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Monitoring land use change in the Brazilian rainforest and savanna with Landsat time series

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M.Sc. Geoökologie Hannes Müller

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Dekan: Prof. Dr. Elmar Kulke

Präsident der Humboldt-Universität zu Berlin
Prof. Dr. Jan-Hendrik Olbertz

Gutachter:
Prof. Dr. Patrick Hostert
Prof. Dr.Tobia Lakes
Prof. Dr. Björn Waske

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Abstract

Reconciling trade-offs between economic growth, food security and ecosystem services is one of the major challenges for today's society. One prominent example is Brazil with its immense rainforest (Amazon) and savanna (Cerrado) areas. While both biomes are vital components of the global climate system and important biodiversity hotspots, they experienced high rates of deforestation for agricultural expansion in the last decades. This dissertation aims to monitor status and changes of land use and land cover (LULC) in the Brazilian rainforest and savanna employing time series-based analysis of Landsat imagery. First, it was investigated how temporal information facilitates the separation of cropland, pasture and natural vegetation in a heterogeneous savanna landscape of the Brazilian Cerrado (Chapter II). Second, a long-term record of satellite imagery was used to uncover historic deforestation (Chapter III) and regrowth processes (Chapter IV). Monitoring of LULC in the Brazilian Cerrado was established through an image compositing framework and the creation of spectral-temporal metrics from annual to multi-annual image stacks. This framework was consequently transferred and adapted for reconstructing deforestation and regrowth processes in an Amazonian deforestation frontier along the BR-163 highway in the states of Mato Grosso and Pará. Outcomes of the LULC assessment demonstrated a high additional value of temporal information for separating cropland, pasture and natural vegetation in complex land use systems of savanna landscapes. In regard to the long-term deforestation analysis (1984-2012), spatio-temporal clearing patterns emphasized the relevance of historical deforestation along the BR-163 with half of the overall deforestation being detected before 2000. Investigating post-deforestation regrowth dynamics, results revealed secondary vegetation on up to 50% of the deforested area in Pará and a maximum of 25% in Mato Grosso. Higher regrowth rates in Pará indicated a lower management intensity on the dominating pasture systems compared to Mato Grosso. Differences in historic deforestation and regrowth dynamics shed a new light on possible impacts of political incentives in the 90s after the collapse of the military regime in 1984. In this context, the results set a valuable basis to investigate the influence of proximate and underlying drivers on land change in the region. Spatially explicit information on long-term deforestation and regrowth dynamics further allows to refine estimates on the regional carbon balance and to identify core areas for landscape restoration. The underlying approaches provide a valuable contribution to linking compositing procedures and methods of time series analysis to large-scale land use monitoring.

Zusammenfassung

Die Abwägung von Wirtschaftswachstum, Nahrungsmittelsicherheit und Bewahrung natürlicher Ökosystemdienstleistungen ist eine der wesentlichen Herausforderungen für die heutige Gesellschaft. Nirgendwo wird diese Herausforderung so sichtbar wie am Beispiel Brasiliens. Landesweite Regenwald- und Savannenvorkommen (Amazonas bzw. Cerrado) stellen unverzichtbare Bestandteile des globalen Klimasystems dar und beherbergen eine einmalige Pflanzen- und Tierwelt. Gleichzeitig fallen bereits seit Jahrzehnten große Teile der Landschaft der Expansion von landwirtschaftlich genutzten Flächen zum Opfer. Diese Dissertation zielt darauf ab, mit Hilfe von zeitreihenbasierten Fernerkundungsmethoden den Status und die Veränderungen von Landnutzung, und Landbedeckung im brasilianischen Regenwald und der Savanne zu erfassen. Dabei wurde untersucht, inwieweit der Einsatz zeitlicher Information die Trennung von Ackerland, Weideland und natürlicher Vegetation in einer heterogenen Savannenlandschaft erleichtert (Kapitel II). Im Anschluss wurden langfristige Zeitreihen von Satellitenbildern genutzt, um die historische Entwaldung (Kapitel III) und das Nachwachsen der Sekundärvegetation (Kapitel IV) nachzuvollziehen. Die Landnutzung und Landbedeckung im brasilianischen Cerrado wurde durch die Ableitung spektraler Metriken im Rahmen eines Compositing-Verfahrens für verschiedene Zeiträume (saisonal, jährlich, mehrjährig) erfasst. Dieses Verfahren wurde anschließend für die Rekonstruktion der Entwaldung und das Nachwachsen der Sekundärvegetation angepasst und in einem der größten Entwaldungskorridore im brasilianischen Amazonas eingesetzt, der Bundesstraße BR-163 in den Bundesstaaten Mato Grosso und Pará. Der verfolgte Ansatz stellte deutlich den Mehrwert zeitlicher Information zur Trennung von Ackerland, Weideland und natürlicher Vegetation in den komplexen Landnutzungssystemen der Savannenlandschaften heraus. Die langzeitlichen Analysen zur Entwaldungsdynamik zeigten erstmals die Bedeutung der historischen Abholzung entlang der BR-163. Hier wurde die Hälfte aller Abholzung zwischen 1984-2012 vor dem Jahr 2000 registriert. Weiterhin konnte gezeigt werden, dass auf bis zu 50% der Abholzungsflächen in Pará und maximal 25% der Abholzungsflächen in Mato Grosso Sekundärvegetation aufgewachsen ist. Die höheren Aufwuchsraten in Pará deuten auf eine geringere Bewirtschaftungsintensität der dominierenden Weidesysteme im Vergleich zu Mato Grosso hin. Zudem werfen die unterschiedlichen Dynamiken von Abholzungs- und Aufwuchsprozessen ein neues Licht auf die politischen und ökonomischen Rahmenbedingungen der 90er Jahre, nach dem Zusammenbruch des Militärregimes im Jahr 1984. Darüber hinaus helfen die räumlich expliziten Informationen zur langfristigen Entwaldung und Wiederaufwuchs dabei, die Schätzungen der regionalen Kohlenstoffbilanz zu verfeinern und Kernbereiche für die Wiederherstellung der Landschaft zu identifizieren. Die zu Grunde liegenden methodischen Ansätze liefern einen wertvollen Beitrag zur Verknüpfung von Compositing-Verfahren und Methoden der Zeitreihenanalysen zum großflächigen Landnutzungsmonitoring.

Contents

List of Figures

List of Tables

Chapter I:
Introduction

1 Global land use change and environmental consequences

Land use is defined as the purpose for which humans exploit the Earth's surface, while land cover describes the biophysical features of the terrestrial environment (Cihlar and Jansen, 2001). Although land was already significantly used in Asia and Europe by 3000 B.C. (Ellis et al., 2013), the expansion of human land use systems rapidly sped up globally only during the last three centuries (Goldewijk et al., 2011). The most significant changes in land use and land cover (LULC) were related to agricultural expansion (Ramankutty and Foley, 1999), which has come at the expense of natural habitats, especially temperate and Mediterranean forests and woodland (Fig. I-1). Within the last 60 years, land conversions shifted towards tropical forest and savanna systems. Today 40% of the land surface are under human use (Foley et al., 2005) and no ecosystem is free of human influence (Vitousek et al., 1997). The strong effects on the global water, energy and nutrient cycles have coined the term "anthropocene" as a new geological era (Crutzen, 2002).

While the immense transformations of natural systems allowed to sustain human population growth and economic development in the past, it raises concerns regarding local and global environmental impacts and its consequences for human well-being (MEA, 2005a). Surface run-off and river discharge increase when natural vegetation (especially forest) is cleared (Sahin and Hall, 1996), triggering extreme flooding events and soil erosion. Soil fertility is also threatened in arid areas, where agricultural systems are prone to desertification affecting 2.5 billion people (Reynolds et al., 2007). Moreover, fertilizers and atmospheric pollutants degrade local freshwater quality (Matson et al., 1997; Bennett et al., 2001) and cause severe aspiration diseases (Davis, 2002; Huang et al., 2009). At the landscape scale, fragmentation and conversions of habitats have severely degraded biological diversity (Pimm and Raven, 2000; Wood et al., 2000) with widespread effects on ecosystem functionalities relevant for human well-being such as pollination (Clermont et al., 2015). In addition to these local to regional impacts, tropical deforestation has a severe impact on the global circulation system by directly influencing essential water cycles (Betts et al., 2004; Malhi et al., 2008). Overall, 35% of the anthropogenic emission of CO_2 equivalents since 1850 can be directly traced to land cover change (Foley et al., 2005) rendering land cover change an important contributor to global climate change.

Improved understanding of global land use change and its negative environmental impacts lead to the formulation of sustainable development goals. These goals claim that at least

70% of species in any ecosystem and 70% of forests should be retained (Griggs et al., 2013). At the moment, we are far from those goals. According to the concept of the human ecological footprint, the area of land needed to provide resource consumption in a sustainable way exceeds the Earth's capacities by about 20% (Wackernagel et al., 2002). In 2100, the world population will include more than 10 billion people (UN, 2011) and the demand for energy, food and urban areas will continue to increase pressure on remaining natural ecosystems, especially if consumption driven lifestyle is targeted (Godfray et al., 2010). It is estimated that agricultural lands could occupy an additional 200-300 million ha globally in the next 40 years (Chaplin-Kramer et al., 2015) mainly in the tropics and savannas, as virgin lands in the temperate zones have already been exploited (Fig. I-1).

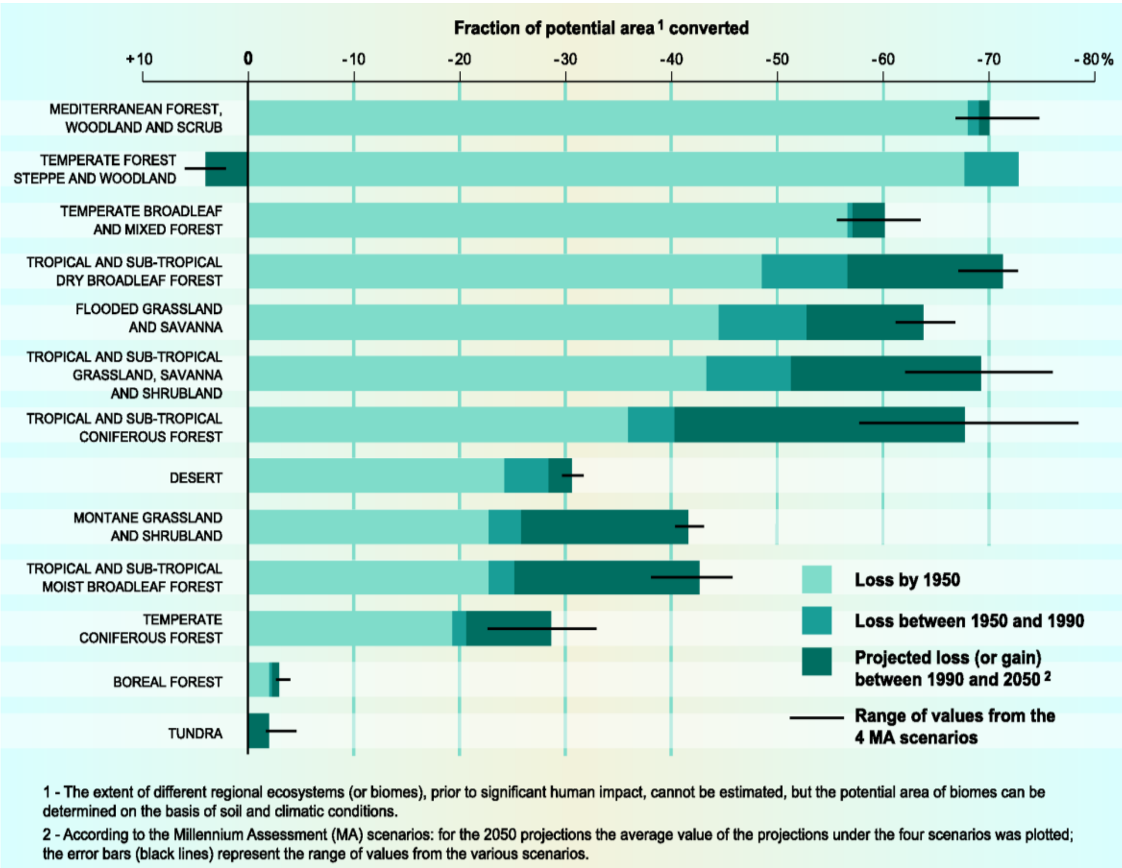

Fig. I-1: Global conversion of ecosystems by humans. Source: MEA (2005b).

To counteract unsustainable land use practices, a reinterpretation of short term capital driven land use decision is necessary (Lambin and Geist, 2006). This is extremely challenging as markets are increasingly teleconnected at the global scale. One key example is Latin America, the region that experienced the most rapid changes in land use during the twenty-first century (Graesser et al., 2015). Soybeans produced on millions of hectares of former seasonally dry forests in Brazil, Bolivia, Paraguay, and Argentina are shipped to

China as animal fodder to supply the increasing demand of meat consumption (Aide and Grau, 2004). A shift towards policies for sustainable land management in Latin America might avoid future land conversion but possibly lead to displacement of agricultural production towards other tropical regions which have access to the global market. Even there is no silver bullet in sight yet, a promising way for reconciling human well-being and environmental protection is the combination of agricultural intensification, land use zoning, forest protection and restoration of degraded ecosystems (Lambin and Meyfroidt, 2011). In addition, alternative farming practices (integrated systems, e.g. agro-silvo-pastoral) have increasingly reached attendance (Tremblay et al., 2015) and current farming practices have long been questioned (Fearnside, 1990). For example, clearing of natural forests and savannas in Latin America has largely been conducted for cattle farming (Graesser et al., 2015), the most traditional but inefficient way to produce meat in Latin America (Cassidy et al., 2013).

Application of new land use strategies can only be achieved if it is supported by institu-tions strengthening the relevant social and economic processes. In this context, sound knowledge on goods, people, and capital that connect local land use with global scale factors is necessary (Lambin and Meyfroidt, 2011). From this integrated perspective, land systems can be identified which are similar in terms of their production and ecological trade-offs, which helps to discuss unified management strategies. One important aspect is timely information on LULC change for interpreting ecosystem status (Turner et al., 2007). But also long-term land use legacies need to be considered, as historic management significantly changed ecological conditions of today´s landscapes (Foster et al., 2003). In face of the current land conversion rates, there is an urgent need for better information on LULC changes in tropical forest and savanna areas (Fig. I-1). In this context, Brazil is a prime example to study LULC dynamics, as large areas of rainforests and savanna ecosystems are constantly threatened by agricultural expansion (Graesser et al., 2015).

2 Land use change in Brazil

Reconciling trade-offs between food security, economic growth and ecosystem services is one of the major challenges of today’s society (Godfray et al., 2010). This is especially true for Brazil, which is one of the largest soybean, coffee, sugar and beef producers worldwide (Rada, 2013; FAOSTAT, 2015). At the same time, the country encompasses a vast tract of the world’s largest continuous tropical forest and savanna ecosystem, the Amazon and Cerrado biomes, covering 74% of the Brazilian territory (IBGE, 2005) (Fig. I-2). Both biomes have consistently emerged as a vitally important component of the global climate system and host a unique diversity of plant and animal species (Myers et al., 2000; Aragão et al., 2014). So far, the conversion of forest and savannah areas for agricultural production affected 40%–50% of the Cerrado (Klink and Machado, 2005) and 20% of the Brazilian rainforest (INPE, 2014). While the Brazilian Cerrado is used for cropland and pasture systems, the rainforest areas are mainly covered by pastures due to poor soils or unfavourable topography (INPE, 2015b; Fig. I-2). Given its potential for yield improvements and its large arable land availability (Lapola et al., 2014), Brazil is expected to contribute a large fraction to global food security in future. So far, ecological costs of future LULC changes remain unclear, but in case of uncontrolled pasture expansion into rainforest areas, local precipitation is supposed to decrease and 50% of the Amazon basin might be replaced by savanna by the end of the 21st century (Zhang et al., 2015; Silvério et al., 2013).

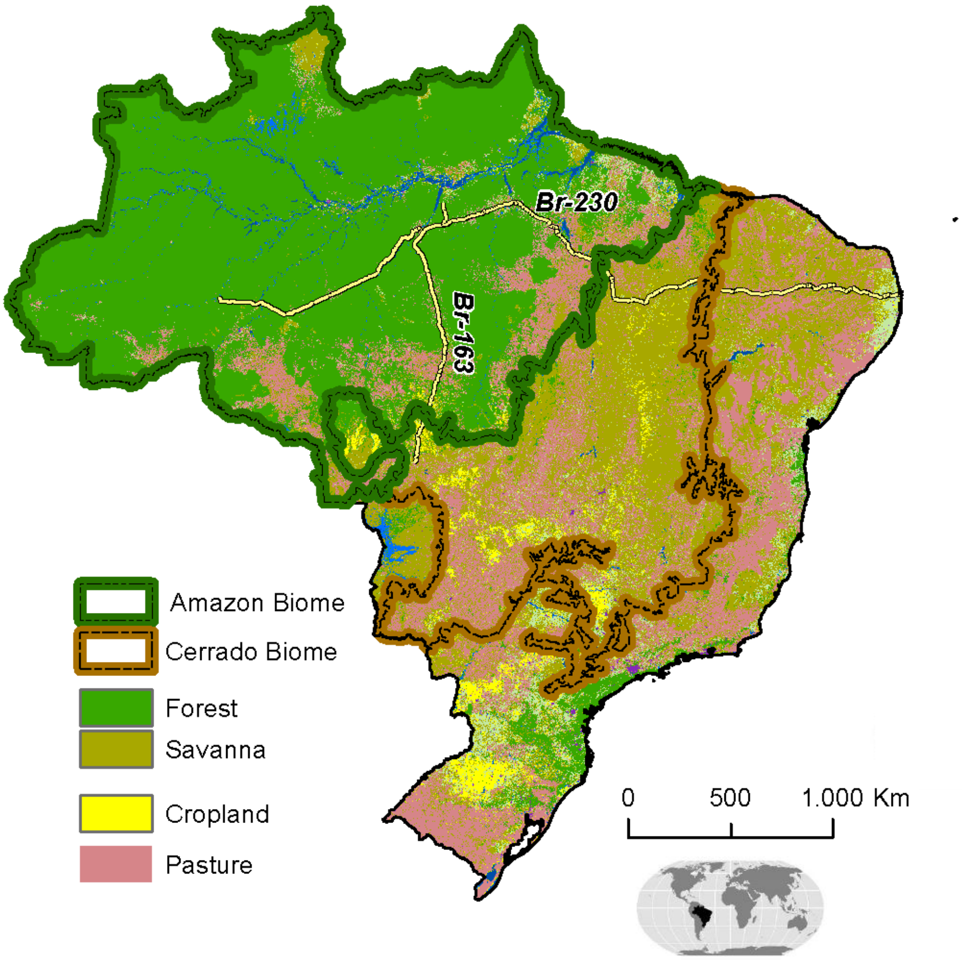

Fig. I-2: Cropland and pastures distribution across forest and savanna areas in Brazil. Source: Pastoral lands 2010 (Lapig, 2010); MODIS land cover product 2006 (Friedl et al., 2010)

The history of land conversions in Brazil started with the colonisation of Portuguese explorers nearly 500 years ago, who established sugar cane and coffee plantations along coastal areas, clearing large tracts of Atlantic forest (Mata Atlantica) (Ribeiro et al., 2009). Migration towards the inner part of the country were motivated by gold mining activities in Mina Gerais (Williams, 1990) and rubber extraction in Amazonia (Salati et al., 1990). In the last two centuries, agricultural activities expanded towards the Cerrado, dominated by cattle farming because of challenging soil conditions. Productivity drastically increased within the last decades due to introduction of new farming practices and seed varieties by the Brazilian Agricultural Research Corporation (EMBRAPA) founded in 1972 (Kaster and Bonato, 1980). With high input of machinery and fertilizer, former pasture areas were partly intensified into croplands and new agricultural land was acquired by cattle expansion into natural savanna and rainforest areas including the Brazilian Amazon

(Kaimowitz and Smith, 2001) (Fig. I-3). The migration towards the Amazon was further supported by the government and the political slogan "Lands without men for men without land", became a synonym for the colonisation driven land use perception at this time (Mendes and Porro, 2015). Cheap land prices and major governmental road building projects such as the Transamazonica highway (BR-230 in 1970), and the Cuiabá to Santarém highway (Br-163 in 1973) (Fig. I-2) opened up colonisation frontiers for the next decades (Fearnside, 2005). Within these frontiers, land was dominantly used for subsidence agriculture, cattle farming and land speculations (Fearnside, 1990). Cattle farming strategies mainly relied on slash and burn practices, and productivity was generally low with stocking densities below one animal per hectare (Valentim and Andrade, 2009). Limited access to financial resources hampered the input of machinery and labor for pasture maintenance which lead to several fallow years and the encroachment of secondary vegetation (Nepstad et al., 1996; Moran et al., 2000) (Fig. I-3).

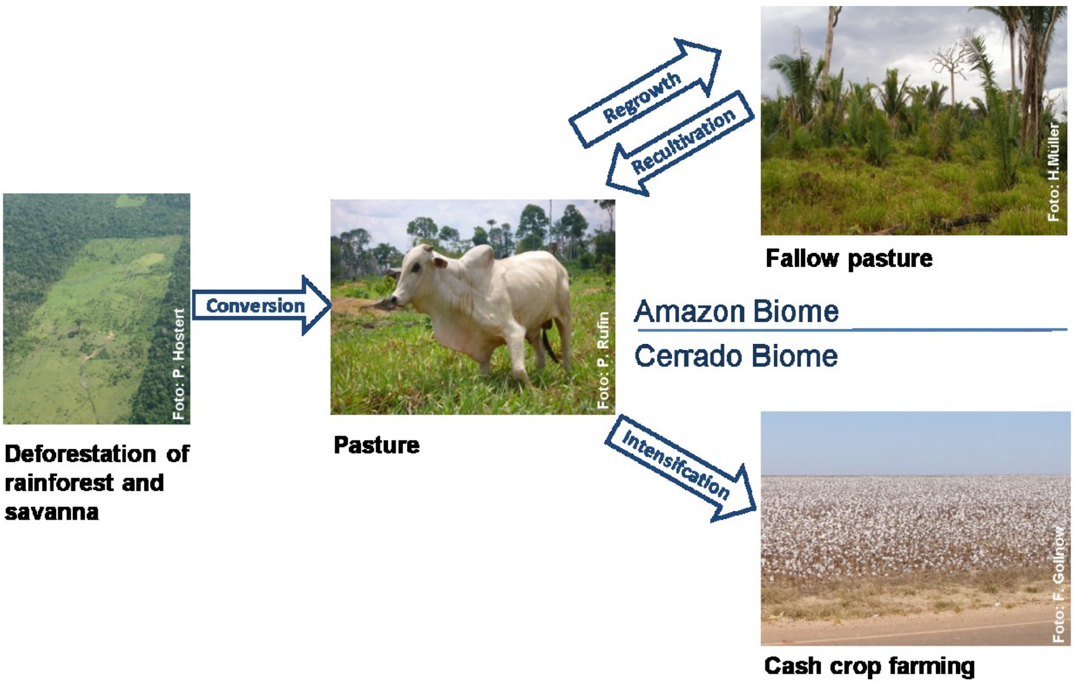

Fig. I-3: Simplified scheme of typical land use transitions in Brazil.

