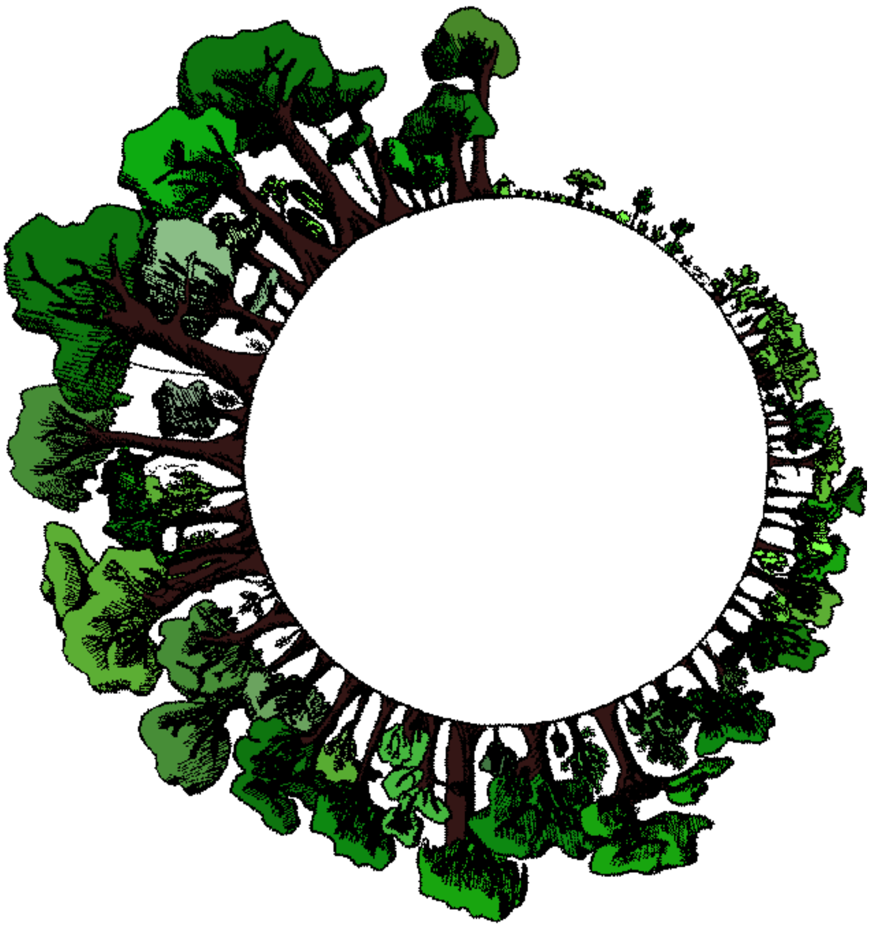
Laboratory of Geo-Information Science and Remote Sensing

Thesis Report GIRS-2016-18

ASSESSMENT OF REFORESTATION FOR THE SUBTROPICAL HUMID FOREST IN SOUTH-EAST BRAZIL

A comparison of datasets to assess discrepancies in area, evaluate agreement in overlap and analyse the accuracy for monitoring reforestation

Froede Vrolijk



03-06-2016

WAGENINGEN UNIVERSITY
WAGENINGEN UR

ASSESSMENT OF REFORESTATION FOR THE SUBTROPICAL HUMID FOREST IN SOUTH-EAST BRAZIL

Froede Vrolijk

Registration Number: 901006919020

<u>Supervisor:</u>

Dr. Valerio Avitabile

A Thesis Submitted in Partial Fulfilment of the Degree of Master of Science

At Wageningen University and Research Centre,

The Netherlands

03-06-2016
Wageningen, The Netherlands

Thesis code number: GRS-80436
Thesis report: GIRS-2016-18

Wageningen University and Research Centre
Laboratory of Geo-Information Science and Remote Sensing

Abstract

Tropical forests provide important ecosystem services, contain high biodiversity and sequester large amounts or carbon. These forests are declining globally, posing serious negative consequences for environmental sustainability. In recent years however, a trend towards forest regrowth is described in literature. In Brazil, large tracts of forest land have historically been converted into cattle pasture and agricultural land. These land change patterns were followed by land abandonment, which resulted in large areas of secondary forest growth. These forests grow rapidly and sequester large amounts of carbon. Planted forests also play an important role in Brazil, where tree plantations are expanding fast, with approximately 5000 km^2 per year. Moreover, initiatives such as REDD+ aim to promote sustainable management of forests and enhance forest carbon stocks, in addition to reducing deforestation and forest degradation. Reforestation is now believed to be one of the most prominent solutions for combatting environmental issues. The aim of this study is to quantify annual forest regrowth according to existing datasets, and to asses their monitoring methods. Additionally, we assess the type of forest (natural or plantation) that is detected by each dataset. Our goal is to reveal the discrepancies between the datasets and validate the accuracy of each dataset for monitoring forest regrowth in south-east Brazil. The JRC land cover dataset, the FAO land use dataset and Hansen forest gain dataset were used to calculate the amount of regrowth in the study area. Additionally, a time series method was applied to a sample area of the study region. The regrowth area calculations show the highest amount of regrowth for the Hansen dataset (1304 km^2), whereas JRC detects 295 km^2, and the FAO dataset shows 28 km^2 of change to forest land per year. The inter-comparison between the datasets reveals the agreement between datasets for assigning a regrowth label, using paired comparisons. The overlay of the JRC and Hansen datasets shows the highest percentage in overlap (54.25 %), followed by FAO – Hansen (20.25 %; using FAO as a reference) and JRC – FAO (0.54 %) when using the JRC dataset as a reference. The validation of the datasets using visual analysis in the entire study area was implemented for the JRC and FAO datasets, and shows an accuracy of 65.4 percent for the JRC dataset and 13.6 percent for the FAO dataset. Moreover, the validation of the Hansen dataset and time series method was implemented for the selected sampling site. The Hansen dataset shows an overall accuracy of 86 percent, and the time series approach shows an accuracy of 64 percent. The type of regrowth (natural, plantation or mixed) that is detected varies largely for each dataset. The JRC and Hansen datasets mostly detect plantation forests, covering 54 and 94 percent, respectively. The FAO dataset and time series method mostly detect natural forest, covering 45 percent and 76 percent, respectively. We conclude that there is a strong need for large-scale validation of datasets, in order to assess the uncertainty that accompanies each dataset. The validation of the datasets in this study shows a commission error only, and does not include the omission error. Further research is needed to quantify omission errors.

Keywords: Tropical secondary forest, regrowth, visual analysis, reforestation, dataset comparison, time series analysis, REDD+

Acknowledgments

I would like to express my gratitude to my supervisor Valerio Avitabile. His comments were very helpful to structure the report in a consistent way. The constructive criticism and advice helped me a lot to reflect on my own work. The discussions have proven to be fruitful and enjoyable.

I would also like to thank the people from the geosciences department that I asked for advice during my thesis, for sharing their knowledge.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

BFAST	Breaks for Additive Season and Trend
CDM	Clean Development Mechanism
ESPA	Centre Science Processing Architecture
FMASK	Algorithm for Cloud Masking Remote Sensing Imagery
FAO	Food and Agriculture Organisation of the United Nations
FRA	Forest Resources Assessment
GE	Google Earth
JRC	Joint Research Centre of the European Commission
LEDAPS	Landsat Ecosystem Disturbance Adaptive Processing System
UNFCCC	United Nations Framework Convention on Climate Change
MODIS	Moderate Resolution Imaging Spectroradiometer
MOSUM	Moving Sums of the Residuals
NDMI	Normalised Difference Moisture Index
NDVI	Normalised Difference Vegetation Index
NIR	Near Infrared
REDD+	Reducing Emissions from Deforestation and Forest Degradation
RSS	Remote Sensing Survey
SWIR	Short Wave Infrared
TR	Tropical Reforestation
USGS	United States Geological Survey

1 Introduction

1.1 Tropical forest functions

The greatest terrestrial biodiversity is found in tropical rainforests, but this area is under great pressure, and in danger to be lost (T. M. Brooks et al. 2002; Myers et al. 2000). The largest rainforest on the planet – the Amazon – is thought to contain about 16,000 tree species, for which many the ecological importance has yet to be determined (Steege et al. 2013). Moreover, estimates uncovered that more than half of all terrestrial animal and plant species live in forests (Millennium Ecosystem Assessment 2005). Tropical forests are essential for maintaining ecosystem functions that control fluxes of water, energy, nutrients and organic matter in the environment (Cardinale et al. 2012). On a global scale, tropical forests sequester vast amounts of carbon and thereby heavily regulate the climate (Zarin 2012). As a consequence, rainforests are a preferred asset for carbon sequestration and climate change mitigation (Silver, Ostertag, and Lugo 2000).

Tropical forest habitat persists to decline globally, which has serious negative consequences for environmental sustainability (Rudel 2005). Land cover change studies have long been dominated by a focus on deforestation. This deforestation rate remains high with 13 million hectares per year (FAO 2006). However, in recent years, an increasing amount of literature has described a trend towards forest regrowth in various regions across the world, showing that forest cover in 18 countries has begun to increase, as a result of afforestation, and natural regeneration (Chazdon 2008). More specifically, in the past 15 years reforestation and forest restoration have gained momentum around the world. Reforestation is now believed to be one of the most prominent solutions to the environmental crisis the world is facing today (Brancalion et al. 2013; Aronson and Alexander 2013; Chazdon 2013; Chazdon 2008)

1.1.1 Potential of secondary forests as carbon sink

Tropical forests around the world are increasingly being used and modified by human activities. In the last decades, land use change has converted forests largely into cattle pasture or agricultural land. In the Amazon, these land change patterns were followed by land abandonment, which has led to large areas of second-growth forest. These forests grow rapidly, and consequently sequester large amounts of carbon. However, they tend to be ignored because climate and carbon sequestration debates are generally more focussed on the conservation of old-growth forest (Bongers et al. 2015).

In contrast, recent studies have demonstrated that the net carbon uptake of old-growth forests has declined by a third over the period 1990 until 2010 (Brienen et al. 2015; Kintisch 2015). Forest regeneration is often overlooked as an important factor for carbon sequestration, although the regeneration potential of tropical forests is high (Guariguata and Ostertag 2001;

Brown and Lugo 1990a). The forests have a pattern of biomass accumulation that follows an asymptotic curve. This curve begins to level off after about 20 years, and is influenced by certain factors such as land-use history, climatic zone and landscape structure. For example, in the Pará region in Brazil, about 25% of the previously deforested area was covered by second-growth forests in 2010 (Bongers et al. 2015). These forests contain only about 45 to 48 percent of the carbon stocks found in old-growth forests, but their net carbon sequestration rate is up to 20 times higher in comparison to old-growth forests (4.6 to 5.8 Mg carbon ha^{-1} $year^{-1}$) (Pan et al. 2011; Brienen et al. 2015). Furthermore, about one-quarter of Amazonian forests are used for timber production. These forests have the potential for high carbon sequestration rates, particularly when reduced impact logging techniques are used (2.8 Mg carbon ha^{-1} $year^{-1}$ compared to 0.5 Mg carbon ha^{-1} $year^{-1}$ for conventionally logged forests) (West, Vidal, and Putz 2014). Therefore, it is important to include second-growth, and logged forests in the climate debate, and recognise the potential impact of these forests as carbon sinks.

Tropical deforestation has been an important contributor of greenhouse gas emissions. The reforestation of these lands has a recognised potential for recovering carbon stocks and mitigating climate change (Houghton 2012). In comparison to other climate mitigation practices, forest restoration methods can offer a low-cost approach for reduction of greenhouse gas emissions (Turner, Oppenheimer, and Wilcove 2009). The majority of global commitments to reforestation are motivated by climate objectives to mitigate climate change through carbon sequestration. However, tropical reforestation fulfils many other functions, such as the regulation of land-atmosphere interactions, pollination and societal adaptation to climate variability and climate change. These forest functions are particularly important because adaptation to climate change, reduction of forest cover loss and conservation of ecosystem services are more challenging in the tropics than elsewhere (Harvey et al. 2014).

Tropical forests have high rates of primary aboveground biomass, and store approximately 216 Pg C (Petagrams of Carbon) (Brown et al. 1993; Dixon et al. 1994). Secondary tropical forests can accumulate up to 5 Mg C ha^{-1} yr^{-1} during the first 10-15 years of regrowth (Brown and Lugo 1990b), with an average of 2-3.5 Mg C ha^{-1} yr^{-1}. These secondary forests do not produce the same amount of timber in comparison to plantations, but are nonetheless vital for carbon sequestration. This importance of secondary forests and forest fallows is the main form of carbon recovery in the tropics due to the large amount of land involved (Lugo and Brown 1992).

1.1.2 Tropical reforestation for mitigating climate change

When reforestation is approached beyond its role in mitigating climate change by means of carbon sequestration, reforestation of tropical landscapes shows to influence global and regional climates in many different ways. Reforestation has biophysical effects on climate, which can contribute to climate change mitigation. These biophysical effects include changes in surface albedo (the fraction of solar energy reflected from Earth into space), surface roughness canopy conductance, evapotranspiration and changes in volatile organic compound emissions (Locatelli et al. 2015). The overall effect – which is dependent on the magnitude and direction of change - can be climatic warming (Kirschbaum et al. 2011) or cooling (Zhao and Jackson 2014), which depends on the latitude. In other words, in boreal forests, reforestation may cause a net increase in regional temperatures through albedo, surface roughness and evapotranspiration, by affecting the amount and forms of energy transfer to the atmosphere. On the other hand, the most likely net effect of reforestation in the tropics is cooling (Anderson et al. 2011).

Large scale reforestation can also affect precipitation levels locally and regionally (Swann, Fung, and Chiang 2012). Furthermore, forests recycle and generate atmospheric water vapour flows on a regional and continental scale (Ellison, Futter, and Bishop 2012). Reforestation can also contribute to climate mitigation by providing sustainable forest produce, such as bioenergy from forest plantations, that may replace traditional sources of energy that are responsible for large greenhouse gas emissions (Lippke et al. 2011). Appendix A shows a comprehensive overview of the types of contributions of tropical reforestation to climate change mitigation, and adaptation to climatic variability.

1.1.3 Tropical reforestation for climate change adaptation

Reforestation areas that are well managed can contribute to adaptation of climate change. This is achieved by reducing the vulnerability of people and ecosystems to climate hazards and (future) climate change (Doswald et al. 2014). This adaptation to climate change can follow different pathways (Appendix A).

First, tropical reforestation can improve livelihood diversification, which provides a safety net in case of climate irregularities. For example in case of a poor agricultural harvest, a forest can supply products such as firewood, fruits and fodder to provide alternative sources of income, food and materials (Pramova et al. 2012).

Second, tropical reforestation can protect water supplies for human use (e.g. agriculture) by stabilising catchment hydrology, increasing base flow during drought, reducing flooding during heavy rainfall events, and by improving water quality (Locatelli et al. 2015). However, different types of reforestation (e.g. natural vs. plantation regrowth) can lead to a variety of outcomes with regard to catchment-scale water cycles (Uriarte et al. 2011; Ponette-Gonzalez et al. 2014).

Third, tropical reforestation can reduce the impact of extreme weather events for the local society and ecosystems. For example, the reforestation of hillslopes can help to reduce intense runoff, and stabilise the land to protect it against dangerous ground movements (e.g. landslides), in case of heavy rainfall events (Locatelli et al. 2015). Additionally, a restored tree cover can help in the regulation of microclimatic conditions, and thereby limit an urban populations' exposure to heat waves. The restored forest can provide shade an and evaporative cooling, as well as protecting agricultural lands by controlling temperature, humidity and exposure to winds (Bowler et al. 2010).

Fourth, reforestation may contribute to biodiversity conservation by increasing species' resilience to climate change (Travis 2003). Additionally, increased forest cover can improve long-term persistence of forest-dependent species in climate refugia. New reforestation areas can also improve habitat connectivity, which allows for species' migration in order to adapt to climate variability (Carnus et al. 2006).

1.2 Expansion of tropical tree plantations in Brazil

The expansion of planted forests in the world has seen a rapid increase in area coverage in many parts of the world. Data from the FAO (2011) shows a 48.1 percent increase in planted forests from approximately 178 million hectares in 1990 to 264 million hectares in 2010. From the tropical regions, South America and Asia and the Pacific show the largest changes with an increase in planted forest area of respectively 67 and 61.6 percent.

Brazil has seen a rapid growth in tree plantation area in the last decade, and reached an area of 7.6 million hectares in 2013 (Brazilan Tree Industry 2014). Of this total, Eucalyptus plantations represent 72 percent, followed by pine, covering 20.7 percent. Acacia, teak and rubber trees are among the other tree species that are planted in Brazil. Eucalyptus roundwood is mainly used for pulp and paper, as well as for charcoal and industrial firewood, while Pinus timber most often is used for wood panels, lumber and other solid products. Particularly pulp is largely exported around the world. Brazil is becoming the leading global exporter of chemical pulp, shipping mostly to China, the USA and Germany (Finnish Forest Industries Federation 2009). The rising demand from China for paper and pulp products is forcing pressure on the Brazilian land, and encourages the expansion of plantations. Moreover, climate change is expected to have a negative effect on yields – for example through increased droughts – which requires an increased plantation area. It has been estimated that 4.5 times the current area for tree plantations will be required in 2050 to meet demand (Fearnside 1999). The required expansion may be substantially higher, as a result of the high global demand for forest plantation products. In South America, tree plantations are expanding fast, currently with 5000 km^2 per year (Jobbágy, Baldi, and Nosetto 2011).

1.3 Problem description and justification

Worldwide changes in tropical forest ecosystems that occurred in recent decades have had an enormous environmental impact, which has contributed drastically to climate change (Gullison et al. 2007) and loss in biodiversity (Laurance et al. 2012). Various initiatives have been set up to reduce the amount of carbon emissions into the atmosphere. One major initiative is the Reducing Emissions from Deforestation and forest Degradation (REDD+) program which aims to reduce deforestation and forest degradation, promote sustainable management of forests and enhance forest carbon stocks in developing countries (UNFCCC 2009). Programs such as REDD+ provide opportunities for the ecological restoration of damaged ecosystems as part of their framework to reduce emissions from forests (Alexander et al. 2011), because reforestation can contribute to restoration of ecosystem services through natural regeneration of forests or human induced reforestation (Chazdon 2008).

The FAO Forest Resources Assessment (FRA) has long been the standard reference for global scale forest resource information, which is produced at decadal intervals (FAO 2010a). However, this dataset has been criticised for several reasons. One major pitfall of this dataset is the lack of independent validation for the submitted changes in forest cover. Other major limitations include the use of inconsistent methods between countries and the change of forest definitions that are used in reports (Grainger 2008). In recent years, a variety of tropical forest observation systems have been developed in order to support monitoring of land cover changes, and in particular forest changes. The increased availability of satellite imagery - such as the opening of the Landsat archive to the public in 2008 – has resulted in more possibilities for mapping forest cover changes (DeVries, Decuyper, et al. 2015). Datasets that report forest cover changes are important systems for monitoring purposes and mapping of forest changes. For the REDD+ programme, this is organised by the Measuring, Reporting and Verification (MRV) system. The MRV system is a crucial requirement for the implementation of REDD+ to assess forest-related emissions (Herold and Skutsch 2011; DeVries and Herold 2013).

Change detection methods for mapping forest cover increasingly use Landsat time series, indicating a shift away from bi-temporal change detection methods (Coppin et al. 2004). A prominent dataset that maps land cover change is the Hansen global forest change map (Hansen et al. 2013a). Moreover, time series methods such as Breaks For Additive Season and Trend (BFAST) have been used for near real-time forest disturbance detection (Verbesselt, Zeileis, and Herold 2012). Various studies have used Landsat time series to map tropical forest regrowth dynamics, with different purposes, such as classification and temporal trajectory based methods (e.g. (Carreiras et al. 2014; Schmidt et al. 2015).

With different datasets that report on forest resources, a comparison of reported regrowth areas may reveal discrepancies between datasets. Moreover, it is of interest to know why differences are present between the datasets, and what are the characteristics of the dataset that are responsible for these differences. There is a need for validation of the datasets for assessment of their accuracy in a comprehensive and consistent way. The usage of a certain dataset has policy implications and has a major importance for donor-funds aimed at ecosystem restoration or carbon sequestration. As for initiatives such as REDD+ and the Clean Development Mechanism (CDM) of the Kyoto Protocol, it is crucial to know forest cover changes for projects that are aimed at promoting afforestation and reforestation. For such applications there is a need for consistent, transparent quantification of forest cover changes that back up policy measures and payments for carbon sequestration measures. For donors and funding agencies of ecological restoration initiatives it is crucial to monitor the progress made by implementing initiatives. Forest resource information is also a key tool to raise public awareness of the scale and rate of tropical forest change (DeVries, Decuyper, et al. 2015) The choice for using one dataset over the other can communicate a completely different story to the public.

Forest resources assessment has long been dominated by research focussing on deforestation monitoring. The growing extent of secondary forests, and the increasing amount of forest plantations show a new trend in land cover change that has long been overlooked. This thesis aims to provide a comparison of the most comprehensive data sources for assessing reforestation. The four datasets used in this research are compared in outcome of forest regrowth area. The validation of the datasets assesses the accuracy of each dataset to gain a better understanding of their quality. The dataset characteristics are discussed, and the definitions used for monitoring regrowth are compared. This helps to obtain a better understanding of similarities and discrepancies between datasets that form the basis for policy implementations and carbon sequestration mechanisms.

