelson and Steinwand, 2015) helped to overcome those challenges by creating equidistant cloud free time series on a seasonal or annual basis.

Several studies have demonstrated the potential of Landsat time series to describe various aspects of secondary vegetation dynamics in the tropics. Carreiras et al. (2014) employed three different mono-temporal classification approaches on three different study sites in the Brazilian Amazon to detect forest, secondary forest and non-forest areas based on near-annual Landsat time series from 1973 to 2011. In a post classification approach, regrowth duration and frequency of regrowth cycles was determined, but reliability of results suffered from the difference in classification methods between study sites. Rufin et al. (2015) used spectral-temporal metrics derived from intra-annual Landsat time series to describe trajectories of woody vegetation on pastures in the southern Pará, Brazil between 1984 and 2012. Schmidt et al. (2015) employed phenological breakpoint detection and trend analysis to detect regrowth of woody vegetation in a forest-savanna landscape in Australia between 2000 and 2012. DeVries et al. (2015) applied structural change monitoring to measure regrowth in forest systems of southern Peru between 1990 and 2013.

As Landsat time series are increasingly used to monitor regrowth of secondary vegetation, algorithms and concepts for extracting temporal regrowth characteristics are in continuous development. Kennedy et al. (2010) developed the regression based trend analysis “LandTrendR” for temperate forest systems but the underlying concept of gradual processes hampers applying this algorithm to fast and cyclic regrowth in agricultural systems across the tropics (Fearnside, 2000). Regarding fast regrowth processes, great advances have been made by optimizing the Breaks for Additive Season and Trend (BFAST) family of methods (Verbesselt et al., 2010; Verbesselt et al., 2012) for the use in tropical forest systems. This largely data driven approach integrates the decomposition of time series into trend, seasonal, and remaining components. While the approach is most promising for intra-annual time series, it requires a high observation density through e.g. the combined use of Landsat and MODIS imagery (Schmidt et al., 2015) or careful re-calibration towards data gaps (DeVries et al., 2015). It has also not been designed to detect long term regrowth processes (DeVries et al., 2015). For annual time series, parsimonious procedures are needed to extract complex dynamics of tropical regrowth characteristics without requiring additional intra-annual observations. In this context,

knowledge based approaches, for instance decision trees as employed by Hansen et al. (2013), or spectral-temporal thresholding provide great opportunities for regrowth characterization as such methods can be specifically tuned to regional characteristics of vegetation succession. Moreover, spectral-temporal thresholding is highly intuitive and the transparency of the method greatly supports the interpretation of mapping results and facilitates cross study comparisons.

Building up on a previous long-term deforestation study by Müller et al. (2016) we used Landsat data coupled with a threshold-based regrowth detection approach to monitor secondary vegetation and regrowth dynamics in two different land use systems: the extensive pastoralism in Pará and the capital-intensive agriculture in Mato Grosso. The study areas follows the BR-163 highway, which crosses the entire Southern Amazon from Cuiabá in Mato Grosso to Santarém in Pará and represents a major axis driving deforestation and agricultural development in Brazil since decades (Fearnside, 2007). From a land systems perspective, the BR-163 region covers a gradient of socio- economic development, which is exemplarily for the majority of states in the Brazilian Amazon. In this context, we address the following research questions:

- What are the annual rates and spatial patterns of secondary vegetation establishment along the BR-163 highway?
- How do regrowth extent, duration, frequency of regrowth cycles and lag times vary between Mato Grosso and Pará?

2. Data and methods

2.2 Study area

Our study area represented a corridor of 50 km to each side of the BR-163 highway, which is the suggested distance of clearing activities related to road networks (Soares-Filho et al., 2006). The corridor is almost equally divided between the states of Mato Grosso and Pará, covering a distance of 1000 km from Lucas de Rio Verde in the South to Novo Progresso in the North (Fig. 1). Its extent is congruent with regional colonisation and settlement processes over the last 30 years (Coy and

Klingler, 2011; Coy et al., 2016) and allows to investigate long term regrowth dynamics across a spatio-temporal gradient of socio-economic development.