To increase financial output, cattle ranchers often expanded their territory by illegal deforestation (Fearnside, 2005) or recultivated fallow pastures via slash and burn methods (Fig. I-3) (Dias-Filho, 2011). The uncontrolled colonisation process was accompanied by a weak law enforcement and triggered a series of social conflicts, regarding land tenure in the colonisation frontiers (Fearnside, 2001). This development was not surprising as the whole country was in stage of transition during the 70s and 80s. Brazil´s government changed from a 20 years' military dictatorship to a democracy in 1985 with widespread constitutional changes. Development of Brazil`s economy was hampered by inflation until 1994 when a substantial monetary reform package called "Plano Real" was established (Sachs and Zini, 1996). With the change of the political and economic system and in face of constantly increasing deforestation rates and social conflicts in the deforestation frontiers, the perception of land use processes in the Brazilian Amazon drastically changed (Mendes and Porro, 2015). Accompanied by an increasing environmental consciousness, serious governmental and non- governmental efforts to curb agricultural expansion were introduced (Tab. I-1).

The most important environmental law in regard to agricultural expansion is the Brazilian forest code (FC). First formulated in 1965, it was drastically revised in 1996 to counteract the ever rising deforestation rate at this time. The forest code requires landowners to conserve native vegetation on their private properties and to restore illegal deforested areas. In the Amazon biome 80% of the property area are legally protected and 35% in the Cerrado. The law also designates environmentally sensitive areas such as riverside forests, hilltops, high elevations, and steep slopes to conserve water resources and prevent soil erosion. While the forest code legally restricts deforestation on private properties, rigorous enforcement and compliance was hampered by unknown or ambiguous property rights, particularly in the Amazon (Soares-Filho et al., 2014). To better track deforestation activities in the Amazon, remote sensing based monitoring programs were established (DETER) or enhanced (PRODES) in the early 2000s (INPE, 2014; Assunção et al., 2013). As deforestation rates peaked again in the year 2004, the plan to prevent and control deforestation (PPCDAm) was launched, defining additional areas of preservation and fiscalisation of municipalities with high deforestation rates. This development was supported by zero deforestation agreements among almost all soybean processors and exporters in 2006 (soy moratorium) and by the major meat packing industry in 2009b (beef moratorium) (Boucher et al., 2013; Nepstad et al., 2014). The combined effect of governmental policies and supply chain intervention drastically reduced deforestation between 2005 and 2014 in the Brazilian Amazon. Moreover, in 2009, the Brazilian government committed to 80% reduction of clear-cut deforestation until 2020 compared to the 1996-2005 period (National climate change mitigation plan, Nepstad et al., 2014). Thus, we can expect the deforestation and illegal land appropriation control actions to be maintained the next years. However, since August 2014 forest clearing rates strongly increased, possibly triggered by the rising currency inflation rate, the weakened position of environmental politics and the ongoing investments for infrastructure projects (Fearnside, 2015). This underlines the fragility of current environmental protection measures in case of the Amazon region.

Tab. I-1: Overview of governmental and private actions on agricultural expansion and deforestation in Brazil.

Year	Incentive	Description
1965	Forest law	50% of private property in the Amazon reserved for conservation
1972	Foundation of EMBRAPA	Cattle breeding and introduction of new crop and grass species
1970-1980	Road building into Amazon	Strategic territorial occupation by the military government and civil colonisation by private real estate companies
1988	Revised constitution	Incentives for higher land based production and foundation of environmental protection agency IBAMA
1994	Plano Real	Introduction of the new currency “Real” to fight inflation
1996	Revised forest law	80% on private property in the Amazon reserved for conservation, 35% in the Cerrado, 20% elsewhere
2000	PRODES Digital	Improved remote sensing based deforestation monitoring
2004	PPCDAm	-Creation of environmental areas -Black listing of municipalities to limit access to credits -Increased law enforcement
2004	DETER	Remote sensing based “Real time monitoring” of the Amazon to coordinate environmental police (IBAMA)
2006	Soy moratorium	Initiative of major soy trader. No soy from areas deforested after 2006.
2009	Cattle moratorium	Initiative of meat packing industry. No beef from farms without land title.
2009	CAR registration	Increase of land registration due to cattle moratorium
2012	2. revision of forest law	Amnesty of deforested areas before 2008 and reduction of protection status of specific landscape elements.

Until today, reforms that were established for the Amazon biome since the 2000s did not reach any equivalent in the Cerrado region due to the veto of the agrarian lobby. The influence of the agrarian lobby in the political decision process became obvious when Blairo Maggi, the largest soybean entrepreneur in Brazil, was elected as governor of Mato Grosso for the 2003–2006 period. As a consequence of the low protection status of Cerrado vegetation (35% on private properties), annual deforestation shows constant rates of 12,000 km² since 1990 (Beuchle et al., 2015) and partly outcompetes deforestation rates in the Amazon (INPE, 2014). Moreover, rural properties in the Cerrado region show low compliance to the forest code and a systematic governmental monitoring system for attaining the objectives of the forest code is still lacking (Soares-Filho et al., 2014). First attempts to establish a monitoring system for the Cerrado region were conducted by the remote sensing department of the Federal University of Goiás (SIAD) in the year 2006 (Lapig, 2014; Rocha et al., 2011). However, the program only focuses on deforestation, thus monitoring general land use in the Cerrado biome is lacking. Accordingly, consistent spatially and temporally explicit data on the distribution of cropland and pasture is still missing, which causes high uncertainties for estimating environmental and socio-economic impacts of the land changes in this region.

The Cerrado and Amazon region strongly differ in their land use dynamics (Fig. I-3) and current rates of deforestation (Beuchle et al., 2015; Fearnside, 2015) show the fragility of applied measures to curb legal and illegal land change processes. To improve understanding of land change processes and related impacts, a comprehensive reconstruction of LULC changes in both biomes is needed. So far, little is known about the spatial distribution of agricultural areas in the Cerrado and the long-term deforestation and regrowth processes in the Brazilian Amazon (prior to the establishment of the monitoring systems). In particular, regrowth of secondary vegetation on Amazonian pastures has long been overlooked in regard to its legal implications and potential for both, landscape restoration and land use intensification. The incomplete knowledge of current and long-term land use processes might trigger false assumptions in the political land use discussion and hampers the evaluation of ecosystem impacts. Better information on current and long-term land use processes is therefore crucial for reconciling trade-offs between food security, economic growth and ecosystem services. Remote sensing plays a key role in detecting, characterizing, and monitoring land cover and land use reliably, consistently, and at appropriate spatial scales over time. Spatially explicit information on land use types and land use changes build the basis for estimating ecosystems status. This knowledge is a key element to support decision processes and evaluate the impacts of past policies.

3 Remote sensing of land use characteristics

Remote sensing allows for repeated and spatially explicit observations of the land surface, covering large areas irrespective of political or ecological boundaries. Since the first earth observation satellite was launched into orbit 1972, space borne remote sensing has advanced to an important tool for detecting, characterizing, and monitoring land cover and land use change (Lillesand et al., 2014). Today, a multitude of space borne sensors operationally acquires data with different spatial, temporal resolutions (Tab. I-2).

Tab. I-2: Commonly used optical earth observation sensors from space.

	Sensors and platforms	Pixel size	Observation frequency
Low resolution	Moderate-Resolution Imaging Spectroradiometer (MODIS), Satellite Pour l'Observation de la Terre VEGETATION (SPOT-VGT)	250-1000m	daily
Medium resolution	Landsat, Sentinel 2	10-60m	weekly-monthly
High resolution	Rapid Eye, Quick Bird World View 1 & 2	<10m	unregular

Low resolution sensors such as MODIS and SPOT-VGT (Tab. I-2) provide repeatedly observations allowing to observe temporal changes of the earth surface across large geographical extents. The temporal information give unique insights into phenological characteristics of plants, which can be used to distinguish different crop types (Arvor et al., 2011a) or tree species (Waring et al., 2006). Due to the large spatial coverage, low resolution data is often used to perform regional to global scale analysis with comparably low effort. However, low resolution data does not provide the spatial detail to detect certain landscape features such as small scale farming, selective logging or road networks. Instead, small scale landscape features can be detected with high resolution sensors such Quick Bird, Rapid Eye or World View (Lillesand et al., 2014). Those datasets provide enormous spatial details but are costly to obtain and are only available since the 2000s. Furthermore, satellites are tasked for priority regions which make it difficult to extent the analysis above the local scale and to receive repeated imagery for temporal analysis.

Reconciling the trade-off between spatial and temporal sensor characteristics towards the processes of interest is one important aspect in LULC based remote sensing applications. Medium resolution sensors such as Landsat or Sentinel-2 represent a compromise between low and high resolution data (Tab. I-2). The spatial resolution of 10m - 30m is well suited to monitor land cover changes and regularly repeated observations (weekly-monthly) allow for temporal analyses (Cihlar, 2000; Cohen and Goward, 2004). With the beginning of the Landsat mission in 1972, the largest continuous record of earth observation imagery has been created, which renders Landsat imagery a key element in remote sensing for LULC analysis. Importance of Landsat imagery for LULC change research have again increased in 2008, when the US government decided to provide Landsat data for free (Woodcock et al., 2008) along with a standardized geometric pre-processing and archive consolidation (Wulder et al., 2012). Moreover, international ground station holdings are being consolidated into the USGS archive including precision terrain correction (L1T). In case of the Brazilian Landsat archive, this process was finished in 2013 and now enables the creation of consistent Landsat time series for South America.

The new developments regarding quality and availability of Landsat data have allowed to move from mono-temporal or multi-temporal LULC classifications towards temporal analysis of gradual long-term processes (e.g. forest regeneration) and accurate timing of highly dynamic processes (e.g. tropical deforestation, cropland rotations). Moreover, multiple observations over time allow a better discrimination among land cover types by incorporating phenological information (e.g. separating natural grasslands and pastures). 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 in the magnitude of months and years (Song et al., 2001; Kovalskyy and Roy, 2013). Recently, atmospheric correction and cloud screening became operationalised (Masek et al., 2006; Zhu et al., 2012), which has improved the potential of Landsat data for temporal applications.

Time series methods in the domain of remote sensing strongly depend on the process of interest and the availability of cloud free observations (Hostert et al., 2015). For example, North America shows highest temporal coverage of Landsat imagery with monthly to bi-weekly observations within the last 15 years (Kovalskyy and Roy, 2013). In this region, conventional time series approaches can be applied, which have long been restricted to sensors with near-daily revisit times like MODIS and AVHRR. The conventional time series analysis includes fitting of a sinusoidal function to a phenological signal, which allows to characterize system properties (e.g. crop types) or “real time” changes (Zhu and Woodcock, 2014). In tropical regions and sub-tropical savanna areas, frequent cloud coverage and varying acquisition schemes reduce data availability. In these cases, temporal metrics can be derived by calculating mean, range, and standard deviation of available observations for seasonal windows, single years or multiple years (Griffiths et al., 2013a; Hansen et al., 2013). These metrics are especially useful to characterise LULC across large areas with varying observation densities and have been combined with image compositing frameworks to expand the spatial coverage to regional (Potapov et al., 2011; Griffiths et al., 2013a) and global scales (Hansen et al., 2013). During the compositing step, multiple Landsat images are decomposed on the pixel level and rearranged into a continuous cloud free synthetical image following a suit of user defined rules (White et al., 2014; Nelson and Steinwand, 2015). This approach allows to directly generate seamless spectral-temporal metrics across large areas, which can then serve as input for classification of land cover types or for temporal analysis of forest degradation or regrowth processes (e.g. regression methods suggested by Kennedy et al. (2010).

So far, application of time series based Landsat analysis have mainly focused on forest ecosystems (Huang et al., 2010; Kennedy et al., 2010; Pflugmacher et al., 2012; Zhu et al., 2012) or agricultural areas in temperate zones (Griffiths et al., 2013a; Zhu and Woodcock, 2014). However, high potential exists to improve current LULC maps of heterogeneous savanna landscapes or dynamic shifting cultivation systems in the tropics, which are still deficient (Fritz et al., 2013). Moreover, spectral-temporal metrics can help to exploit the Landsat archive towards information that supports deciphering land use intensification or extensification patterns such as changes in fallow cycle frequency.

4 Research questions and study area

This dissertation aims to improve monitoring of Brazilian LULC and associated long-term changes with time series-based remote sensing methods. So far, LULC maps are notorious inaccurate for savannah areas and the deforestation processes in the Brazilian Amazon is largely unknown for the 80s and 90s. The absence of public available long-term deforestation data prevents to extract and investigate temporal dynamics of regenerating secondary vegetation after forest clearing. This knowledge is crucial for evaluating restoration of illegal deforested areas as required by the current forest law. First attempts are being carried out by the LULC monitoring program TerraClass (INPE, 2015b), but the mapping approach does not capture long-term dynamics.

Since the Brazilian Landsat archive has been transferred to the archive of the United States Geological Survey (USGS) in 2013 and converted to precision terrain corrected (L1T) Landsat format, the creation of consistent Landsat time series for South America became feasible. Time series based methods unfold new opportunities to improve LULC mapping in Brazil, but challenges remain in identifying the relevant metrics to analyse land use processes of varying temporal and spatial scales. In this context, two overarching research questions arise:

1. **How can monitoring of LULC in savanna and rainforest areas be improved using the temporal depth of the Landsat archive?**
2. **How do LULC change over time considering political and private initiatives?**

The first research question concentrates on the remote sensing methodology, which builds the methodological backbone of the following core chapters. The second research question focuses on the temporal dynamics of LULC change with regard to the governmental and private actions summarized in Tab. I-1. The design of this dissertation aims at investigating relevant examples for socio- economic gradients and ecological units. In this context, we selected two study sites of regional extent, one deforestation frontier crossing the rainforests of Mato Grosso and Pará and one consolidated agriculture region in the south eastern Cerrado of Mato Grosso (Fig. I-4). The agricultural region is located in the Rio das Mortes watershed and represents one of the major centres for highly mechanized soy, corn and cotton production in Mato Grosso (Grecchi et al., 2013). The deforestation frontier follows the BR-163 highway, which has been constructed as an export corridor for agricultural products from Cuiabá in Mato Grosso to the harbor of Santarém in Pará.

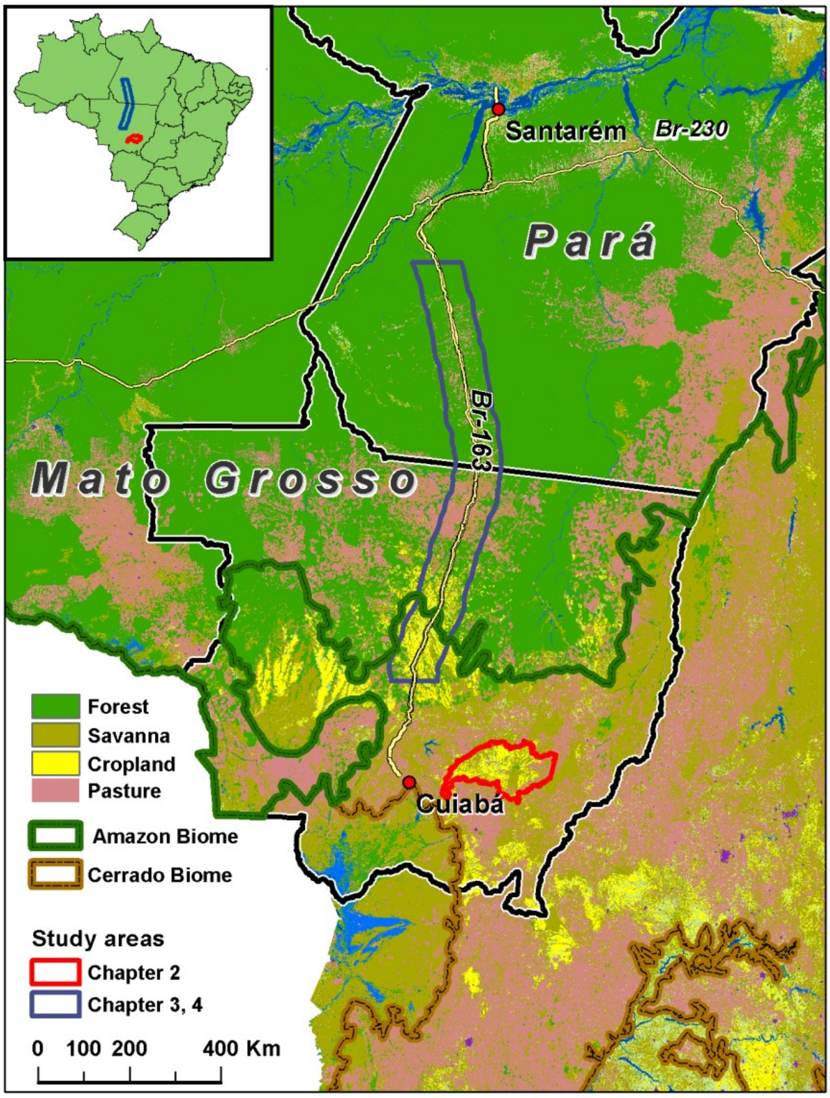

Fig. I-4: Overview on study areas. The red study area is located in the Rio das Mortes watershed and covers one of the major centres for highly mechanized soy, corn and cotton production in Mato Grosso. The blue study area follows the BR-163 highway across a highly dynamic deforestation frontier.

The study sites include contrasting socio-economic realities, namely extensive pastoralism in Pará and the capital-intensive agriculture in Mato Grosso (Richards, 2012; Coy and Klingler, 2014). Both systems require better understanding of land use processes, which we address by the following three research objectives:

Research objective 1 (Chapter II): Determining the potential of Landsat time series to improve the separation of cropland and pasture in a heterogeneous Brazilian savanna landscape

So far, governmental programs do not cover the Brazilian savannas (Cerrado), despite the fact that this region is dominated by progressive deforestation and cropland expansion. Separating croplands, pastures and natural vegetation in the

Cerrado with Landsat imagery is challenging due to a high spatial and spectral heterogeneity of pasture, cropland and natural vegetation. In Chapter II we focus on the potential of Landsat time series these three LULC types in the Rio das Mortes watershed and discuss the potential to transform our approach into a monitoring system.

Research objective 2 (Chapter III): Uncovering long-term deforestation dynamics within a highly dynamic deforestation along the BR-163.

The great success of the Brazilian deforestation program "PRODES digital" has shown the importance of annual deforestation information for understanding and mitigating deforestation and its consequences in Brazil. However, there is a lack of similar information on deforestation for the 1990s and 1980s. Such maps are essential to understand deforestation frontier development and related carbon emissions. In Chapter III we address this knowledge gap for the dynamic deforestation frontier along the BR-163, by analyzing long-term Landsat time series.

Research objective 3 (Chapter IV): *Determining long-term regrowth dynamics within a highly dynamic deforestation frontier along the BR-163.*

Regrowth of secondary vegetation is a widespread phenomenon in the Brazilian Amazon and helps to restore ecosystem services lost during deforestation. Reasons for the establishment of secondary vegetation are manifold and range from afforestation projects to low land use intensity due to unsuitable geographic conditions and limited access to markets, finance, labor and machinery. The multiple dimensions of ecological and socio-economic processes related to secondary vegetation prove the importance of monitoring specific spatial pattern and temporal dynamics. So far, spatial patterns and temporal dynamics of secondary vegetation in the Brazilian Amazon remain poorly understood, especially in regard to different land management regimes. In Chapter IV we use long-term Landsat time series to extract regrowth dynamics for the BR-163 region, covering different land use regimes across the border of Mato Grosso and Pará.

5 Overall structure of the dissertation

This dissertation is divided into three core chapters (Chapter II–IV), each related to one of the research objectives described above. The first research objective provides the methodological background of this thesis by deriving and testing Landsat spectral-temporal metrics within a large area compositing approach. The spectral-temporal metrics were used to describe the state of the agricultural system by separating cropland, pasture and savanna vegetation. The 2nd and 3rd research objective aim at characterizing deforestation and regrowth processes over time. Accordingly, the compositing framework was transferred towards the creation of annual time series of spectral-temporal metrics to analyse long-term deforestation and regrowth dynamics (Fig. I-5).

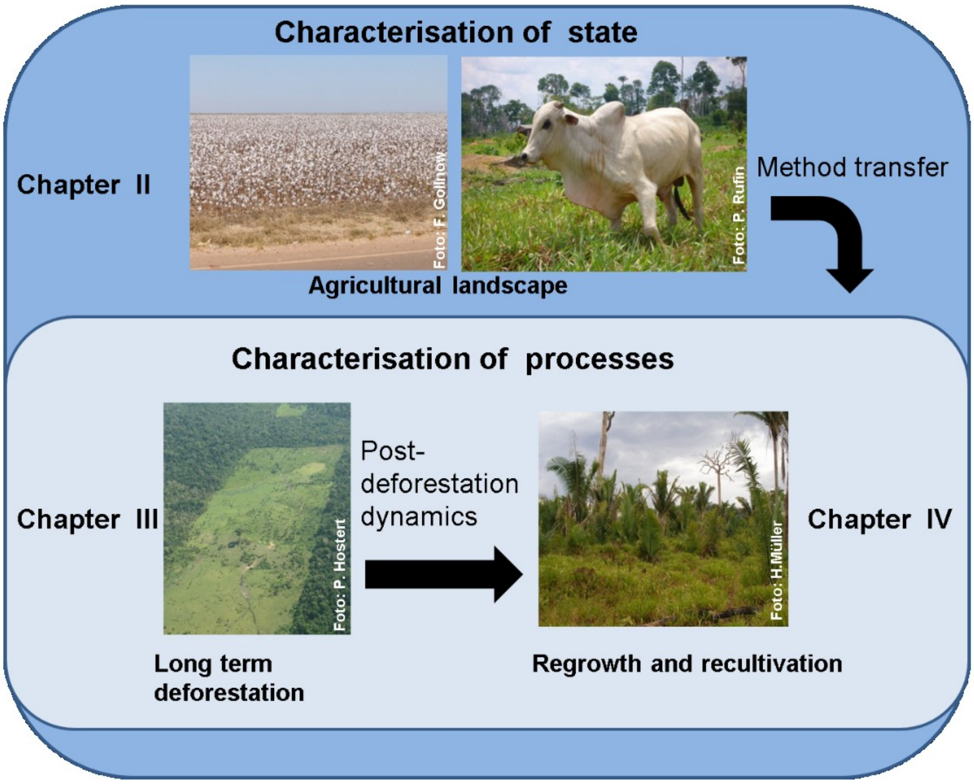

Fig. I-5: Conceptual framework of core chapters. In Chapter II, temporal information was used to monitor the state of LULC in the Brazilian Cerrado. In Chapter III and IV, the monitoring approach was expanded to characterize deforestation and regrowth processes by incorporating long-term Landsat time series.