1.4 Research objective and research questions

Research objective:

To quantify forest regrowth according to existing datasets and a time series approach, and to assess their monitoring methods, compare the regrowth estimates, reveal the discrepancies and assess the accuracy of each dataset.

Research questions:

(i) How much reforestation has occurred annually in south-east Brazil in 2000 – 2010?

(ii) How much discrepancy is there between the existing datasets and the time series approach?

(iii) What is the accuracy of the datasets for mapping forest regrowth when validated using visual analysis?

1.5 Definition of forest regrowth and reforestation

For assessing re-establishment of forests, a main differentiation has to be made, which results in two major types of forest regrowth: reforestation and afforestation. Reforestation is the re-establishment of forest formations after a temporary condition with less than 10 percent canopy cover due to human-induced or natural perturbation. Afforestation is the conversion from other land uses into forest, or the increase of the canopy cover to above the 10 percent threshold (FAO 2000). The definition used by the UNFCCC is more detailed: "Afforestation is the direct human-induced conversion of land that has not been forested for a period of at least 50 years to forested land through planting, seeding and / or the human-induced promotion of natural seed sources." And "Reforestation is the direct human-induced conversion of non-forested land to forested land through planting, seeding and / or the human-induced promotion of natural seed sources, on land that was forested but that has been converted to non-forested land." (UNFCCC 2001).

With these two main types of forest regrowth, there are four ways in which reforestation or afforestation can take place (Lamb 2010; Calle et al. 2013):

- Spontaneous regeneration may naturally occur on former agricultural land
- Assisted natural regeneration of forests (ecological restoration)
- Agroforestry, silvopastoral systems and fallow management
- Restoration through commercial tree plantations

In this thesis, these four main ways are aggregated into one forest regrowth / reforestation / afforestation group. In other words, any type of increasing canopy cover is considered forest regrowth / reforestation. As a result, the naming of the forest regrowth may differ within this document, depending on the context and the dataset that is used. One dataset may refer to an increasing canopy cover as forest gain, whereas another dataset may use the term forest regrowth.

1.6 Study area

The study area is located in south-east Brazil, and covers the states of Paraná, Santa Catarina, Rio Grande do Sul and a small portion of the state of São Paulo. Brazil is well-known for its deforestation rates, and recent efforts to monitor forest change. This study area was selected because it has a large amount of both natural and plantation forest. The FAO provides ecological zoning for the world to define and group areas based on common ecological characteristics. These zoning areas are useful in different kinds of forestry research, such as calculation of above-ground biomass (De Sy et al. 2015; Langner, Achard, and Grassi 2014). The study area is limited by two boundaries: the administrative boundary of Brazil, and the ecological zone 'subtropical humid forest' of the FAO (2001) (Figure 1). The total study area in Brazil covers 421733 km^2. The climate of this area is characterised by mild winters and hot humid summers. The average annual temperature in this zone is 15° to 21° Celsius. The annual precipitation ranges from 1000 to 1500 mm a year, with a relatively even distribution throughout the year (FAO 2001).

2 Materials and methods

2.1 Datasets

2.1.1 JRC land cover and FAO land use

Initiatives that aim to tackle deforestation and forest degradation – or monitor other (inter)national processes related to forests – require accurate information regarding tree cover and forest resources. However, the quality and quantity of data for reporting varies largely among countries. Forest definitions differ among authors and organisations, and the methodology and purpose of the assessment vary largely. Furthermore, many countries lack consistent, historical records on land cover and land use changes. Another problem is the lack of technical or financial capacity to be able to report on forest area changes (FAO 2009).

The Forest Resources Assessment (FRA) Remote Sensing Survey (RSS) is a partnership between the FAO and the European Commission Joint Research Centre (JRC), and participating countries. The FRA RSS was established in order to strengthen the national technical capacity of countries, and thereby improving forestry-related information gathering and reporting. This FRA RSS approach uses satellite imagery to improve information on tree cover and land use changes around the world (FAO, JRC, SDSU and UCL 2009).

The choice of the FAO and JRC to use remote sensing is based on the distinct advantages this approach offers in comparison to field-collected data and other methods. Satellite remote sensing offers the advantage of broad area coverage along with systematic observations. It also offers the ability to use standardised and repeatable analyses to characterise the earth's surface. The global coverage of this monitoring approach makes the RSS one of the few comprehensive sources of information available for monitoring forested areas on earth (FAO, JRC, SDSU and UCL 2009).

The RSS produces results on both land cover and land use. Land cover is examined by the JRC, whereas land use is examined by the FAO. Land cover refers to the biophysical attributes of the earth's surface. This can be directly observed by satellite imagery from a remote sensing instrument, such as Landsat. Land use involves a human dimension or purpose that is characterising a location (Lambin et al. 2001). Land use can be inferred from remote sensing data, but is in need of verification with local, expert knowledge, or from data that is collected during field inspections. Information on land use is important in order to assess the drivers of land use change, which in turn may be used to develop effective policies and strategies to reverse forest loss. A combination of the land cover and land use assessment of the RSS aims to adequately describe physical tree cover, and the – often variably – area defined as 'forest' (FAO, JRC, SDSU and UCL 2009).

The RSS uses a systematic sample of a 10 x 10 km area of a satellite image, which is extracted at each 1-degree intersection of latitude and longitude (Mayaux et al. 2005; Ridder 2007). The RSS uses a systematic sampling grid which covers the globe between 75 degrees north and south latitude. The sample sites were analysed to inspect the quality of the locations, and subsequently remove sampling sites with a poor quality. These 'no data' locations represent areas that are obscured by clouds, or lacking data as a result of poor satellite coverage or low-quality (FAO and JRC 2012). These areas were omitted for further analyses in the RSS. Ultimately, 13066 sites were processed and used in the RSS analysis. In the tropics, a total of 4016 sample sites were identified. This area of the world is most affected by clouds and shadow effects in the imagery (Ju and Roy 2008; Asner 2001). South America is covered by 1542 sample units, with 1392 of them remaining after removal of the ones with missing data. Brazil is covered by 707 sample units. The overall sampling rate in Brazil is 3.4% in (Eva et al. 2010). The study area contains 46 sampling sites (Figure 1). Due to missing data and intersection of sampling sites with the study area boundary, the sampling rate of 3.18 percent in the study area is lower than the overall sampling rate of Brazil.

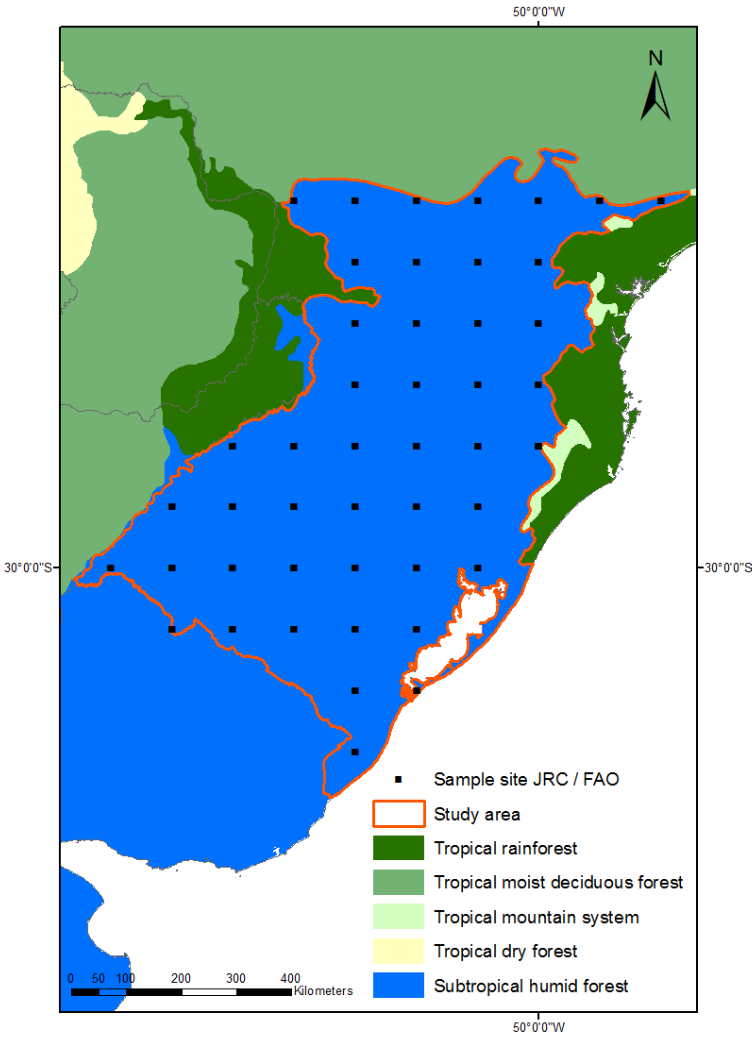


Figure 1 Location of the sample units (FAO and JRC 2012) and FAO ecological zones (FAO 2001) in the study area.

The processing of the JRC and FAO data is done using Landsat data. After pre-processing, image segmentation is applied which groups similar pixels into patches (i.e. polygons), based on spectral similarity and spatial distinctions. Following is the automated classification of land cover types. A comprehensive overview of the JRC and FAO processing method is provided in Appendix B.

2.1.2 Hansen

The third dataset used in this study is provided by Hansen et al. (2013a). They have evaluated global forest changes, both forest loss (2000-2014) and forest gain (2000-2012). The authors of this dataset define gain as the inverse of loss, or a non-forest to forest change entirely within the study period. Longer lived regrowing stands of tree cover that were initially not characterised as non-forest within the study period were not mapped as forest gain (Hansen et al. 2013b). For this dataset, trees are defined as all vegetation taller than 5 m in height. Forest gain is related to the percentage tree crown cover that is above 50 percent, and is reported as a twelve year total.

The dataset by Hansen allows the data to be downloaded from an online portal[1] for further analysis. The following three tiles cover the entire study area, and are used to assess forest gain for the period 2000 - 2012:

- 30S, 60W
- 20S, 60W
- 20S, 50W

The Hansen dataset is based on Landsat data, and the analysis is performed using Google Earth Engine; a cloud platform for earth observation data analysis for large scale applications and parallel processing of geospatial data to determine per pixel the tree cover using a supervised learning algorithm. This was done as follows: after pre-processing the images, three groups of metrics were extracted for each band: (i) reflectance values of minimum, maximum and selected percentile values (e.g. 10%, 25%); (ii) reflectance values between selected percentiles (e.g. 10-25%); and (iii) the slope of linear regression reflectance values of the bands against the image date. Training data to link to the Landsat metrics were derived from image interpretation methods, by mapping the presence or absence of a crown cover by using high resolution imagery, using existing tree cover layers from Landsat, and by rescaling MODIS tree cover maps. Finally, the forest gain (as well as percent tree cover and forest loss) training data were related to the time-series metrics using a decision tree. To create the global forest cover map, 20 terapixels of data were processed using one million CPU-core hours on 10,000 computers (Hansen et al. 2013b).

[1] http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.2.html

The Hansen dataset uses 1 and 0 values i.e. there is either a pixel with forest regrowth (1), or there is no forest regrowth for that particular pixel (0) over a twelve-year period. A map of the forest regrowth in 2000 – 2012 for the study area can be found in Appendix C.

2.1.3 Overview definitions JRC, FAO and Hansen

To summarise, an overview of the used datasets is provided in Table 1. In this table the used definitions regarding land cover / land use change are provided for each dataset. The tree canopy cover threshold and the dataset timeframe for monitoring regrowth are important characteristics, and vary largely among the datasets. The JRC dataset has a timeframe from 2000 until 2010. The FAO dataset covers only five years: from 2000 until 2005, and the Hansen dataset covers 2000 until 2012. The canopy cover threshold used in this study comprises a change to more than 70 percent (Chapter 2.2.2). The canopy cover change for the FAO dataset uses the definition of forest land use (FAO 2000). The Hansen dataset uses the 50 percent canopy cover threshold for assigning a forest gain label (Hansen et al. 2013b). These definitions are used in the discussion chapter of this study to reflect on the outcome and characteristics of each method for monitoring reforestation.

Table 1 Overview of JRC, FAO and Hansen forest definitions for mapping forest cover / forest land use.

Dataset	JRC	FAO	Hansen
Land cover / land use	Land cover	Land use	Land cover
Tree canopy cover threshold	≥ 70 percent	≥ 10 percent	≥ 50 percent
Height threshold	≥ 5 meter trees	≥ 5 meter trees	≥ 5 meter vegetation
Minimum mapping unit	5 hectares	0.5 hectares	0.09 hectares (30 x 30 meter pixels)
Time period	2000 - 2010	2000 - 2005	2000 - 2012

2.1.4 Forest regrowth monitoring using time series analysis

The last method used in this study for assessing forest regrowth is structural change monitoring using a time series approach. Structural change monitoring uses a stable historical period as a baseline for detecting unexpected behaviour (i.e. disturbance or regrowth). A breakpoint is defined when the time series deviates significantly from the model assumptions (using a statistically defined stability boundary) (E. B. Brooks et al. 2014). For this research the Breaks for Additive Season and Trend (BFAST) method will be used to detect disturbances (Verbesselt et al. 2010; Verbesselt et al. 2010; Verbesselt, Zeileis, and Herold 2012)(Verbesselt, Zeileis, and Herold 2012)(Verbesselt et al. 2012)(Verbesselt, Zeileis, and Herold 2012). After detection of disturbances, forest regrowth can be identified. The algorithm uses a decomposition of pixel time series into trend, season and noise components. It has been shown to be robust against sensor noise when using irregular Landsat time series (DeVries, Verbesselt, et al. 2015).

The BFAST method is used to identify a disturbance, after which the post-disturbance dynamics are analysed. Hence, this approach only focusses on the classification of regrowth after a clear disturbance. The time series will be monitored by observing the moving sum of residuals (MOSUM) (Leisch, Hornik, and Kuan 2000). This method flags areas where a statistical boundary is exceeded in order to show a disturbance. For mapping regrowth a similar logic is applied, however in the opposite way. With forest regrowth the MOSUM signal is expected to return to a near-zero value, which indicates that the canopy is closed once again. Several ecological parameters need to be incorporated into the method in order to avert erroneous flagging of regrowth areas as much as possible. An example of this is the minimum time between the disturbance and the occurring regrowth. The recent release of an extension on BFAST by DeVries, Decuyper, et al. (2015) allows for the integration and adaption of various settings to obtain the best classification result. The time series method will be applied to one sampling site of JRC / FAO (i.e. a 10 x 10 km area), as discussed in chapter 2.2.5.

Data acquisition and pre-processing

The United States Geological Survey (USGS) has produced, archived and distributed Landsat data since 1972. Users of the archive are given the possibility to order data and imagery using the Centre Science Processing Architecture (ESPA)[2] (Jenkerson 2013) On Demand Interface. The interface allows for bulk ordering of remotely sensed imagery. The data portal allows for specification of the required surface reflectance-based spectral indices such as NDVI and NDMI. Moreover, it is possible to select smaller pieces of one Landsat image (i.e. the reforested areas), without the need for the whole uncut version of the image. These are important benefits, especially with the application of time series analysis where large amounts of data are needed. To obtain useable imagery with the required surface reflectance, the LEDAPS (Masek et al. 2006) algorithm is applied. For cloud masking, the FMASK (Zhu and Woodcock 2012) algorithm is used.

---

[2] https://espa.cr.usgs.gov/

2.2 Methods

2.2.1 Workflow

The regrowth analysis for this thesis is divided into different sections, which are linked to the three research questions. These sections are (i) the area calculation for forest regrowth, (ii) an inter-comparison between datasets and (iii) a validation of the datasets (Figure 2). The following subchapters discuss the processing for each section. The chapters where each sections' methodology and results are discussed are displayed between brackets in Figure 2.

- The **area calculation** for the study area of the datasets calculates the area of regrowth according to each dataset (Chapter 2.2.2).
- The **inter-comparison** for the study area compares the quantitative outcomes and location of the regrowth (Chapter 2.2.3).
- The **validation** chapter discusses the comparison of the datasets for the study area against a higher resolution validation dataset (Chapter 2.2.4).

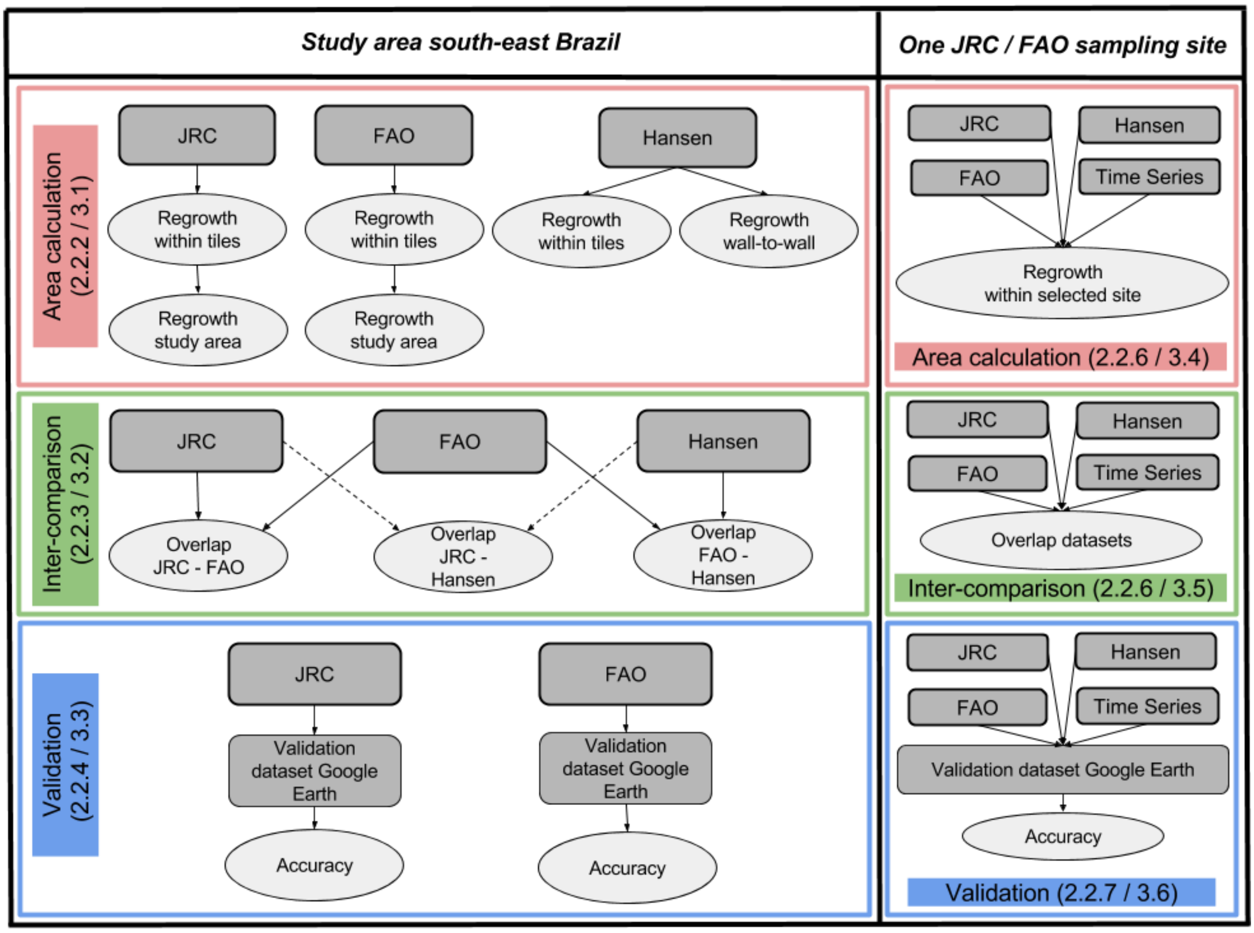


Figure 2 Flowchart for reforestation assessment. Grey rectangles represent datasets; oval shapes represent processing outcomes. Chapters of each component are shown between brackets (methodology / results).

For the inter-comparison and the validation, one dataset has to serve as a reference dataset for the comparisons. This study uses the JRC dataset as a reference, for the following reasons: The JRC dataset looks at land cover, which can be validated with high resolution imagery, without the need for expert field knowledge – as would be the case with the FAO dataset. Moreover, the dataset contains information on the type of forest and land cover changes. This is not the case with the Hansen dataset, which only shows a binary value as a twelve-year average. The reasons for choosing the JRC dataset will be further elaborated in the chapters regarding the inter-comparison and validation.

Besides the area calculation, inter-comparison and validation of the JRC, FAO and Hansen datasets in the entire study area, one JRC / FAO sampling site is selected to compare all four datasets (Chapter 2.2.6 and 2.2.7). The calculations for the time series method are carried out in only one JRC / FAO sampling site because of validation and computational restrictions.

Conclusively, the area calculation, inter-comparison and validation for the selected sampling site consist of three main sections:

- The time series analysis approach for **area calculation** of forest regrowth, which is compared with the area estimates from the other datasets for the **selected sampling site** (Chapter 2.2.6).
- The **inter-comparison** within the **selected sampling site** discusses the overlap between the datasets (Chapter 2.2.6).
- The **validation** chapter discusses the accuracy for each dataset within the **selected sampling site** (Chapter 2.2.7).