Highway construction started in the early 1970s to build an export corridor for agricultural products from Cuiabá to Santarém. The BR-163 now represents the main artery connecting central Mato Grosso and Pará and has become an important deforestation frontier in the Brazilian Amazon (Coy and Klingler, 2011; Fearnside, 2007). Until the early 2000s, deforestation activity along the BR-163 highway mainly concentrated around the cities of Sinop and Guaranã do Norte in Mato Grosso with annual deforestation rates of 1-4% (Müller et al., 2016). However, from 2000 to 2004, deforestation activity drastically declined in Mato Grosso and moved northwards into the forests of Pará, resulting in a new deforestation hotspot around the city of Novo Progresso.

Fig. 1: Study area with corresponding Landsat footprints along the BR-163. Cropland and pasture areas from TerraClass are shown for the year 2008 (INPE, 2008, 2015). Inset: Studied corridor along the BR-163 highway across the federal states of Mato Grosso and Pará. (1.5 column figure)

The region's development since the 1970s resulted in different land use systems along the BR-163. While capital intensive cropland and pasture systems dominate in Mato Grosso, extensive and traditional cattle farming are the main land use in Pará (Fig. 1). In traditional pasture systems of Pará, regrowth of secondary vegetation lowers grass productivity several years after initial pasture establishment. To remove secondary vegetation, pasture burning and resowing of forage grasses often takes place towards the beginning of the wet season (Asner et al., 2004; Landers, 2007).

Consequently, regrowth remains a temporary phenomenon with estimated durations of regrowth cycles between 4 and 5 years (Almeida, 2009). In contrast, pasture systems in Mato Grosso are managed with higher input of machinery and fertilizer, due to better access to markets, labor and finance (VanWey et al., 2013; Coy and Klingler, 2014). Here, fallow periods and farmland abandonment or unsuitable topography can lead to establishment of secondary vegetation on croplands and pastures. Additional regrowth can be expected in areas of agroforestry and sustainable forest management.

The region's climate is characterized by a strong seasonality with rainfall intensity between 120-350 mm during the dry season and 1700-2200 mm during the wet season (Fig. 2). The seasonality increase from north (Novo Progresso) to south (Lucas do Rio Verde) and natural vegetation changes from dense evergreen forests (north) to transitional evergreen-seasonal forests (south), including areas of savanna vegetation (Cerrado) (Radambrazil; DNPM, 1983). Water constraints during the dry season lead to a loss of biomass in grass dominated systems, such as savanna and pasture areas. In contrast, dense evergreen forest areas show a stable amount of green biomass throughout the year.

Fig. 2: Climatic averages of precipitation and temperature for the northern (Novo Progresso) and southern part (Lucas do Rio Verde) of our study area. Data source: AmbiWeb (2016). (2 column figure)

2.2 Landsat imagery

We processed 2,224 images of the Landsat TM and ETM+ sensors from 1984 to 2012 to capture long term regrowth dynamics of secondary vegetation across 11 footprints. The dataset was obtained by USGS EROS archive and restricted to imagery in precision terrain corrected (L1T) format. For each year, we downloaded all imagery available between May 24th and September 7th with less than 80% cloud coverage. This temporal window represents the dry season, which is the crucial time to separate emerging secondary vegetation from grasslands (Rufin et al., 2015). Furthermore, the dry season provides the highest observation density due to low cloud coverage. We converted all imagery to surface reflectance employing the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) atmospheric correction algorithm to ensure comparability of input data across different Landsat sensors, footprints, and acquisition dates (Masek et al., 2006; Schmidt et al., 2013). Cloud, cloud shadow and water masks were calculated for all imagery using FMask (Zhu and Woodcock, 2012).

Tasseled cap wetness (TCW) is the third component of the tasseled cap transformation and is highly influenced by the SWIR bands (Crist and Ciccone, 1984). Previous studies have shown that the tasseled cap wetness image transformation is highly sensitive to vegetation structure (Jin and Sader, 2005; Czerwinski et al., 2014) and well suited for monitoring secondary vegetation establishment (Rufin et al., 2015). We therefore converted all available imagery into TCW following the parameterization of Crist (1985) for reflectance data. A separate parameterization for the TM 5 and TM 7 sensor was not necessary, because the radiometric and atmospherical correction (LEDAPS) corrects for those differences. We then employed the compositing algorithm developed by Griffiths et al. (2013) to extract the minimum TCW value for each pixel within the dry season period (TCW_{min}). The minimum metric efficiently captures spectral differences of forage grasses and woody vegetation (Rufin et al., 2015), which are triggered by water stress and grazing pressure towards the end of the dry season. During the compositing procedure, cloud and cloud shadow masks were used to exclude contaminated observations for the selection of the TCW_{min} value. With this processing step we