The core chapters (Chapter II–IV) of this dissertation were written as stand-alone manuscripts and published in international peer-reviewed journals:

Chapter II

Müller, H., Rufin, P., Griffiths, P., Siqueira, A. J. B., & Hostert, P. (2015). Mining dense Landsat time series for separating cropland and pasture in a heterogeneous Brazilian savanna landscape. Remote Sensing of Environment, 156, 490-499.

Chapter III

Müller, H., Griffiths, P., & Hostert, P. (2016). Long-term deforestation dynamics in the Brazilian Amazon—Uncovering historic frontier development along the Cuiabá–Santarém highway. International Journal of Applied Earth Observation and Geoinformation, 44, 61-69.

Chapter IV

Müller, H., Rufin, P., Griffiths, P, Hissa, L., & Hostert, P. (submitted). Beyond deforestation: Differences in long-term regrowth dynamics across land use regimes in southern Amazonia. (In review for Remote Sensing of Environment).

Chapter II:
Mining dense Landsat time series for separating cropland and pasture in a heterogeneous Brazilian savanna landscape

Remote Sensing of Environment 159 (2015) 490-499

Hannes Müller, Philippe Rufin, Patrick Griffiths, Auberto Siqueira, Patrick Hostert

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Abstract

Better spatial information on the global distribution of croplands and pastures is urgently needed. Without reliable cropland-pasture separation it will be impossible to retrieve high-quality information on agricultural expansion or land use intensification, and on related ecosystem service provision. In this context, the savanna biome is critically important but information on land use and land cover (LULC) is notoriously inaccurate in these areas. This is due to pronounced spatio-temporal dynamics of agricultural land use and spectral similarities between cropland, pasture, and natural savanna vegetation. In this study, we investigated the potential to reliably separate cropland, pasture, natural savanna vegetation, and other relevant land cover classes employing Landsat-derived spectral-temporal variability metrics for a savanna landscape in the Brazilian Cerrado. In order to better understand the surplus value and limitations of spectral-temporal variability metrics for classification purposes, we analyzed four datasets of different temporal depth, using 344 Landsat scenes across four footprints between 2009 and 2012. Our results showed a reliable separation between cropland, pasture, and natural savanna vegetation achieving an adjusted overall accuracy of 93%. A similar accuracy and spatial consistency of LULC classification could not be achieved based on spectral information alone, indicating the high additional value of temporal information for identifying LULC classes in the complex land use systems of savanna landscapes. There is great potential for transferring our approach to other savanna systems which still suffer from inaccurate LULC information.

1 Introduction

Food security is of global concern, and land-based production has to meet the demands of an estimated 9 billion people in 2050 (Godfray et al., 2010). To define an optimum trade-off or even create win-win situations between agricultural expansion and intensification on the one hand, and sustainable ecosystem service provision on the other hand, reliable information about the global distribution of croplands and pasture areas is required (Fritz et al., 2013; Garnett et al., 2013). In this context, the savanna biome is critically important for three reasons: firstly, it suffers from enormous land conversion pressure (MEA, 2005a; Ramankutty et al., 2006). Secondly, sustainable land use is a key concern in savanna ecosystems because they are biodiversity hotspots hosting much of the world`s last remaining mega-fauna and provide ecosystem services of global importance such as carbon storage and climate regulation (MEA, 2005a). Thirdly, spatially explicit mapping of land use and land cover (LULC) is notoriously challenging and inaccurate in these areas, which hampers monitoring of ecosystem changes and therefore does not support the development of appropriate policies to steer land conversion in a sustainable manner (Herold et al., 2008; Fritz et al., 2011).

Savanna ecosystems cover approximately 20% of the Earth's surface, with important shares in Asia, Australia, Africa, and South America. Over the past 35 years, the Brazilian Cerrado (savanna woodlands) has experienced one of the largest expansions of agro-pastoral lands worldwide (Ramankutty et al., 2002; Ramankutty et al., 2006). The Brazilian Cerrado is one of the world´s hotspots of biodiversity (Myers et al., 2000), comprising 2M km² of woodlands, savannas, grasslands, gallery and dry forests (Eiten, 1972; Ribeiro et al., 1981). Despite its outstanding ecological value, only 2.2% of the biome is protected, and 40%-50% of the original vegetation had been cleared for agro-pastoral land uses by 2002 (Machado et al., 2004; Klink and Machado, 2005; Sano et al., 2010). These major transformations increased carbon emissions, trigger biodiversity loss and reduce ecosystem services (Silva et al., 2006; Batlle-Bayer et al., 2010). In addition, the Cerrado biome became subject to widespread land use intensification (Galford et al., 2008; Barretto et al., 2013), such as the expansion of cash crops on previously extensively managed pasture areas and shifting from "single-cropping" to "double-cropping" systems. Statistical analyses suggest that this development leads to a displacement of pasture areas to regions of natural vegetation and can be regarded as an indirect driver of deforestation in the Amazon and Cerrado biome (Barona et al., 2010; Arima et al., 2011). However, consistent spatially and temporally explicit data on the distribution of cropland and pasture is still missing, which causes high uncertainties for estimating environmental and socio-economic impacts of the land changes in the Brazilian Cerrado. Across large areas, remote sensing plays a key role in detecting, characterizing, and monitoring land cover and land use reliably, consistently, and at appropriate spatial scales over time (Lambin and Geist, 2006; Kuemmerle et al., 2013).

So far, the majority of remote sensing studies in Brazil focused on the Amazon biome, including governmental programs like the annual deforestation monitoring (PRODES), the real time system for detection of deforestation (DETER), and the program for land use classification in deforested areas (TerraClass) (INPE, 2008a; Assunção et al., 2013). First attempts to build similar knowledge for the Cerrado region are conducted by the remote sensing department of the Federal University of Goiás, who created a Systematic Monitoring of Deforestation in the Cerrado Biome (SIAD) in the year 2006 (Ferreira et al., 2007; Rocha et al., 2011; Lapig, 2014). However, no program has been established for monitoring general land use in the Cerrado biome and remote sensing faces numerous challenges there.

Besides the strong seasonality of natural vegetation and the high diversity of crop types in space and time (Sano et al., 2007b), spectral similarities between cropland, pasture, and natural savanna vegetation complicate differentiating LULC in the Brazilian Cerrado (Sano et al., 2010; Grecchi et al., 2013). This confusion results from spectral similarity between land cover types as well as a high spectral heterogeneity within each land cover type (Ferreira et al., 2003; Brannstrom et al., 2008; Hill et al., 2011). Due to these spectral ambiguities, most classification approaches predominantly rely on dense temporal information, such as time series data obtained from the Moderate Resolution Imaging Spectrometer (MODIS) for separating natural savanna vegetation, cropland, and pasture areas (Morton et al., 2005; Galford et al., 2008; Adami et al., 2011; Arvor et al., 2011a; Trabaquini et al., 2011). However, MODIS-based analyses cannot monitor LULC before 2000 (when the satellites became operational) and often do not capture fine-scale patterns in heterogeneous savanna ecosystems such as the Brazilian Cerrado or South-African savannas (Huete et al., 2002; Fritz et al., 2011; Munyati and Mboweni, 2013). Recent approaches therefore include Landsat imagery (30m resolution) to overcome the limitation of the MODIS spatial scale (250m resolution) and temporal extent in heterogeneous savanna regions (Schmidt et al., 2012; Grecchi et al., 2013).

With the opening of the Landsat archive, analysis strategies now shift from a scene-based perspective to more meaningful study area delineations, such as political / administrative units or natural entities, like complete watersheds across multiple Landsat footprints (Wulder et al., 2008; Hansen and Loveland, 2012). In this context, the Brazilian Landsat archive has recently been transferred to the archive of the United States Geological Survey (USGS) and converted to precision terrain corrected (L1T) Landsat format. The high geometric accuracy of this new dataset, coupled with state of the art atmospheric correction (e.g. LEDAPS by Masek et al., 2006) and cloud screening methods (e.g. FMask by Zhu and Woodcock, 2012), now enables the creation of consistent Landsat time series for South America.

So far, most Landsat-based time series have been created on an annual basis to monitor forest cover dynamics (Kennedy et al., 2007; Powell et al., 2010; Kennedy et al., 2012; Griffiths et al., 2012). Recent research highlights the potential of using intra-annual time series for grassland mapping (Schuster et al., 2015). We therefore hypothesize that identifying complex LULC classes within agricultural systems will profit from intra-annual information to capture phenological characteristics as well. However, due to Landsat's 16-day repeat cycle, cloud contaminations, and long-term acquisition plans, regular spacing of intra-annual acquisitions is difficult and direct quantification of phenological metrics is challenging (Kovalskyy and Roy, 2013). To overcome these limitations, interpolation and curve fitting methods have been successfully employed for regions with high data availability, notably in North America (Melaas et al., 2013; Zhong et al., 2014). However, it is questionable whether single dates of phenological characteristics in regions of low observation density should be extracted, given the degree of generalization involved in bridging large temporal data gaps. Less specific but more robust phenological indicators can be derived by simply calculating mean, range, and standard deviation of available observations for seasonal windows, single years or multiple years (Griffiths et al., 2013a; Hansen et al., 2013). These spectral-temporal variability metrics (from now on "spectral-temporal metrics") capture important phenological information and can be analyzed on a seasonal, annual or multi-annual basis, allowing for a wide range of applications for characterizing land use systems in space and time.

In this study, we aimed to investigate the potential of Landsat-derived spectral-temporal metrics to reliably separate cropland, pasture, natural savanna vegetation, and forest in a heterogeneous savanna landscape. To estimate the additional value of phenology in our classification approach and to understand limitations related to varying observation densities, we analyzed five datasets of different temporal depth, based on a total of 344 Landsat scenes across four footprints that were acquired between 2009 and 2012. Our overall research objectives were:

- Use spectral-temporal metrics to separate cropland, pasture, and natural vegetation in a heterogeneous savanna landscape.
- Understand the influence of seasonality and observation density on classification results.
- Compare LULC classification solely based on spectral information with classifications of spectral-temporal information.

2 Data and methods

2.1 Study area and description of LULC classes

To evaluate the potential of the Landsat-derived spectral-temporal information for distinguishing LULC classes in the Brazilian Cerrado, we conducted a case study in the Rio das Mortes watershed, a tributary of the Araguaia River that drains into the Tocantins River, the central fluvial artery of Brazil. This macro-catchment is part of the Chapada dos Guimarães, a plateau region located near the city of Cuiabá in Mato Grosso state. The watershed boundaries were derived from a digital elevation model with 90m spatial resolution (van Zyl, 2001; SRTM, 2008) and delineate an area of about 18,000 km² (Fig. II-1). The regional climate exhibits a distinct dry season from May to September and corresponds to a tropical savanna (Aw), according to the Köppen climate classification (Moreno et al., 2005). Annual precipitation of 1,500 mm accumulates mainly between November and March.

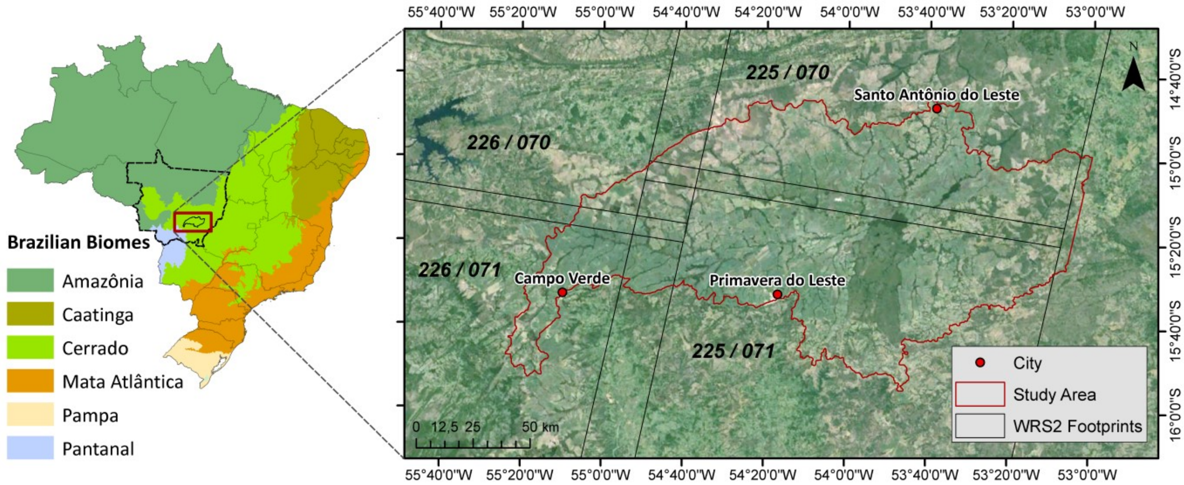

Fig. II-1: Left: Distribution of the predominant biomes in Brazil and Mato Grosso state. Right: Close-up of the study area based on Google Earth imagery.

The watershed is located in the Cerrado biome and natural vegetation comprises woody grassland (Campo Cerrado), woodland Cerrado (Cerrado sensu stricto), woody Cerrado (Cerradão), and gallery forest along the rivers (Furley, 1999). Parts of the watershed are also covered by wetlands, which are located close to the northern border of the Sangradouro-Volta Grande Indigenous Reserve, an area of approximately 1,000 km².

The Rio das Mortes watershed has undergone significant LULC change since the 1970s and is one of the major agricultural production centers of Mato Grosso, inhabited by 80,000 people. Despite its unique ecological functions, the Brazilian forest code allows conversion of 65% of natural vegetation on private properties in the Cerrado (Federal Law 12.727, 2012; summarized by Soares-Filho et al., 2014), which has permitted major land cover changes over the last 40 years. Land conversion started in the 1970's with the establishment of pastures for cattle ranching. In the 1980's, soybean cultivation was introduced and corn and cotton have been cultivated in the study area since the 1990's. Production of soy boomed in the early 2000s, and national statistics show that the cropped area reached its maximum in 2005 for the six major municipalities in the study area (approx. 10,600 km², IBGE, 2010). After 2005, cropland expansion stopped due to changes in world market prices and yield gaps caused by a new soybean disease, the "Asian rust" (Arvor et al., 2009). To avoid new outbreaks of the disease, a phytosanitary measure was introduced that prohibits the cultivation of soy from July to September (Seixas and Godoy, 2007). Due to these restrictions, the main sowing season for soy starts with the wet season between September and October. Sowing and harvesting practices differ for individual rotation systems (single- or “double-cropping”) and crop type (e.g. cotton, corn), but the production cycle usually ends with the last harvests at the beginning of the dry season in July (Fig. II-2a, Arenas-Toledo et al., 2009; Arvor et al., 2011b).

To characterize the predominant LULC classes in the study region, we differentiate forest, savanna, cropland, pasture, non-vegetated land and water bodies. The non-vegetated land class includes the built-up environment, open soils and rock outcrops. The savanna class comprises woody grassland (Campo Cerrado), woodland Cerrado (Cerrado sensu stricto) and wooded Cerrado (Cerradão). Croplands include both “single” and “double-cropping” systems for soy, corn and cotton. During our field visits it was apparent that these systems can also include fallow cycles with grassland and temporary cattle ranching. Pasture areas contain planted grasslands used exclusively for cattle ranching. These areas are often characterized by scattered residuals of woody savanna vegetation, indicating the absence of large- scale mechanized agriculture.

2.2 Analysis strategy

Our analysis strategy comprised two stages. First, we evaluated the overall accuracy and spatial consistency of the LULC classification (section 2.6), which was based on 31 spectral-temporal variability metrics. These metrics were obtained from all available Landsat acquisitions within a three-year period, from January 2nd 2009 to February 28th 2012 (hereafter referred to as “benchmark dataset”, Tab. II-1). The analysis method requires that no major land conversions occurred during this period of time. This assumption is supported by field interviews, existing literature and agrarian statistics (IBGE, 2010; Grecchi et al., 2013).

Second, we performed a sensitivity analysis to better understand limitations of spectral-temporal metrics as input for LULC classifications in relation to varying observation densities across the dry and wet seasons. For this sensitivity analysis, we performed a stepwise reduction of the number of observations included in the benchmark dataset, resulting in three additional datasets of different temporal depth (Tab. II-1). For each of the additional datasets, a decision tree based LULC classification was conducted and classification accuracy, confusion between different classes of interest and spatial patterns in the mapping results were compared.

The first reduction of the benchmark dataset limits the available observations to a 1-year instead of a 3-year period (2011-2012, "single year dataset"). The single year dataset allows investigating the robustness of our classification approach towards a considerably reduced observation density (70% reduction compared to benchmark dataset, Tab. II-1). Also, it resembles the often considered "yearly case" that avoids inter-annual change in a time series. The second reduction limits the available observations to the 2011 dry season. This is a frequent setting, as observations can be poor or entirely missing for the wet season due to dense cloud cover. The third reduction refers to a best observation composite without information from spectral-temporal variability metrics (section 2.5). This last setup allows us evaluating the added value of phenological information included in the three spectral-temporal datasets (benchmark, single year, dry season) and serves as a comparison to single image classification approaches.

Tab. II-1: Temporal and spectral properties of the datasets. The number of cloud free observations per pixel is calculated as the median number of clear observations for each spectral-temporal dataset. A wet-dry season ratio of 0.5 indicates twice as much dry season observations as wet season observations

	Benchmark dataset	**Single year dataset**	**Dry season dataset**	**August composite**
Period	Jan 2nd 2009- Feb 28th 2012	Jan 1st 2011- Feb 28th 2012	Apr 29th 2011- Oct 22nd 2011	Aug 2011*
No. predictor variables	31 spectral-temporal metrics	31 spectral-temporal metrics	31 spectral-temporal metrics	6 spectral bands
No. of images	344	104	54	6
Cloud free obs. per pixel	54	17	12	1
Wet-Dry season ratio	0.52	0.65	n.a.	n.a.

* For creating the target date image, best pixel observations from mid-July to mid-August were used.

2.3 Satellite imagery, atmospheric correction and cloud masking

We exclusively used TM and ETM+ Landsat data in precision terrain corrected (L1T) format and converted all imagery to surface reflectance using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) atmospheric correction algorithm (Masek et al., 2006) to ensure comparability of input data across different Landsat sensors, footprints, and acquisition dates. Cloud and shadow masks were calculated for all imagery using FMask (Zhu and Woodcock, 2012). The FMask algorithm uses textural and spectral information to detect cloud and cloud shadows on a probabilistic basis. To capture as many clouds and cloud shadows as possible, the cloud probability threshold was set to a highly conservative value (1%). Scenes from different UTM zones were reprojected to WGS 84 UTM 21 South.

2.4 Background and extraction of spectral-temporal variability metrics

Spectral similarities between cropland, pasture, and natural savanna vegetation complicate differentiating LULC in the Brazilian Cerrado (Sano et al., 2010; Grecchi et al., 2013). In contrast, temporal profiles of the normalized difference vegetation index (NDVI) show differences in amplitude and frequency for representative cropland, pasture, and savanna sites (Fig. II-2b). Accordingly, the use of spectral-temporal variability metrics should allow for a better separation of relevant LULC classes through the incorporation of seasonal characteristics. In the Brazilian Cerrado, the cropland profile is typically dominated by rapid changes between full vegetation cover and bare soil twice a year, indicating a “double-cropping” system (Fig. II-2a & b). Savanna vegetation is characterized by a higher and more stable NDVI signal, which decreases sharply during the dry season. NDVI values of pasture follow a moderate sinusoidal curve, with pronounced phases of transition between dry and wet season. Since these phenological patterns translate into a low standard deviation for pasture and savanna areas and a low mean value for pasture and cropland areas, the combination of both variability metrics should support distinguishing the three major LULC classes in the Brazilian Cerrado (Fig. II-2c).

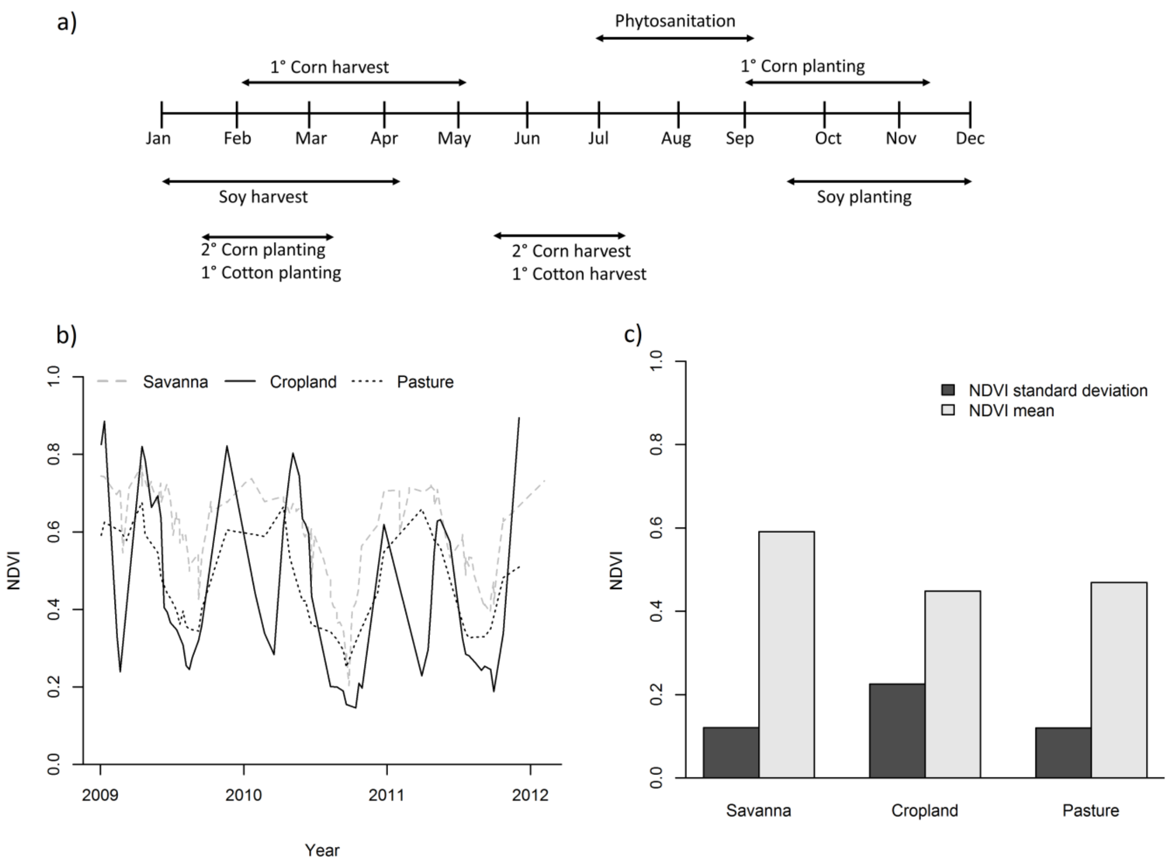

Fig. II-2: a) Crop calendar of common cropping practices in Mato Grosso since 2006 (modified after CEGN, 2008). b) Representative NDVI time series for a double cropping system, pasture area, and savanna vegetation. c) Mean and standard deviation of the respective NDVI values over time in b).