2.2.2 Area calculation of forest regrowth within study area

JRC

The starting point of the dataset comparison was the acquisition of the data from the JRC science hub[3] – the online portal for downloading data for monitoring tropical forest change. The data were downloaded for the study area for the period 2000 - 2010; in total 46 sample sites. Both shapefile and TIFF are available for download. The shapefile (containing segments of change) data were imported into ArcGIS (version 10.3.1) for analysis. First, the shapefiles were clipped to the boundary of the study area. After that, a model was constructed that iterates over the shapefiles in the study area, and reprojects them into the 'WGS 1984' projection. Furthermore, the polygons that show regrowth are extracted from the dataset and grouped per tile and regrowth class. Subsequently, the area of the polygons is calculated for each tile, grouped per forest regrowth class. The area calculation within the sampling sites is extrapolated in order to estimate the total regrowth within the study area.

[3] http://forobs.jrc.ec.europa.eu/trees3/

Within the sampling sites, segments of land cover have been created by JRC. From the total of 46 sampling sites, 15997 polygons were created by the JRC method (Appendix B). From these segments, the change classes that depict forest regrowth were used for further analysis i.e. showing a change to a *forest* canopy cover of 70 percent or more. The regrowth classes used in this study are divided into three land cover change classes (showing the canopy cover between brackets):

- Other land cover (< 30 %) → Tree cover (≥ 70 %)
- Other wooded land (≥ 70 %) → Tree cover (≥ 70 %)
- Tree cover mosaic (30 – 70 %) → Tree cover (≥ 70 %)

Land cover change for the other land cover and 'tree cover mosaic' are based on a canopy cover change from less than 70 percent to a canopy cover of 70 percent or more. The 'other wooded land' class requires a canopy cover of at least 70 percent, but for this class the layer of vegetation consists of scrubs, tree regrowth or a mixed vegetation with a mainly woody component (Appendix B). A visualisation of such regrowth polygons is provided in Figure 3.

Figure 3 JRC land cover change tile 26 south 51 west with land cover changes for the period 2000 – 2010.

FAO

The model developed for the JRC dataset is applied to the data of the FAO land use change dataset over the period 2000 – 2005. This dataset contains 15716 polygons in total for the study area. Here the polygons that depict a change to forest land use are divided into two classes:

- Other land use (< 5 %) → Forest (≥ 10 %)
- Other wooded land (5 – 10 %) → Forest (≥ 10 %)

The FAO dataset contains one change type less that the JRC dataset, but uses the same type of change as defined in the JRC / FAO methodology (Appendix B). A complete overview of the land cover / land use types and change classes can be found in Appendix D.

Hansen

The Hansen dataset has a wall-to-wall coverage over the entire study area. Therefore, it is possible to calculate the forest gain area directly, without the need for extrapolation of the results from the sampling sites. Forest gain for the Hansen dataset was also calculated for the area within the JRC / FAO sites. This was done for two reasons. First, this allows for an assessment whether the sample sites of the JRC / FAO are representative of the entire study area, by taking the regrowth in the sample sites, and compare it to the wall-to-wall method. Second, it allows for a fairer comparison of the regrowth area with the JRC and FAO datasets, because the same sample size and sample locations are used for the area calculations. Figure 4 shows the JRC / FAO sampling site and the Hansen forest gain within and outside of this block.

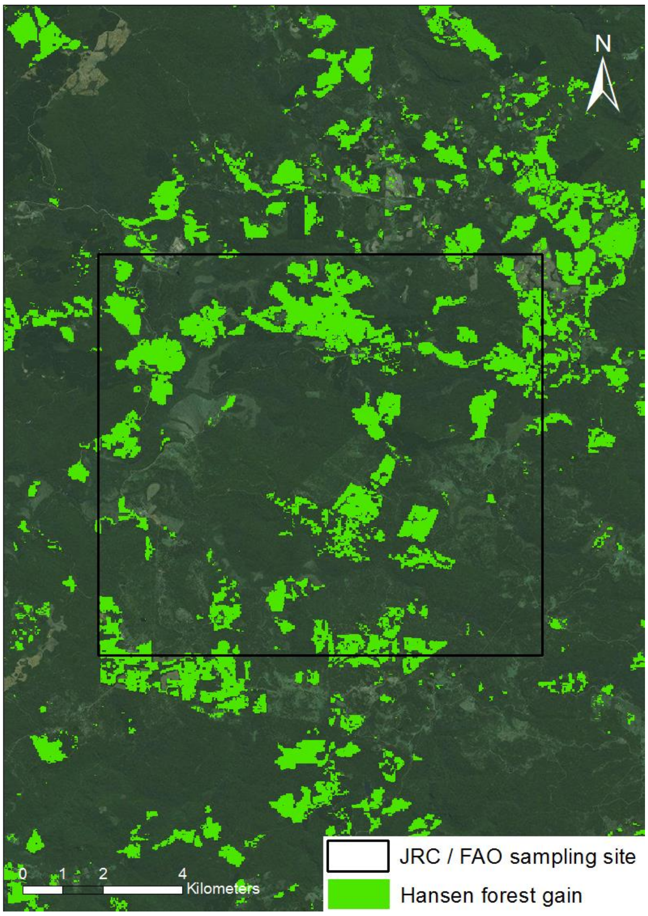


Figure 4 Hansen forest gain with outline of JRC / FAO sampling site 26 south 51 west.

2.2.3 Inter-comparison datasets within study area

This section discusses the method for the inter-comparison between the datasets JRC – FAO, JRC – Hansen and FAO – Hansen. This inter-comparison between the three datasets is carried out to assess the discrepancies between the datasets.

JRC – FAO

The datasets of the JRC and FAO both contain regrowth polygons, and these polygons can overlap. The overlapping polygons are used to calculate an area of agreement between the datasets (Figure 5). A detailed overview of the overlapping polygons between JRC and FAO can be found in Appendix I.

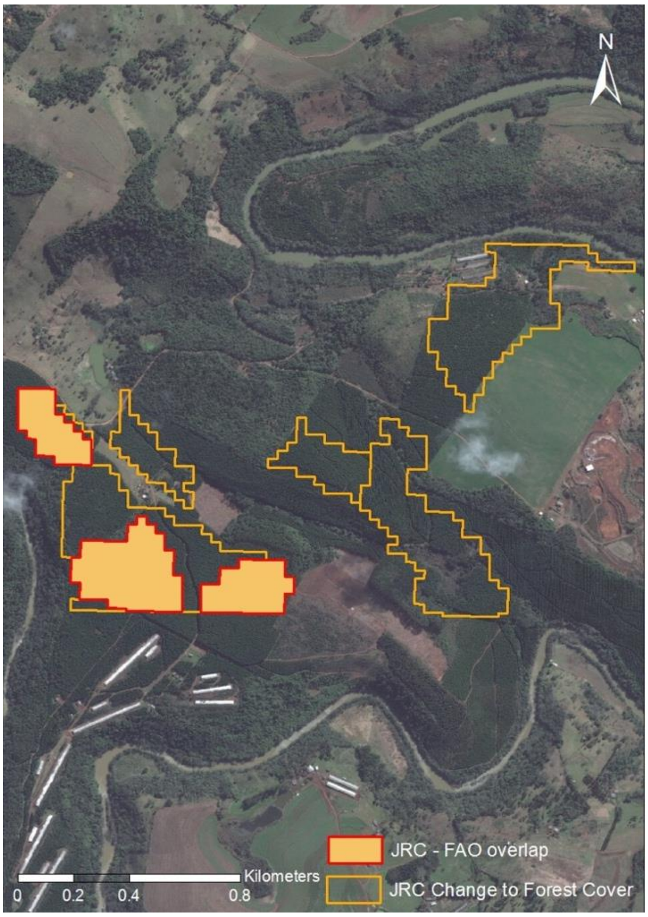


Figure 5 Inter-comparison between JRC and FAO forest regrowth polygons.

JRC – Hansen

For the JRC and Hansen datasets, the overlapping area of the Hansen pixels within the JRC polygons is calculated (Figure 6). The JRC regrowth polygons are used as a boundary in which the Hansen forest gain pixels are counted. Thus, the overlap will be given as a percentage of Hansen forest gain pixels within JRC regrowth polygons, where JRC is used as a reference.

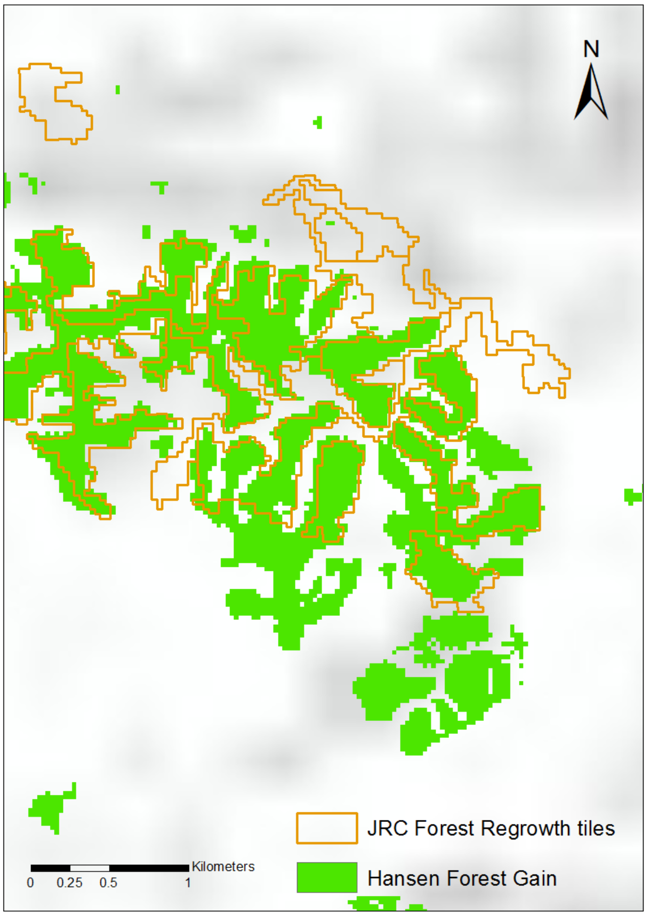


Figure 6 Overlap between JRC regrowth polygons and Hansen forest gain pixels.

FAO – Hansen

Similarly as the JRC – Hansen overlap calculation, another calculation of the Hansen pixels within the FAO polygons (with a change to forest land use) is performed. For this comparison, the FAO dataset is used as a reference, where a percentage of Hansen forest gain pixels within FAO polygons is calculated.

2.2.4 Validation of JRC and FAO datasets using visual analysis

Virtual globes have seen a rapid growth for the management of geospatial information. Since 2005, an increasing number of papers have been published in peer reviewed journals within various disciplines. Virtual globes allow scientists to visualise and communicate their research findings in an intuitive map environment. In particular Google Earth (GE) has experienced a rapid growth in published papers from 2005 to 2010 (Yu and Gong 2012). The GE tool developed rapidly, and has been used in many sectors. The advantages of high spatial resolution imagery provided as a free and open data source has greatly supplemented traditional land cover mapping (Clark et al. 2010; Mering, Baro, and Upegui 2010).

The use of GE for research projects can be summarised in several major categories, such as visualisation, data collection, data exploration, data integration, modelling and simulation, validation and communication of results (Gould et al. 2008; Stensgaard et al. 2009). The first use of GE imagery as reference data was demonstrated by Helmer, Lefsky and Roberts (2009). They show how optical imagery with a fine spatial resolution in GE can be used as reference data for land cover related applications. The use of this data made it possible to distinguish many different land-cover types, such as old-growth forest, secondary forest and pasture. According to the authors, even recently cleared land is visible when using GE. However, a main drawback that they point out is the non-optimal date of the imagery when using GE as reference data. However, this drawback is also common with other reference data. Therefore, the use of GE is a desirable option to use as reference data and for the visual analysis of the regrowth areas.

A list of attributes was constructed to add information to the regrowth polygons of the JRC and FAO datasets. This information is retrieved from high resolution GE imagery and will build a reference dataset for assessing the accuracy of the forest change datasets. This newly created dataset will also give information about the characteristics of the detected forest regrowth type, the canopy cover and quality of GE imagery, among other information. The added information consists of 13 attributes (Table 2).

Table 2 Information retrieved from Google Earth imagery to supplement and validate the JRC and FAO datasets.

Information derived from GE to supplement and validate the JRC and FAO datasets
Date of first observation (i.e. around 2000)
Date last observation (i.e. around 2005 / 2010)
Regrowth or not (yes / no)
Confidence of regrowth (low, medium, high)
Type of regrowth (natural or plantation)
Confidence type of regrowth (low, medium, high)
Canopy cover first observation (in percentages, arranged in deciles)
Canopy cover last observation (in percentages, arranged in deciles)
Regrowth pattern (random, uniform or clustered, or any combination of these)
Number of historical images in Google Earth
Quality of historical Google Earth imagery (low, medium, high)
Source of error in historical Google Earth imagery (clouds, resolution, image colouring)
Source of imagery for first observation (Google Earth / Landsat)

A detailed description of the added information can be found in Appendix E.

The JRC and FAO datasets both contain monitoring periods for 1990 – 2000, and for 2000 – 2010 and 2000 – 2005 for the JRC and FAO respectively. The quality of Google Earth imagery available is essential for executing a proper visual analysis. For this reason, the timeframes 2000 – 2010 and 2000 - 2005 were selected, instead of 1990 – 2000. The availability for the 1990 – 2000 timeframe is much lower (on average only around 10 percent of Google Earth imagery could be used, based on the availability of images in 1990 and 2000). The use of 30-meter resolution Landsat imagery makes it more difficult to assess forest regrowth with a high confidence level. Also the regrowth type is not distinguishable with this resolution. Moreover, the canopy cover increase would be very difficult to assess (if not impossible). Nevertheless, Landsat imagery was used when no GE imagery was available for a certain area, or when the GE image date deviated to much from the observation date of the dataset.

2.2.5 Time series analysis within one JRC / FAO sampling site

2.2.5.1 Selection of the sampling site

In the selected sampling site all three datasets and the time series approach are compared for area estimates. To make this comparison within the 10 x 10 km sample site representative, various attributes from the visual analysis are used to select the site with the highest diversity of regrowth types. This is an important step because a sampling site should not only contain one change type (e.g. 'other wooded land to forest cover') or forest type (e.g. only plantation forest), since this might favour one dataset or monitoring method over the other and makes the area calculation, inter-comparison and validation less representative. The preferred tile should ideally contain the highest amount of accurate information extracted from Google Earth. From the newly created validation dataset (Table 2), the following attributes (supplementing the JRC dataset) are considered fundamental for the selection of the sampling site for the time series analysis:

- Occurrence of regrowth (for all three change classes), along with the confidence level (low, medium, high);
- Type of regrowth (natural / plantation / mixed), along with the confidence level (low, medium, high);
- Number of historical images in Google Earth, and the quality of these images.

The JRC regrowth polygons distributed over the 46 sampling sites formed the input data for the selection of the time series sampling site. The selection of the sampling site took al six attributes into consideration, following the order as described above. From this (JRC / FAO) sampling site selection, the three highest ranking sites – with the most desirable attribute values – were chosen. From these three, one site was chosen randomly: JRC / FAO sampling site: 24S – 50W, located within the Landsat tile at path 221 and row 77 (Figure 7). This JRC / FAO sampling site has the second highest number of regrowth polygons (44), a fair share of both natural and plantation forest and on average a high number of historical images in Google Earth (10). It is also relatively close to the centre of the Landsat tile (in vertical direction) which is beneficial as it does not suffer from much data loss due to the broken scan line corrector of Landsat 7.

2.2.5.2 Time series analysis method

The time series analysis will use all available adequate data from the archive for the years 1990 – 2010. Adequate data is defined as imagery with no more than 60 percent cloud cover. In total 196 images were used for the period 1990 – 2010. This period is long enough to create a historical stable period from 1990 - 2000 and have a monitoring period from 2000 – 2010.

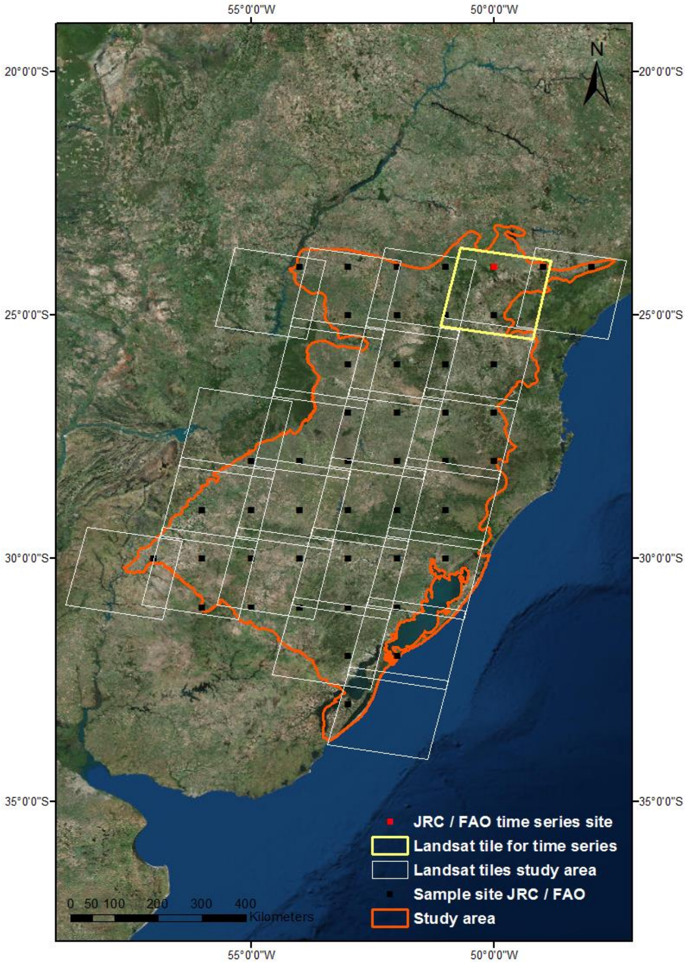


Figure 7 Landsat tiles and JRC / FAO sampling site covering the study area. The selected Landsat tile is depicted in yellow, and the JRC / FAO sampling site used for the time series analysis is shown in red.

The time series method uses a statistical method for a monitoring period to determine if a change (i.e. forest disturbance or regrowth) occurred. For each monitoring period, a harmonic model is derived from all available Landsat data before it is projected onto the time series. Subsequently the Landsat data is compared with the model by using a Moving Sums of the Residuals (MOSUM). This method calculates for each time point (*t*) how well the observed data fit the model using the following formula:

$$MO_t = \frac{1}{\hat{\sigma}\sqrt{n}} \sum_{s=t-h+t}^{t} (y_s - \hat{y}_s)$$

Where $\hat{\sigma}$ is the predicted variance which is estimated from the history period, *n* is the number of observations and y-$\hat{y}$ compute the residuals. h is defined as a fraction of the number of observations in the sample. This component can be adjusted to increase or decrease the sensitivity to a forest disturbance. This parameter is set to 0.5 for this study. For each time window the structural stability is determined. This means that a structural breakpoint is formed when the null hypothesis (stability of the pattern) is rejected. This method additionally allows for several (ecological) parameters to be incorporated in the time series analysis. For example, regrowth is flagged when the period between a disturbance and the returned regrowth signal spans at least three years (as used in this study). The MOSUM values should also remain below the stability boundary for at least one year to receive the regrowth label. In this way, falsely detected regrowth can be undone. Figure 8 shows an example by DeVries, Decuyper, et al. (2015) using the MOSUM method.

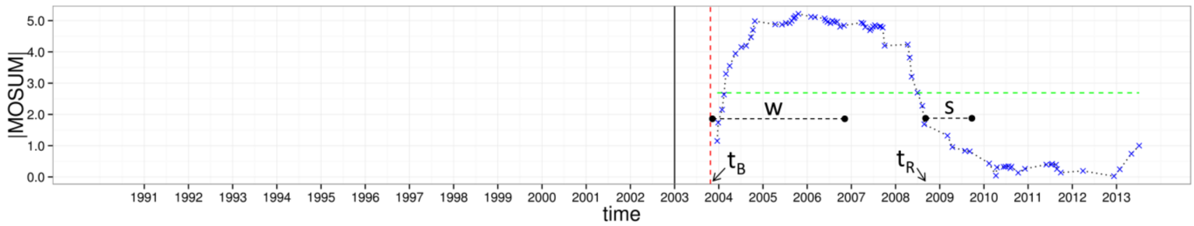


Figure 8 Demonstration of the MOSUM regrowth method. The MOSUM values are depicted in blue, and start to increase after a disturbance (at tB). The green line shows the statistical stability boundary. A regrowth label is assigned if the MOSUM values return below the boundary at least w years after the disturbance, and remain below that boundary for an additional s years (DeVries, Decuyper, et al. 2015).

Indices which use the difference between the NIR and the SWIR regions of the electromagnetic spectrum are useful for discriminating between age classes of the forest (Fiorella and Ripple 1993), since they are sensitive to canopy moisture content (Jin and Sader 2005). These are also known to be successful in irregular Landsat time series for mapping post-disturbance regrowth (DeVries, Verbesselt, et al. 2015). The MOSUM method as used by DeVries, Decuyper, et al. (2015) is shown to be effective with this NIR and SWIR ratio, using the Normalised Difference Moisture Index (NDMI). This index is also used for the detection of post-disturbance regrowth in this thesis. The implementation of the time series uses the package 'Rgrowth' by DeVries et al. (2015), which is an extension to the BFAST monitor (Verbesselt et al. 2010), and is implemented in the statistical programming language 'R'.