generated annual, spatially continuous cloud free TCW_{min} composites covering the entire study area. Data gaps remained when image availability was low and did not compensate for cloud cover and shade related image contaminations. For the majority of TCW_{min} composites we observed data gaps for less than 1% of the study area (Fig. 3). Higher amounts of data gaps were detected in 1984, 1985 and 1990. Here, data gaps affected 4 to 7% of the study area, mostly in primary forest areas of Pará in the northern parts of the study area.

However, across all 29 TCW_{min} composites (1984-2012) spatial distribution of the data gaps affected the states of Mato Grosso and Pará equally and no regions of permanent data gaps could be identified. To systematically detect the first possible begin of the regrowth process, data gaps were filled with TCW_{min} values of the following year. All data gaps influencing the regrowth detection were counted to report the affected share of regrowth in the results section.

Fig. 3: Relative area of data gaps in the TCW_{min} composites per year. Spatial distribution of data gaps is indicated by the median of the latitudinal pixel coordinates. The median of the latitudinal distribution reads as: “half of the data gaps are located north of [...]”. To aid visual interpretation, latitudinal positions of Sinop, State border and Novo Progresso are indicated (for spatial detailed position see Fig. 1). The latitude refers to “Albers conical equal area projection with South American Datum (SAD) 1969”. (2 column figure)

2.3 Additional datasets

We used the deforestation data provided by Müller et al. (2016) to identify the year and location of cleared areas in our study region. The dataset provided annual deforestation data from 1985-2012 in a 50km corridor around the BR-163 highway with an overall accuracy of 85%. Müller et al. (2016) used Landsat image compositing based on the approach by Griffiths et al. (2013) and employed a random forest classifier (Breiman, 2001; van der Linden et al., 2015) to derive deforestation information at 30m resolution.

The Amazon-wide land use classification TerraClass2008 (INPE, 2008, 2015) was employed as reference data to identify areas with low and high fractions of secondary vegetation. The dataset includes pastoral lands, croplands and secondary vegetation at 30m spatial resolution. Pastoral lands were divided into grass-dominated pastures, pastures with low levels of secondary vegetation (<50%) and pastures with high levels of secondary vegetation (50-90%). TerraClass 2008 was generated based on visual image interpretation with a minimum mapping unit of 6.25 ha. Imagery for visual interpretation was obtained from Landsat, moderate resolution imaging spectrometer (MODIS) and China-Brazil Earth Resources Satellite Program (CBERS). The resulting land use polygons accordingly include pixels of heterogeneous land cover and omitted small patches of secondary vegetation. Therefore, a comparison between TerraClass 2008 and our results is unsuitable at the pixel scale. Instead, we compare overall regrowth patterns for evaluating general plausibility of our regrowth detection approach in the discussion section.

2.4 Regrowth mapping

We here define regrowth as the process that leads to the dominance of secondary vegetation in the area of a Landsat pixel on formerly cleared lands. Secondary vegetation includes perennial bushes, palms and tree species which colonize forest gaps or overgrow stands of forage grasses on pasture areas. Secondary vegetation shows higher TCW_{min} values than areas of forage grasses (intensive pastures) and croplands but spectral heterogeneity is generally high (Fig. 4a). Next to its spectral features, regrowth of secondary vegetation is a temporal process and annual time series of the

TCW_{min} metric improve the characterization of this process (Fig. 4b). We therefore used a combination of spectral and temporal criteria for detecting secondary vegetation.