We chose five statistical metrics (mean, median, standard deviation, 75% quartile, and interquartile range), which should capture most phenological characteristics of the investigated LULC classes. We carefully selected these metrics to minimize potential outlier effects across different observation densities of the investigated datasets (Tab. II-1). To include all spectral information, the five statistical metrics were calculated for each spectral band individually. We also calculated a SWIR-Index as the sum of SWIR/NIR reflectance normalized over the number of clear observations. The SWIR-Index serves as an integrated measure, which potentially supports the separation of pasture and cropland areas. Metrics were computed from all cloud/cloud shadow-free observations as described by (Griffiths et al., 2013b) and resulted in a total of 31 spectral-temporal metrics per pixel (Tab. II-2).

Tab. II-2: Overview of the 31 spectral-temporal variability metrics.

No. of variables	Metric	Spectral bands
6	Mean	1-5, 7
6	Median	1-5, 7
6	Standard deviation	1-5, 7
6	75% Quantile	1-5, 7
6	Interquartile range (25%-75%)	1-5, 7
1	SWIR-Index	4, 5, 7

2.5 Creating a best observation composite

We created a best observation composite over the four footprints using the compositing algorithm developed by (Griffiths et al., 2013b). The algorithm uses scoring functions to identify the best available observation based on each pixel's spatial distance to clouds as well as the temporal distance (i.e. days) to the target day-of-year (DOY). We processed all available imagery for the year 2011 and defined August 8^{th} 2011 as the target date for compositing (DOY=220). This date was chosen because it falls in the middle of the dry season, which facilitates comparisons across datasets (e.g. dry season dataset) and minimizes temporal variations in the final composite triggered by cloud contamination. The final best observation composite showed high temporal consistency, with 68% of the pixels observed on August 12^{th} 2011 and 99% of the pixels observed between July 19^{th} 2011 and August 12^{th} 2011.

2.6 Land cover mapping and validation

LULC mapping for all datasets was performed using a random forest (RF) classifier (Breiman, 2001). Being a machine learning classifier, the RF classifier creates multiple decision trees, which are calibrated by a random subset of training data and input variables. Key advantages for remote sensing applications are computational performance, classification accuracy and the ability to handle large and heterogeneous feature spaces based on relatively few training samples (Prasad et al., 2006; Rodriguez-Galiano et al., 2012). Model calibration and prediction was carried out using the statistical software CRAN R (R Development Core Team, 2011) and the "randomForest" package (version 4.6-7 by Liaw and Wiener, 2002).

For model calibration, we randomly selected 500 training points. These were amended with 126 interactively selected points to account for underrepresented classes (Tab. II-3). To classify the training points, we utilized very high-resolution imagery of Google Earth from 2009 to 2012 (Quickbird, GeoEye). If recent Google Earth imagery was not available, Landsat images and calculated variability metrics were used as reference data. In uncertain cases, the labeling was conducted in favor of conservative cropland estimates, as it is the most dominant and heterogeneous land use class in the study area. A minimum distance criterion of 350m was defined to avoid spatial clustering of training points and related autocorrelation. Due to spatial coherence of the water class and areas of non-vegetated land, no minimum distance criterion was employed for these classes.

Unequal sample sizes in the training data can lead to an underestimation of classes with low sample sizes during the classification processes. We tested for negative effects of an imbalanced training dataset by running the RF model in a balanced mode and setting the "sample" parameter to a constant number of 20 samples per class. In this case, the balanced RF uses all reference data, but draws each bagged sample in a stratified manner. Hence, the overall training data is imbalanced, but each tree is trained in a balanced way. As the balanced RF prediction resulted in higher class confusions, we employed the unbalanced RF model for all further analyses, using a standard parameterization for the number of trees (500), the number of training data for each tree (63% of sample size per class), and the number of predictor variables tried at each split (5, approximated by the square root of 31 predictor variables).

The predicted LULC maps were validated using a stratified random sampling design. We initiated the validation with 62 random samples per class and a minimum distance of 350m to avoid spatial autocorrelation. Due to the minimum distance criterion, only 42 points for the non-vegetated land class were selected, resulting in 362 validation points. We used this initial validation dataset to derive a first estimate of user's and producer's accuracies. Based on these estimates we calculated a sufficient number of validation samples following the procedure of (Cochran, 1977) and targeting a standard error for the overall accuracy of 0.01. We determined the adequate sample size of 470 validation points and added 108 additional, stratified randomly selected samples to the initial validation dataset for the final accuracy assessment (Tab. II-3).

Tab. II-3: Number of training and validation samples for each LULC class.

Class name	Training samples	Validation samples
Forest	65	93
Cerrado	108	84
Cropland	232	115
Pasture	143	62
Water	37	74
Non-vegetated land	41	42
Total	626	470

We performed the validation point labeling in the same way as the training data labeling, primary using Google Earth imagery. To account for the stratified random sampling design, overall accuracies and area estimates were adjusted after (Olofsson et al., 2013). In addition, confidence intervals for the adjusted overall accuracy were calculated to report uncertainty of the accuracy estimates introduced by the number of validation points (Congalton and Green, 2009).

3 Results

3.1 Benchmark classification

Cropland was identified as the dominant land use class, covering approximately 51% (9,096 km²) of the study area (Fig. II-3,

Fig. II-4). Savanna areas were ranked as the second largest land cover type (24%, 4,298 km²) and can be found in the indigenous reserve, along gallery forests and within the extensively managed eastern and northern parts of the watershed.

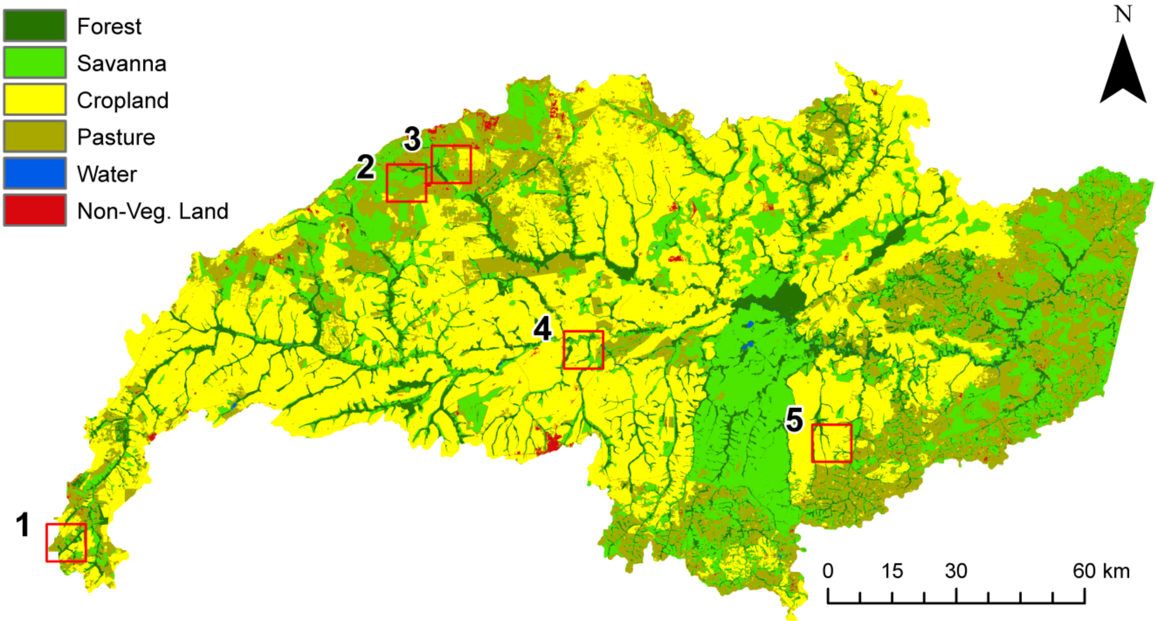

Fig. II-3: Classification results of the Rio das Mortes watershed based on the benchmark dataset. Red squares indicate subsets enlarged in Fig. II-6.

The savanna areas form a mosaic with patches of cattle farming which cover 15% (2,682 km²) of the study site. Forest areas are dominantly located along river streams and account for 9% (1,737 km²) of the total land cover. In the southwestern part of the watershed, small amounts of forest show a characteristic rectangular pattern which is typical for eucalyptus plantations. Non-vegetated land was identified in the cities of Campo Verde, Primavera do Leste and Santo Antônio do Leste. In addition, this class was detected in close proximity to cropland and pasture areas representing 0.8% of the study area.

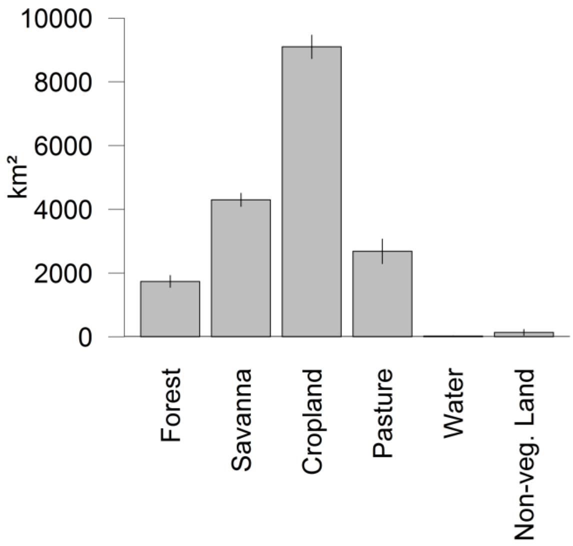

Fig. II-4: Error adjusted area estimates and 95% confidence intervals for all six LULC classes. Results are based on the benchmark dataset.

The LULC classification for the benchmark dataset achieved an adjusted overall accuracy of 93% with a 95% confidence interval margin of ±2%. Highest reliability was observed for the forest, savanna and water classes that revealed user`s and producer`s accuracies greater than 90% (Tab. II-4). No commission error was observed for the cropland class.

Tab. II-4: Confusion matrix of validation results for the benchmark dataset. User`s and producer`s accuracy are normalized between 1 (100%) and 0 (0%). User`s and producer`s accuracy translate into omission and commission error as follows: omission error = 1-producers accuracy, commission error = 1-user`s accuracy.

	Reference data							
Classified data	**Forest**	**Savanna**	**Cropland**	**Pasture**	**Water**	**Non-veg. land**	**Total**	**User`s accuracy**
Forest	90	3	0	0	0	0	93	0.97
Savanna	2	78	0	0	0	0	80	0.98
Croplands	0	0	92	0	0	0	92	1
Pasture	1	2	21	58	0	1	83	0.7
Water	0	0	0	0	73	0	73	1
Non-veg. land	0	1	2	4	1	41	49	0.84
Total	93	84	115	62	74	42	470	
Producer`s accuracy	0.97	0.93	0.8	0.94	0.99	0.98		
(Error adjusted)	(-0.91)	(-0.97)	(-0.89)	(-0.99)	(-0.92)	(-0.67)		

Main class confusion arose from the overestimation of pasture at the expense of cropland. This effect resulted in a commission error of 30% for the pasture class and an omission error of 11% for the cropland class after error adjustment. A minor omission error of 1% for pasture originated from the overestimation of non-vegetated land on pasture areas, leading to a commission error of 16% for non-vegetated land.

3.2 Sensitivity analysis of temporally reduced datasets

Error adjusted overall accuracies decreased with decreasing temporal depth from 93% to 72% (Tab. II-5).

Tab. II-5: Adjusted and non-adjusted overall accuracies for all four datasets and the corresponding 95% confidence interval margins (for dataset description see Tab. II-1).

	Benchmark	**Single year**	**Dry season**	**August composite**
Adjusted overall accuracy [%]	92.61 ± 2.15	85.95 ± 3.11	79.43 ± 3.67	71.61 ± 4.05
(Overall accuracy)	(-92.19)	(-87.87)	(-84.89)	(-79.15)

Errors of omission and commission increased for most LULC classes, including the savanna, cropland, and pasture class (Fig. II-5). Here, reducing the temporal observation window led to an overestimation of savanna and cropland areas at the expense of the pasture class. As a result, the omission error of the pasture class increased to 20%-50% when not using the benchmark dataset. In contrast, omission and commission errors for the forest and water classes remained stable for all datasets. This picture changed when adjusting omission errors after (Olofsson et al., 2013) to account for the heterogeneity of spatial extents of LULC classes. As a result, land use classes of small spatial extent yielded very high omission errors after adjustment (80-88% for water and non-vegetated land), especially for the dry season dataset and the August composite.

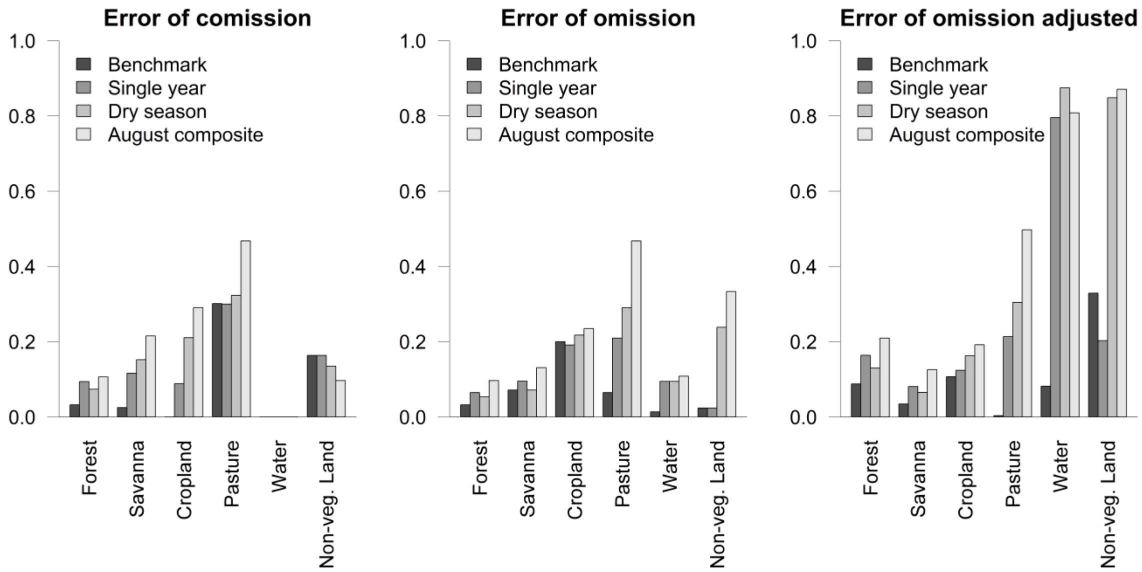

Fig. II-5: Errors of omission and commission for the four different datasets (for dataset description see Tab. II-1). Adjustment of the omission error was conducted following Olofsson et al. (2013) and strongly affected the LULC classes with small spatial extent (water and non-veg. land).

In general, the overestimation of cropland at the expense of pasture was most visible for the dry season dataset and August composite (Fig. II-6, subset 3). The August composite also showed SLC-off effects and some unrealistic spatial patterns for all LULC classes, indicating a strong bias due to the cropland and pasture harvest regimes (Fig. II-6, subset 1, 2, and 4). Irrigated cropland areas, for example, were classified as savanna or forest areas depending on the growth stage of the respective crops (circular features in Fig. II-6, subset 4). In contrast, high agreement was observed between classification results of the benchmark and the single year dataset (90% of pixels are classified identically).

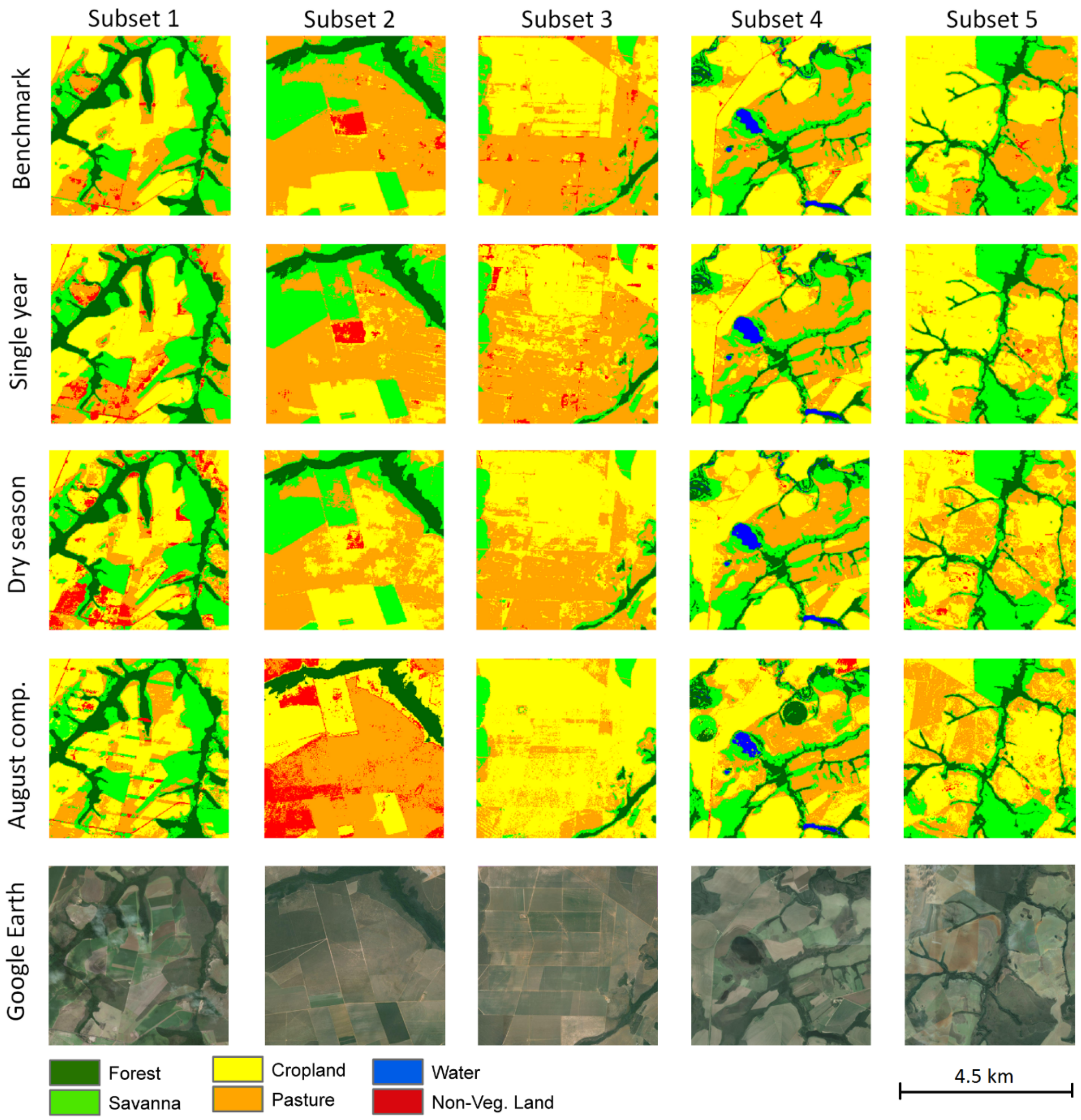

Fig. II-6: Spatial patterns of LULC for five subsets in the study area and the four datasets. High resolution imagery from Google Earth is shown for visual comparison (imagery acquisition dates of subsets 1-5: June 2010, unknown, unknown, March 2013, June 2003). For subset locations see Fig. II-3.

4 Discussion and conclusions

LULC classification of the benchmark dataset achieved an overall accuracy of 93% and class-wise uncertainty was generally low, including the target classes of cropland and pasture. We therefore conclude that our spectral-temporal classification approach provided a reliable separation between cropland, pasture, and natural savanna vegetation. Remaining errors in the benchmark dataset mainly relate to the slight overestimation of the pasture class and can be explained by two factors: firstly, we labeled our training data in favor of a conservative estimation of the cropland class, as it is the most dominant and heterogeneous land use class in the study area. Therefore, the commission error of the cropland class is generally low at the expense of a slightly overestimated pasture class. Secondly, there are extensively managed cropland areas that are used as pastures during one or two rotational cycles. These mixed systems appear as croplands in the validation data but are most likely classified as pastures. Major land conversions during our observation period could also hamper the explanatory power of our spectral-temporal variability metrics. However, such land conversions are unlikely, given our analysis period compared to knowledge on recent land use dynamics (section 2.2).

To better understand the reliability of our approach towards annual or intra-annual classifications we conducted a sensitivity analysis. The sensitivity analysis showed that annual classifications are still rather reliable with an overall classification accuracy of 86% compared to 93% for the benchmark classification. The observed classification error results from the overestimation of croplands at the expense of pastures. As cash crops are mainly grown in the wet season, the amplitude of croplands between the dry and the wet season is unique (Fig. II-2a & b). For the single year dataset, less wet season observations are available resulting in a higher phenological similarity between cropland and pasture and higher commission errors for the cropland class (Tab. II-1). However, the influence of missing wet season observations becomes more important for the dry season dataset. Here classification accuracy decreases from 85% (single year dataset) to 79% indicating that seasonal information is crucial for separating the chosen LULC classes. This outcome is in line with results from Prishchepov et al. (2012), who investigated the importance of image dates for LULC classifications in Eastern Europe using multi-temporal Landsat imagery.

The overall importance of temporal information for our LULC classification was investigated by conducting a classification based on spectral information only, using a composited and cloud-free image of 6 spectral bands (August composite). The classification results revealed considerably lower overall accuracies and inconsistent spatial patterns of LULC classes compared to multitemporal classifications (benchmark, single year and dry season dataset). The spatial patterns relate to different harvesting times and growth stages of croplands in August, when transitioning between the phytosanitary phase (July to September) and the first planting of soy and corn (Fig. II-2a). In general, these results confirm that classifications based on monotemporal data only will not allow separating LULC classes with similar spectral properties during different phenological stages. Therefore, specifically the classification of phenologically complex land use systems will profit from our deep time-series approach.