The processing steps for the time series analysis are displayed in Figure 9. The downloaded images from the selected Landsat tile are first clipped to the extent of the JRC / FAO sampling site. After that, the cloud mask (FMASK) is applied to remove clouds in the imagery. With these cleaned scenes the NDMI is calculated. Subsequently, a historical model is fitted, which iterates over all pixels and years. This results in a disturbance map for the selected sampling site. With the disturbance map, regrowth processes are calculated. The area for post-disturbance regrowth is calculated, and also the year of regrowth is derived with this method.

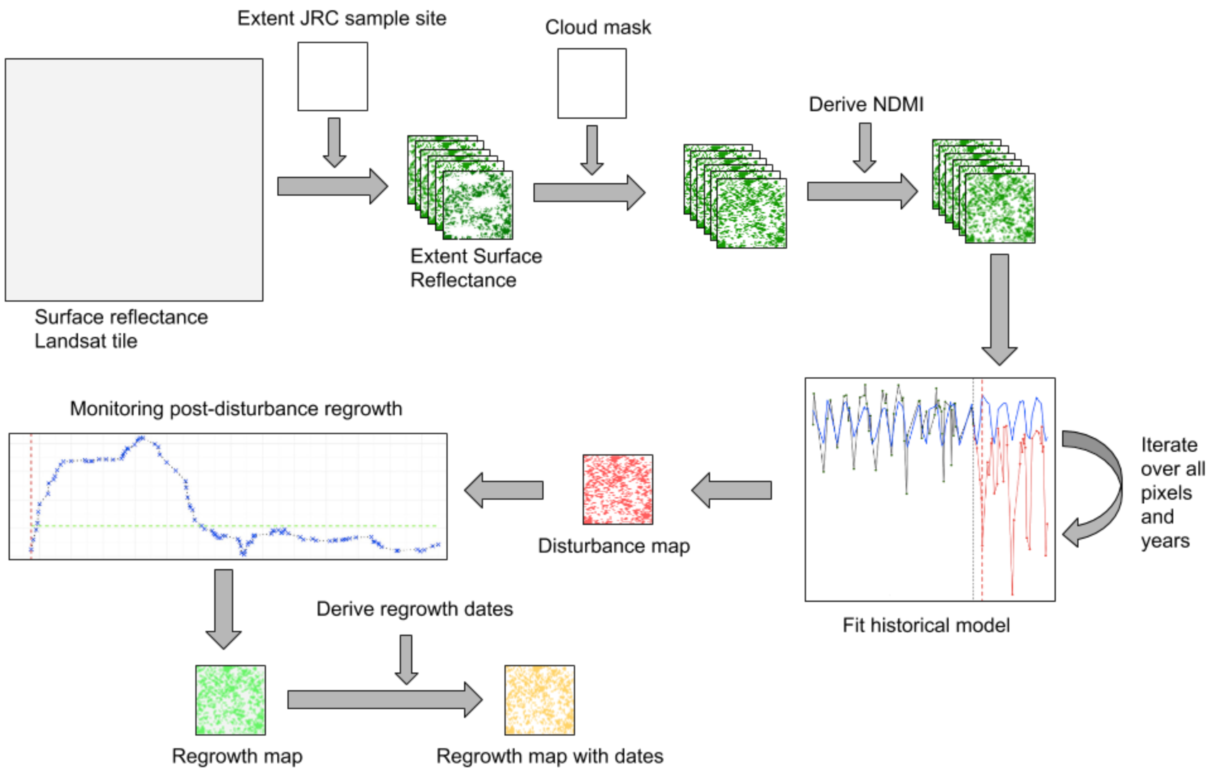


Figure 9 Flowchart showing pre-processing and analysis steps of the time series method.

2.2.6 Area calculation and inter-comparison within selected sampling site

The area calculation of the JRC, FAO and Hansen datasets is implemented for the selected sampling site (Chapter 2.2.5.1) as described in Chapter 2.2.2. The time series method uses the analysis steps described in Chapter 2.2.5.2 to obtain the forest regrowth area.

The approach discussed in Chapter 2.2.3 is used to compare the datasets within the selected sampling site. The inter-comparison of the datasets is performed using paired comparisons to derive the amount of overlap for monitoring forest regrowth. The calculation of regrowth according the the time series method as discussed in Chapter 2.2.5.2 is used to compare all four datasets within the selected sampling site.

2.2.7 Validation within the selected sampling site

A validation using visual analysis of Google Earth imagery is carried out for the selected sampling site. The selected area does not contain any change polygons of land use from the FAO dataset. For the JRC dataset the validation is performed as described in section 2.2.4.

For the validation of a pixel based forest regrowth map (e.g. the Hansen dataset and the time series approach) there are various possibilities to do the validation. Because of the scattered pixels in these datasets (as opposed to the aggregated polygons of the JRC and FAO datasets), a sampling approach for individual pixels is used in this study. The Hansen dataset is validated by using 100 random pixels from the forest gain dataset, within the sampling site. Similarly, the time series approach also uses 100 randomly selected pixels for validation. For these two pixel based datasets, the occurrence of regrowth is recorded (yes / no), as well as the type of regrowth for a particular pixel (natural / plantation).

Figure 10 Example location of pixels for validation of Hansen dataset and time series method.

3 Results

In this chapter, the results of the area calculation (Chapter 3.1), inter-comparison (Chapter 3.2) and validation (Chapter 3.3) are of the entire study area are discussed. A summary of the results is provided in the first subchapter (i.e. Chapters 3.1.1, 3.2.1 and 3.3.1), which sums up the main findings. Subsequently, the results are discussed in more detail in the remaining part of each chapter. After the results for the entire study area, the area calculation, inter-comparison and validation of the selected JRC / FAO sampling site are discussed in chapter 3.4, 3.5 and 3.6, respectively.

3.1 Forest regrowth area for JRC, FAO and Hansen

3.1.1 Summary forest regrowth area calculation

Table 3 shows the calculated regrowth areas for each dataset. For the JRC and FAO datasets the area estimates within sampling sites are shown. These estimates are extrapolated to the entire study area (Table 3 – middle column). This table also shows a comparison with the Hansen dataset in twofold: the 'sampled' forest gain dataset (within the JRC / FAO sampling sites), and a calculation of the original wall-to-wall coverage of Hansen. The area calculation for the original Hansen wall-to-wall coverage is based on the entire study area (Appendix C) whereas the 'sampled' version is a calculation of the forest regrowth within the JRC / FAO polygons (Appendix J). This area of regrowth is then extrapolated to the entire study area, using the same method as was used for the JRC and FAO datasets.

The datasets all start their monitoring period in 2000, but each dataset has a different final year for their timeframe: FAO until 2005, JRC until 2010 and Hansen until 2012. Therefore, an additional calculation was made to assess the regrowth per year, for each dataset. In this way, it is possible to give a better estimate of forest regrowth per year (Table 3).

Table 3 Overall regrowth for each dataset, given the dataset's timeframe. The 'Area estimate within sampling sites' is extrapolated to the entire study area to obtain the 'Area estimate study area', which shows the regrowth for each dataset within the dataset's timeframe. The 'yearly regrowth study area' shows the corrected annual amount of regrowth in the study area.

Dataset	Area estimate within sampling sites (km^2)	Area estimate study area (km^2)	Timeframe dataset	Yearly regrowth study area (km^2)
JRC	93	2952	2000 – 2010	**295**
FAO	4	138	2000 – 2005	**28**
Hansen 'sampled' (extrapolated)	523	16447	2000 – 2012	**1371**
Hansen original (wall-to-wall)	-	15642	2000 – 2012	**1304**

These yearly regrowth estimates are suitable for a comparison between the datasets. The yearly Hansen estimate that is extrapolated from the JRC / FAO sampling sites to the entire study area shows the largest area of regrowth. When this is compared to the wall-to-wall coverage for the entire study area, it shows a higher level of regrowth with a yearly difference of approximately 67 km^2. For the entire monitoring period of twelve years, the regrowth estimates are 16447 km^2 and 15642 km^2 for the 'within tiles' estimate and original Hansen dataset, respectively. The JRC dataset shows a total regrowth of 2952 km^2 for the 10-year timeframe, and a yearly regrowth of 295 km^2. Lastly, the FAO dataset has a total regrowth for the period 2000 – 2005 of only 138 km^2, with an annual regrowth of 28 km^2. The datasets show large differences in the estimates for forest regrowth. There are several important factors that influence the outcome of the estimates, which are reviewed in the discussion chapter of this thesis.

3.1.2 Area calculation within sampling site

JRC

In total 442 polygons were extracted from the JRC dataset containing regrowth. The total regrowth that was found in the study area according to the JRC totals to 93.9 km^2. The number of polygons that show regrowth differ among the land cover change classes. The 'other land cover to tree cover' class has the highest number of polygons (278), followed by 'tree cover mosaic to tree cover' (107) and 'other wooded land to tree cover' (57). The regrowth per land cover change class is displayed in Table 4. The timeframe of this dataset is from 2000 until 2010.

Table 4 Regrowth within sampling sites for the JRC dataset for period 2000 – 2010, grouped per land cover class.

Class	Number of JRC polygons	Total area JRC polygons (km^2)
Tree cover mosaic to tree cover	107	22.7
Other wooded land to tree cover	57	10.4
Other land to cover to tree cover	278	60.9
Total	**442**	**93.9**

FAO

The regrowth in the FAO dataset was analysed in the same way as the JRC dataset. The number of polygons that show a change to forest is much lower for this dataset: only 22 in total for the entire study area. Of the 22 polygons, 11 are of the change type 'other wooded land to forest', and the other 11 are of change type 'other land use to forest'. This dataset shows a regrowth area of 4.4 km^2 for the period 2000 – 2005.

Table 5 Regrowth within sampling sites for the FAO dataset for period 2000 – 2005, grouped per land use class.

Class	Number of JRC polygons	Total area FAO polygons (km^2)
Other wooded land to forest	11	1.8
Other land use to forest	11	2.6
Total	**22**	**4.4**

Hansen

The wall-to-wall method allows for a direct calculation of the total number of pixels depicting forest gain in the study area. The total study area in Brazil covers 421734 km^2. The number of pixels that show 'forest gain' represent 3.71 percent of the total study area. This results in 15644 km^2 of forest gain for the period 2000 – 2012 (Table 6). The calculation of Hansen forest gain can be found in Appendix H - 1.

Table 6 Regrowth area calculation according to Hansen for period 2000 - 2012. The table shows the area within the JRC / FAO tiles (extrapolated to the whole study area), as well as the original wall-to-wall coverage.

Measuring method	Regrowth area (km^2)
Regrowth within tiles (within JRC / FAO tiles)	523
Hansen 'sampled' (extrapolated from JRC / FAO tiles)	16448
Hansen original (wall-to-wall)	15644

However, this calculation is for the entire study area, and not for the sampling sites used by JRC and FAO. In order to make a proper comparison with the reforestation found in the JRC / FAO sampling sites, another calculation uses the pixels within these sampling blocks, named the 'sampled' Hansen outcome. The extrapolated area for the Hansen dataset (Table 6 – Hansen 'sampled') uses the area within these sampling sites to calculate the forest gain for the entire study area, by extrapolating the values. The total area within the tiles is 13411 km^2, representing a proportion of 3.18 percent of the total study area, distributed over 46 tiles. This is a bit lower than the overall sampling rate of Brazil at 3.4 percent (Eva et al. 2010). This is due to one tile with missing data, and two tiles that were clipped to a new extent to remove an area covered by water. The forest gain in the 'sampled' Hansen map shows a forest gain of 3.96 percent. Since the tiles represent 3.18 percent of the entire study area, the 'sampled Hansen' forest gain results in an area of 16448 km^2. The calculation for forest gain pixels within the sampling sites can be found in Appendix H -2.

A comparison of the 'sampled' Hansen forest cover versus the wall-to-wall computation is reviewed in the discussion chapter of this thesis.

3.2 Inter-comparison datasets with JRC as reference

This chapter discusses the dataset comparison by using JRC regrowth polygons as a reference. The dataset comparison is in threefold: Hansen – JRC, FAO – Hansen and JRC – FAO. For the FAO – Hansen comparison, FAO is used as a reference.

3.2.1 Summary inter-comparison

The inter-comparison between the datasets consisted of three comparisons: JRC – Hansen, FAO – Hansen and JRC – FAO (Table 7). First, The JRC – Hansen comparison shows an overall overlap of 54.3 percent. The FAO – Hansen comparison shows and overall overlap of 20.3 percent between the datasets, using the FAO polygons as a reference. The JRC – FAO comparison is based on the overlapping polygons from JRC (n = 442), and FAO (n = 22), using the JRC dataset as a reference. This results in a total overlap of eight polygons, with only 0.5 percent overlap in area as a total of the JRC polygons (Table 7).

Table 7 Overall dataset overlap in percentages for JRC – Hansen, FAO – Hansen and JRC – FAO.

Datasets	Dataset overlap (%)
JRC – Hansen	54.3
FAO – Hansen	20.3
JRC – FAO	0.5

3.2.2 Overlap JRC – Hansen

An overlay of JRC with the Hansen dataset shows the number of forest gain pixels within the JRC regrowth polygons. This Hansen-pixel, JRC-polygon comparison was grouped per forest regrowth class, as used by the JRC (Table 8).

Table 8 Inter-comparison between JRC and Hansen dataset, showing percentage overlap per JRC class, and the total overlapping area in km^2.

Class	Nr. of JRC polygons	Total area JRC polygons (km^2)	Overlap (%)	Overlap (km^2)
Tree cover mosaic to tree cover	107	22.7	16.5	3.8
Other wooded land to tree cover	57	10.4	42.3	4.4
Other land cover to tree cover	278	60.9	70.3	42.8
Total	**442**	**93.9**	**54.3**	**50.9**

Table 8 displays the total number of JRC regrowth polygons (442) found within the sampling sites, grouped in three classes. Each class shows the number of polygons, followed by the percentage overlap of Hansen forest gain pixels within JRC regrowth polygons. Lastly, the area of overlap between the Hansen and JRC dataset is given in Table 8, which is based on the percentage overlap and the total JRC area. This results in an overall overlap of 50.9 km^2 out of 93.9 – the total amount of regrowth found in the JRC polygons. This corresponds to an overlap of 54.3 percent. The overlap percentages show large differences for the three classes. 'Tree cover mosaic to tree cover' has only 16.5 percent overlap with Hansen forest gain pixels, 'other wooded land to tree cover' shows 42.3 percent overlap, and the 'other land cover to tree cover' class has the highest overlap with Hansen: 70.3 percent.

3.2.3 Overlap FAO – Hansen

The comparison between the FAO land use classes and Hansen forest gain dataset shows the overlap of Hansen pixels within FAO polygons. From the 15716 segments created by the segmentation method of the FAO, only 22 polygons were identified as regrowth (equally distributed over two land use change classes). Table 9 shows the overlap of FAO polygons and Hansen pixels in the study area.

Table 9 Inter-comparison between FAO and Hansen datasets, showing the percentage of overlap per FAO land use change class, and the total overlapping area in km^2.

Class	Number of FAO polygons	Total area FAO polygons (km^2)	Overlap (%)	Overlap (km^2)
Other wooded land to forest	11	1.8	11.0	0.2
Other land use to forest	11	2.6	26.9	0.7
Total	**22**	**4.4**	**20.3**	**0.9**

The results of Table 9 show that the total number of 22 FAO polygons cover 4.4 km^2, and that the overlap with the Hansen dataset covers 0.9 km^2. This corresponds to 20.3 percent overlap between the datasets – 11 percent for the 'other wooded land to forest' class, and 26.9 percent for the 'other land use to forest 'class.

A review of the JRC – Hansen and FAO – Hansen dataset comparison can be found in the discussion chapter of this thesis.

3.2.4 Overlap JRC – FAO

Lastly, an inter-comparison between the JRC and FAO datasets shows the overlapping polygons of these two datasets. This comparison created an overlay between the three change classes of the JRC dataset and the two change classes of the FAO dataset. This resulted in a total of eight intersections between the polygons of the two datasets. Appendix I shows an overview of these polygons with the change type of both the JRC and FAO polygons, and the overlapping area. The total area of overlap is 0.5 km^2, which corresponds to an overlap of only 0.54 percent, when JRC is used as the reference (Table 7). This is the proportional overlap as compared to the total amount of regrowth in the JRC polygons (93.9 km^2). When the FAO dataset is used as a reference, the percentage of overlap is higher. The total forest regrowth of the FAO dataset covers 4.4 km^2. The overlap corresponds to 11.5 percent of the total FAO regrowth dataset.

3.3 Validation

3.3.1 Summary of the results from the validation dataset

This first subchapter discusses the results of the validation for the JRC and FAO methods for detecting forest regrowth. This was done using high resolution imagery. From the recorded attributes (Table 2), a subset was constructed that evaluates the quality of the JRC and FAO datasets to detect forest regrowth. The following attributes were used for validation of the JRC and FAO datasets:

- Regrowth (yes / no)
- Confidence regrowth (low / medium / high)
- Type of regrowth (natural / plantation / mixed)
- Confidence type of regrowth (low / medium / high)

A summary of the validation results is shown in Table 10.

The JRC dataset containing 442 polygons divided over three regrowth classes was validated using visual analysis. The validation of the JRC dataset shows an overall agreement of 65.4 percent with the validation dataset (Table 10).

This validation using high resolution imagery was in 79.9 percent of the polygons determined with high confidence. Particularly if there was little (< 30 percent; Appendix B) forest cover in the first observation (year 2000), over 90 percent was confirmed to have regrowth (Appendix F -1). For land cover classes where already a substantial part of the polygon is covered by forest (i.e. ‘tree cover mosaic to forest cover’ and ‘other wooded land to forest cover’), the level of confidence drops considerably (Figure 12).

Next, the type of regrowth was assessed, with three possible classes: natural, plantation and mixed. The type of regrowth occurring in the JRC polygons as a proportional percentage is 16.7 percent of natural forest, 54.3 of plantation forest, and 29 percent is recognised as a mix of natural and plantation forest (Table 10). The ‘other land cover to tree cover’ contained the highest percentage of plantation forest of the three regrowth classes, followed by the ‘other wooded land to tree cover’ class (Figure 13). This seems consistent with the forest cover definition of the classes: plantations are generally harvested in rotation, cutting down all the trees at once, leaving a bare soil. This class has plantation forest growing in 72.3 percent of the polygons that were examined. The ‘tree cover mosaic to tree cover’ class has the lowest percentage of plantation forest (11.2 percent), and the largest proportion of mixed forest (50.5 %). The ‘other wooded land to tree cover’ class has a rather equal distribution of all three types of forest regrowth.

Lastly, the confidence level for assigning a forest regrowth type is overall high (91.2 %) (Table 10). The overall change in canopy cover increases from 26.1 percent in 2000 to 84.4 percent in 2010, according to the visual analysis. The changes per regrowth class, in comparison with the JRC forest cover definitions are examined in the discussion of this thesis (Chapter 4.1).

The date of the imagery that was used for the visual analysis was also recorded, for the observation at the start of the dataset timeframe (i.e. 2000) and at the end (i.e. 2010). From all regrowth polygons of the JRC dataset, 82 percent was validated with a Google Earth image deviating no more than two years from the first observation year. For the second observation year, 94 percent of the polygons had a validation image deviating no more than two years from the dataset observation year.

The FAO dataset shows an overall lower accuracy for monitoring regrowth accurately, with only 13.6 percent correctly classified (Table 10). The land use change of the FAO consists for 45.5 percent of natural forest, 22.7 percent of plantation forest, and 31.8 percent of mixed forest. The confidence level for assigning a label for the occurrence of regrowth or the type of regrowth is also considerably lower compared to the JRC dataset (Table 10). This is the result of a low number of change polygons (n = 22) where the imagery for validation was often obstructed as a result of low quality imagery, clouds and an image date deviating largely from the monitoring years (i.e. 2000 or 2005). The canopy cover changes from 41.4 percent to 55 percent for the FAO dataset.

The imagery dates in Google Earth were also recorded for the FAO dataset. For the year 2000, all polygons were validated with imagery deviating no more than two years from the start date. For the year 2005, only 45 percent deviated no more than 2 years from the original timeframe of the dataset. Over 30 percent deviated five years or more from the year 2005, which resulted in a relatively large share of low confidence for the validation (Table 10). If no adequate imagery was available in Google Earth, Landsat imagery was used as a validation source.

Table 10 Summary of the validation for the JRC and FAO datasets in percentages. The accuracy for monitoring forest regrowth and the type of regrowth are displayed, along with the confidence of assigning a label to each class.

Regrowth accuracy			**Confidence regrowth**			**Type of regrowth**			**Confidence type of regrowth**	
JRC	FAO		JRC	FAO		JRC	FAO		JRC	FAO
65.4	13.6	High	79.9	31.8	Natural	16.7	45.5	High	91.2	72.7
		Medium	9.7	4.5	Plantation	54.3	22.7	Medium	6.8	22.7
		Low	10.4	63.7	Mixed	29.0	31.8	Low	2.0	4.6

3.3.2 Validation JRC dataset using visual analysis

The following section examines the outcome of the aforementioned validation attributes in more detail by using graphs that show the outcome per JRC regrowth class. The classes have a varying number of polygons within the study area:

- Other land cover to tree cover – 278 polygons
- Other wooded land to tree cover – 57 polygons
- Tree cover mosaic to tree cover – 107 polygons

The graphs show a proportional stacked bar chart as a percentage of the total number of polygons within each group. A detailed overview of the outcome in table form can be found in Appendix F.