Fig. 4. a) TCW_{min} distributions for 6 different land use classes sampled from TerraClass 2008 (INPE, 2008, 2015). GD: grass dominated pasture, LSV: pasture with low levels of secondary vegetation (<50%), HSV: pasture with high levels of secondary vegetation (50-90%), sec.veg: full coverage of secondary vegetation. b) Temporal trajectory of TCW_{min} values for an exemplary pixel. The green areas relate to the three tested thresholds (-0.872,-1.191,-1.534), i.e. different sensitivities for flagging a pixel as “regrowth”. In this example, deforestation takes place in 1988 and regrowth onset varies between 1995 and 1997 according to the three different thresholds. Recultivation takes place in 2002/2003. (2 column figure)

To determine the spectral threshold, we derived a random sample of 10,000 TCW_{min} values from areas of secondary vegetation (5,000 samples) and from pastures with high levels of secondary vegetation (5,000 samples) according to TerraClass 2008. We derived three different thresholds of the overall sample (Table 1) and tested these thresholds towards their sensitivity for capturing secondary vegetation and related regrowth patterns (section 2.4.1). The most appropriate threshold was then selected for the final regrowth analysis. For separating secondary vegetation from active agricultural areas, we defined a minimum regrowth period of 2 years. This temporal threshold aims at detecting perennial vegetation related to the first stage of tropical forest succession in our study region (Uhl et al., 1988). Consequently, we did not consider cleared land to be covered by secondary vegetation if the spectral threshold was not met for at least two consecutive years.

Regrowth processes can be interrupted by recultivation of fallow areas (Fig. 4b). This includes burning or clearing of secondary vegetation for pasture maintenance or expansion. In those cases, recultivation events marked the end of a regrowth phase and the regrowth process was regarded as being cyclic with one or multiple regrowth cycles. To separate recultivation events from spectral outliers (e.g. undetected cloud shadows) and data gaps, we defined a minimum duration of two years. Shorter interruptions of the regrowth process were ignored and the process was labeled as continuous regrowth. This rule did not apply for the year 2012, because it marked the end of the time series. The temporal definitions for the regrowth duration and regrowth interruption relate to different processes and are mutually exclusive.

2.4.1 Selection of spectral regrowth threshold

To determine the influence of the spectral thresholds on our regrowth detection approach, we performed a separate analysis based on 10,000 single-pixel time series. These single-pixel time series were derived from the annual TCW_{min} composites, being selected from areas labeled as secondary vegetation and pastures with high levels of secondary vegetation in TerraClass 2008 employing a stratified random sampling procedure. Based on the 10,000 samples, we tested our regrowth detection approach with the median (-0.872), mean (-1.191) and 25% quantile (-1.534) thresholds (Table 1). As TerraClass 2008 is a single year object based product, these samples include considerable proportions of forage grass and primary forest pixels (see section 2.3). Therefore, achieving a high agreement with TerraClass 2008 is not part of the threshold selection procedure. Employing the most liberal threshold (-1.534), we detected regrowth for 79% of our 10,000 samples, which is three times the amount of the most conservative threshold (23%) (Table 1). In addition, mean duration of regrowth was twice as long in case of the liberal threshold (8.8 years) compared to the conservative threshold (4.7 years).

Table 1: Comparison of regrowth area and regrowth duration identified with different spectral regrowth thresholds.

Regrowth area was normalized to the area sampled from TerraClass 2008.

Threshold [TCW _{min}]	Regrowth area [%]	Mean regrowth duration [years]
-0.872	23	4.7
-1.191	58	7.3
-1.534	79	8.8

The high differences in regrowth area and regrowth duration between the liberal (-1.534) and conservative spectral threshold (-0.872), indicate a high abundance of secondary vegetation in early successional stages. In general, early successional stages are not captured by the conservative regrowth threshold, which leads to decreased spatial and temporal regrowth detections. However, early stages of secondary succession can easily be confused with mature stands of specific forage grass species, especially if the wet season is prolonged. In these cases, deep rooting structures of secondary vegetation gain no additional water benefit compared to shallow rooting forage grasses. As a result, difference in greening between forage grasses and secondary vegetation diminishes within the observation period. To balance the commission and omission error of secondary vegetation detection, we argue for the mean value threshold (-1.191). This threshold provides a conservative estimate of early stage secondary vegetation, thereby minimizing the risk for commission errors (see Table 1).