To our best knowledge, this is the first study employing Landsat-derived, spectral-temporal information for classifying LULC in the heterogeneous Brazilian Cerrado. In a regionally comparable Landsat-based study, Grecchi et al. (2013) reported an overall accuracy of 85% when including MODIS data and pre-existing land cover maps, and not separating forest and savanna areas. This supports our finding that multitemporal information is important in such a setting to separate spectrally similar classes reliably. Other studies that exclusively employed Landsat data reached overall accuracies of above 80% only when fusing cropland and pasture into an agro-pastoral class (Jepson, 2005; Brannstrom et al., 2008). Such aggregation, however, limits linking remote sensing based results with ecological or management processes of great importance, e.g. how pastoralism versus intensive cropping alters savanna ecosystems. Our results therefore emphasize the potential of employing high-resolution spectral-temporal variability metrics for identifying LULC in heterogeneous savanna regions.

So far, it is a great challenge to operationally observe LULC in savanna landscapes on a large spatial scale. Sano et al. (2010) used a monotemporal wall to wall mosaic for manual interpretation of 170 Landsat images for the entire Cerrado Biome and reported high class confusion between croplands and pastures (OA= 71%). These results are in line with our monotemporal classification (August composite, OA=72%) and suggest great potential for improvement by using multitemporal Landsat data. A preliminary screening of the Landsat archive showed that 80% of the entire Cerrado biome has a similar Landsat coverage compared to our study area (+-20% scene availability in 2009-2012), rendering our multitemporal classification approach highly applicable. However, the northern Cerrado might be a critical region due to higher cloud coverage during the wet season (Sano et al., 2007a) and frequent land conversions since 2002 (Lapig, 2014; Rocha et al., 2011). These areas need to be analyzed within a more restricted temporal window (annual or seasonal), which limits data availability even more. In case of data scarcity and missing seasonal information, our approach could profit from an external cropland mask. The cropland mask might be useful to minimize the confusion between the pasture and cropland class. Several studies have shown that high temporal coverage of MODIS data allows to reliably identify cropland, even though it fails to separate pastures from natural savanna vegetation because of the limited spatial resolution (Arvor et al., 2011a; Fritz et al., 2011; Galford et al., 2008).

The methods presented here use satellite data across multiple seasons to reliably differentiate LULC classes but our approach could also be used to identify land use change by comparing several multi-season classifications. Since post classification change detection is highly sensitive to error propagation from single classifications (Coppin et al., 2004), our method will likely improve change detection accuracies if enough imagery is available across phenological cycles – a scenario that will become realistic once Landsat and forthcoming sentinel-2 data can be combined (Drusch et al., 2012; Roy et al., 2014).

5 Outlook

Our spectral-temporal classification approach provides a reliable separation between cropland, pasture, and natural savanna vegetation. Similar accuracy and consistency of LULC classification could not be achieved from spectral information alone, proving the additional value of temporal information for LULC classifications in complex savanna landscapes. We are optimistic that our spectral-temporal classification approach will be expandable within the Cerrado biome and transferable to other savanna regions worldwide. This is specifically true once data scarcity in more clouded or dynamic savanna regions is further reduced by combining Landsat and upcoming Sentinel-2 imagery. Multi sensor constellations will therefore be an important step towards annual LULC mapping and operational monitoring of savanna ecosystems, which will be crucial for conservation purposes and sustainable land management strategies.

6 Acknowledgements

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Chapter III:
Long-term deforestation dynamics in the Brazilian Amazon –uncovering historic frontier development along the Cuiabá –Santarém highway

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Hannes Müller, Patrick Griffiths, Patrick Hostert

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Abstract

The great success of the Brazilian deforestation program “PRODES digital” has shown the importance of annual deforestation information for understanding and mitigating deforestation and its consequences in Brazil. However, there is a lack of similar information on deforestation for the 1990s and 1980s. Such maps are essential to understand deforestation frontier development and related carbon emissions. This study aims at extending the deforestation mapping record backwards into the 1990s and 1980s for one of the major deforestation frontiers in the Amazon. We use an image compositing approach to transform 2,224 Landsat images in a spatially continuous and cloud free annual time series of Tasseled Cap Wetness metrics from 1984 to 2012. We then employ a random forest classifier to derive annual deforestation patterns. Our final deforestation map has an overall accuracy of 85% with half of the overall deforestation being detected before the year 2000. The results show for the first time detailed patterns of the expanding deforestation frontier before the 2000s. The high degree of automatization exhibits the great potential for mapping the whole Amazon biome using long-term and freely accessible remote sensing collections, such as the Landsat archive and forthcoming Sentinel-2 data.

1 Introduction

Deforestation and land use change in the Brazilian Amazon raises global concerns regarding the loss of biodiversity and climate change impacts (Lapola et al., 2014). Long-term deforestation information increases our knowledge on the early stages of deforestation front formation and allows studying related carbon emissions. The Landsat archive is the only satellite image record suited for analyzing long-term deforestation processes (Hansen and Loveland, 2012; Roy et al., 2014). Recently, the Brazilian Landsat archive has been transferred to the archive of the United States Geological Survey (USGS) and converted to precision terrain corrected (L1T) Landsat format. The high geometric accuracy of this new dataset now enables the creation of consistent Landsat time series for South America back to the 1980s.

Most Landsat derived annual deforestation information for the Brazilian Amazon is provided since the early 2000s, such as the annual deforestation monitoring product (PRODES; INPE, 2014) and the global forest cover maps provided by Hansen et al. (2013). However, main deforestation activities in Maranhão, Mato Grosso, Pará, Rondônia and Acre already started with infrastructure projects in the 1970s (Alves, 2002; Galford et al., 2011). In 1988 the Brazilian government tried to control the expansion of the deforestation frontier with an revised constitution that allowed the communization of forest areas inside private lands with limited agricultural use (Richards, 2012). In addition, the Brazilian forest law was revised in 1996 to protect 80% of forest areas on private properties in the Amazon (MMA, 1996). Little is known about the consequences of those political actions in different local contexts because spatial explicit long-term deforestation information is only available for the State of Rondônia (Toomey et al., 2013). For the states of Maranhão, Mato Grosso, Pará and Acre, deforestation information is restricted to 1978, 1988, 1990 and 1997 (Skole and Tucker, 1993; Achard et al., 2002; Kim et al., 2014). These temporal restrictions hamper long-term characterization of deforestation dynamics and limit our ability to analyze effects of socio-political and economical changes on deforestation dynamics in a spatial explicit way. We therefore, see a strong need for the complete reconstruction of spatio-temporal deforestation patterns in the Brazilian Amazon.

Landsat–based change detection approaches now allow creating long-term deforestation products across large areas. These methods can be divided into highly automated and semi-automated approaches. Highly automated approaches such as LandTrendr (Kennedy et al., 2007) and Vegetation Change Tracker (Huang et al., 2010) are designed to capture forest disturbances without using additional training data. They rely on single- date spectral information per year and show good results for temperate forests (Griffiths et al., 2012; Stueve et al., 2011). However, the transferability to tropical forest systems still has to be proven since tropical ecosystems are generally much more dynamic e.g. concerning recovery rates after forest disturbances (Broich et al., 2011). In contrast, semi-automated methods rely on training data, which capture certain characteristics of deforestation events. In addition, recent approaches employ image compositing to derive equidistant cloud free time series over larger areas and to extract intra-annual characteristics such as the mean, minimum and standard deviation of all available observations per year (Griffiths et al., 2013a; Hansen et al., 2013). This intra-annual information can be essential to identify forest disturbances in a highly dynamic and cloud contaminated tropical forest ecosystem.

In this paper, we use a semi-automated classification approach for tackling an important knowledge gap on long-term deforestation in Mato Grosso and Pará. The BR-163 highway cuts more than 1000 km of rainforest and deforestation activities date back 40 years, but little is known about the deforestation dynamics before the year 2000. Understanding historic dynamics in a spatio-temporally explicit manner provides new insights into historic frontier development in that region. We therefore ultimately aim at extending current knowledge on deforestation activities to the 1980s and 1990s by employing compositing methods to derive annual cloud free Landsat time series from 1984-2012. Two research questions govern our approach:

- How sensitive are Landsat-based time series for automatizing deforestation monitoring in the Brazilian Amazon back to the 1980s?
- How did deforestation activities vary in time and space and how do those patterns relate to socio-political changes?

2 Data and methods

2.1 Study area

The historic deforestation process along the BR-163 highway was triggered by frontier development following the highway construction that started in 1976 as an export corridor for agricultural products from Cuiabá to Santarém (Coy and Klingler, 2011; Fearnside, 2007). Accordingly, our study area represents a corridor of about 1,000 km latitudinal extent, from Lucas de Rio Verde in the South to Novo Progresso in the North. It extends 50 km to each side of the highway (Fig.III-1), which is the suggested distance of clearing activities related to road networks (Soares-Filho et al., 2006). The study area is almost equally divided between the states of Mato Grosso and Pará. Its extent is congruent with the latitudinal South-North development of one of Amazonia's major deforestation frontiers, capturing the spatio-temporal dynamics of the full frontier development over the last 30 years.

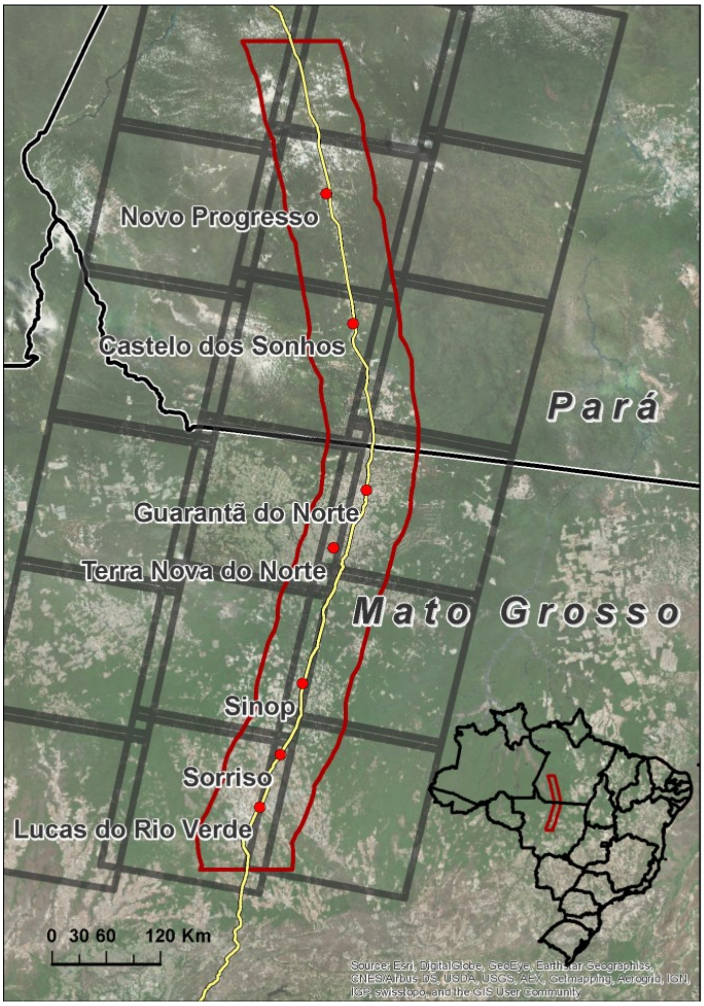

Fig.III-1: Study area (red) and corresponding Landsat footprints (grey) along the BR-163 (yellow).Inset: Study area location corridor in Brazil and across the federal states of Mato Grosso and Pará.

Natural vegetation changes from dense evergreen forests in the north to transitional evergreen-seasonal forests in the south of the study area, including patches of Cerrado vegetation (Radambrazil; DNPM, 1983). This general gradient is partly interrupted by geologic formations and areas of hilly terrain covering seasonal forests and open woodlands. Rainfall intensity changes between 120-350 mm during the dry season and 1700-2200 mm during the wet season (AmbiWeb, 2015). Deforestation activities are mainly restricted to the dry season because excessive rainfall renders logging and transport roads unusable during the wet season (Aragão et al., 2008; Gascon et al., 2001).

2.2 Datasets and pre-processing

To capture annual deforestation between 1985 and 2012 we processed 2,224 images of the Landsat TM and ETM+ sensors in precision terrain corrected (L1T) format. The dataset covers 11 footprints and includes all imagery being acquired between day-of-year (Doy) 144 and 250 with less than 80% cloud coverage. This temporal window represents the dry season, which is the main period for deforestation activities in our study area (see section 2.1). During the dry season, the spectral contrast between primary forest and deforested patches is highest, triggered by drying of residual vegetation on deforested areas (Fig.III-2). In contrast, wet season imagery is highly cloud contaminated and intensive greening of sub canopy vegetation can disguise deforestation activities.

We converted all imagery to surface reflectance employing the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS; Masek et al., 2006) atmospheric correction algorithm to ensure comparability of input data across different Landsat sensors, footprints, and acquisition dates (version 1.3; for code description see Schmidt et al., 2013; Schmidt, 2015). Cloud, cloud shadow and water masks were calculated for all imagery using FMask (version 2.3; for code description see Zhu and Woodcock, 2012; Zhu, 2015). The FMask algorithm extracts textural and spectral information to detect cloud and cloud shadows on a probabilistic basis. To capture as many clouds and cloud shadows as possible, the cloud probability threshold was set to the most conservative value (1%). Implementation of FMask and LEDAPS for batch processing followed the documention by Mönkemeier (2015).

Next to Landsat imagery, we used the deforestation product “PRODES digital” (INPE, 2014) provided by the Brazilian National Institute for Space Research (INPE) to mask areas of Cerrado vegetation (section 2.4), to sample training data (section 2.4) and to discuss our results in a methodological context (section 5). PRODES digital provides yearly updated deforestation maps covering the whole Brazilian Legal Amazon since 2001. It captures annual forest clearings larger than 6.25 ha based on Landsat imagery using a spectral unmixing approach and visual interpretation of the resulting cover fractions (Câmara et al., 2006). Before 2001, PRODES was conducted in a non-digital way, so-called “PRODES analog”, which provides annual deforestation rates at state level since 1988 and spatially aggregated deforestation maps for 1978 to 1997 and from 1997 to 2000.

We compare our results with global forest cover maps provided by Hansen et al. (2013). Similar to this study, the authors used Landsat compositing to derive a broad range of intra-annual spectral metrics. Based on these metrics, a decision tree classifier is then used to detect annual deforestation from 2000-2012 on a per-pixel basis. Their definition of forest (vegetation above 5m) and deforestation (stand-replacing disturbance) was globally applied, but training and prediction of the classifier was performed for each continent individually.

2.3 Large area compositing of annual tasseled cap wetness observations

Previous studies have shown that tasseled cap wetness (TCW) is highly sensitive for forest change in temperate and tropical forest ecosystems (Griffiths et al., 2012; Healey et al., 2005; Jin and Sader, 2005). We therefore converted all available imagery into TCW.

We then modified the compositing algorithm developed by Griffiths et al. (2013b) to convert the TCW imagery into annual, cloud free image composites. The modified algorithm identifies all cloud free pixel observations between Doy 144 and 250 and extracts the minimum TCW observation (TCW_{min}) per pixel. This approach ensures that only the maximum vegetation cover decrease is represented in annual composites, avoiding the influence of fast recovery processes after deforestation (Fig.III-2).

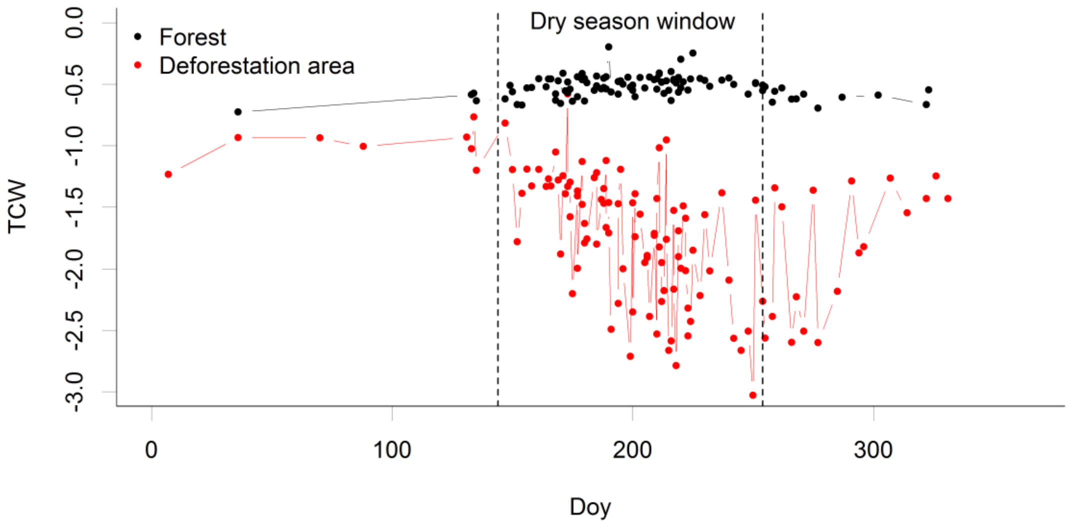

Fig.III-2: TCW values for two selected pixels of a primary forest and a deforested area with grass and shrub coverage close to Novo Progresso in Pará. Values are derived from all available imagery between 1985 and 2012 and ordered by Doy. Highest differences are observed at the end of the dry season.

Several data gaps remained in the annual TCW_{min} time series during the 1980s and 1990s due to cloud contaminations and limited image availability in the USGS Landsat archive (Fig.III-3). The data gaps were accordingly filled with TCW_{min} values of the following year. The gap-filled values were flagged in the accompanying meta-data to allow tracking the influence of data gaps in the classification results.

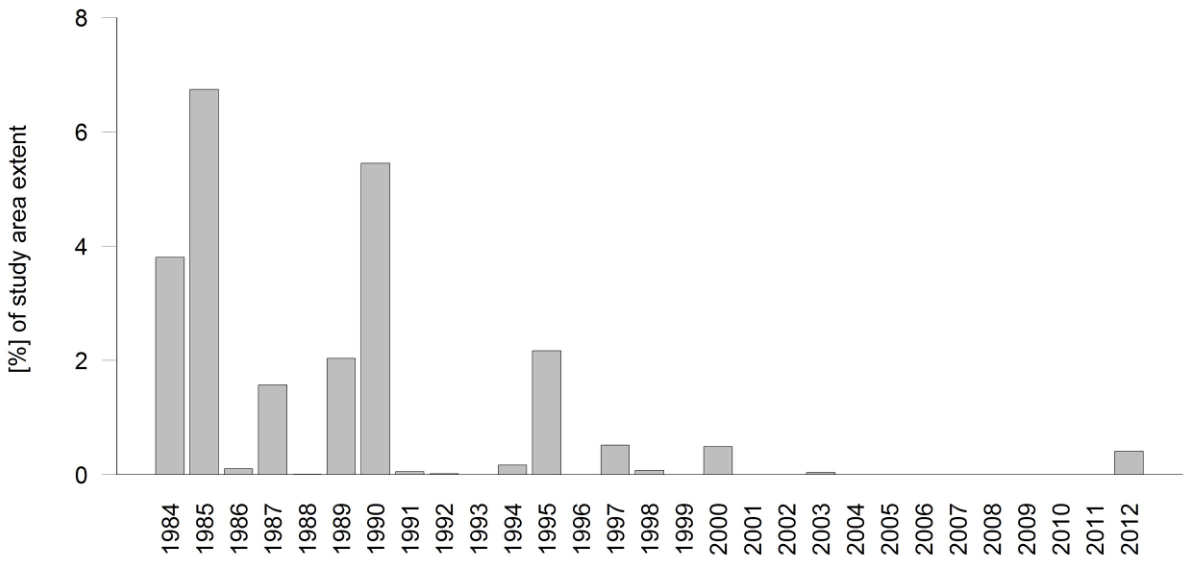

Fig.III-3: Annual distribution of data gaps in the TCW composites.

2.4 Deforestation detection

We mapped old-growth tropical forests (forested in the first year of our time series), non-forest areas in 1984 and annual deforestation between 1985 and 2012. The non-forest areas included clearings before 1985, settlements and outcrops. Areas of Cerrado vegetation and open woodlands were masked using the PRODES digital “non-forest” class.

We employed a random forest (RF) classifier (Breiman, 2001) to detect yearly deforestation based on the annual TCW_{min} time series for each pixel. The RF classifier creates an ensemble of decision trees, which are calibrated by manually chosen training data. Model calibration and prediction was carried out using the statistical software CRAN R (R Development Core Team, 2011) and the “randomForest” software package (version 4.6-7; Liaw and Wiener, 2002).

We used a random sample design based on the forest mask provided by the PRODES digital 2012 product to derive training samples for all 30 classes of interest. We iterated the sampling process several times until we reached a minimum of 20 samples per deforestation class, resulting in a total of 1141 training samples. Labeling of training data was performed on spectral values of reflectance images and annual TCW_{min} observations.

In our study region, the conversion of primary forest to clear cut areas with full canopy removal is usually conducted within a single dry season (Fig.III-4a). However, 14% of our training data showed deforestation processes which spanned several dry seasons until full canopy removal was reached (Fig.III-4b). These low intensity deforestation processes were labeled as deforestation in case they resulted in a clear cut during the next 3 years and showed a spatial extent larger than 2ha. This conservative estimate of low intensity deforestation activities is necessary to avoid false positives in seasonal forests (Fig.III-4c).