Regrowth

The visual analysis first examined the occurrence of regrowth, and was therefore focussed on assessing if there was indeed regrowth occurring, which was recorded as a binary variable (yes or no) for each polygon with a regrowth class according to JRC. Figure 11 shows the proportional percentage for each JRC class (a detailed overview of the number of polygons and percentages can be found in Appendix F). The 'other wooded land to tree cover' class shows the highest amount of false flagging of regrowth. 'Other land cover to tree cover' has the lowest amount of misclassifications according to the visual analysis. For the 'tree cover mosaic to tree cover' class roughly half of the polygons were identified to be correct. The overall correct classification is 65.4 percent for all JRC regrowth polygons.

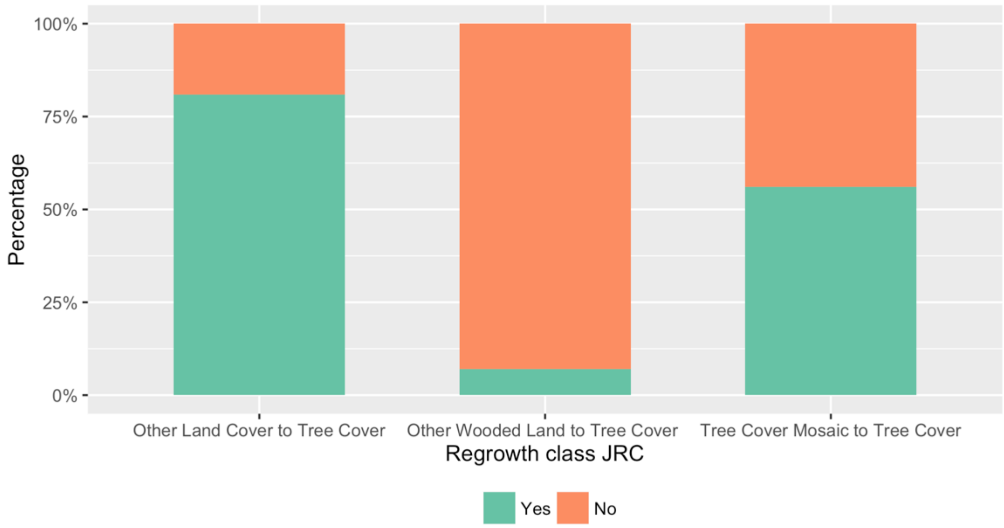


Figure 11 Validation of the JRC regrowth attribute, showing if there is indeed regrowth in the polygons, grouped by JRC forest regrowth class. The graph displays a proportional value, for each of the three classes.

Confidence regrowth

The next step in the visual analysis focussed on the level of confidence for the occurrence of regrowth. There is a distinct difference between the change classes ‘other wooded land’, and ‘tree cover mosaic’ opposed to the ‘other land cover’ class (with a forest cover of less than 30 percent – Appendix F). In case of the ‘other land cover to tree cover’ class, it was in most cases easy to determine (with high confidence) that there was indeed regrowth occurring in the polygons (Figure 12). Overall, 10.4 percent of the regrowth was assigned with low confidence, whereas 9.7 percent was assigned with medium confidence. The remainder of the regrowth (79.9 percent) was assigned with high confidence.

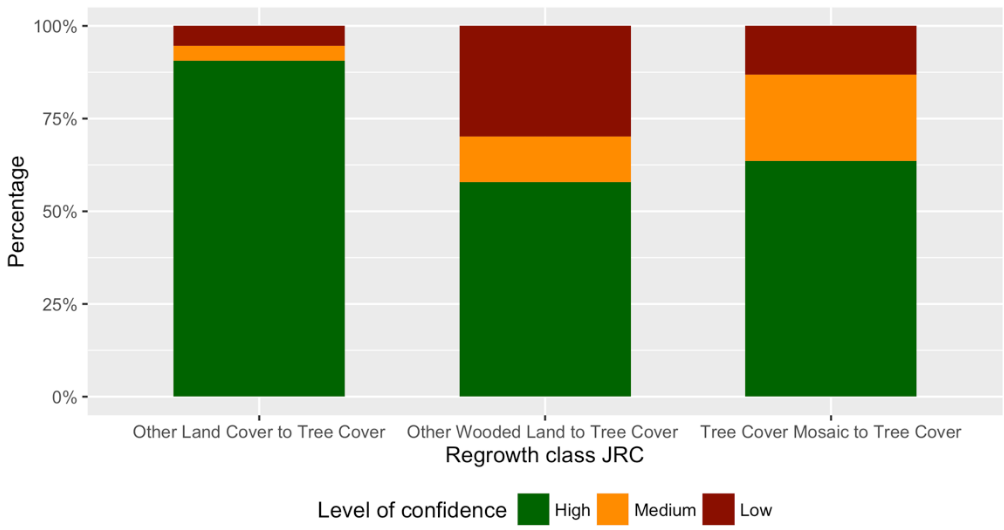


Figure 12 Level of confidence for the occurrence of regrowth in the JRC polygons.

Type of regrowth

Following was the assessment of the forest regrowth type that is present in the polygons. Three classes were distinguished: natural, plantation, and a mix of these two within the polygons (Figure 13). The ‘tree mosaic to tree cover’ shows the highest amount of natural and mixed forest. ‘Other land cover to tree cover’ has the largest percentage of polygons that show plantation regrowth. In the ‘other wooded land to tree cover’ class shows a fair share from all three classes. Overall for all three change types, 16.7 percent was assigned to the ‘natural’ class during the visual analysis. Moreover, 54.3 percent was recognised as plantation forest in the study area. The remaining 29 percent was labelled as mixed forest, containing any ratio of natural and plantation forest within a polygon. It must be noted that the relatively high proportion of mixed forest is partly due to the labelling of any combination of natural and plantation as ‘mixed’. This may be 90 percent natural, and 10 percent plantation forest, or vice versa.

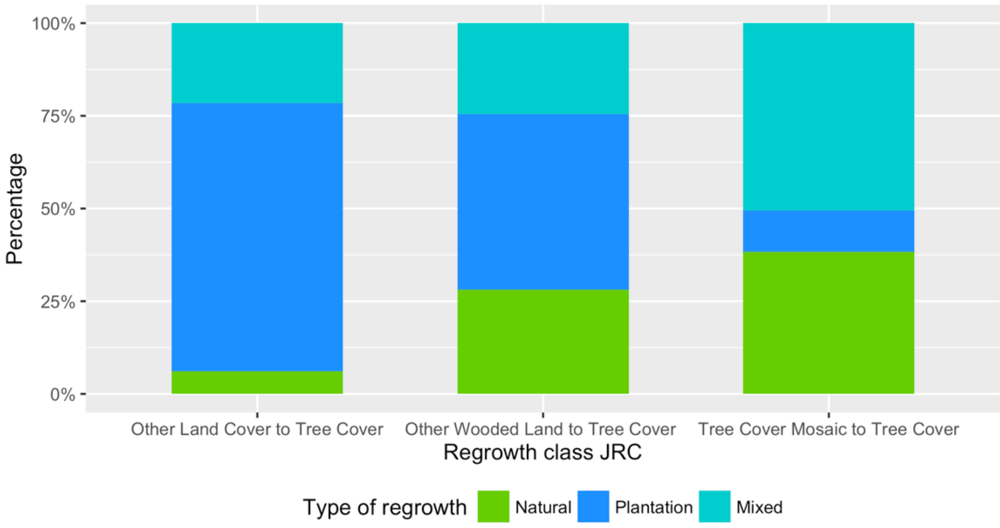


Figure 13 Type of regrowth occurring within each JRC forest regrowth class.

Confidence for the type of regrowth

Lastly, the confidence for assigning a type of regrowth to a polygon was examined (Figure 14). The results show that the confidence levels for regrowth classes do not differ substantially. Only the 'tree cover mosaic to tree cover' class has slightly more cases with a medium level of confidence for determining what type of forest is occurring in the polygon. Only 2 percent of the total 442 polygons was given a low confidence label for recognising the forest type. Moreover, 6.8 percent was recognised with medium confidence, and 91.2 percent with high confidence.

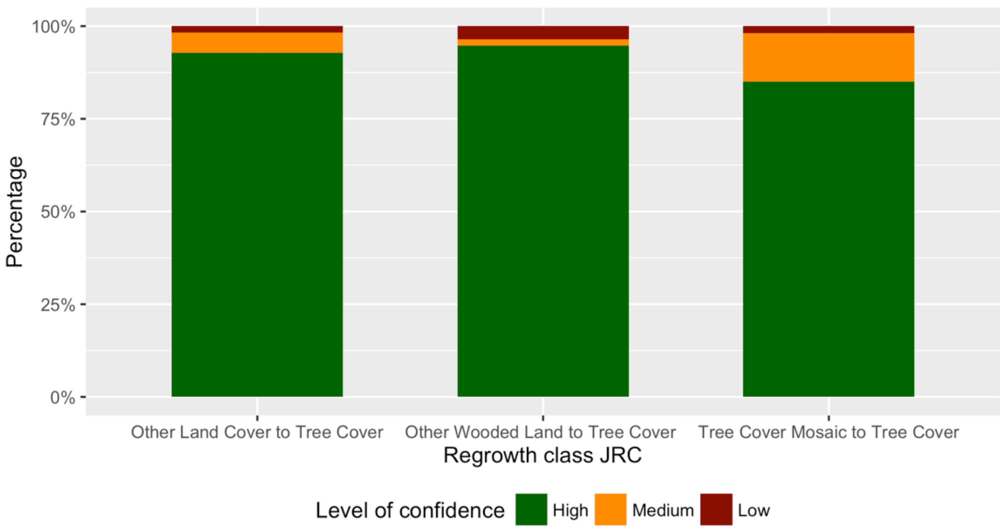


Figure 14 Level of confidence for the type of regrowth in each class for the JRC polygons.

3.3.3 Validation FAO dataset using visual analysis

Similarly as for the JRC dataset, the regrowth of the FAO dataset was validated using high resolution imagery. The occurrence of regrowth, the confidence of the occurrence of regrowth, the type of regrowth, and the confidence level of the type of regrowth were validated. A detailed overview of the outcomes from the FAO visual analysis can be found in Appendix G.

Regrowth

Overall, the occurrence of regrowth is confirmed in 13.6 percent of of cases. The ‘other land use to forest’ change class shows no accurately labelled polygons whereas the ‘other wooded land to forest’ class shows three correctly classified polygons (27.3 %) (Figure 15).

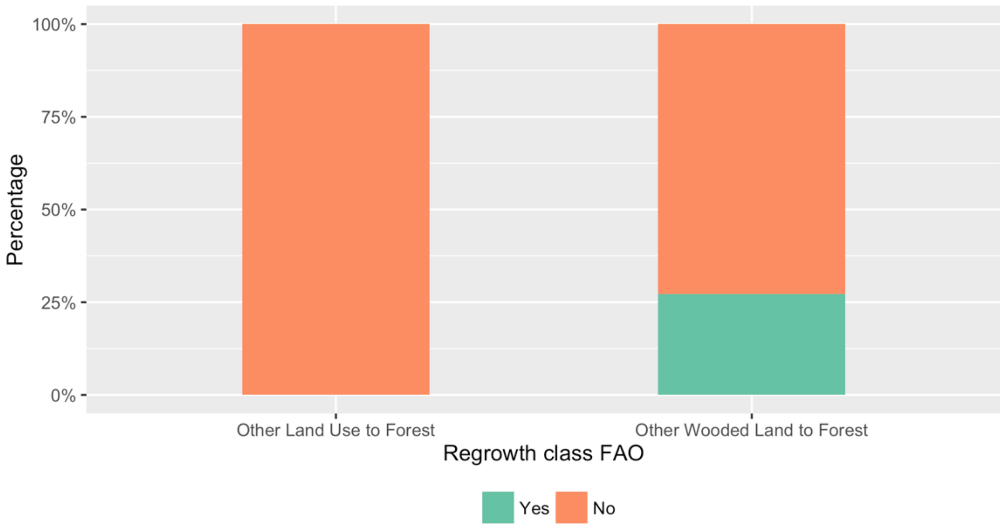


Figure 15 Validation of the FAO attribute, showing if there is indeed regrowth in the polygons, grouped by FAO forest regrowth class.

Confidence regrowth

The confidence for the occurrence of regrowth was also assessed for the FAO, and shows an overall low confidence. In 63.6 percent of the cases, a low confidence label was given to the occurrence of regrowth. Moreover, 4.5 percent received a medium level of confidence, and and 31.8 percent was allocated with high confidence. The two land use changes show approximately similar levels of confidence for the occurrence of regrowth (Figure 16).

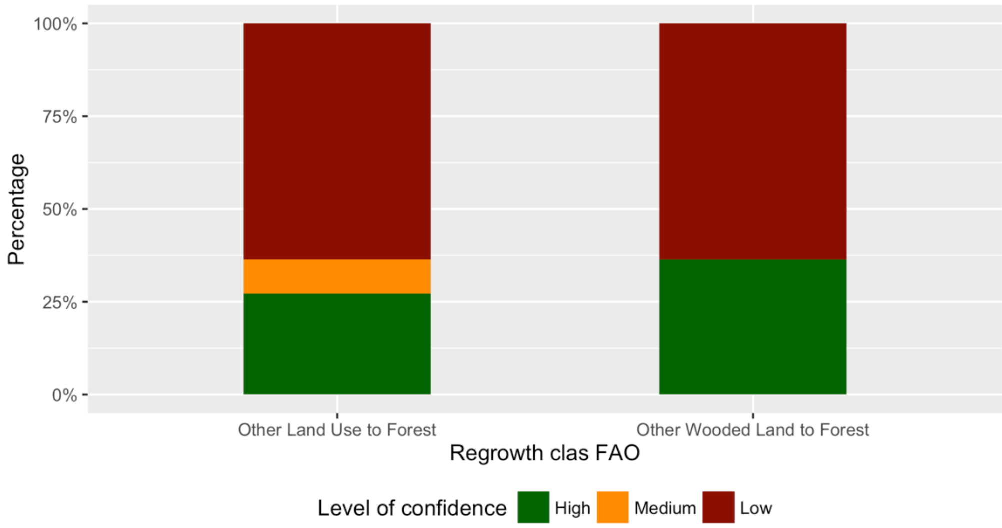


Figure 16 Level of confidence for the occurrence of regrowth in the FAO polygons.

Type of regrowth

The FAO validation dataset shows that 45.5 percent of the polygons is covered by natural forest. Moreover, 22.7 percent is covered by plantation forest and 31.8 percent contains a mix of the two forest types. The fraction of natural forest is the same for both change types, and also the plantation and mixed classes show very similar proportions (Figure 17).

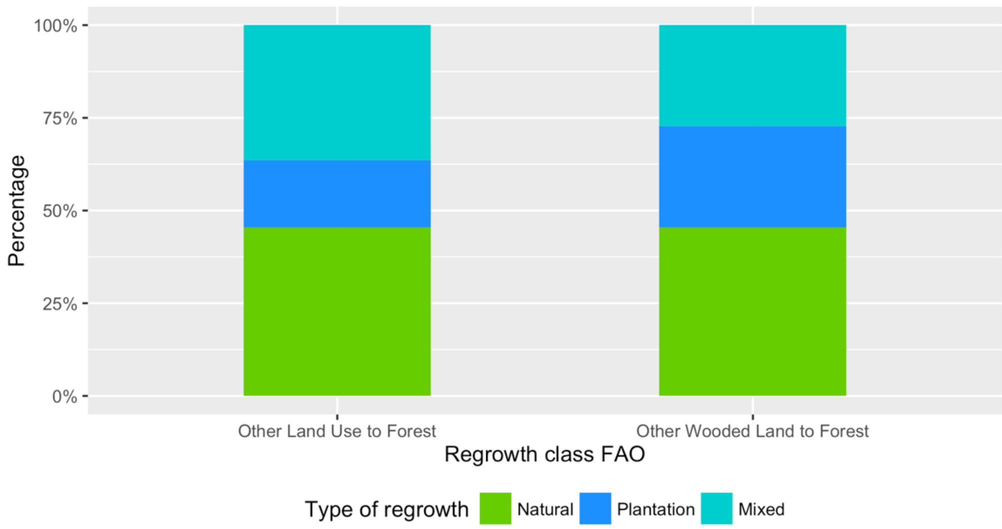


Figure 17 Type of regrowth occurring within each FAO forest regrowth class.

Confidence type of regrowth

Lastly, the confidence level for the type of regrowth was examined. Overall, 72.7 percent of the polygons was given a forest type label with high confidence. Moreover, 22.7 percent was labelled with medium confidence, and 4.5 percent with low confidence. Also for this attribute of the visual analysis, the differences between the groups is not substantial (Figure 18).

Figure 18 Level of confidence for the type of regrowth in each class for FAO polygons.

3.4 Forest regrowth area calculation in the selected sampling site

This chapter discusses the forest regrowth area calculation of the selected sampling site for the datasets and the time series approach. The FAO dataset did not have any change to forest land use. This chapter therefore discusses the area calculation of the JRC, Hansen and time series analysis within the selected sampling site.

The regrowth areas of the JRC and Hansen datasets were already calculated for the entire study area, and therefore the area calculation was done accordingly, but now targeted at only the selected sampling area. JRC shows the lowest amount of regrowth within the sampling site, followed by Hansen. The time series approach shows the highest amount of regrowth (Table 11). The area calculation outcome from Table 11 is visualised on a map in Figure 19.

Table 11 Regrowth area calculation for datasets.

Dataset	JRC	Hansen	Time Series	FAO
Total regrowth (km^2)	0.7	1.3	2.0	0.0

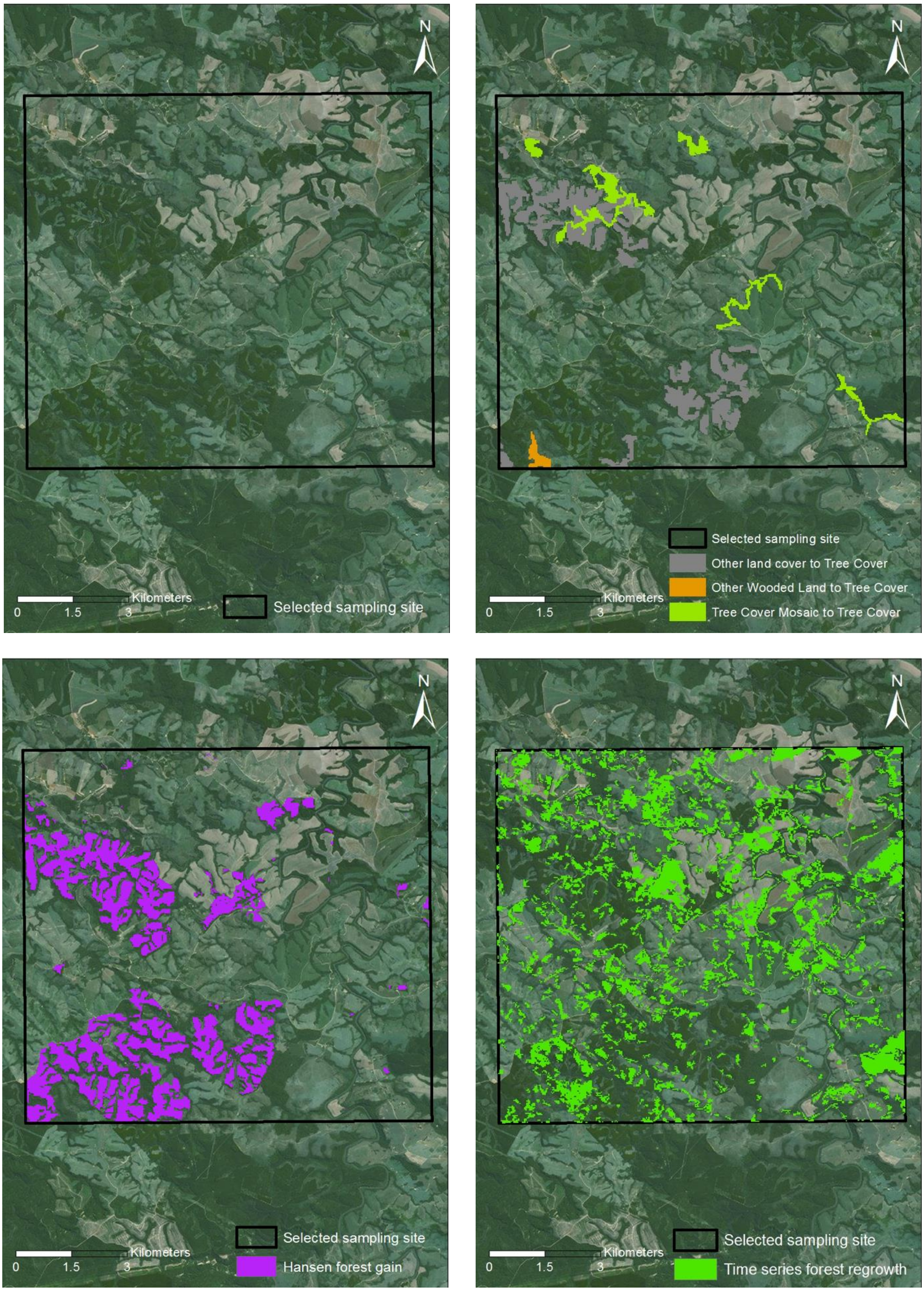


Figure 19 Forest regrowth within selected sampling site for the datasets. Upper left: selected sampling tile for dataset comparison. Upper right: JRC regrowth (2000 – 2010). Lower left: Hansen forest gain (2000 – 2012). Lower right: time series approach showing forest regrowth (2000 – 2010).