2.4.2 Regrowth analysis in relation to forest edge

High seed dispersal and low grazing pressure renders pasture edges in proximity to forests a key area for secondary vegetation succession in the Brazilian Amazon (Nepstad et al., 1996). To determine the amount of regrowth in proximity to forest edges, we created annual forest masks using the deforestation data provided by Müller et al. (2016) and calculated the Euclidean distance to the forest edge for each year and pixel. We aggregated the distance values for all regrowth pixels annually to quantify the share of secondary vegetation for three distance classes (<60m, 60-180m, >180m). To investigate potential differences in temporal regrowth characteristics regarding the

distance to forest edge, we separately analyzed all regrowth at distances <60m as “edge regrowth”. Regrowth in distances higher 60m to forest edges was analyzed as “core regrowth” in the sense that it occupies the core areas of formerly cleared lands.

2.5 Accuracy assessment

Only very high resolution imagery allows visual assessment of woody secondary vegetation and forage grasses. Accordingly, we assessed the accuracy of our regrowth results using very high resolution imagery provided by Google Earth, following a similar strategy as described by DeVries et al. (2015). For the spatial sampling, we selected 500 random points within areas labelled as regrowth. Since these areas are not constantly covered by secondary vegetation, the sampling strategy allows to validate the regrowth and non-regrowth class in their mutual occurrence. After rejecting sample pixels where interpretation was not possible (lack of sufficient VHR data), our final reference dataset consisted of 190 pixels. We then follow the standard procedure by deriving a confusion matrix and calculating the overall accuracy (OA), omission and commission error for the regrowth and non-regrowth class. To account for the different spatial class proportions we adjusted the overall accuracy following Olofsson et al. (2014). In addition, we calculated the 95% confidence interval to quantify the uncertainty of the adjusted overall accuracy in relation to the number of validation points (Congalton and Green, 2009).

3 Results

3.1 Accuracy of regrowth detection

Our regrowth detection approach yielded an overall accuracy of 89% which decreased to 86% after error adjustment with a 95% confidence interval margin of $\pm 5\%$ (**Error! Reference source not found.**). The reference dataset (Google Earth imagery) was strongly biased towards the years 2010 and 2012, which covered 70% of our validation sample. Omission and commission errors indicate an underestimation of the true regrowth area. Commission error of the regrowth class partly arose from

commission errors in the disturbance mask and dense stands of forage grasses. In contrast, omission error of the regrowth class was caused by a comparably low greening of woody vegetation.

Table 2: Count based confusion matrix for the regrowth and non-regrowth class, including the omission (OE) and commission error (CE), overall accuracy (OA) and error adjusted overall accuracy (OA adj.).

	Reference							
		Non-regrowth	Regrowth	Total	OE [%]	CE [%]	OA [%]	OA adj. [%]
Predicted	Non-regrowth	71	17	88	4	19	89	86±5
	Regrowth	3	99	102	15	3	-	
	Total	74	116	190	-	-	-	

Remaining data gaps in the TCW_{min} composites mainly affected primary forest areas (see section 2.2) and barely influenced the regrowth detection. In total, only 0.7% of the regrowth onset was affected by data gaps.

3.2 Rates and pattern of secondary vegetation

Overall, 33% of the deforested area has been covered by secondary vegetation at least once during the 1984-2012 period (Fig. 5). The majority of all regrowth occurred on the pastoral areas of northern Mato Grosso (67%), in proximity to Terra Nova do Norte and Garantã do Norte. In general, observed regrowth patterns were characterized by scattered and fine scaled features, including networks of regenerating logging decks in areas of former selective logging activity (Fig. 5). In addition, clear rectangular shapes were commonly visible and indicated an external barrier, such as forest edges, road networks, or property borders.

Fig. 5: Regrowth duration and number of regrowth cycles from 1985 to 2012. Regrowth duration is the sum of regrowth years across all regrowth cycles. For interpretation of the reference colors in this figure legend we refer to the web version of this article. Interactive visualization of regrowth duration is available at http://r.geo.hu-berlin.de/~muellehx/regrowth/regrowth_map.html. (2 column figure)

Absolute regrowth rates were higher in Mato Grosso than in Pará, especially from the mid-1980s to the mid-1990s (Fig. 6a). However, absolute regrowth rates strongly depended on the overall amount of deforested area. In terms of regrowth relative to deforested area, Pará showed almost constantly twice as much relative regrowth as compared to Mato Grosso (Fig. 6b), ranging from 50% in 1990 to 17% in 2005. In contrast, Mato Grosso reached relative regrowth areas between 25% and 8%. Despite considerable differences in the amounts of absolute and relative regrowth areas, both states showed a synchronic decrease in relative regrowth from 1995 to 2000 (Fig. 6b).