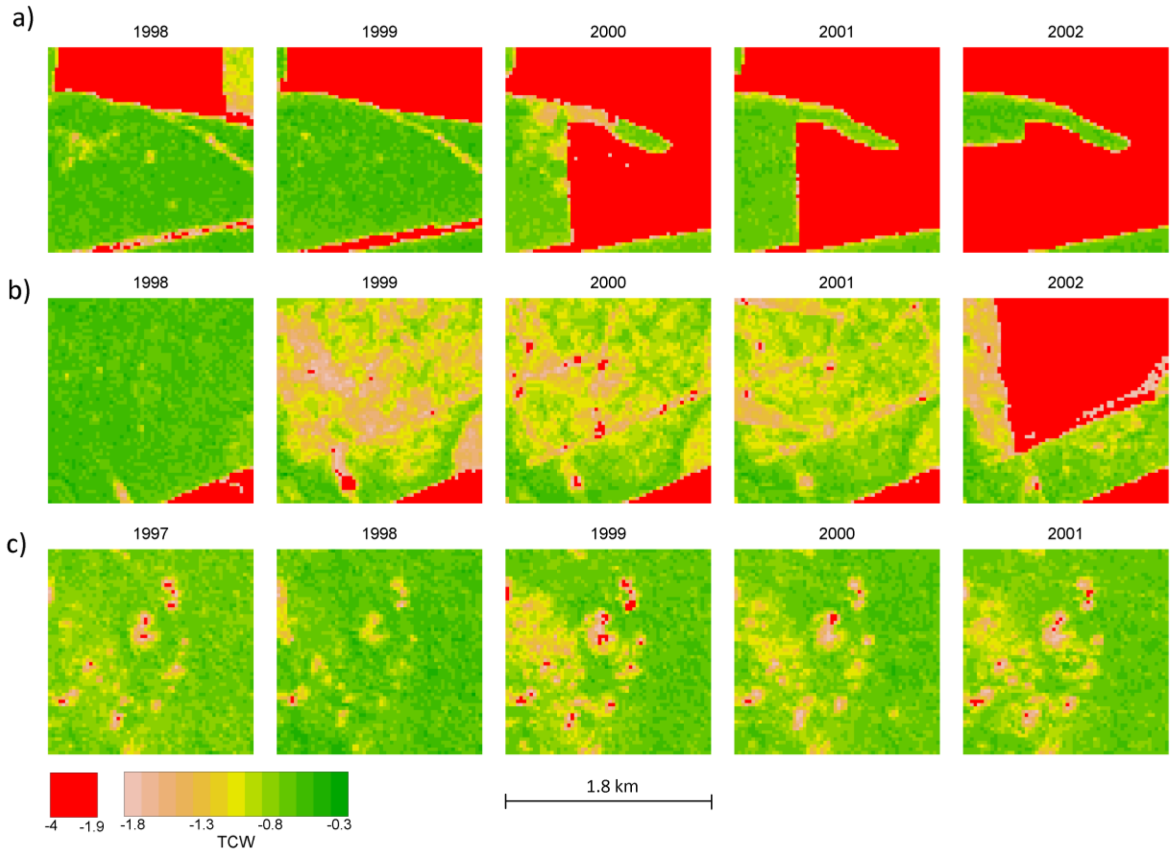

Fig.III-4: Examples of annual TCW_{min} close-ups used for training data labeling. a) High intensity deforestation b) low intensity deforestation, c) rock outcrops and natural variation of neighboring seasonal forest patches.

2.5 Validation strategy

We determined a sufficient number of validation samples following the procedure of Cochran, 1977). This includes a first estimate of the overall accuracy and the class-wise omission and commission errors. We used the out-of-bag (OOB) confusion matrix provided by the random forest classifier to derive this first estimate. The OOB accuracy is related to the bootstrapping procedure of the random forest model. It provides unbiased accuracy measures as long as the training data was obtained via probability sampling, which is the case for our study (Rodriguez-Galiano et al., 2012). Based on the first accuracy estimate, we determined an adequate sample size of 1,200 validation points for the final accuracy assessment and chose a stratified random sampling design to sample 40 validation points for each of the 30 target classes. As the forest class dominates the study area and impacts the final deforestation map, we added 30 additional points for the forest class.

To account for the stratified random sampling design, we adjusted the overall accuracy following Olofsson et al. (2014). In addition, confidence intervals for the adjusted overall accuracy were calculated to report on the uncertainty of the accuracy estimates in relation to the number of validation points (Congalton and Green, 2009).

3 Results

Overall, 45% of the original forest area in our study region was deforested until 2012 (Fig.III-5 and Fig.III-6). Half of this deforestation occurred before 2000 and was concentrated in the state of Mato Grosso, mostly around the cites of Sinop, Terra Nova do Norte and Guarantã do Norte (Fig.III-5 B).

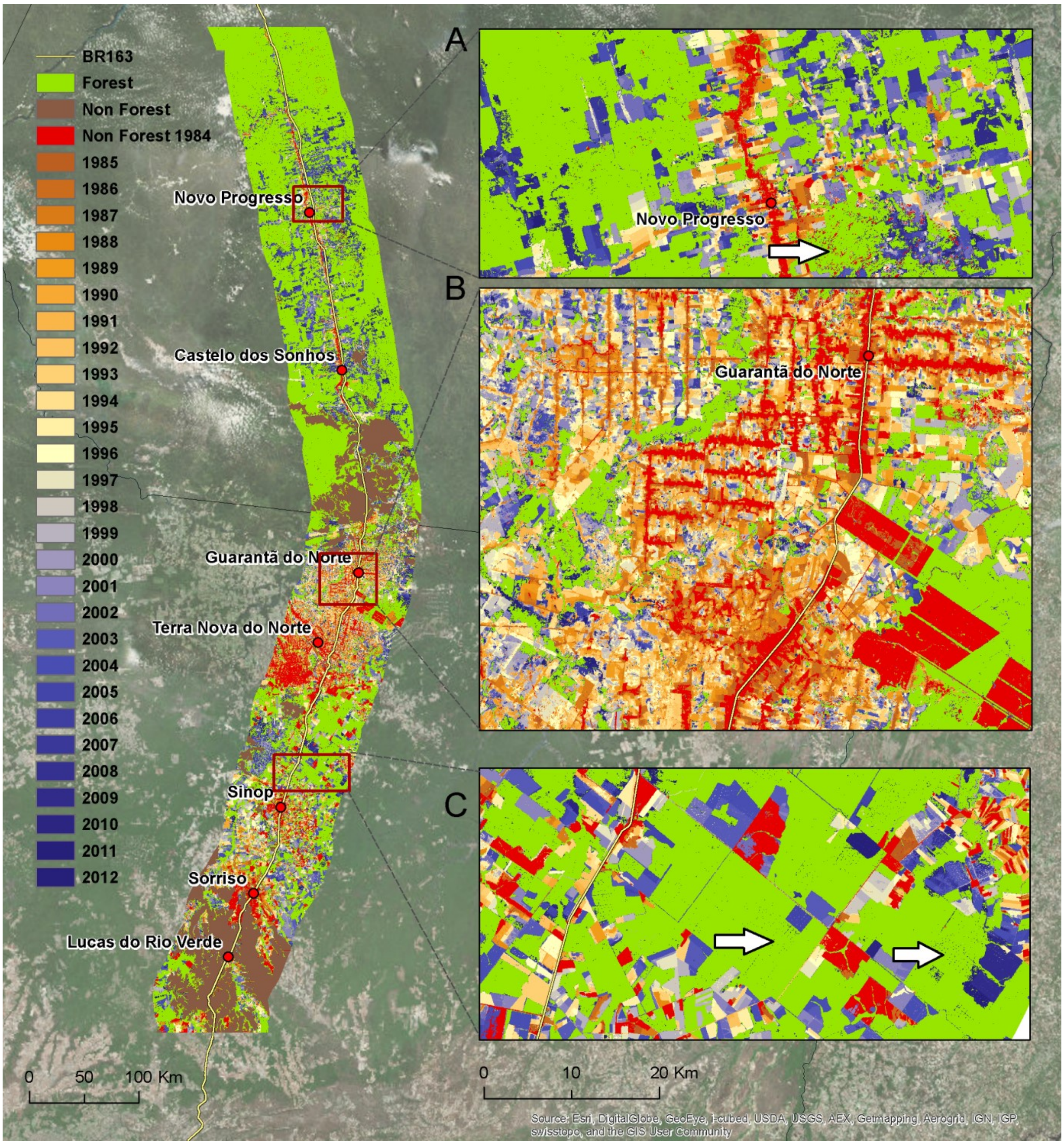

Fig.III-5: Deforestation map with magnified insets (A-C). A) Recent deforestation activities in the region of Novo Progresso. Outcrops in hilly terrain are marked by the arrow. B) Historic deforestation between Guarantã do Norte and Terra Nova do Norte. C) Small scale deforestation patterns, indicating logging decks close to Sinop (see arrows). Online visualisation is available at: http://r.geo.hu-berlin.de/~muellehx/deforestation/map.html.

In the state of Pará, such early deforestation activities only occurred near the highway (Fig.III-5 A). Between 1985 and 2002 we observed annual deforestation rates of 1- 2% per year. This constant period was followed by a moderate rise in deforestation in 2003 and 2004 (3% yearly) and a shift of deforestation activities towards the state of Pará (Fig.III-6). While the northern shift of deforestation activities continued for the rest of the study period, deforestation rates dropped to 0.5-1.5% per year until 2012.

Deforestation patches showed clear rectangular shapes, which often included small scale, linear structures such as roads and gallery forests along rivers. Symmetric networks of small deforestation patches represent logging decks in areas with selective logging (Fig.III-5 inset C). Irregular small scale patterns of variable vegetation density cover outcrops in hilly terrain close to Novo Progresso and Castelo dos Sonhos (Fig.III-5, inset A).

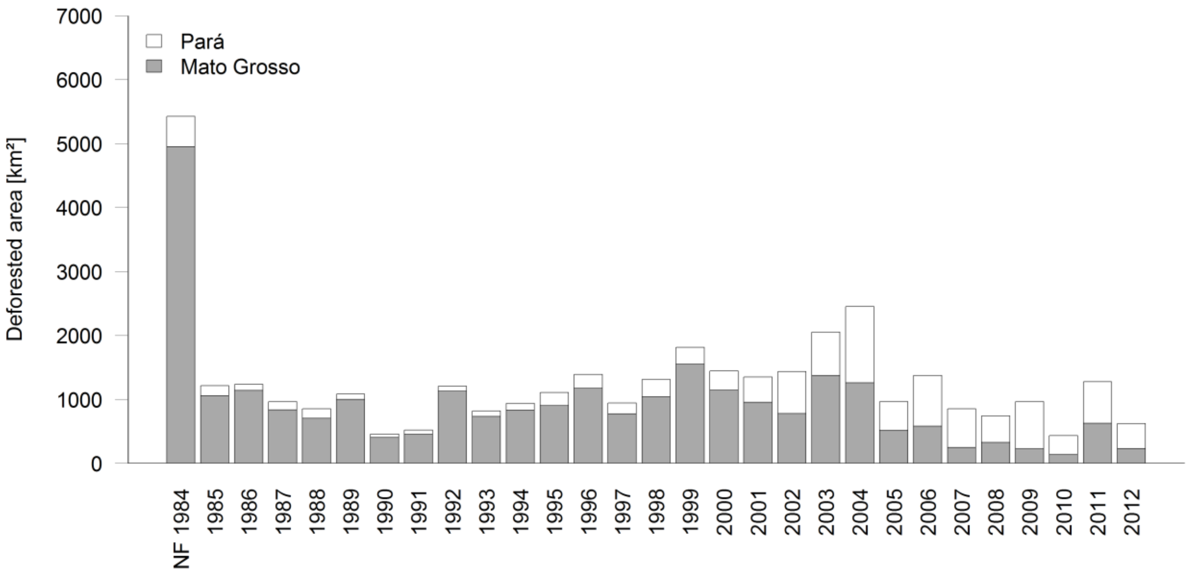

Fig.III-6: Annual deforestation in Mato Grosso and Pará along the BR-163 buffer-zone (Fig.III-5).

The deforestation classification achieved an adjusted overall accuracy of 85% with a 95% confidence interval margin of ±2%. Despite data gaps in the TCW_{min} composites (Fig.III-3), only 1% of the overall deforestation activity was tracked after a missing observation. Most data gaps in the source imagery appeared several years before or after the deforestation events without influencing our classification results. Deforestation activity tracked after a missing observation implied an uncertainty of "+ one year", because we systematically decided for the earliest possible deforestation year.

With 49 early and 67 late detections, the classification error slightly tended towards late detections (Tab. III-1). While the commission error did not exceed 22% for any year, omission errors peaked in 1990 and 2000 with 31% and 35%, respectively (Fig.III-7). In the latter case, the majority of class confusion was related to overestimating stable forests (Tab. III-1).

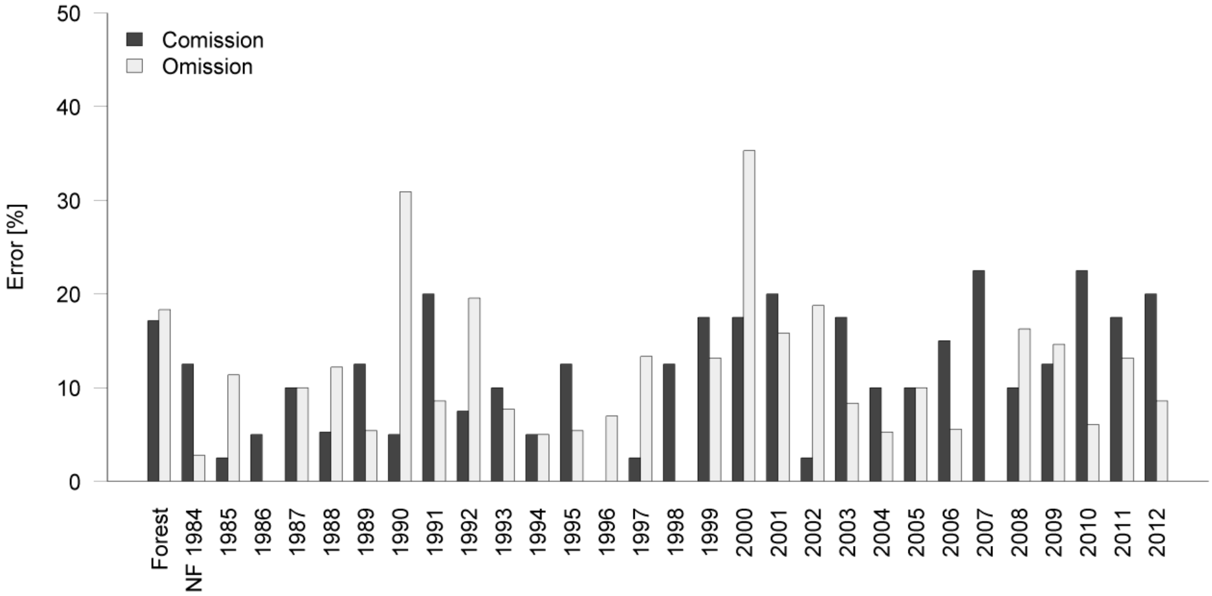

Fig.III-7: Distribution of unadjusted omission and commission errors based on 1230 independent validation samples. No commission error was observed in 1996. No omission errors were observed in 1986, 1998 and 2007. NF 1984=Non Forest in 1984.

While our accuracy assessment suggested a tendency to underestimate the deforested area, we overall observed 18% more deforestation than PRODES and 13% more deforestation than Hansen et al. (2013) from 2001 to 2012 (Fig.III-8). For PRODES, most differences can be attributed to the years 2010-2012, where PRODES deforestation rates dropped by more than 50% compared to our dataset and Hansen et al. (2013). However, all three products show the same general deforestation process, with an increase of deforestation rates from 2001 to 2004 and decreased rates from 2005 to 2012.

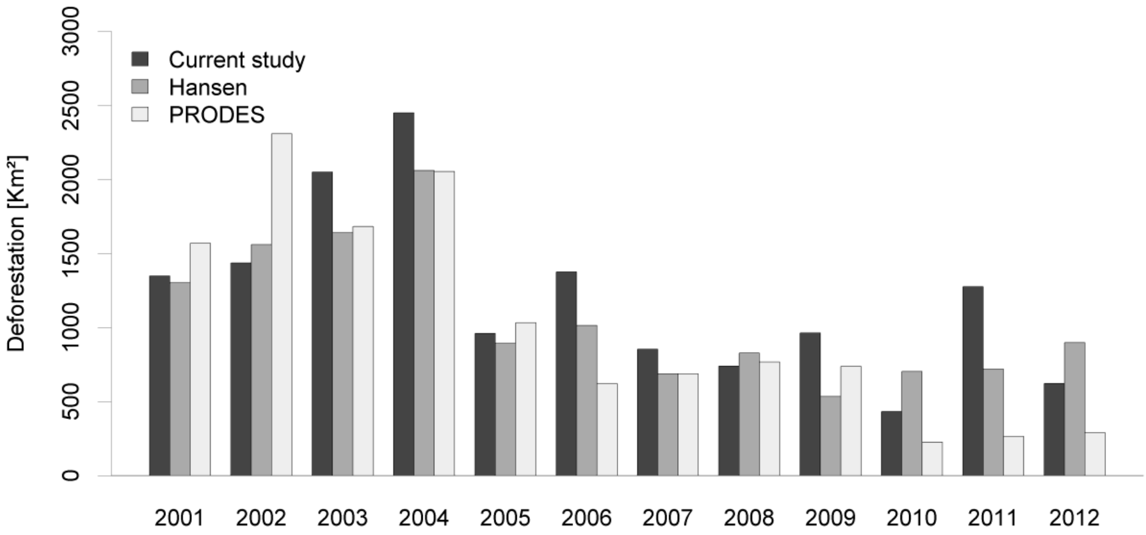

Fig.III-8: Comparison of deforestation rates with Hansen et al. (2013) and PRODES (INPE, 2014). The comparison is restricted to the time period covered by all three products.

Tab. III-1: Confusion matrix including omission error (OE) and commission error (CE). The sum of the upper and lower triangle results into 49 early- and 67 late detections. NF 1984=Non Forest in 1984.

Classified data	Reference data Forest	NF 1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	SUM	**CE [%]**
Forest	58	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	1	6	1	1	-	-	-	-	-	-	-	-	2	-	70	**17**
NF 1984	-	35	4	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**12**
1985	-	-	39	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**3**
1986	-	-	-	38	1	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**5**
1987	-	-	-	-	36	1	-	1	-	1	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**10**
1988	-	-	-	-	-	36	1	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**5**
1989	-	1	-	-	-	-	35	1	-	3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**12**
1990	-	-	-	-	-	-	-	38	-	1	-	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**5**
1991	-	-	-	-	-	1	-	4	32	3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**20**
1992	-	-	-	-	-	-	-	-	1	37	1	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**7**
1993	-	-	-	-	-	1	1	2	-	-	36	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**10**
1994	-	-	-	-	-	-	-	-	-	-	1	38	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**5**
1995	-	-	-	-	1	1	-	-	-	1	-	-	35	1	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**12**
1996	-	-	-	-	-	-	-	-	-	-	-	-	-	40	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**0**
1997	-	-	-	-	-	-	-	-	-	-	1	-	-	-	39	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**3**
1998	-	-	1	-	-	-	-	2	-	-	-	1	-	-	-	35	1	-	-	-	-	-	-	-	-	-	-	-	-	-	40	**12**
1999	-	-	-	-	1	-	-	1	-	-	-	-	1	-	1	-	33	2	1	-	-	-	-	-	-	-	-	-	-	-	40	**18**
2000	-	-	-	-	-	-	-	2	-	-	-	-	-	-	-	-	1	33	2	-	-	-	-	-	-	1	1	-	-	-	40	**18**
2001	1	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	1	32	5	-	-	-	-	-	-	-	-	-	-	40	**20**
2002	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	39	1	-	-	-	-	-	-	-	-	-	40	**3**
2003	1	-	-	-	1	-	-	2	-	-	-	-	-	-	1	-	-	1	-	-	33	-	-	-	-	1	-	-	-	-	40	**18**
2004	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2	1	-	-	36	-	-	-	-	-	-	-	1	40	**10**
2005	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-	2	-	-	-	-	36	1	-	-	-	-	-	-	40	**10**
2006	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	2	-	1	-	34	-	-	-	-	1	-	40	**15**
2007	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	1	-	-	1	-	2	-	31	2	-	1	1	-	40	**22**
2008	1	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-	1	-	-	1	-	-	-	-	36	-	-	-	-	40	**10**
2009	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-	-	1	35	1	-	1	40	**12**
2010	2	-	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	1	2	-	-	1	-	31	1	1	40	**22**
2011	4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	2	-	33	-	40	**18**
2012	2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	1	-	-	-	1	-	-	3	-	-	32	40	**20**
SUM	71	36	44	38	40	41	37	55	35	46	39	40	37	43	45	35	38	51	38	48	36	38	40	36	31	43	41	33	38	35	1228	
OE [%]	**18**	**3**	**11**	**0**	**10**	**12**	**5**	**31**	**9**	**20**	**8**	**5**	**5**	**7**	**13**	**0**	**13**	**35**	**16**	**19**	**8**	**5**	**10**	**6**	**0**	**16**	**15**	**6**	**13**	**9**		

4 Discussion

We detected annual deforestation events in 45% of the original forest area between 1985 and 2012. Half of this deforestation took place before 2000, indicating the importance of long-term analyses. Constantly high deforestation rates occurred between 1985 and 2004, lacking any clear effect of the revised constitution in 1988 and the restricted forest code in 1996 (MMA, 1996). The historic deforestation rates suggest a high robustness of frontier development along the Br-163 towards counteracting political incentives. With the national soy boom from 2000 to 2004 (Richards, 2012), deforestation rates reached their maximum of 3% and expanded into forest areas of Pará. The northward expansion coincided with private initiatives for pavement of the BR-163 in 2002 and triggered land speculations due to rising land prices (Coy and Klingler, 2014; Richards et al., 2014). Accordingly, Cattle farmers, loggers and land speculators from southern Brazil migrated to the unconsolidated parts of the BR-163 in southern Pará (Richards, 2012). Intensified environmental monitoring (DETER; INPE, 2008b) and governmental efforts to control deforestation (PPCDAm; MMA, 2013) started in 2004 but did not decrease deforestation activities along the BR-163 in Pará, indicating a weak law enforcement of local authorities (Fearnside, 2007; Macedo et al., 2012). In contrast, policy measures and market initiatives (soy moratorium; Rudorff et al., 2011) seemed to have effectively counteracted deforestation in Mato Grosso, resulting in decreased deforestation rates along the southern part of the BR-163 after the soy boom in 2004 (Macedo et al., 2012; Gollnow and Lakes, 2014; Gibbs et al., 2015b).

Overall classification accuracy reached 85%, indicating a reliable detection of annual deforestation. Despite a constrained availability of Landsat data for the 1980s and 1990s (Fig.III-3), only 1% of the mapped deforestation activity was affected by data gaps, illustrating the high potential of the Landsat archive for studying of long-term deforestation processes. In regard to our classification results, errors were slightly biased towards late detections, confirming the conservative labeling of the training data in case of low intensity deforestation processes. Commission errors were found in hilly terrain where tree density is lower due to rock outcrops. In these regions, drying of natural vegetation partly triggered deforestation detection on the pixel level, leading to “salt-and-pepper” like effects in the classified imagery.