The time series approach also derives the year of regrowth in the sampling tile. This shows when the canopy cover is closed again (after the initial disturbance). Here we see that there are no clear patterns of forest regrowth. The regrowth is also quite scattered around the tile, with only few larger tracts of land that show regrowth in one location. These areas are mostly plantation forests that are planted in the same year. The characteristics of the dataset for monitoring forest regrowth are discussion in chapter 4.5.

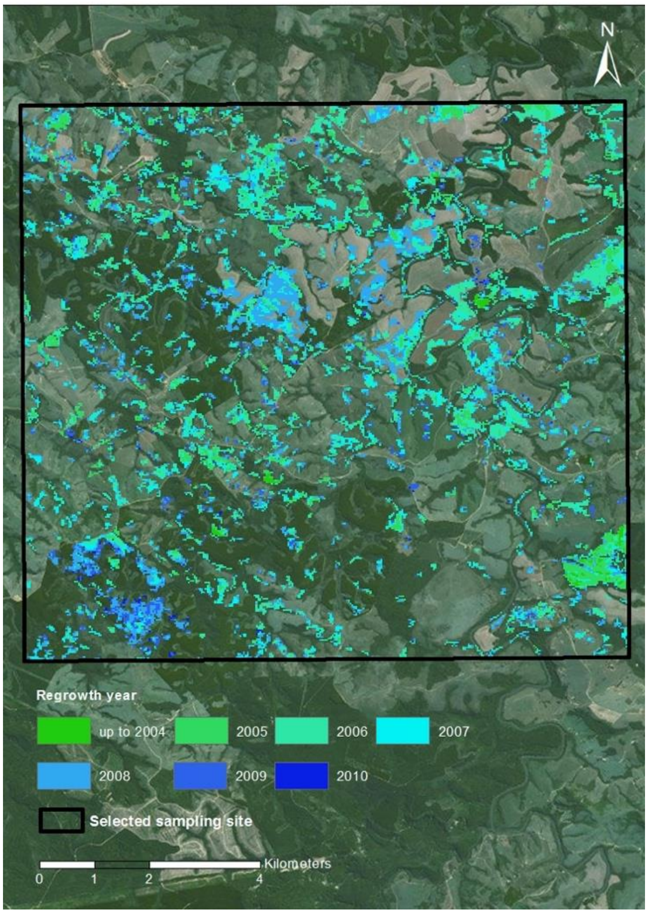


Figure 20 Time series forest regrowth with years.

3.5 Inter-comparison datasets for selected sampling site

With the calculated areas for the datasets a comparison in overlap shows how much agreement there is for identifying forest regrowth. A comparison of agreement for (any combination of) two datasets shows an overlap of 0.77 km^2. The overlapping area for regrowth of all three datasets is only 0.036 km^2 (Figure 21).

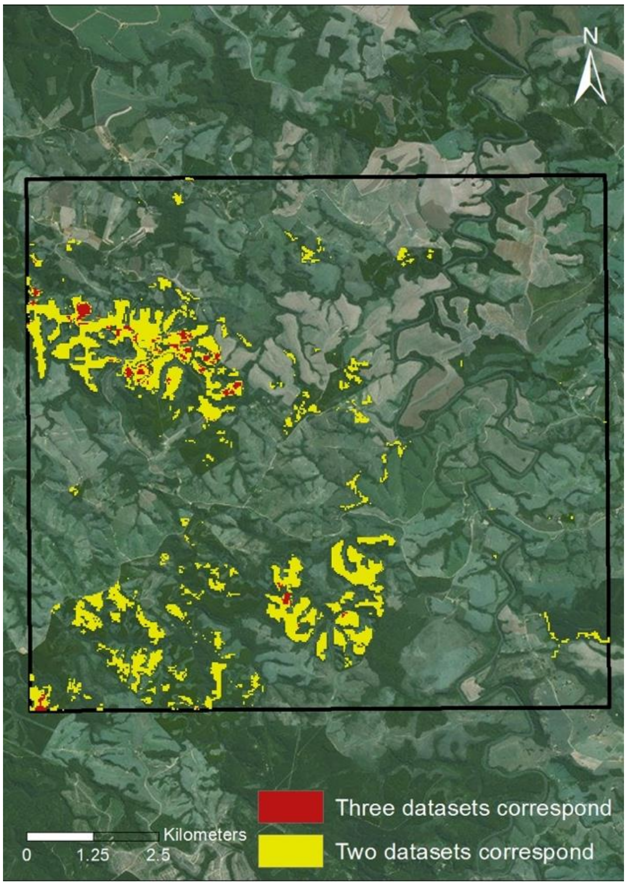


Figure 21 Agreement of two datasets compared to agreement of all three datasets.

There is a low agreement for all three datasets, when compared to the total area of regrowth according to the datasets. To find the main source of discrepancy in agreement, we compared pairs of datasets and their overlap. Paired comparisons show how much the dataset correspond (Table 12; Figure 22). This comparison reveals a rather large overlap between the JRC and Hansen datasets, and a small overlap of the time series approach with both the JRC and Hansen datasets. An explanation for this large difference can be found in the discussion (Chapter 4.5).

Table 12 Paired comparison area calculation.

Dataset pair	Area (km^2)
JRC - Hansen	5.2
Hansen – Time series	2.1
JRC – Time series	1.0

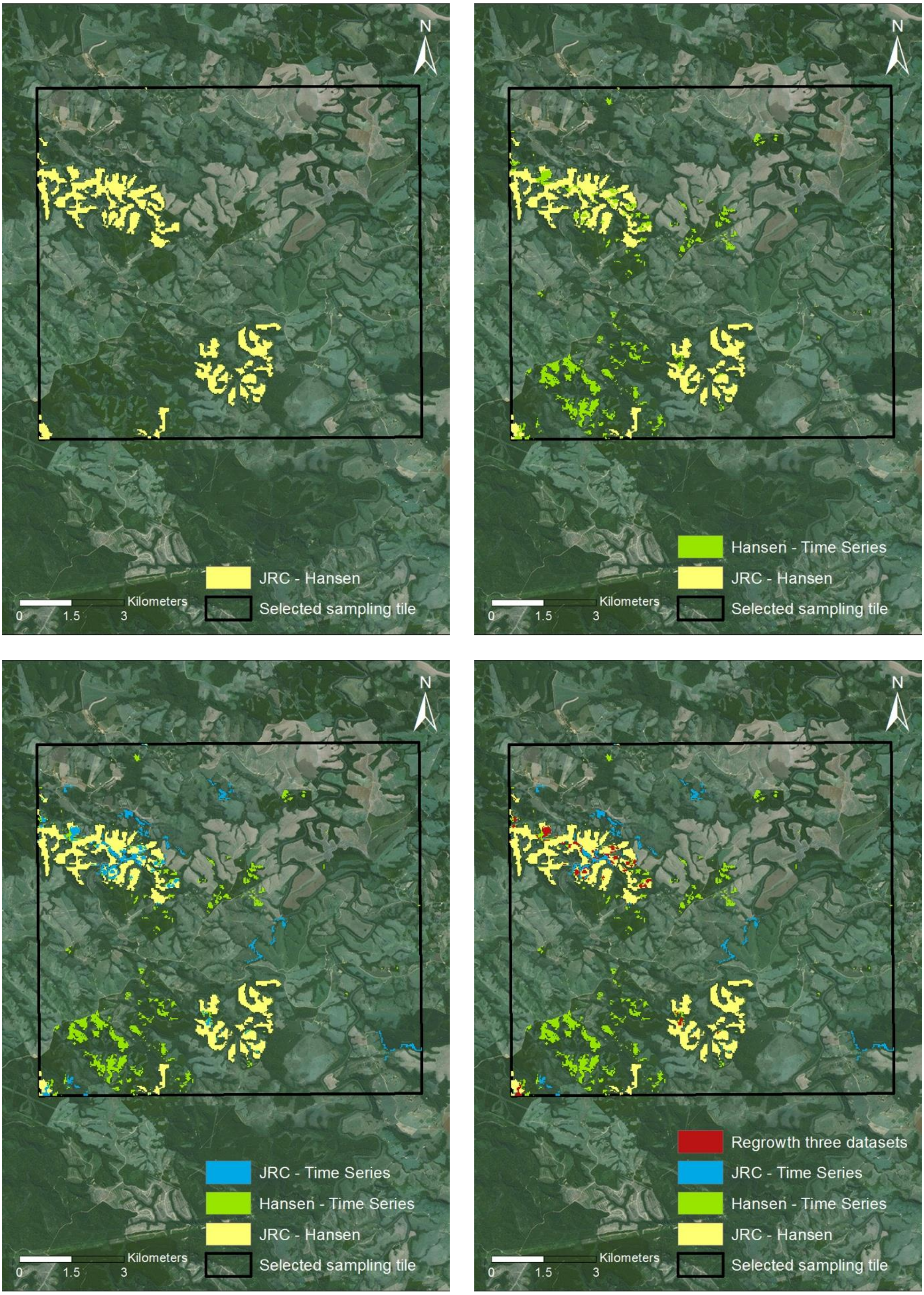


Figure 22 Overlap between different datasets within sampling tile. Upper left: overlap between JRC and Hansen. Upper right: added overlap between Hansen and time series approach. Lower left: added overlap between JRC and time series approach. Lower right: Agreement of regrowth for all three datasets.

3.6 Validation datasets for selected sampling site

The validation of the three datasets in the selected sampling site were validated for their accuracy of mapping forest regrowth. The visual analysis also recorded the type of forest that is detected by each dataset or monitoring method (Table 13).

The selection for the sampling site (Chapter 2.2.5.1) was based on certain attributes from the JRC dataset, such as the accurate classification of regrowth per sampling site. The JRC dataset within the sampling site shows a 100 percent accuracy for the occurrence of regrowth. The visual analysis for the JRC dataset reveals that the majority of assigned regrowth labels are of the type plantation forest (80 %), followed by natural forest (16 %) and mixed forest (4 %).

The Hansen dataset shows a classification accuracy of 86 percent, with the vast majority of the regrowth being labelled as plantation forest (94 %). This is in correspondence with the overall regrowth visualisation for the sampling site (Figure 19).

The time series method has the lowest accuracy (64 %), which mostly detects natural regrowth (76 %) and to a lesser extent plantation forest (24 %). The validation of the Hansen dataset and time series analysis were pixel based, and therefore show no mixed forest.

Table 13 Accuracy assessment datasets.

Dataset	JRC	Hansen	Time series
Occurrence regrowth accuracy (%)	100	86	64
Type of regrowth (%)			
Natural	16	6	76
Plantation	80	94	24
Mixed	4	-	-

4 Discussion

4.1 FAO land use compared to land cover dataset

This chapter discusses the characteristics of the datasets that were used in this thesis, and the factors that influence the outcome of the area estimates. Firstly, each dataset has its own definition of forest regrowth. There is a clear distinction between the JRC and FAO datasets, since the former is observing land cover, and the latter land use. Although they both use image segmentation and classification in an automatic procedure, they have their own definition of forest regrowth: land cover refers to the biophysical attributes of the earth's surface, whereas FAO involves the human dimension, and the purpose of the land (Lambin et al. 2001). Similarly, where land cover can be objectively inferred from remote sensing imagery, land use characterisation is in need of local, expert knowledge. The need for human interpretation and potential subjective analysis may influence the way that polygons receive a land use label.

The FAO provides an additional explanatory note regarding forest land use (FAO 2000):

"Forests are determined both by the presence of trees and the absence of other predominant land uses. The trees should be able to reach a minimum height of 5 meters in situ. Areas under reforestation which have yet to reach a crown density of 10 percent or tree height of 5 m are included, as are temporarily unstocked areas, resulting from human intervention or natural causes, that are expected to regenerate."

Furthermore, a note regarding forest plantations is included:

"The term specifically includes:…plantations primarily used for forestry purposes, including rubberwood plantations and cork oak stands".

When considering the definition of the FAO, which in particular includes natural forest that is expected to regenerate as well as forest plantations, the change to forest is low compared to the other datasets. The area estimates are in strong contrast with the other dataset estimates, and also the overlap is the lowest for the paired comparison. The classification for assigning a forest land use class appears not to be in agreement with the reality.

Particularly the outcome of the FAO dataset is noticeable for its substantially lower outcome compared to the other datasets. This section aims to identify the explanations of these substantial differences. A number of possible explanations may be justifying this. First, the FAO dataset is the only one in this research that looked at land use instead of land cover. Although changes in canopy cover may change a lot by the year, land use does not necessarily change rapidly. Forest plantations can remain on the same piece of land for decades without changing in terms of land use. The forest cover of short term plantations may increase and decrease frequently through planting, thinning and harvesting. Thus, land cover can show a change from a closed canopy cover to land temporarily without tree cover, and still be called forest.

Second, the translation from land cover to land use starts with a conversion from land cover classes to preliminary land use labels. However, an accurate quantification of the true class changes in land use is complicated. For this conversion process not only the vegetation cover has to be known, but also how the land will respond in the future in an ecological context, for example through reforestation and deforestation processes (Kurz 2010). The assignment of land use labels of the FAO requires expert human interpretation to accurately categorise land use. For this study no expert field knowledge was available to validate the FAO dataset on a land use level.

For natural forest a change from ‘other land use’ or ‘other wooded land’ may also not be quickly assigned as a land use change class if little expert knowledge is available for a certain location. The time frame of only 5 years may not be sufficient to grasp the conversion process of future land use processes. This is particularly imperative because the land use is based on the land cover. Therefore, first a change has to be detected with the automatic procedure (Appendix B) before visual checks are conducted for the conversion of land cover to land use.

4.2 Choice for land cover and land use change classes

For the JRC dataset three types of change were considered as regrowth in the analysis (Table 14). However, there are other classes that potentially may contain forest regrowth, which are: ‘burnt’, ‘water’, ‘cloud and shadow’, ‘no data’ and ‘unclassified’ (Appendix D). In particular, the ‘cloud and shadow’ and ‘no data’ classes could contain changes that were not considered in this research. Therefore, regrowth estimates may be lower than in reality. Likewise, FAO has a ‘no data’ class which was not used in this analysis.

To check these classes for possible regrowth, the change from ‘burnt’, ‘water’, ‘cloud and shadow’, ‘no data’ and ‘unclassified’ classes to forest were assessed. For the JRC dataset, only a change from ‘water’ to ‘other land cover’ was found, covering approximately 11 km^2. However, this does not depict a change to forest cover, as used in this study. Moreover, a change from land cover to any of the previously described classes was checked. Only a change to the ‘cloud and shadow’ and ‘water’ classes was found. The ‘cloud and shadow’ class shows a total change of of less than 1 km^2 for any of the used land cover classes (‘tree cover’, ‘tree cover mosaic’, ‘other wooded land’ and ‘other land cover’). Moreover, a change from any of the used land cover classes to ‘water’ shows a total area of approximately 18 km^2. The change from the ‘water’ class to the land cover classes and vice versa can be balanced out, showing a total change of 7 km^2 to the ‘water’ class. The FAO dataset does no show a change from ‘no data’ to a land use class, or vice versa.

Table 14 Dataset timeframes and description of regrowth classes used for comparison.

Dataset	Timeframe	Regrowth classes
JRC	2000 – 2010	Other land cover to tree cover Other wooded land to tree cover Tree cover mosaic to tree cover
FAO	2000 – 2005	Other land use to forest Other wooded land to forest
Hansen	2000 - 2012	Binary, either 1 (gain) or 0 (no gain)

Moreover, the change types that were used only considered the change to ‘tree cover’ and ‘forest’ for JRC and FAO, respectively. It can be argued that any change from JRC class ‘other land cover’ (or ‘other land use’ for FAO) towards ‘other wooded land’ or ‘tree cover mosaic’ is regrowth as well. This may substantially increase the estimates for forest regrowth. In this thesis, the change towards a forest with a closed canopy was analysed, consisting of trees (instead of scrubs as would be the case for the ‘other wooded land’ class). Hence, a change to a forest cover of 70 percent or more was considered regrowth, and not the regrowth from ‘other wooded land’ (< 30 percent canopy cover) to ‘tree cover mosaic’ (between 30 and 70 percent canopy cover).

In conclusion, taking all regrowth types into consideration (any increasing forest cover change) from the ‘other land cover’ class would result in three additional classes to use in the analysis. This potentially increases the estimated regrowth area of JRC substantially. Similarly, the FAO dataset would gain one additional change type, from ‘other land use’ to ‘other wooded land’.

4.3 Validation dataset

The validation of the regrowth areas was done with high resolution Google Earth imagery, and Landsat was used if this was not available for a certain area. The results of the validation depend on the quality of these images. The temporal consistency is also important to use imagery close to the original dataset timeframe (i.e. 2000, 2005 or 2010). The validation of the JRC dataset was mostly done with high resolution Google Earth imagery. Fortunately, for the year 2010, Google Earth could provide all the necessary imagery for the validation. For the year 2000, only about 26 percent of the imagery was provided by Google Earth – the remainder was validated using Landsat data. This lower resolution imagery makes it more difficult to determine if there is a forest present in the year 2000, and to estimate the canopy cover at that moment. This introduces several other possible errors for the visual analysis, such as a lower confidence level. The sources of error in the Google Earth / Landsat imagery were documented. Approximately 71 percent of the imagery was without major errors. About 12 percent was influenced by a low resolution, 7 percent was obstructed by clouds, and four percent by a combination of the two. The remaining 6 percent suffered from a low availability of imagery or image colouring combined with low resolution imagery. Overall, the validation for the year 2000 may be less accurate.

The visual analysis was not compared with a second validation dataset created by another observer. This may introduce a subjective interpretation that can influence the outcome of the visual analysis. One possible solution for this issue is to allow another person to perform a sample (e.g. 10 %) of the visual analysis, in order to compare the outcomes. When the outcomes match, it gives more certainty that the outcome of the visual analysis is not largely influenced by subjective interpretation. The high levels of confidence (Figure 12, Figure 14) suggest that there is little need for an additional validation. The lower confidence levels of the FAO dataset are the result of poor quality Google Earth imagery and temporal inconsistency.

The validation of the regrowth only provides a commission error i.e. falsely classified regrowth areas. We do not know how much regrowth has been omitted by the datasets. To obtain the omission error, the entire study area (or sampling site) should have been subject to a validation with high resolution imagery. With this information it is possible to calculate for each dataset how much regrowth is omitted. This is important information to obtain a better understanding of each dataset’s capability to approximate the true area of regrowth, and determine how much of it is not detected.

4.4 Changes in canopy cover

JRC

Regarding canopy cover for the ‘tree cover’ class, JRC states that (Appendix B):

“70% or more of a mapping unit is covered by a continuous layer of trees”

The recorded canopy cover percentages can determine if the definition of each class matches the values found during the visual analysis. These values are an average value for all polygons within a class. The mean canopy cover for each class that was found during the visual analysis matches the definition for the year 2010 – all averages are higher than 70 percent (Table 15). The ‘other land cover to tree cover’ and ‘tree cover mosaic to tree cover’ also have a correct mean canopy cover for the year 2000. The ‘other wooded land to tree cover’ class has a mean canopy cover in 2000 that is too low (43.0 %) to be in assigned to this class. However, this layer requires a layer of scrubs, tree regrowth or small woody vegetation with a maximum height of 5 meters (Appendix B). This is often not clearly visible with only high resolution imagery. The ‘other wooded land to tree cover’ change class also shows the highest standard deviation for the year 2000.

Table 15 Canopy cover change observed during the visual analysis for the JRC dataset, compared to the required canopy cover according to the JRC definition.

Class	Required canopy cover 2000 (%)	Canopy cover year 2000 (mean and st. dev., in%)	Required canopy cover 2010 (%)	Canopy cover year 2010 (mean and st. dev., in%)
Other land cover to tree cover	< 30	15.0 ± 18.7	≥ 70	85.1 ± 20.6
Other wooded land to tree cover	≥ 70*	43.0 ± 31.3	≥ 70	85.3 ± 19.2
Tree cover mosaic to tree cover	30 - 70	45.9 ± 24.4	≥ 70	82.0 ± 17.9

* layer of vegetation is < 5 meter (Appendix B).

FAO

The definitions for the FAO dataset (Appendix B) show a much more deviating canopy cover for the change from 2000 to 2005. The canopy cover requirements for the ‘other land use to forest’ and ‘other wooded land to forest’ classes are less than 5 percent and 5 - 10 percent respectively (Table 16). The changes in canopy cover for both classes show little correspondence with the required canopy cover for assigning these land use labels. This corresponds with the first section of this discussion (Chapter 4.1) where reasons for the large differences in regrowth area are given. The use and validation of a land use dataset is difficult without the expert knowledge about processes regarding land use.

Table 16 Canopy cover change observed during the visual analysis for the FAO dataset, compared to the required canopy cover according to the FAO definition.