Fig. 6: a) Absolute and b) relative area of secondary vegetation in Mato Grosso and Pará. To aid interpretation of the absolute amount of regrowth areas, we added the cumulative deforestation curve for Mato Grosso (MT) and Pará (PA) in a). The deforestation data was derived from Müller et al. (2016). (2 column figure)

Compared to TerraClass 2008, we detected slightly more secondary vegetation (11.6% vs 13.2%) and less than 5% of the regrowth detected after the year 2008 was located on previously cropped land.

3.3 Forest edge analysis

Secondary vegetation largely occurs in small patches in proximity to forest edges (Fig. 5). Full vegetation recovery of previously deforested patches is rare, indicating relatively constant land occupation of formerly cleared lands. Instead, secondary vegetation dominantly occurs alongside forest edges (distance $\leq 60\text{m}$) in both states and throughout the entire study period (Fig. 7).

Secondary vegetation in direct proximity to the forests contributed approximately to 85% of the regrowth in Pará and 70% in Mato Grosso. The state wise differences were especially relevant from 1985 to 1990. Secondary vegetation was comparably infrequent further off forest edges and represented at most 35% of total regrowth (in Mato Grosso in 1995).

Fig. 7: Relative fractions of secondary vegetation in Mato Grosso (left) and Pará (right) in relation to forest edge distance.

(2 column figure)

3.4 Characteristics of regrowth cycles

Regrowth characteristics differ strongly between Pará and Mato Grosso. While Mato Grosso is clearly dominated by cyclic regrowth in core and edge areas, Pará shows a disproportionally high amount of non-cyclic regrowth at forest edges (39%, Fig. 8a). Investigating cyclic regrowth in more detail, revealed that about 90% of the total observed regrowth was restricted to a single cycle (Fig. 8b), rendering multiple regrowth cycles a rare occurrence.

Fig. 8: a) State wise fractions of cyclic and non- cyclic regrowth in core and edge areas. b) Fraction of cyclic regrowth per state according to the number of regrowth cycles. (2 column figure)

Average regrowth durations were generally longer in Mato Grosso and decreased with the number of regrowth cycles (Fig. 9). Average length of regrowth cycles ranged from 8 years at forest edges in Mato Grosso to 3 years in core areas of cleared lands in Pará. In both states, most regrowth occurred within the first three years after clearing of primary forest. In case of multiple regrowth cycles, the lag time between regrowth cycles increased from 2 to 4 years.

Fig. 9: Left: Average duration and standard deviation of non-cyclic and cyclic regrowth along forest edges and in core areas of cleared lands. Right: Duration of lag times between regrowth cycles. (2 column figure)

4 Discussion

4.1 Rates and pattern of secondary vegetation

Our results showed regrowth on up to 50% of the deforested area in Pará and a maximum of 25% in Mato Grosso (Fig. 6b). The high regrowth rates in Pará are an indicator for the lower management intensity of the dominating pasture systems. In Mato Grosso, where the input of fertilizer and machinery for agricultural production drastically intensified in the last decades (VanWey et al., 2013), relative regrowth on pastures is comparably low, especially since 1999 (less than 10%). Overall forest conversion and agricultural expansion in Pará was much lower than in Mato Grosso, resulting into a higher share of forest edges per hectare of cultivated land. Similar to Nepstad et al. (1996), we found forest edges to be critically important for secondary vegetation growth (Fig. 7). Consequently, the higher share of forest edges per hectare of cultivated land in Pará supports a higher amount of relative regrowth compared to Mato Grosso.