Compared to current state of the art deforestation datasets, we found higher deforestation rates than INPE and Hansen et al. (2013). For PRODES, most differences were observed for the years 2010 to 2012 and might be related to small scale deforestation (<6.25 ha), which accounts for 28% of the observed deforestation from 2010 to 2012. Small scale deforestation increased after the implementation of the action plan to prevent and control deforestation (PPCDAM) in 2004 (Rosa et al., 2012) and could not be detected by PRODES (minimum mapping unit of 6.25 ha, section 2.2). This observation is supported by the results of Hansen et al. (2013) as their methodology allowed detecting small scale deforestation. Similar to our findings, they observed higher deforestation rates from 2010 to 2012 than PRODES. Further conclusions from comparing the three datasets relate to our definition of low intensity deforestation processes (Fig.4). Low intensity deforestation often takes 2-3 years for full canopy removal and leads to late or no detections in the dataset of Hansen et al. (2013). In this regard, our regional calibrated deforestation detection differs from Hansen et al. (2013), who followed a continental calibration strategy (see section 2.2), which resulted in a more conservative estimate of the overall deforestation process within our study area.

5 Conclusions and Outlook

Our classification approach allowed characterizing deforestation between 1985-2012 despite the reduced availability of Landsat data in the 1980s and 1990s. Gaps in the source data only affected 1% of the deforestation detected, indicating the great potential of the Landsat archive for analyzing long-term deforestation processes. Furthermore, our results showed the relevance of historical deforestation in the Amazon region with half of the overall deforestation being detected before 2000. The historic deforestation patterns have not been captured by current global (Hansen et al., 2013) and national datasets (INPE, 2014) and provides new possibilities to study deforestation frontier development and related carbon emissions.

Our study region covers a large transect of rainforest types, rendering our approach highly transferable to other regions with limited deforestation information available in the Brazilian Amazon. This is especially true with regard to overall data availability. A preliminary screening of the Landsat archive showed that 92% of the entire Brazilian Amazon biome is covered by three or more Landsat images (L1T, cloud<80%) per dry season between 1984 and 2012. Critical regions are limited to the central part of the Amazon basin where cloud coverage is constantly high. For future applications, data scarcity in more clouded regions can be dramatically reduced by combining Landsat and upcoming Sentinel-2 imagery. Multi sensor constellations will therefore be an important step towards annual deforestation mapping and operational monitoring of rainforest ecosystems, which will be crucial for sustainable land management strategies.

6 Acknowledgments

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

Remote Sensing of Environment (in review)

Hannes Müller, Philippe Rufin, Patrick Griffiths, Letícia Hissa, Patrick Hostert

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 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.

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). Moreover, secondary vegetation dynamics received increasing attention for restoring fragmented landscapes (Latawiec et al., 2015) and compensating carbon emissions generated by deforestation and forest degradation (Brown and Lugo, 1990; Chazdon, 2008). Abandoned or fallow farmland also bears great potential for land use intensification, which would allow to spare pristine tropical forest areas by avoiding further agricultural expansion (Strassburg et al., 2014).

The multiple dimensions of ecological and socio-economic processes related to secondary vegetation emphasize the importance of monitoring specific spatial patterns and temporal dynamics. However, defining secondary vegetation conceptually and mapping it across larger regions remains challenging due to its complex biophysical properties. These properties change with geographic location (habitat type) and along successional stages, ranging from bushy pioneer species to secondary forest stands (Guevara et al., 1986; Guariguata and Ostertag, 2001). 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 Poccard-Chapuis, 2012). In the deforestation frontiers of Pará, cattle farming is the dominant land use practice with stocking densities frequently below one animal per hectare (Valentim and Andrade, 2009). After pasture establishment, regrowth is widespread (Moran et al., 2000) and often starts along forest edges, where seed dispersal is concentrated (Nepstad et al., 1996). Land speculations and restricted access to financial resources can lead to several fallow years, triggering regrowth of secondary vegetation. Since 1996, the Brazilian forest code requires landowners to conserve native vegetation on 80% of their rural properties in the Amazon and 20% to 35% in the Cerrado and grasslands (WWF, 2011; Soares-Filho et al., 2014). The law also designates environmentally sensitive areas such as riverside forests, hilltops, and steep slopes. Compliance to these rules is often lacking, but in recent years restoration of illegally deforested areas has slowly increased (Stickler et al., 2013; Soares-Filho et al., 2014). This is especially true in Mato Grosso, where law enforcement is more prevalent (Fearnside, 2001; Soares-Filho et al., 2014). Apart from restoration of illegally deforested areas, regrowth of secondary vegetation in Mato Grosso takes place through agroforestry (Gil et al., 2015) and in areas of sustainable forest management (Siqueira et al., 2015). In contrast to Pará, agricultural areas are characterized by cattle ranching and cropland farming with higher input of fertilizers and machinery, rendering multi- year fallow cycles a rare occurrence (VanWey et al., 2013). Current datasets on the extent of secondary vegetation, like the Amazon-wide land use product TerraClass (INPE, 2015b) 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. A better understanding of these 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. Medium-resolution satellite sensors, such as the Moderate Resolution Imaging Spectroradiometer (MODIS), provide consistent data with high temporal resolution for assessing farmland abandonment and related regrowth at broad geographic scales (Alcantara et al., 2013; Estel et al., 2015). Apart from those favorable characteristics, the temporal extent of this data is limited to the 2000s and thus does not allow mapping long-term dynamics. Furthermore, the spatial resolution of 250m does not capture fine scaled regrowth processes in heterogeneous landscapes. Alternative approaches rely on Landsat imagery (30 m resolution) to overcome the limitation of the MODIS spatial scale and the limited time period of MODIS data availability (Griffiths et al., 2014; Czerwinski et al., 2014). In the past, limitations in data availability and standardized input data restricted analyzing deep time series of Landsat data and favored mono-temporal or temporally sparse classifications (Hostert et al., 2015). However, assessments of secondary vegetation employing such classifications was found to be challenging due to high spectral ambiguity of different successional stages (Lucas et al., 2002; Vieira et al., 2003; Carreiras et al., 2014). 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 strongly facilitated the use of temporal information for characterizing secondary vegetation. 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). While atmospheric correction and cloud screening became operationalised (Masek et al., 2006; Zhu et al., 2012), compositing methods (Griffiths et al., 2013b; Roy et al., 2014; White et al., 2014; Nelson and Steinwand, 2015) helped to overcome those challenges by creating equidistant cloud free time series over larger regions.

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 cylces 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.

In this study 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. Our 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

2.1 Study area

Our study area represented a corridor of 50 km to each side of along 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. IV-1). Its extent is congruent with regional colonisation and settlement processes over the last 30 years (Coy and Klingler, 2011) and allows to investigate long-term regrowth dynamics across a spatio-temporal gradient of socio-economic development. 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 (AmbiWeb, 2015). Natural vegetation changes from dense evergreen forests in the north to transitional evergreen-seasonal forests in the South, including areas of savanna vegetation (Cerrado) (Radambrazil; DNPM, 1983).

Highway construction started in the early 1970s to build an export corridor for agricultural products from Cuiabá to Santarém and now represents 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 Guarantã do Norte in Mato Grosso with annual deforestation rates of 1-4% (Müller et al., 2016). The high deforestation rates relate to the rapid agro-economic development of Mato Grosso, which is now one of major agricultural production centers in Brazil (IBGE, 2010; VanWey et al., 2013). 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.

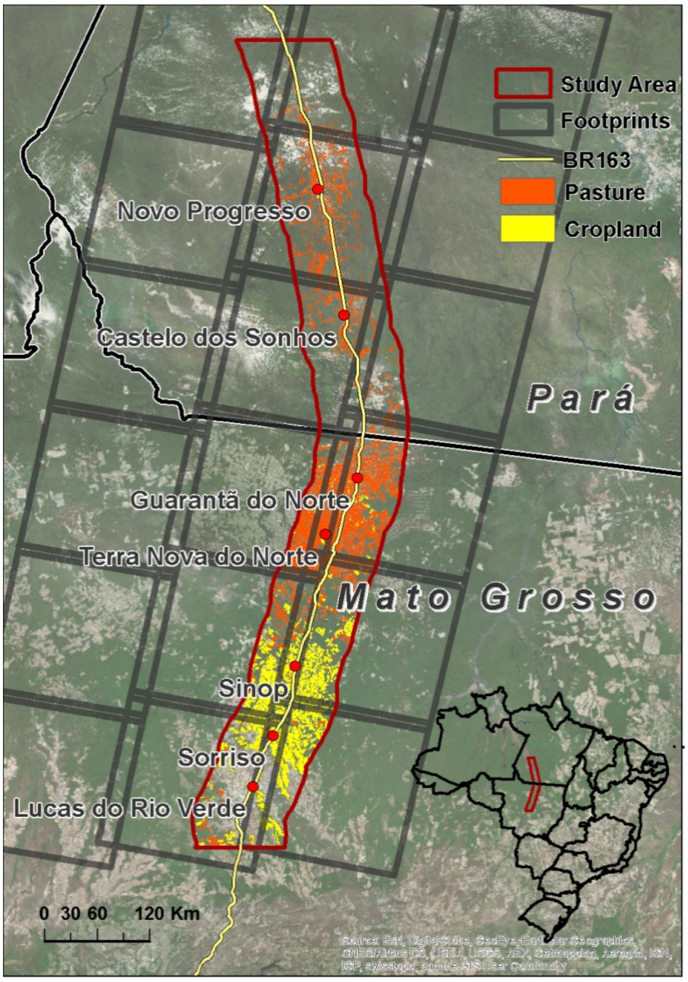

Fig. IV-1: Study area with corresponding Landsat footprints along the BR-163. Cropland and pasture areas from TerraClass are shown for the year 2008 (INPE, 2008c, 2015b). Inset: Studied corridor along the BR-163 highway across the federal states of Mato Grosso and Pará.

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. IV-1). Poor quality of local infrastructure and social conflicts due to the absence of state authorities hampered migration and settlement processes in Pará for decades (Coy and Klingler, 2014; Fearnside, 2001).

Cattle farming has always played an important role along the BR-163 and in the majority of pasture systems, the African grass species *Brachiaria brizantha* was used as main forage grass until the mid-2000s (Landers, 2007). In recent years, additional African grass species *Panicum Maxium* cv *Mombaça* and *MG5* were introduced to fight increasing frequency of pests such as "*morte subita"* (Dias-Filho, 2006). Apart from pest outbreaks, grass biomass strongly decreases on pasture systems towards the end of the dry season, due to grazing pressure and water constraints. 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). However, topography can restrict the use of machinery in various locations along the BR-163, promoting the establishment of secondary vegetation. In general, most fertile soils in flat terrain are used for cash crop farming with one or two rotational cycles per year (Arvor et al., 2011b). Here, establishment of secondary vegetation only occurs in the rare event of an extensive fallow period. *S*oils are dominated by Acrisols in Pará and Ferrasols in Mato Gosso, both with medium to low nutrient availability (Quesada et al., 2011). Without the use of fallow cycles, liming and fertilizers, these soil types are subject to nutrient leaching and soil degradation on cultivated lands, which might lead to farmland abandonment and permanent regrowth of secondary vegetation.

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. The dataset covered 11 footprints and included all imagery in precision terrain corrected (L1T) format that was acquired between day-of-year (Doy) 144 and 250 (May 24th and September 7th, respectively) 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). 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).

Previous studies have shown that the tasseled cap wetness image transformation (TCW) 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 avail-able imagery into TCW and employed the compositing algorithm developed by Griffiths et al. (2013b) to extract the minimum TCW value for each pixel within the dry season period (TCW_{min}). With this processing step we generated annual, continuous cloud free TCW_{min} composites covering the entire study area. 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. Several data gaps remained in the annual TCW_{min} composites during the 1980s and 1990s due to cloud contaminations and limited image availability. The data gaps were accordingly filled with TCW_{min} values of the following year.

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. (2013b) 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, 2008c, 2015b) 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%). Imagery for visual interpretation was obtained from Landsat, moderate resolution imaging spectrometer (MODIS) and China-Brazil Earth Resources Satellite Program (CBERS). TerraClass 2008 was generated based on visual image interpretation with a minimum mapping unit of 6.25 ha. 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

Secondary vegetation shows higher TCW_{min} values than areas of forage grasses (intensive pastures) and croplands but spectral heterogeneity is generally high (Fig. IV-2a). Next to its spectral features, regrowth of secondary vegetation is a temporal process and annual time series of the TCW_{min} metric improve characterizing this process (Fig. IV-2b). We therefore used a combination of spectral and temporal criteria for detecting secondary vegetation.

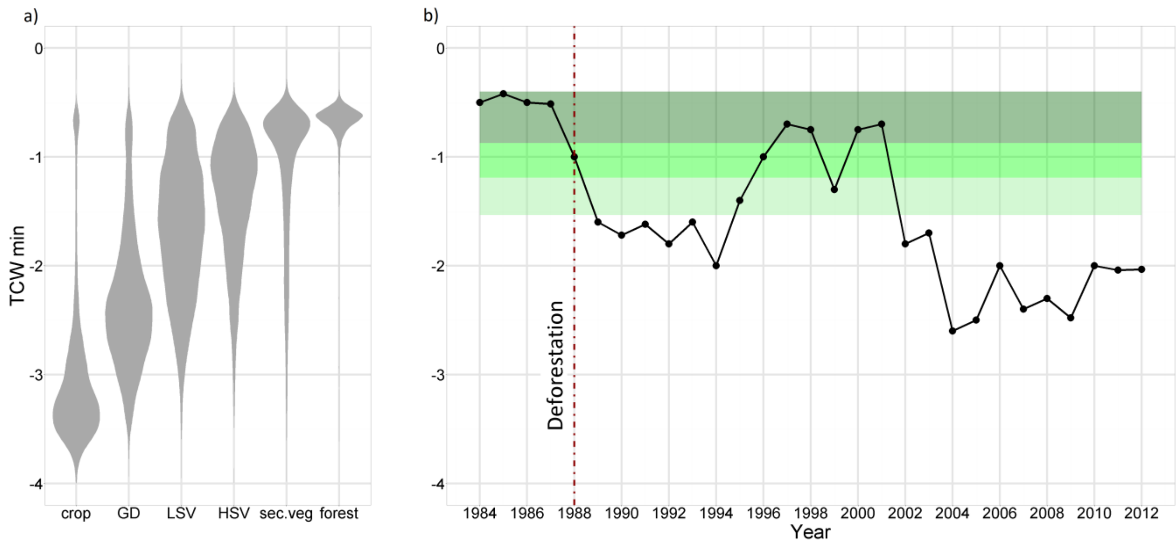

Fig. IV-2. a) TCW_{min} distributions for 6 different land use classes sampled from TerraClass 2008 (INPE, 2008c, 2015b). GD: grass dominated pasture, LSV: pasture with low levels of secondary vegetation (<50%), HSV: pasture with high levels of secondary vegetation (50-90%), sec.veg: full coverage of 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 duration varies between 5 and 7 years. Recultivation takes place in 2002/2003.

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. In the first place, we derived three different thresholds of the overall sample (Tab. IV-1), namely the median (-0.872), mean (-1.191) and 25% quantile (-1.534). We than tested these thresholds towards their sensitivity for capturing secondary vegetation and related regrowth patterns (section 2.4.1) and selected the most appropriate threshold 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. IV-2b). 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), 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.

2.5 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. 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 (see section 2.4). 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%) (Tab. IV-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).

Tab. IV-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.

Spectral 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 woody vegetation 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 Tab. IV-1).

2.6 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.

3 Results

3.1 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. IV-3).The majority of all regrowth occurred on the pastoral areas of northern Mato Grosso (67%), in proximity to Terra Nova do Norte and Guarantã 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. IV-3). In addition, clear rectangular shapes were commonly visible and indicated an external barrier, such as forest edges, road networks, or property borders.

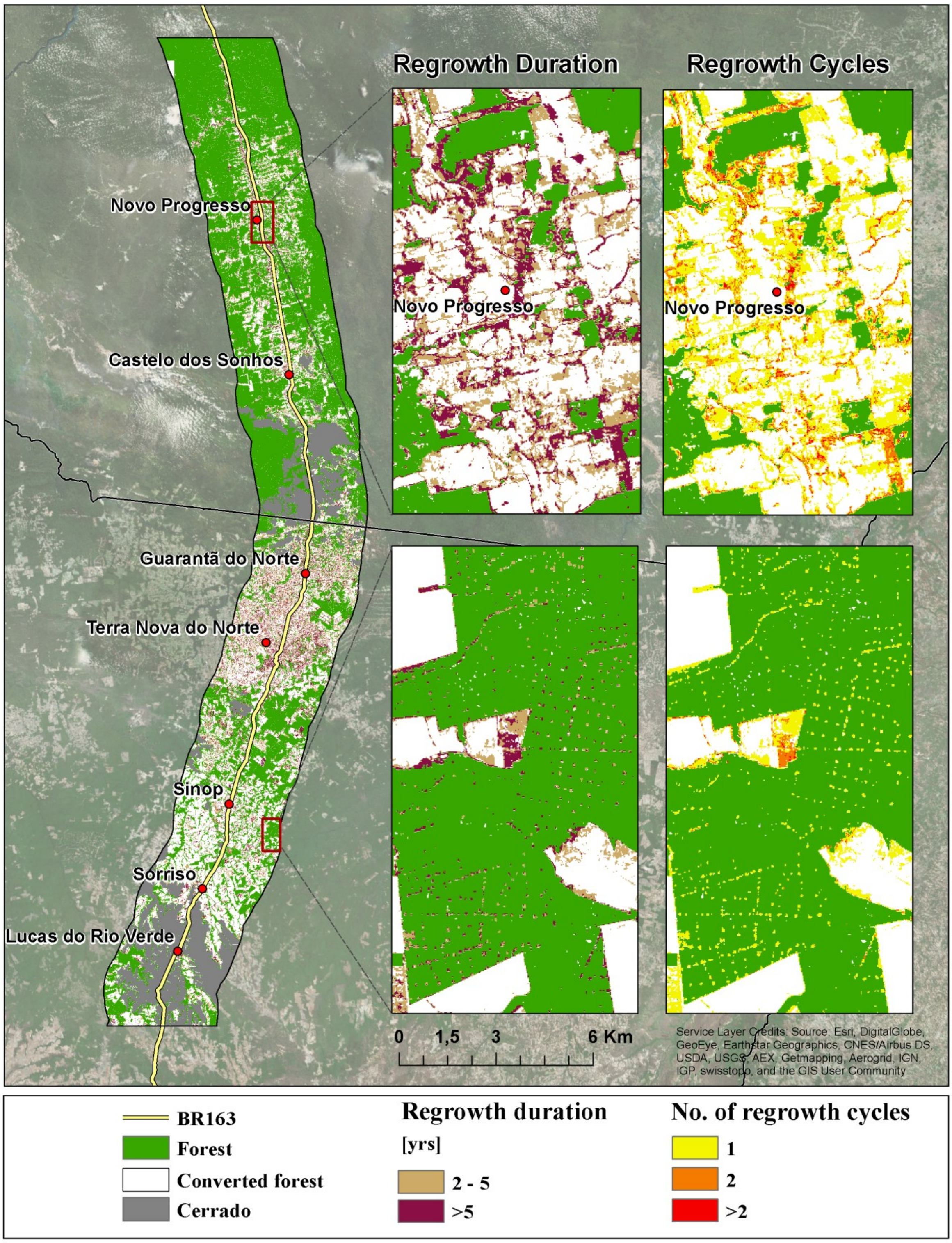

Fig. IV-3: Regrowth duration and number of regrowth cycles from 1985 to 2012. Regrowth duration is the sum of regrowth years across all regrowth cycles. For interpretation of the reference colors in this figure legend we refer to the web version of this article. Interactive visualization of regrowth duration is available at http://r.geo.hu-berlin.de/~muellehx/regrowth/regrowth_map.html.

Absolute regrowth rates were higher in Mato Grosso than in Pará, especially from the mid-1980s to the mid-1990s (Fig. IV-4a). 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. IV-4b), 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. IV-4b).

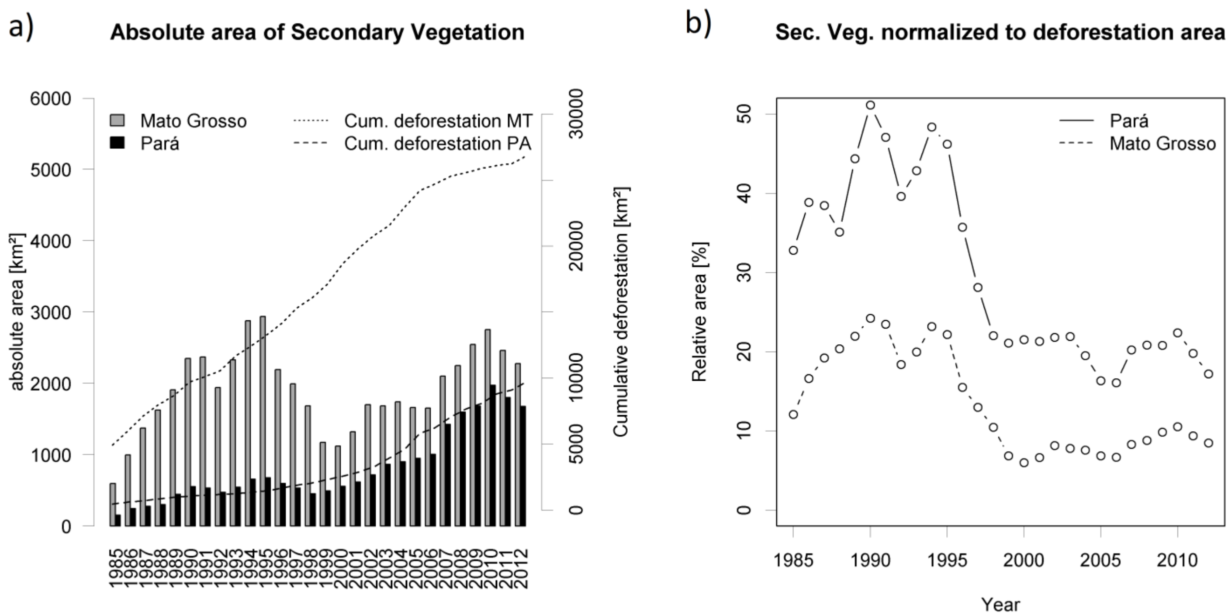

Fig. IV-4: a) Absolute and b) relative area of secondary vegetation in Mato Grosso and Pará. To aid interpretation of the absolute amount of regrowth areas, we added the cumulative deforestation curve for Mato Grosso (MT) and Pará (PA) in a). The deforestation data was derived from Müller et al. (2016).

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.

3.2 Forest edge analysis

Secondary vegetation largely occurs in small patches in proximity to forest edges (Fig. IV-3). 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 <= 60m) in both states and throughout the entire study period (Fig. IV-5). 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).