Class	Required canopy cover 2000	Canopy cover year 2000 (mean and st. dev., in%)	Required canopy cover 2005 (%)	Canopy cover year 2005 (mean and st. dev., in %)
Other land use to forest	< 5	60 ± 27.9	≥ 10	60 ± 30
Other wooded land to forest	5 - 10	22.7 ± 30.4	≥ 10	50 ± 41.5

Hansen

This section discusses the characteristics of the Hansen dataset including the pros and cons for monitoring regrowth with this approach. The Hansen dataset has shown the highest amount of regrowth in the study area using a pixel based approach. The results of the pixel based approach show either a forest gain or no forest gain. The map gives the result of a forest change for 2000 – 2012, and is reported as a total twelve-year total. A major downside of this approach is that the forest gain was not recorded annually (whereas the forest loss map does show an annual change). Thus, this dataset cannot provide annual updates on forest gain, neither can annual forest trends be detected.

The Hansen dataset relates the classification of forest gain to a percentage canopy cover from below a 50 percent threshold to above the 50 percent threshold (Hansen et al. 2013b). The definition used by Hansen results in detection of non forest or open canopy woodlands to a closed canopy. The results of this study show that natural forests are hardly ever detected if there is already a canopy cover is present. In such cases, the Hansen method does not detect a change from below the 50 percent canopy cover threshold to above the 50 percent canopy cover threshold. The selection of the sampling tile was partly based on the type of forest present in the JRC / FAO tile. Therefore, both natural and plantation forest are sufficiently present in selected sampling site. The time series method and JRC method do detect these changes in natural forests.

The Hansen dataset defines forest cover as trees with a minimum height of 5 meters. This may put countries with large areas of scrubland (such as the Caatinga region in east Brazil) and tree regrowth at a disadvantage. The JRC dataset does make this differentiation with the 'other wooded land' class. Forest regrowth is a gradual dynamic process that often does not meet the 5-meter minimum height requirement in its initial stages, which may result in omission of forest regeneration.

4.5 Time series regrowth trajectories

The calculations of the time series analysis within the selected sampling site (Table 11) are based on certain assumptions (Table 2). The time series method for monitoring regrowth looks specifically at post-disturbance regrowth. The implications for the results of this method are discussed in this chapter.

What is noticeable is the large amount of forest plantation land that is not detected by the time series method. This is clearly depicted in Figure 23, where almost no reforestation of plantation land is detected by the time series approach, whereas the JRC and Hansen dataset do detect this type of forest.

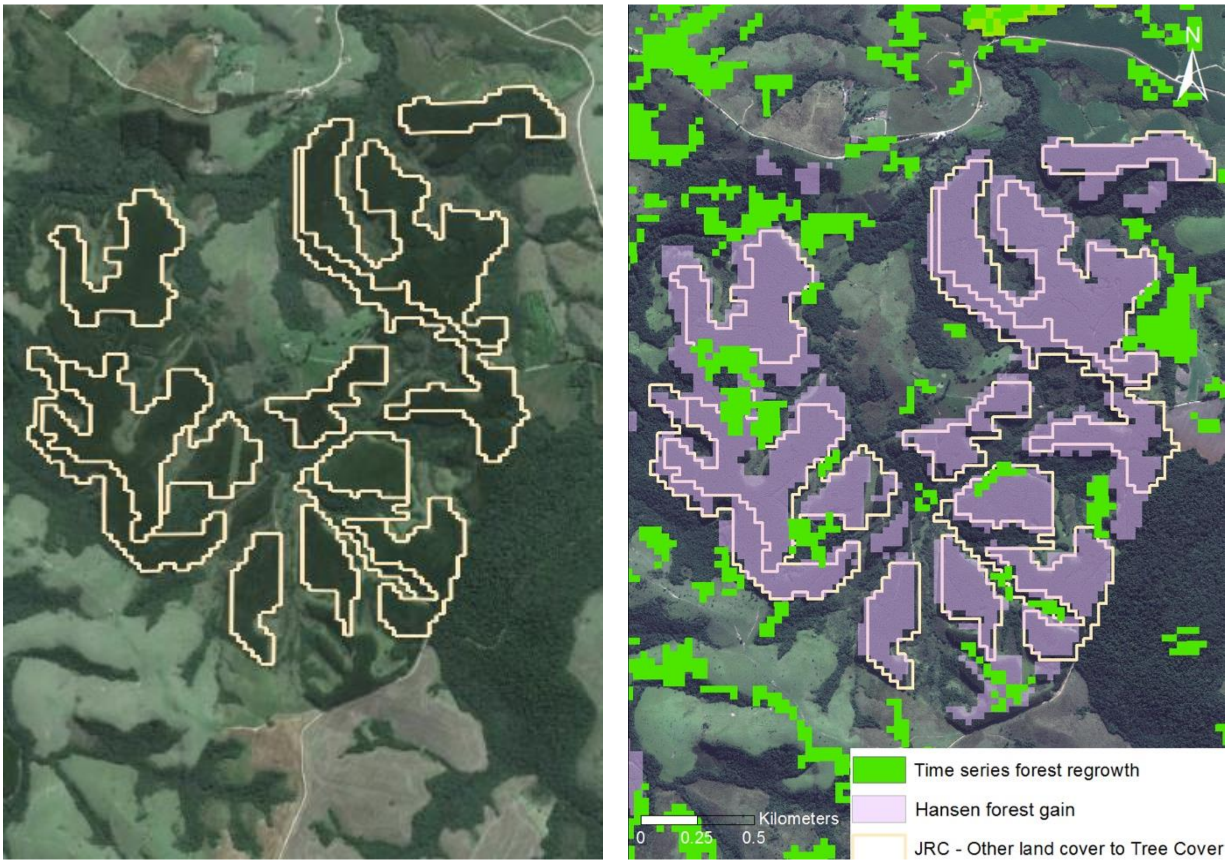


Figure 23 Detection of regrowth by JRC, Hansen and the time series method. Left image shows land cover around 2000 with the JRC regrowth areas depicted in orange. The right image shows the situation around 2010, where reforestation has taken place and is clearly detected by the JRC and Hansen dataset. The time series approach does not label these areas as forest regrowth.

The monitoring period for regrowth starts in January 2000. The time series method requires a disturbance of the forest canopy before a regrowth flag can be assigned further on in the time series. This type of canopy cover change is conceptually depicted by the red line in Figure 24. During the visual analysis a validation image close to the year 2000 is used to compare it to an image close to the year 2010, in order to validate if the method accurately monitored forest regrowth. A cloud-free validation Landsat image was selected from September 1999. This image shows that there are large tracts of land with plantation forest that was already harvested before September 1999 (Figure 23 – left image). However, the monitoring period of the time series analysis started in January 2000 (Figure 24 – yellow dotted line). The areas that did not receive a disturbance after January 2000 therefore cannot be assigned a regrowth label. For this reason, the time series method leaves out large tracts of land that would otherwise be assigned a regrowth label.

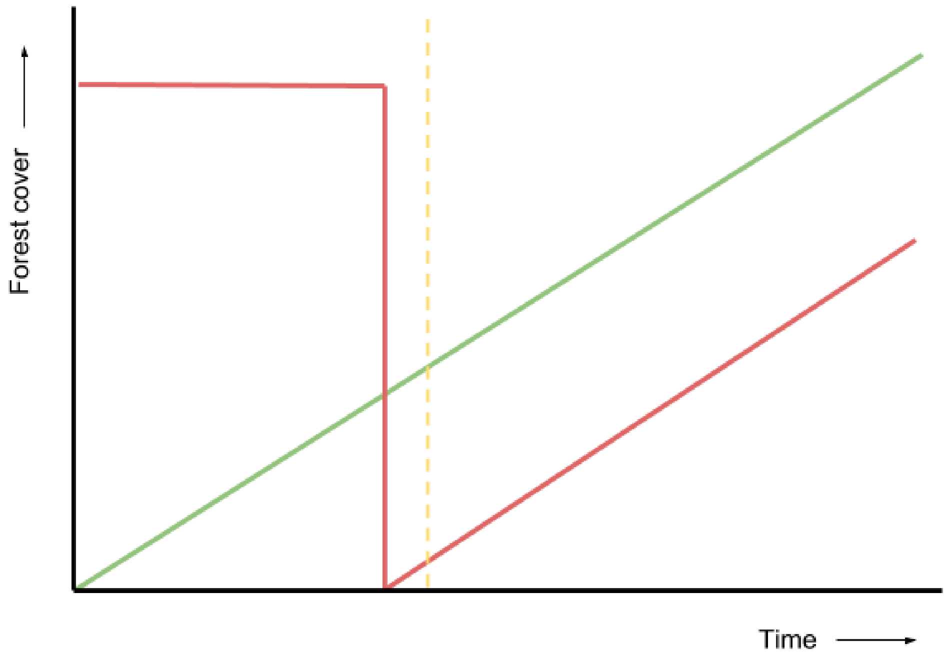


Figure 24 Pathways of forest regrowth. The green line depicts typical forest regrowth as analysed in this study – moving from a non-forest or low canopy cover to a more closed canopy. The red line depicts the type of regrowth that can be monitored with the time series analysis. The yellow dotted line gives a conceptual idea as the start of the monitoring period, which was started after a plantation harvest. This was the case for large tracts of land in the selected sampling site. Regrowth depicted by the green line will not be detected with the time series method used in this study.

A major benefit of the time series method are the regrowth dates that can be derived, which may be useful information for recognising patterns in regrowth and subsequently help to determine why regrowth occurs at certain locations. The accuracy of assigning the regrowth label can be validated in order to check the ability of the time series method to accurately derive dates. However, in this study the date of the recovery of the signal (i.e. regrowth) could not be accurately determined because of a lack of Google Earth imagery. The previously described limiting factor of Google Earth imagery seems applicable for this study as well. Helmer, Lefsky and Roberts (2009) describe that a main drawback of using Google Earth imagery is the non-optimal date of the imagery when using it. The lack of a temporal consistent availability of Google Earth imagery is indeed a limiting factor for accurately determining the regrowth date of forest land in the study area.

4.6 Study strengths and weaknesses

Strengths:

- To our knowledge, no or little research has been done focussing on this kind of dataset comparison. The study examined the discrepancies between datasets in terms of area, overlap between regrowth locations, definition and validated the accuracy of each dataset.
- The datasets were analysed for the type of regrowth that each dataset picks up. This gives important insights into the characteristics and methods for monitoring regrowth. It also helps in understanding the outcome of each dataset for policy implications and applied use by development mechanisms for improved carbon sequestration through afforestation and reforestation.
- The study defines the source of discrepancy between datasets by overlapping pairs of datasets. The outcome of this comparison is consequently linked to the forest definitions and methodology.
- The validation of the JRC and FAO datasets was not based on a sample, but all polygons showing regrowth were used to validate the accuracy of the datasets.

Weaknesses:

- The validation of the datasets only calculated the commission error and not the omission error, which would give a more complete understanding of accuracy for each dataset.
- Selection of JRC and FAO regrowth change types was only considered with a change to a forest cover, forest land use. This was not compared to a change with a more open canopy (e.g. change from ‘other land use’ to ‘other wooded land’).
- The visual analysis may be subjective, and was not validated with a second person carrying out a validation of the validation.
- This study could not accurately validate the regrowth years’ accuracy of the time series approach due to a lack of high resolution imagery.
- The differences among datasets in terms of timing and forest definition limit a good comparison.

4.7 Recommendations

This study and the cited literature of this thesis reveal some important issues for the analysis of regrowth, making use of the comparison between datasets and their characteristics. This section discussed the outcomes for recommendations, and may also provide new directions for future research.

- The validation in this research was done using only Google Earth imagery. This was not always sufficient for creating a proper validation dataset due to low availability of high resolution imagery and the lack of more in-depth knowledge and better information about the state of the forest. Examples of this are a better estimate of the canopy cover, the structure of the forest and the occurrence of regrowth. Google Earth is not always sufficient due to a lack of imagery, the quality of the imagery or the temporal inconsistency. With field measurements, more information may be provided, and disturbances and regrowth situations can be provided. Other attributes that can be controlled are the time of disturbance, and the intensity of the disturbance in a forest plot. A possible approach would be make use of an existing network, such as ForestPlots[4], which can be used to measure and monitor forest plots with different characteristics to test various methods and datasets for monitoring regrowth.

- The regrowth datasets cover a complex dynamic process of forest cover change. Although the JRC dataset does differentiate between types of forest cover, no information is available regarding the type of forest (natural or plantation forest). This is important information with regard to biodiversity and carbon sequestration, which are very different for these types of forests. For programmes such as the Clean Development Mechanism, focussing on afforestation and reforestation, this is vital information. This would be an interesting topic for future research. One example of this type of research was carried out by le Maire et al. (2014).

- The validation of the Hansen dataset and the time series approach was done using single pixels. It might be interesting to make a comparison between a validation approach using a sampling approach (as in this research) and an aggregation approach. With an aggregation approach clustered pixels would be grouped and consequently validated as a regrowth polygon.

- The regrowth classes that were chosen for the JRC dataset only considered growth towards a closed canopy forest (i.e. from ‘other wooded land to forest cover’). An interesting comparison can be made using other change classes that show regrowth, but do not result in a completely closed canopy (i.e. ‘other land use to other wooded land’). Specifically, an area comparison of regrowth with the other datasets may reveal interesting results.

[4] https://www.forestplots.net/

- The time series approach looks at post-disturbance regrowth. Therefore, the monitoring period was set to 1990 – 1999 and the monitoring period from 2000 – 2010. The visual analysis only looked at occurrence of regrowth in the latter period and not at the occurrence of disturbances in the former period. This would be an interesting approach for research, in order to analyse if there was indeed a disturbance, and when the regrowth signal on average returned.

- Harmonisation and standardisation of datasets in terms of timing and forest definitions would help to make a better assessment of forest regrowth.

5 Conclusions

This study focussed on the quantification of reforestation in south-east Brazil. It aimed to compare the regrowth area outcomes of the different datasets and methods, and to explain the differences with regard to dataset characteristics and forest definitions.

First, the area of regrowth for each dataset was calculated. The used datasets have different timeframes for monitoring regrowth, and therefore a yearly area of regrowth was calculated. The regrowth area calculations show that the Hansen dataset indicates the highest amount of annual regrowth with an area of 1304 km^2. The JRC dataset shows a regrowth area of 295 km^2 per year. The third dataset, from the FAO, detects land use change, as apposed to the other two datasets and determines the change to forest land to be 28 km^2.

The datasets were also compared for the amount of overlap that they show. The inter-comparison consisted of three comparisons: JRC – Hansen, FAO – Hansen and JRC – FAO. The comparison between the JRC and Hansen datasets shows the highest agreement, with 54.3 percent, when using JRC as a reference. The inter-comparison between the FAO and Hansen dataset shows an overlap of 20.3 percent, using the FAO polygons as a reference. The inter-comparison between the JRC and FAO datasets shows an overlap of 0.5 percent when the JRC polygons (n = 442) are used as a reference. When the FAO polygons (n = 22) are used as a reference the overlapping area of the datasets covers 11.5 percent.

The accuracy of each dataset for monitoring regrowth was validated using high resolution imagery. The JRC and FAO datasets show an overall accuracy of 65.4 and 13.6 percent respectively. The type of forest that is detected by the JRC dataset is mostly plantation forest (54.3 %), followed by mixed forest (29.0 %) and natural forest (16.7 %). The FAO mostly detects changes to a natural forest (45.5 %), followed by mixed forest (31.8 %) and plantation forest (22.7 %). The validation within the selected sampling site shows an accuracy for the Hansen dataset and time series method. The Hansen dataset has an accuracy of 86 percent, and mostly detects plantation forest (94 %) and to a lesser extent natural forest (6 %). The time series method has an accuracy of 64 percent, and detects mostly natural forest (76 %), and to a lesser extent plantation forest (24 %).

These accuracies derived from the visual analysis only show the commission error. This study did not determine the omission error, since a 100 percent validation of the study area or sampling site is needed for this. Therefore, it is not possible to determine to what degree each dataset omits the classification of regrowth in the study area, and conclude the true amount of regrowth. The varying timeframes of each dataset and definitions used pose difficulties for the accurate quantification of regrowth. The choice for using one dataset over the other may prove to be influential for policy and management initiatives. We conclude that there is a strong need for large-scale validation of these prominent datasets, in order to quantify the uncertainty that accompanies each dataset.

References

Adger, W. Neil. 1999. “Social Vulnerability to Climate Change and Extremes in Coastal Vietnam.” *World Development* 27 (2): 249–269.

Alexander, Sasha, Cara R. Nelson, James Aronson, David Lamb, An Cliquet, Kevin L. Erwin, C. Max Finlayson, et al. 2011. “Opportunities and Challenges for Ecological Restoration within REDD+.” *Restoration Ecology* 19 (6): 683–689. doi:10.1111/j.1526-100X.2011.00822.x.

Anderson, Ray G, Josep G Canadell, James T Randerson, Robert B Jackson, Bruce A Hungate, Dennis D Baldocchi, George A Ban-Weiss, et al. 2011. “Biophysical Considerations in Forestry for Climate Protection.” *Frontiers in Ecology and the Environment* 9 (3): 174–182. doi:10.1890/090179.

Aronson, James, and Sasha Alexander. 2013. “Ecosystem Restoration Is Now a Global Priority: Time to Roll up Our Sleeves.” *Restoration Ecology* 21 (3): 293–296. doi:10.1111/rec.12011.

Asner, G. P. 2001. “Cloud Cover in Landsat Observations of the Brazilian Amazon.” *International Journal of Remote Sensing* 22 (18): 3855–3862. doi:10.1080/01431160010006926.

Beuchle, René, Hugh Douglas Eva, Evaristo Eduardo de Miranda, Wilson Anderson Holler, Osvaldo Tadatomo Oshiro, Fréderic Achard, EMBRAPA Monitoramento por Satélite, and Av Soldado Passarinho. 2011. “Global Tropical Forest Cover Change Assessment with Medium Spatial Satellite Imagery Using a Systematic Sample Grid–data, Methods and First Results.” In *Embrapa Monitoramento Por Satélite-Artigo Em Anais de Congresso (ALICE)*.

Bongers, Frans, Robin Chazdon, Lourens Poorter, and M. Peña-Claros. 2015. “The Potential of Secondary Forests,” sciencemag.org, , no. vol. 348 nr. 6235(May): 642–643.

Bowler, Diana E., Lisette Buyung-Ali, Teri M. Knight, and Andrew S. Pullin. 2010. “Urban Greening to Cool Towns and Cities: A Systematic Review of the Empirical Evidence.” *Landscape and Urban Planning* 97 (3): 147–155.

Bradshaw, Corey JA, Navjot S. Sodhi, KELVIN S.-H. PEH, and Barry W. Brook. 2007. “Global Evidence That Deforestation Amplifies Flood Risk and Severity in the Developing World.” *Global Change Biology* 13 (11): 2379–2395.

Brancalion, Pedro H. S., Ricardo A. G. Viani, Miguel Calmon, Helena Carrascosa, and Ricardo R. Rodrigues. 2013. “How to Organize a Large-Scale Ecological Restoration Program? The Framework Developed by the Atlantic Forest Restoration Pact in Brazil.” *Journal of Sustainable Forestry* 32 (7): 728–744. doi:10.1080/10549811.2013.817339.

Brazilan Tree Industry. 2014. “Ibá.” Pöyry Consultoria em Gestão e Negócios Ltda.

Brienen, R. J. W., O. L. Phillips, T. R. Feldpausch, E. Gloor, T. R. Baker, J. Lloyd, G. Lopez-Gonzalez, et al. 2015. “Long-Term Decline of the Amazon Carbon Sink.” *Nature* 519 (7543): 344–348. doi:10.1038/nature14283.

Brooks, Evan B., R.H. Wynne, V.A. Thomas, C.E. Blinn, and J.W. Coulston. 2014. “On-the-Fly Massively Multitemporal Change Detection Using Statistical Quality Control Charts and Landsat Data.” *IEEE Transactions on Geoscience and Remote Sensing* 52 (6): 3316–3332. doi:10.1109/TGRS.2013.2272545.

Brooks, Thomas M., Russell A. Mittermeier, Cristina G. Mittermeier, Gustavo A. B. Da Fonseca, Anthony B. Rylands, William R. Konstant, Penny Flick, et al. 2002. “Habitat Loss and Extinction in the Hotspots of Biodiversity.” *Conservation Biology* 16 (4): 909–923. doi:10.1046/j.1523-1739.2002.00530.x.

Brown, Sandra, Charles A. S. Hall, Wilhelm Knabe, James Raich, Mark C. Trexler, and Paul Woomer. 1993. “Tropical Forests: Their Past, Present, and Potential Future Role in the Terrestrial Carbon Budget.” *Water, Air, and Soil Pollution* 70 (1–4): 71–94. doi:10.1007/BF01104989.

Brown, Sandra, and Ariel E. Lugo. 1990a. “Tropical Secondary Forests.” *Journal of Tropical Ecology* 6 (1): 1. doi:10.1017/S0266467400003989.

Brown, Sandra, and Ariel E. Lugo. 1990b. “Effects of Forest Clearing and Succession on the Carbon and Nitrogen Content of Soils in Puerto Rico and US Virgin Islands.” *Plant and Soil* 124 (1): 53–64. doi:10.1007/BF00010931.