In both states, annual regrowth rates drastically dropped after 1996, which coincided with important socio-economic transformations. In 1994 a substantial monetary reform package called “Plano Real” was introduced by the Brazilian government to decrease inflation (Sachs and Zini, 1996). As a result, land prices decreased in the following years and discouraged the acquisition of fallow lands for land speculation in the Amazon (Fearnside, 2002). In the same period, the revision of the forest law (MMA, 1996), the incipient Brazilian soy boom (IBGE, 2010) and the internationalization of Amazonian cattle production (Nepstad et al., 2006) promoted a more intensive use of existing agricultural areas. Furthermore, severe droughts occurred in 1997 and 1998 that also will have hampered woody vegetation regrowth due to higher fire frequency and water constraints on extensively managed lands (Nepstad et al., 2008). This assumption is supported by the recent decrease of regrowth rates in 2005 and 2010. In both years, higher fire frequency and droughts were reported (Aragão et al., 2014). Apart from those anomalies, both states show stable regrowth rates between 2000 and 2012, indicating a new equilibrium of underlying regrowth processes compared to the pre 2000 period.

4.2 Characteristics of regrowth cycles and opportunities for sustainable land management

More detailed analysis of regrowth characteristics showed that Mato Grosso was clearly dominated by cyclic regrowth in core and edge areas, while Pará showed a disproportionally high amount of non-cyclic regrowth, specifically at forest edges (39%). This finding strongly underlines the less intensive pasture management in Pará, which is in line with the high relative regrowth rates. However, in both states, the amount of non-cyclic regrowth in core areas of cleared lands is low (<10%), rendering long-term land abandonment a rare occurrence. The majority of regrowth was restricted to one regrowth cycle in core areas and along forest edges (Fig. 8), starting within the first 3 years after clearing of primary forest (Fig. 9). Similar findings were reported for pastures in Rondônia (Carreiras et al., 2014) indicating a general pattern of land management in southern Amazonia. According to Uhl et al. (1988), a short period of pasture establishment (2-3 years)

between the clearing event and regrowth phase favors rapid biomass accumulation and species richness of secondary vegetation. The relatively short lifetime of secondary vegetation (5 years in average) suggests the dominance of early pioneer species in most regrowth areas. These findings differ from regrowth assessments in central Amazonia close to Manaus, where permanent land abandonment resulted in establishment of permanent secondary forest since several decades (Fearnside, 2002; Prates-Clark et al., 2009).

In case of multiple regrowth cycles, lag time between regrowth cycles increased with the number of cycles (Fig. 9). Further investigations are needed to show if the observed increase in lag times are related to intensified pasture treatment or a decline in local recovery potential (Dias-Filho, 2011). In the latter case, land management strategies could focus on establishing secondary vegetation for improving soil fertility, carbon sequestration and biodiversity, and additionally reach compliance with the current forest law (Soares-Filho et al., 2014). To avoid potential losses in long term pasture productivity, Hohnwald et al. (2015) suggested the implementation of integrated grass- woody vegetation fallow systems. Here, woody vegetation remains in large fraction on the pastures and prevents nutrient leaching and soil erosion. Improved pasture fertility and higher degrees of cattle production might further help to satisfy future demand of cattle products and thus prevent additional deforestation (Strassburg et al., 2014). In this context, our results indicate a high potential for increasing forage grass productivity on young pastures in Pará. However, profitable cattle production can motivate further cattle expansion into primary forests (Fearnside, 2002). Therefore, incentives for land use intensification should be restricted to areas where the potential and risk of unregulated pasture expansion is limited and law enforcement prevents illegal land use activities.

4.3 Potential and limitations of the applied regrowth mapping approach

Next to Carreiras et al. (2014), we here present the second study that directly estimates the number, duration and lag times of regrowth cycles on a long term basis. While Carreiras et al. (2014) remained on a local scale using interactive adaptation of different mono-temporal classification methods, we

expanded the regrowth assessment towards the regional scale with highly automatized preprocessing and analysis procedures. Moreover, temporal resolution and extent of our approach improve upon current studies, which are either limited to near annual assessments (Carreiras et al., 2014) or do not capture regrowth pattern in the 80s and 90s (DeVries et al., 2015; Hansen et al., 2013; Schmidt et al., 2015). An important innovation of our regrowth assessment relates to the compositing approach. This processing step allows to filter noise and phenological effects in the time series, which facilitates the regrowth detection. As a consequence, we can include the first years of the time series dataset for regrowth detection, which is often needed as a reference period for outlier detection and threshold determination in alternative approaches using intra-annual time series (Schmidt et al., 2015; DeVries et al., 2015).