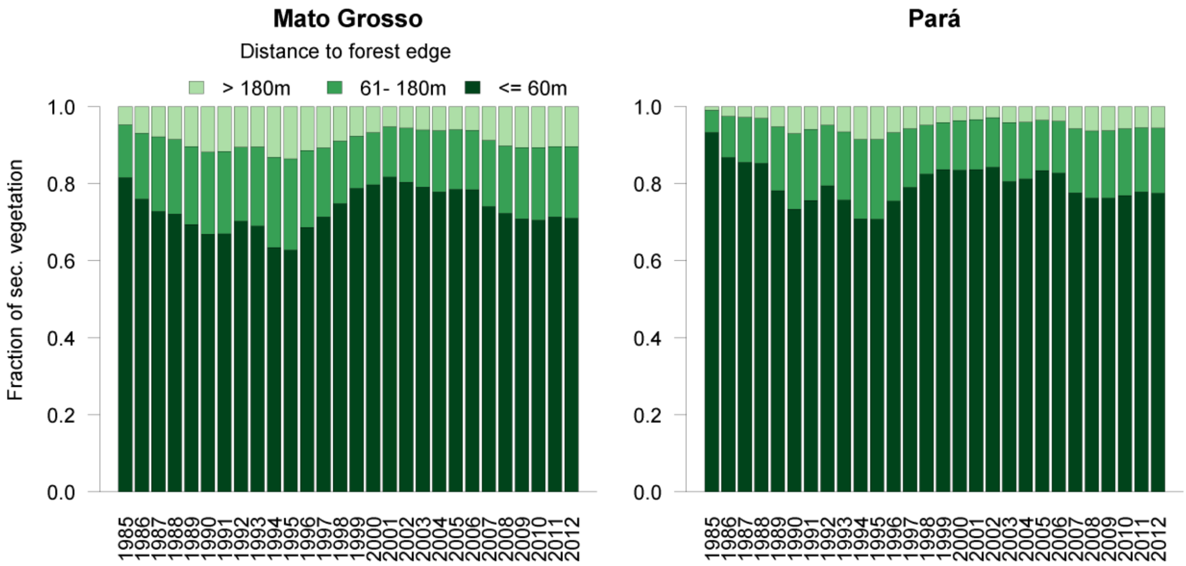

Fig. IV-5: Relative fractions of secondary vegetation in Mato Grosso (left) and Pará (right) in relation to forest edge distance.

3.3 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. IV-6a). Investigating cyclic regrowth in more detail, revealed that about 90% of the total observed regrowth was restricted to a single cycle (Fig. IV-6b), rendering multiple regrowth cycles a rare occurrence.

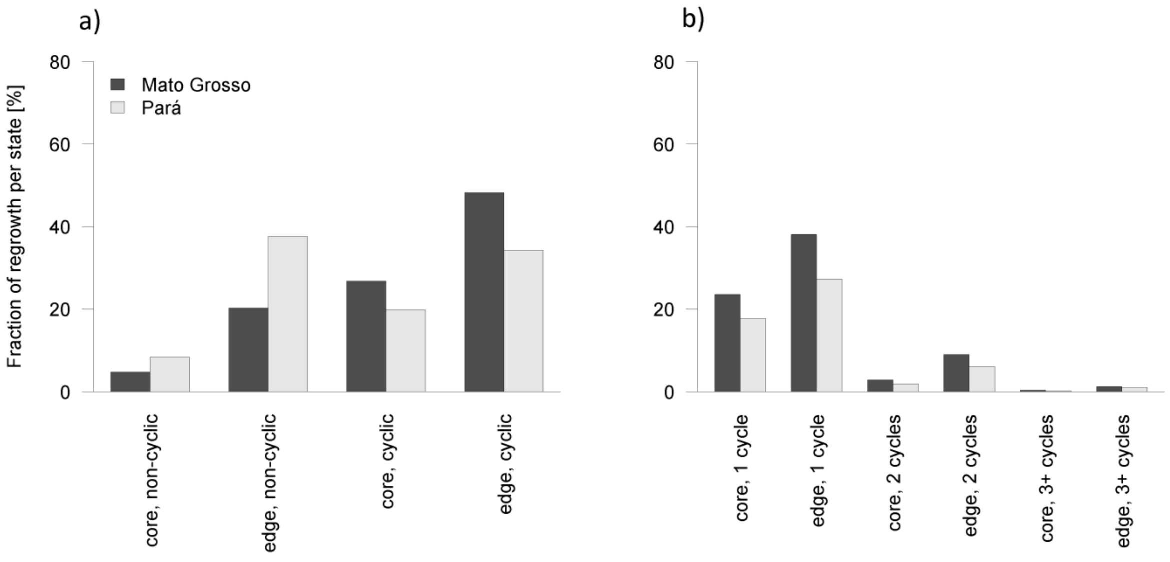

Fig. IV-6: a) State wise fractions of cyclic and non- cyclic regrowth in core and edge areas. b) Fraction of cyclic regrowth per state according to the number of regrowth cycles.

Average regrowth durations were generally longer in Mato Grosso and decreased with the number of regrowth cycles (Fig. IV-7). 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.

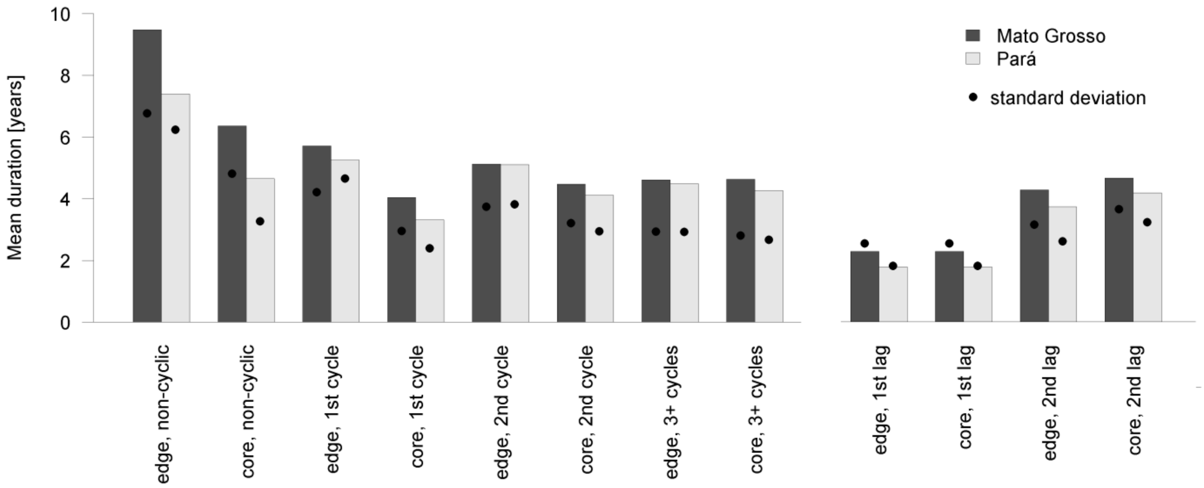

Fig. IV-7: Left: Average duration and standard deviation of non-cyclic and cyclic regrowth along forest edges and in core areas of cleared lands. Right: Duration of lag times between regrowth cycles.

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. IV-4b). 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 ha cultivated land. Similar to Nepstad et al. (1996), we found forest edges to be critically important for secondary vegetation growth (Fig. IV-5). Consequently, the higher share of forest edges per ha 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. IV-6), starting within the first 3 years after clearing of primary forest (Fig. IV-7). 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. IV-7). 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) suggest the implementation of integrated grass-capoeira fallow systems. Here, woody vegetation (capoeira) 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). Additionally, our regrowth definition aims at capturing early stage to late stage secondary vegetation, which remains for at least two years. This further reduces the risk for commission errors triggered by unmasked clouds, cloud shadows or sensor-derived noise in the source dataset. 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 Landsat based regrowth assessments is challenging and requires very high resolution imagery (VHR) or systematic field surveys. Without detailed spatial information it is extremely difficult to visually distinguish perennial secondary vegetation from other vegetation types (DeVries et al., 2015). Except airborne imagery, VHR data is not available for the 80s and 90s and field surveys are usually restricted to small areas and snap shots in time. This strongly hampers validation of long-term regrowth assessments across large areas and requires alternative validation schemes. As suitable reference data or systematic field surveys were not available, we here present some general considerations to evaluate plausibility of our results. Our regrowth approach relies on external deforestation data and errors in the deforestation product can directly affect the regrowth assessment. Especially commission errors often refer to high shares of remaining primary vegetation, which will be falsely detected as secondary vegetation in the regrowth assessment. Deforestation data used in this study was reported to contain commission errors in hilly terrain and open woodland (Müller et al., 2016) and we therefore caution high uncertainty of the regrowth assessment in those regions. 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 (Aguiar 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.

6 Acknowledgments

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Chapter V:
Synthesis

1 Summary

In the following section, findings of the three core research Chapters (Chapter II-IV) are summarized to address the overarching goals mentioned in Chapter I, section 5.

<u>Research objective 1 (Chapter II):</u> *Determining the potential of Landsat time series to improve separation of cropland and pasture in a heterogeneous Brazilian savanna landscape.*

Savanna ecosystems are biodiversity hotspots and provide ecosystem services of global importance such as carbon storage and climate regulation. Sustainable land use is a key concern in savannas, but spatially explicit information on LULC is still inaccurate. In this chapter we aimed at testing the potential of Landsat time series to separate critical land cover classes in the Brazilian Cerrado.

We derived spectral-temporal metrics on a seasonal (Apr.-Oct. 2011), annual (2011) and multi-annual (2009-2012) basis by calculating the spectral means, ranges, and standard deviations of all cloud free observations within the given period. Our results showed that the combination of dry and wet season information is most important for separating the LULC classes. Best classification results were derived from the multi-year dataset with classification accuracy of 93%. For the single year dataset, less wet season observations were available resulting in a higher phenological similarity between cropland and pasture and higher commission errors for the cropland class. For the dry season dataset, classification accuracy decreased from85% (single year dataset) to 79% indicating that seasonal information was crucial for separating the chosen LULC classes.

Our approach clearly showed the high additional value of temporal information for identifying LULC classes in the complex land use systems of savanna landscapes and the high potential of the Landsat archive to deliver this temporal information. A preliminary screening of the Landsat archive showed that 80% of the entire Cerrado biome has a similar Landsat coverage compared to the study area (+−20% scene availability in 2009–2012), rendering the multi-temporal classification approach highly applicable for large scale monitoring of land use change in the whole Brazilian Cerrado.

<u>*Research objective 2 (Chapter III):*</u> *Uncovering long-term deforestation dynamics within a highly dynamic deforestation along the BR-163.*

The lack on historic deforestation information hampers understanding of historic frontier development in the Amazon. Among current frontier regions the BR-163 highway plays an important role as it captures different socio-economic developments of the capital intensive agriculture in Mato Grosso and the extensive pastoralism in Pará within the last 30 years.

To evaluate the long-term deforestation dynamics along the BR-163 an image compositing approach was used to transform 2,224 Landsat images into an annual time series of spectral metrics from 1984-2012. The employed random forest classifier detected deforestation events in 45% of the original forest area between 1985 and 2012 and reached a classification accuracy of 85%. Half of the deforestation took place before 2000 and was concentrated in the state of Mato Grosso, mostly around the cites of Sinop, Terra Nova do Norte and Guarantã do Norte (Fig.III-5). The historic deforestation rates suggested a high robustness of frontier development towards counteracting political incentives, such as the revision of the forest code in 1996. With the national soy boom from 2000 to 2004, deforestation rates reached their maximum of 3% and expanded into forest areas of Pará. After 2004, intensified environmental monitoring (DETER) and governmental efforts to control deforestation (PPCDAm) efficiently decreased deforestation rates in Mato Grosso. The very same incentives did not counteract deforestation activities along the BR-163 in Pará, indicating a weak law enforcement of local authorities until the end of the observation period. By comparing these results with the global deforestation dataset of Hansen et al. (2013) and the Amazon wide monitoring program PRODES, the importance of small scale and low intensity deforestation processes along the BR-163 were shown.

Since the study region covered a large transect of forest types, the applied methods are potentially transferable to other regions with limited deforestation information available in the Brazilian Amazon. Landsat coverage is generally promising for this task, with 92% of the Brazilian Amazon covered by three or more Landsat images per dry season between 1984 and 2012.

Research objective 3 (Chapter IV): *Determining long-term regrowth dynamics within a highly dynamic deforestation frontier along the BR-163.*

While tropical deforestation threatens a broad range of ecosystem services, regrowth of secondary vegetation may help to recover habitats for threatened species and re-establish ecosystem services lost during deforestation. From the socio-economic perspective, increasing and decreasing rates of regrowth can be an indicator of changes in land use intensity, including land abandonment. Despite the ecological and socio-economical relevance of regrowing secondary vegetation in the tropics, spatial patterns and temporal dynamics remain poorly understood, especially in regard to different land management regimes.

In this study, regrowth dynamics across two different land use systems along the BR-163 were analyzed, namely: the extensive pastoralism in Pará and the capital-intensive agriculture in Mato Grosso. The analysis was based on the same spectral-temporal time series (1984-2012) used for the deforestation assessment (Chapter III). Moreover, the deforestation information from Chapter III was used to identify the post deforestation period for each pixel. For the post deforestation period, we used spectral-temporal thresholds to extract regrowth extent, duration, lag time between deforestation and regrowth, and frequency of regrowth cycles. The study showed regrowth on up to 50% of the deforested area in Pará and a maximum of 25% in Mato Grosso. The higher share of regrowth in Pará indicated a lower management intensity of the dominating pasture systems. In both states, annual regrowth rates drastically dropped after 1996, which coincided with a substantial monetary reform in 1994, the revision of the forest code in 1996 and the beginning of the soy boom (1996-2000) (Tab. I-1). In both states, the majority of regrowth was concentrated within 60m distance to forest edges and cleared again after an average of 5 years. The relatively short lifetime of secondary vegetation (5 years in average) suggested the dominance of early pioneer species in most regrowth areas and renders permanent land use abandonment a rare occurrence.

Spatial heterogeneity of short- as well as and long-term regrowth processes emphasized the importance of spatially explicit information to identify hot and cold spots of regrowth over time. This knowledge is highly relevant for regional land use planning, as it allows to identify suitable areas for ecosystem restoration and land use intensification. Besides management implications, high rates of absolute and relative regrowth underpin the importance of secondary vegetation for the regional carbon balance and can be used to refine current carbon bookkeeping models.

2 Conclusion

Ceiling rapid economic growth with sustainable land management is a huge challenge for Brazil, which could serve as an example for other tropical countries (DeFries et al., 2013). A goal of this work was to provide new insights into land use patterns in different ecological and socio economical units of Brazil. Landsat time series were proven to reliably separate land use types (Chapter II) and long-term processes within the land use system (Chapter III, IV). The results cover the most important biomes (Cerrado and Amazon), a consolidated agricultural area (Chapter II) and a dynamic deforestation frontier (Chapter III, IV). To account for the multitude of methodological and thematic insights of this work, the final conclusions are structured along the overarching research question:

1. **How can mapping of LULC in savanna and rainforest areas be improved using the temporal depth of the Landsat archive?**

To monitor LULC in the Cerrado a compositing framework was established to derive spectral-temporal metrics of Landsat imagery (Chapter II). This framework was consequently transferred and adapted to create a spatially extensive annual time series of spectral-temporal metrics which was used for the deforestation and regrowth analysis (Chapter III, IV). The approach has proven Landsat spectral-temporal metrics to be an extremely valuable tool for separating LULC classes in savanna areas and to monitor long-term deforestation and regrowth processes in the Brazilian Amazon. While a set multi-annual temporal metrics was highly effective in separating LULC classes in the savanna area (Chapter II), the annual changes of a single seasonal metric were most useful for the deforestation and regrowth detection in rainforest areas (Chapter III, IV). These findings contribute to the current evolution of new compositing methods by demonstrating the potential of different spectral-temporal metrics for highly relevant applications in the field of land change science.

Decisions on temporal and spectral properties of metric calculation need to consider trade-offs between data density and land use change processes. For example, mapping of LULC classes in dynamic landscapes require higher resolution of spectral-temporal metrics (annual to seasonal). In Chapter II we addressed this methodological challenge by investigating the effects of different spectral-temporal metrics for separating cropland, pasture and savanna vegetation. Sound knowledge of general land use processes on the ground are also essential for change detection. In this context, Chapter III raised awareness of deforestation conceptualisation between regional and global classifications. Comparisons with Hansen et al. (2013) showed that low intensity deforestation processes did not find a representation on the global scale yet. The results further demonstrated the need for pixel based deforestation assessments with a minimum mapping unit below 1 ha. Here, the PRODES Program (INPE, 2014) needs timely adaptations and current estimates are likely to underestimate deforestation processes.

Apart from improved LULC characterization in savanna areas and advancements in deforestation detection, Landsat time series allowed to investigate land change processes in more thematic depth. The temporal analysis in Chapter IV demonstrated a high spatial heterogeneity of short- and long-term regrowth processes and how historic regrowth rates decreased after 1996. As long-term regrowth information is still missing for large parts of the Brazilian Amazon, most carbon bookkeeping models extrapolate more recent regrowth information into the past (Aguiar et al., 2012; Aguiar et al., 2016). Consequently, these studies underestimate historic regrowth rates and complexity of regrowth dynamics along the BR-163 emphasized the need for long-term regrowth information across the whole Brazilian Amazon. The temporal analysis further demonstrated how assumptions of the deforestation assessment directly translate into the outcome of the regrowth detection. In this context, Chapter IV provides an important step towards scalable and consistent regrowth assessments and raises awareness of lacking concepts and guidelines for regrowth detection. The results could help to refine and evaluate regrowth mapping strategies of the TerraClass project (INPE, 2015a), as reliable regrowth information is needed to monitor law compliance and land use intensity in the Brazilian Amazon and beyond.

2. How do LULC change over time considering political and private initiatives?

Implications of political and private initiatives (Tab. I-1) have been widely discussed in regard to the Amazonian deforestation dynamics since the year 2000 (Assunção et al., 2012; Richards et al., 2014). This thesis complements the discussion in several ways- it provides the first information on the early stages of pioneer front formation including the 80s and 90s with cross boarder comparisons between the capital intensive agriculture in Mato Grosso and the extensive pastoralism in Pará. Chapter III and IV showed that historic deforestation and regrowth processes experienced different transitions along the Br-163. While deforestation shifted from Mato Grosso towards Pará in the early 2000s, regrowth rates dropped already in the second half of the 90s. The different dynamics suggested that regrowth and deforestation were independent elements of land use change along the BR-163. While the determination of underlying drivers of these dynamics is beyond the scope of this thesis, the results now allow to evaluate political and private initiatives from two different perspectives (regrowth and deforestation). The combined perspective sheds a new light on possible impacts of political incentives in the 90s after the collapse of the military regime in 1984, such as the Plano Real and the revised forest code (Tab. I-1). During this period, the first major differences in regrowth and deforestation dynamics occurred, indicating a phase of land use intensification. This is an important finding, as land use intensification was reported to have long been hampered by insecure land tenure, especially in Pará (Fearnside, 2001).

In regard to the organization and management of agricultural lands, the BR-163 region is currently in a phase of major transitions. With increasing registration of land properties (CAR) (Gibbs et al., 2015a) and surveillance methods of IBAMA, illegal logging and land occupation is becoming less attractive. Instead, there are alternative pathways arising. Restoration of illegally deforested land can become a profitable business (Latawiec et al., 2015). This restoration process could be coupled with REDD incentives, trading of environmental licenses and tree crop farming. Especially tree crop farming of high value tree species such as rubber, cacao, brazil nut and cashew, has long been proposed as socially, economically and ecologically more profitable than cattle farming (Alcorn, 1990; Peck, 1990). In this context, annual mapping of regrowth might reach the same political relevance as deforestation monitoring with direct legal and economic implications. However, such long-term land use strategies can only be followed if the socio-economic framework remains stable, which requires governmental infrastructure investments (schools, hospitals, security), private investment, innovation and enterprise (Nepstad et al., 2014; Schönenberg et al., 2015).

3 Outlook

LULC information provided in this thesis sets a valuable basis for further analysis in the ecological and socio political domain. From an ecological perspective, landscape fragmentation can be studied in the course of habitat connectivity (Chapter II, III and IV) and information on sensitive landscape elements such as rivers, slopes and hilltops could be derived. In combination with data on land tenure (CAR), legislation compliance could be monitored to evaluate effectiveness of law enforcement. Furthermore, the combination of long-term deforestation and regrowth information (Chapter II, III) could be used to refine estimates on carbon emission in this region. Detailed knowledge on the spatially explicit deforestation and regrowth pattern since the 80s provides input and validation data for land use models investigating the influence of proximate and underlying drivers on LULC change along the BR-163. In this context, information on regrowth is a key feature which has been rarely included so far. Coupled with socio-economic data on labor and yields, regrowth information is essential regarding investigations and discussions on land use intensity and restoration strategies.

Currently, remote sensing workflows are approaching a new era as recent developments towards cloud computing dramatically facilitate processing efforts. Big data management systems like SciDB (Stonebraker et al., 2013) will further improve processing speed. Moreover, the development of advanced Landsat and Sentinel-2 product generation (Roy et al., 2010; WELD, 2014; CNES, 2015) will accommodate for atmospherical corrections, cloud screening and large area compositing, and thus stimulate regional to global land LULC analysis with high thematic detail. Based on these developments, a whole new world of possibilities arises regarding the type of composites and related applications. Experiences from this thesis can help to define standard products which are currently in discussion at the European space agency (ESA). Concepts behind the presented approaches suggest development of hierarchical compositing schemes, such as monthly composites based on spectral information and annual composites based on aggregated spectral indices (mean, standard deviation and trends). The monthly composites could be used for detecting short term processes, whereas a recombination of annual composites allows to monitor multi-annual processes. Such hierarchical composite frameworks might be beneficial in terms of sensor integration (Wulder et al., 2015) and for a wide range of application (e.g. cropland monitoring in contrast to long-term regrowth analysis). Prerequisite for this development is further harmonization of calibration, atmospheric correction and cloud screening techniques for earth observation satellites as soon as Sentinel -2 data will become available. In terms of historic land use processes and land cover determination, opportunities of moderate resolution imagery are limited towards Landsat 4 and 5. Clever conceptual frameworks of determining abrupt and continuous change processes are necessary to fully explore the limited amount of available information. Here, the applied deforestation and regrowth detection approaches provided first ideas, but more guidelines and comparisons with alternative approaches are necessary. Conceptual improvements are also needed in regard to validation strategies. For pixel based regrowth processes, field based validation data or very high resolution data is necessary, which does not exist for historic time frames. In this context “soft validation” schemes based on spatio-temporal plausibility of results and estimates of error propagation along processing steps are possible alternatives.

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