From an ecological point of view, the regrowth definition provides a conservative estimate of secondary vegetation succession omitting very early stage of pioneer establishment and short term regrowth processes (<2 years). The concept is in line with DeVries et al. (2015), who also excluded early stages of vegetation succession by introducing a minimum lag time between deforestation and regrowth of 3 years. However, we emphasize that variations in remote sensing based regrowth definitions might have strong implications for interpretation of results (section 2.4.1) and conceptual frameworks need to be further developed to facilitate consistency across regrowth assessments - similar to what has been developed as state of the art for deforestation mapping (Wulder and Franklin, 2006).

Independent validation of our Landsat based regrowth assessments showed a reliable estimation of the regrowth area with an overall accuracy of 89%. The overall accuracy decreased after error adjustment to 86% which emphasizes the error of the spatially larger non-regrowth class. In summary, the detection approach tends towards a slight underestimation of the regrowth process which suggests a conservative estimation of regrowth area and regrowth duration. Accordingly, we rarely observed commission errors of our regrowth detection approach. These findings are in line with our regrowth definition which aims for secondary vegetation that remains for at least two years.

The two-year rule reduces the risk for commission errors triggered by data gaps, unmasked clouds, cloud shadows or sensor-related noise in the source data. In total, only 0,7% of the detected regrowth was influenced by data gaps, illustrating the high potential of the Landsat archive for studying long term regrowth processes. However, deforestation data used in this study was reported to contain commission errors in hilly terrain and open woodland (Müller et al., 2016), which can lead to commission errors in the regrowth assessment. We therefore caution high uncertainty of the regrowth assessment in those regions.

Our validation strategy relied on VHR imagery provided by Google Earth, which was severely restricted to the years 2012 and 2010. This strongly hampered validation in terms of regrowth duration and regrowth cycles. However, the plausibility of our results are confirmed by Almeida (2009) who estimated the median regrowth duration being 4 to 5 years for most parts of the Brazilian Amazon. Furthermore, the areal extent of secondary vegetation is similar compared to TerraClass2008 (11.6% vs 13.2%), even though spatial location differed considerably due to differences in the underlying forest mask, in the minimum mapping unit and in class definitions (see section 2.3).

In general, our approach allows considerable flexibility on how to define and map secondary vegetation. For decision making processes, more conservative regrowth estimates might be needed which can easily be accommodated by filtering the resulting maps for long term regrowth areas. Furthermore, we see great potential for combining information on regrowth age and regrowth cycles with biophysical properties of secondary vegetation derived from field data. In the best case, this would allow to upscale local biomass estimates based on regrowth characteristics. However, even without field data, spatial explicit regrowth characteristics could be used to replace general regrowth parameters in carbon modelling (Aguilar et al., 2016).

5. Conclusion and outlook

In terms of absolute and relative regrowth rates we found important differences and similarities between the states of Mato Grosso and Pará, which help understanding land use processes in

Southern Amazonia during the last decades. As our study area represents a strong gradient of socio-economic development, we are confident that our findings are relevant well beyond the geographic extent of this work. Our analyses revealed high standard deviations in terms of lag times and regrowth durations, indicating high spatial heterogeneity of short- as well as long-term regrowth processes and emphasized the importance of spatially explicit information to identify hot and cold spots of regrowth over time. This knowledge is extremely valuable to better steer regional management towards ecosystem restoration on the one hand and land use intensification on the other hand. Next to management related issues, the high rates of absolute and relative regrowth underpin the importance of secondary vegetation for the regional carbon balance. Pixel based information on regrowth duration will be valuable for biomass modeling of secondary vegetation to improve regional carbon sequestration potential estimates. As our study region covers a large transect of rainforest types, there is great potential to transfer our mapping approach to other tropical regions within and beyond the Brazilian Amazon. In this context, the advancement of large scale compositing and deforestation products (Hansen et al., 2013; WELD, 2014) can provide great opportunities in regrowth mapping by drastically reducing processing efforts.

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