Calle, Zoraida, Enrique Murgueitio, Julián Chará, Carlos Hernando Molina, Andrés Felipe Zuluaga, and Alicia Calle. 2013. “A Strategy for Scaling-Up Intensive Silvopastoral Systems in Colombia.” *Journal of Sustainable Forestry* 32 (7): 677–693. doi:10.1080/10549811.2013.817338.

Cardinale, Bradley J., J. Emmett Duffy, Andrew Gonzalez, David U. Hooper, Charles Perrings, Patrick Venail, Anita Narwani, et al. 2012. “Biodiversity Loss and Its Impact on Humanity.” *Nature* 486 (7401): 59–67. doi:10.1038/nature11148.

Carnus, Jean-Michel, John Parrotta, Eckehard Brockerhoff, Michel Arbez, Hervé Jactel, Antoine Kremer, David Lamb, Kevin O’Hara, and Bradley Walters. 2006. “Planted Forests and Biodiversity.” *Journal of Forestry* 104 (2): 65–77.

Carreiras, João M. B., Joshua Jones, Richard M. Lucas, and Cristina Gabriel. 2014. “Land Use and Land Cover Change Dynamics across the Brazilian Amazon: Insights from Extensive Time-Series Analysis of Remote Sensing Data.” Edited by Bruno Hérault. *PLoS ONE* 9 (8): e104144. doi:10.1371/journal.pone.0104144.

Chazdon, Robin. L. 2008. “Beyond Deforestation: Restoring Forests and Ecosystem Services on Degraded Lands.” *Science* 320 (5882): 1458–1460. doi:10.1126/science.1155365.

Chazdon, Robin L. 2013. “Making Tropical Succession and Landscape Reforestation Successful.” *Journal of Sustainable Forestry* 32 (7): 649–658. doi:10.1080/10549811.2013.817340.

Clark, Matthew L., T. Mitchell Aide, H. Ricardo Grau, and George Riner. 2010. “A Scalable Approach to Mapping Annual Land Cover at 250 M Using MODIS Time Series Data: A Case Study in the Dry Chaco Ecoregion of South America.” *Remote Sensing of Environment* 114 (11): 2816–2832. doi:10.1016/j.rse.2010.07.001.

Coppin, P., I. Jonckheere, K. Nackaerts, B. Muys, and E. Lambin. 2004. “Digital Change Detection Methods in Ecosystem Monitoring: A Review.” *International Journal of Remote Sensing* 25 (9): 1565–1596. doi:10.1080/0143116031000101675.

De Sy, V., M. Herold, F. Achard, R. Beuchle, J. G. P. W. Clevers, E. Lindquist, and L. Verchot. 2015. “Land Use Patterns and Related Carbon Losses Following Deforestation in South America.” *Environmental Research Letters* 10 (12): 124004. doi:10.1088/1748-9326/10/12/124004.

DeVries, B., and M. Herold. 2013. “The Science of Measuring, Reporting and Verification (MRV).” *Law, Tropical Forests and Carbon: The Case of REDD+*, 151–183.

DeVries, Ben, Mathieu Decuyper, Jan Verbesselt, Achim Zeileis, Martin Herold, and Shijo Joseph. 2015. “Tracking Disturbance-Regrowth Dynamics in Tropical Forests Using Structural Change Detection and Landsat Time Series.” *Remote Sensing of Environment* 169 (November): 320–334. doi:10.1016/j.rse.2015.08.020.

DeVries, Ben, Jan Verbesselt, Lammert Kooistra, and Martin Herold. 2015. “Robust Monitoring of Small-Scale Forest Disturbances in a Tropical Montane Forest Using Landsat Time Series.” *Remote Sensing of Environment* 161 (May): 107–121. doi:10.1016/j.rse.2015.02.012.

Dixon, R. K., A. M. Solomon, S. Brown, R. A. Houghton, M. C. Trexier, and J. Wisniewski. 1994. “Carbon Pools and Flux of Global Forest Ecosystems.” *Science* 263 (5144): 185–190. doi:10.1126/science.263.5144.185.

Doswald, N., R. Munroe, D. Roe, A. Giuliani, I. Castelli, J. Stephens, I. Möller, T. Spencer, B. Vira, and H. Reid. 2014. “Effectiveness of Ecosystem-Based Approaches for Adaptation: Review of the Evidence-Base.” *Climate and Development* 6 (2): 185–201. doi:10.1080/17565529.2013.867247.

Ellison, David, Martyn Futter, and Kevin Bishop. 2012. “On the Forest Cover–water Yield Debate: From Demand- to Supply-Side Thinking.” *Global Change Biology* 18 (3): 806–820. doi:10.1111/j.1365-2486.2011.02589.x.

Eva, Hugh, Silvia Carboni, Frédéric Achard, Nicolas Stach, Laurent Durieux, Jean-François Faure, and Danilo Mollicone. 2010. “Monitoring Forest Areas from Continental to Territorial Levels Using a Sample of Medium Spatial Resolution Satellite Imagery.” *ISPRS Journal of Photogrammetry and Remote Sensing* 65 (2): 191–197. doi:10.1016/j.isprsjprs.2009.10.008.

FAO. 2000. *FRA 2000 On Definitions of Forest and Forest Change*. Working Paper 33. Forest Resources Assessment Programme. Rome: FAO. ftp://ftp.fao.org/docrep/fao/006/ad665e/ad665e00.pdf.

FAO. 2001. *Global Ecological Zoning for the Global Forest Resources Assessment 2000*. Final Report Working Paper Nr. 56. Forest Resources Assessment Programme. Rome. ftp://ftp.fao.org/docrep/fao/006/ad652e/ad652e00.pdf.

FAO. 2006. "Global Forest Resources Assessment 2005." Food and Agricultural Organization of the United Nations, Rome.

FAO. 2009. *The FRA 2010 Remote Sensing Survey. An Outline of Objectives, Data, Methods Nad Approach*. Forest Resources Assessment Programme. Working Paper 155. Rome. Italy. http://www.fao.org/docrep/012/k7023e/k7023e00.pdf.

FAO. 2010a. *Global Forest Resources Assessment 2010*. Main report 163. FAO Forestry Paper. Rome.

FAO. 2010b. "Global Forest Resources Assessment 2010," FAO Forestry Paper, .

FAO and JRC. 2012. *Global Forest Land-Use Change, 1990-2005*. FAO Forestry Paper, No. 169. Rome: Food and Agriculture Organization of the United Nations.

FAO, JRC, SDSU and UCL. 2009. *The 2010 Global Forest Resources Assessment Remote Sensing Survey: An Outline of the Objectives, Data, Methods and Approach.* Forest Resources Assessment Working Paper 155. Published by FAO with FRA RSS partners, Rome.

Fearnside, Philip M. 1999. "Plantation Forestry in Brazil: The Potential Impacts of Climatic Change." *Biomass and Bioenergy* 16 (2): 91–102. doi:10.1016/S0961-9534(98)00072-5.

Finnish Forest Industries Federation. 2009. "The Forest Cluster – A Network of Expertise and Business Activities." Helsinki: Forest Industries Statistics Service.

Fiorella, M., and W.J. Ripple. 1993. "Determining Successional Stage of Temperate Coniferous Forests with Landsat Satellite Data." *Photogrammetric Engineering & Remote Sensing* 59 (2): 239–246.

Food and Agriculture Organization of the United Nations. 2011. *State of the World's Forests 2011.* Rome: Food and Agriculture Organization of the United Nations.

Gould, Michael, Max Craglia, Michael F. Goodchild, Alessandro Annoni, Gilberto Camara, Werner Kuhn, David Mark, et al. 2008. "Next-Generation Digital Earth: A Position Paper from the Vespucci Initiative for the Advancement of Geographic Information Science."

Grainger, Alan. 2008. "Difficulties in Tracking the Long-Term Global Trend in Tropical Forest Area." *Proceedings of the National Academy of Sciences* 105 (2): 818–823. doi:10.1073/pnas.0703015105.

Guariguata, Manuel R., and Rebecca Ostertag. 2001. “Neotropical Secondary Forest Succession: Changes in Structural and Functional Characteristics.” *Forest Ecology and Management* 148 (1): 185–206.

Gullison, Raymond E., Peter C. Frumhoff, Josep G. Canadell, Christopher B. Field, Daniel C. Nepstad, Katharine Hayhoe, Roni Avissar, et al. 2007. “Tropical Forests and Climate Policy.” *Science* 316 (5827): 985–986. doi:10.1126/science.1136163.

Gutman, G., Raymond A. Byrnes, J. Masek, S. Covington, C. Justice, S. Franks, and Rachel Headley. 2008. “Towards Monitoring Land-Cover and Land-Use Changes at a Global Scale: The Global Land Survey 2005.” *Photogrammetric Engineering and Remote Sensing* 74 (1): 5.

Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, et al. 2013a. “High-Resolution Global Maps of 21st-Century Forest Cover Change.” *Science* 342 (6160): 850–853. doi:10.1126/science.1244693.

Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, et al. 2013b. “Supplementary Materials for High-Resolution Global Maps of 21st-Century Forest Cover Change.” *Science* 342 (6160): 850–853. doi:10.1126/science.1244693.

Harvey, Celia A., Mario Chacón, Camila I. Donatti, Eva Garen, Lee Hannah, Angela Andrade, Lucio Bede, et al. 2014. “Climate-Smart Landscapes: Opportunities and Challenges for Integrating Adaptation and Mitigation in Tropical Agriculture.” *Conservation Letters* 7 (2): 77–90. doi:10.1111/conl.12066.

Helmer, Eileen H., Michael A. Lefsky, and Dar A. Roberts. 2009. “Biomass Accumulation Rates of Amazonian Secondary Forest and Biomass of Old-Growth Forests from Landsat Time Series and the Geoscience Laser Altimeter System,” Journal of Applied Remote Sensing, , no. Vol. 3, nr. 33505(January). ftp://fapespclima.ccst.inpe.br/lba/ornlworking/carbon_dynamics/CD37_Biomass_Landsat_GLAS/comp/HelmerLefskyRoberts.2009.JRS033505.pdf.

Herold, Martin, and Margaret Skutsch. 2011. “Monitoring, Reporting and Verification for National REDD + Programmes: Two Proposals.” *Environmental Research Letters* 6 (1): 14002. doi:10.1088/1748-9326/6/1/014002.

Houghton, R.A. 2012. “Carbon Emissions and the Drivers of Deforestation and Forest Degradation in the Tropics.” *Current Opinion in Environmental Sustainability* 4 (6): 597–603. doi:10.1016/j.cosust.2012.06.006.

Imbach, Pablo A., Bruno Locatelli, Luis G. Molina, Philippe Ciais, and Paul W. Leadley. 2013. “Climate Change and Plant Dispersal along Corridors in Fragmented Landscapes of Mesoamerica.” *Ecology and Evolution* 3 (9): 2917–2932. doi:10.1002/ece3.672.

Jenkerson, Calli. 2013. “User Guide: Earth Resources Observation and Science (EROS) Center Science Processing Architecture (ESPA) on Demand Interface.” https://pubs.er.usgs.gov/publication/70057873.

Jin, Suming, and Steven A. Sader. 2005. “Comparison of Time Series Tasseled Cap Wetness and the Normalized Difference Moisture Index in Detecting Forest Disturbances.” *Remote Sensing of Environment* 94 (3): 364–372. doi:10.1016/j.rse.2004.10.012.

Jobbágy, Esteban G., Germán Baldi, and Marcelo D. Nosetto. 2011. “Tree Plantation in South America and The Water Cycle: Impacts and Emergent Opportunities.” In *Forests in Development: A Vital Balance*, edited by Tomás Schlichter and Leopoldo Montes, 53–63. Dordrecht: Springer Netherlands. http://www.springerlink.com/index/10.1007/978-94-007-2576-8_5.

Ju, Junchang, and David P. Roy. 2008. “The Availability of Cloud-Free Landsat ETM+ Data over the Conterminous United States and Globally.” *Remote Sensing of Environment* 112 (3): 1196–1211. doi:10.1016/j.rse.2007.08.011.

Kintisch, Eli. 2015. “Amazon Rainforest Ability to Soak up Carbon Dioxide Is Falling.” *Science*, March. doi:10.1126/science.aab0336.

Kirschbaum, M. U. F., D. Whitehead, S. M. Dean, P. N. Beets, J. D. Shepherd, and A. G. E. Ausseil. 2011. “Implications of Albedo Changes Following Afforestation on the Benefits of Forests as Carbon Sinks.” *Biogeosciences* 8 (12): 3687–3696.

Kurz, Werner A. 2010. “An Ecosystem Context for Global Gross Forest Cover Loss Estimates.” *Proceedings of the National Academy of Sciences* 107 (20): 9025–9026. doi:10.1073/pnas.1004508107.

Lamb, David. 2010. *Regreening the Bare Hills: Tropical Forest Restoration in the Asia-Pacific Region*. Springer Science & Business Media.

Lambin, Eric F., B. L. Turner, Helmut J. Geist, Samuel B. Agbola, Arild Angelsen, John W. Bruce, Oliver T. Coomes, et al. 2001. “The Causes of Land-Use and Land-Cover Change: Moving beyond the Myths.” *Global Environmental Change* 11 (4): 261–269. doi:10.1016/S0959-3780(01)00007-3.

Langner, Andreas, Frédéric Achard, and Giacomo Grassi. 2014. “Can Recent Pan-Tropical Biomass Maps Be Used to Derive Alternative Tier 1 Values for Reporting REDD+ Activities under UNFCCC?” *Environmental Research Letters* 9 (12): 124008. doi:10.1088/1748-9326/9/12/124008.

Laurance, William F., D. Carolina Useche, Julio Rendeiro, Margareta Kalka, Corey J. A. Bradshaw, Sean P. Sloan, Susan G. Laurance, et al. 2012. “Averting Biodiversity Collapse in Tropical Forest Protected Areas.” *Nature* 489 (7415): 290–294. doi:10.1038/nature11318.

le Maire, Guerric, Stéphane Dupuy, Yann Nouvellon, Rodolfo Araujo Loos, and Rodrigo Hakamada. 2014. “Mapping Short-Rotation Plantations at Regional Scale Using MODIS Time Series: Case of Eucalypt Plantations in Brazil.” *Remote Sensing of Environment* 152 (September): 136–149. doi:10.1016/j.rse.2014.05.015.

Leisch, Friedrich, Kurt Hornik, and Chung-Ming Kuan. 2000. “Monitoring Structural Changes with the Generalised Fluctuation Test.” *Econometric Theory* null (6): 835–854. doi:null.

Lippke, Bruce, Elaine Oneil, Rob Harrison, Kenneth Skog, Leif Gustavsson, and Roger Sathre. 2011. “Life Cycle Impacts of Forest Management and Wood Utilization on Carbon Mitigation: Knowns and Unknowns.” *Carbon Management* 2 (3): 303–333. doi:10.4155/cmt.11.24.

Locatelli, Bruno, Carla P. Catterall, Pablo Imbach, Chetan Kumar, Rodel Lasco, Erika Marín-Spiotta, Bernard Mercer, Jennifer S. Powers, Naomi Schwartz, and Maria Uriarte. 2015. “Tropical Reforestation and Climate Change: Beyond Carbon: Tropical Reforestation beyond Carbon.” *Restoration Ecology* 23 (4): 337–343. doi:10.1111/rec.12209.

Lugo, Ariel E., and Sandra Brown. 1992. “Tropical Forests as Sinks of Atmospheric Carbon.” *Forest Ecology and Management* 54 (1–4): 239–255. doi:10.1016/0378-1127(92)90016-3.

Masek, J.G., E.F. Vermote, N.E. Saleous, R. Wolfe, F.G. Hall, K.F. Huemmrich, Feng Gao, J. Kutler, and Teng-Kui Lim. 2006. “A Landsat Surface Reflectance Dataset for North America, 1990-2000.” *IEEE Geoscience and Remote Sensing Letters* 3 (1): 68–72. doi:10.1109/LGRS.2005.857030.

Mayaux, P., P. Holmgren, F. Achard, H. Eva, H.-J. Stibig, and A. Branthomme. 2005. “Tropical Forest Cover Change in the 1990s and Options for Future Monitoring.” *Philosophical Transactions of the Royal Society B: Biological Sciences* 360 (1454): 373–384. doi:10.1098/rstb.2004.1590.

McSweeney, Kendra. 2005. “Natural Insurance, Forest Access, and Compounded Misfortune: Forest Resources in Smallholder Coping Strategies before and after Hurricane Mitch, Northeastern Honduras.” *World Development* 33 (9): 1453–1471.

Mering, Catherine, Johanna Baro, and Erika Upegui. 2010. “Retrieving Urban Areas on Google Earth Images: Application to Towns of West Africa.” *International Journal of Remote Sensing* 31 (22): 5867–5877. doi:10.1080/01431161.2010.512311.

Millennium Ecosystem Assessment. 2005. *Ecosystems and Human Well-Being: Current State and Trends. Findings of the Condition and Trends Working Group. Millennium Ecosystem Assessment Series*. Island press, Washington DC.

Myers, Norman, Russell A. Mittermeier, Cristina G. Mittermeier, Gustavo A. B. da Fonseca, and Jennifer Kent. 2000. “Biodiversity Hotspots for Conservation Priorities.” *Nature* 403 (6772): 853–858. doi:10.1038/35002501.

Oguntunde, Philip G., Babatunde J. Abiodun, Gunnar Lischeid, and Christoph Merz. 2014. “Modelling the Impacts of Reforestation on the Projected Hydroclimatology of Niger River Basin, West Africa.” *Ecohydrology* 7 (1): 163–176.

Paavola, Jouni. 2008. "Livelihoods, Vulnerability and Adaptation to Climate Change in Morogoro, Tanzania." *Environmental Science & Policy* 11 (7): 642–654.

Pan, Y., R. A. Birdsey, J. Fang, R. Houghton, P. E. Kauppi, W. A. Kurz, O. L. Phillips, et al. 2011. "A Large and Persistent Carbon Sink in the World's Forests." *Science* 333 (6045): 988–993. doi:10.1126/science.1201609.

Ponette-Gonzalez, A. G., E. Marin-Spiotta, K. A. Brauman, K. A. Farley, K. C. Weathers, and K. R. Young. 2014. "Hydrologic Connectivity in the High-Elevation Tropics: Heterogeneous Responses to Land Change." *BioScience* 64 (2): 92–104. doi:10.1093/biosci/bit013.

Pramova, Emilia, Bruno Locatelli, Houria Djoudi, and Olufunso A. Somorin. 2012. "Forests and Trees for Social Adaptation to Climate Variability and Change." *Wiley Interdisciplinary Reviews: Climate Change* 3 (6): 581–596.

Raši, Rastislav, Catherine Bodart, Hans-Jürgen Stibig, Hugh Eva, René Beuchle, Silvia Carboni, Dario Simonetti, and Frédéric Achard. 2011. "An Automated Approach for Segmenting and Classifying a Large Sample of Multi-Date Landsat Imagery for Pan-Tropical Forest Monitoring." *Remote Sensing of Environment* 115 (12): 3659–3669. doi:10.1016/j.rse.2011.09.004.

Ridder, Ralph M. 2007. "Global Forest Resources Assessment 2010: Options and Recommendations for a Global Remote Sensing Survey of Forests." *FAO For. Resour. Assess. Programme Work. Pap* 141. http://www.fao.org/3/a-ai074e.pdf.

Righelato, Renton, and Dominick V. Spracklen. 2015. "Carbon Mitigation by Biofuels or by Saving and Restoring Forests?" Accessed December 4. http://www.gatsby.ucl.ac.uk/~pel/environment/biofuel_science07.pdf.

Robledo, Carmenza, Martin Fischler, and Alberto Patiño. 2004. "Increasing the Resilience of Hillside Communities in Bolivia: Has Vulnerability to Climate Change Been Reduced as a Result of Previous Sustainable Development Cooperation?" *Mountain Research and Development* 24 (1): 14–18.

Rudel, Thomas K. 2005. *Tropical Forests: Regional Paths of Destruction and Regeneration in the Late Twentieth Century*. Columbia University Press. http://www.jstor.org/stable/10.7312/rude13194.

Schmidt, Michael, Richard Lucas, Peter Bunting, Jan Verbesselt, and John Armston. 2015. "Multi-Resolution Time Series Imagery for Forest Disturbance and Regrowth Monitoring in Queensland, Australia." *Remote Sensing of Environment* 158 (March): 156–168. doi:10.1016/j.rse.2014.11.015.

Scott, D. F., L. A. Bruijnzeel, J. Mackensen, and others. 2005. "The Hydrological and Soil Impacts of Forestation in the Tropics." *Forests, Water and People in the Humid Tropics*, 622–651.

Seebach, L., P. Strobl, and P. Vogt. 2010. *Pilot Study in Europe for the Global Forest Remote Sensing Survey*. Publications Office.

Sendzimir, Jan, Chris P. Reij, and Piotr Magnuszewski. 2011. "Rebuilding Resilience in the Sahel: Regreening in the Maradi and Zinder Regions of Niger." *Ecology and Society* 16 (3): 1.

Shoo, Luke P., Collin Storlie, Jeremy VanDerWal, Jeremy Little, and Stephen E. Williams. 2011. "Targeted Protection and Restoration to Conserve Tropical Biodiversity in a Warming World." *Global Change Biology* 17 (1): 186–193.

Silver, W. L., R. Ostertag, and A. E. Lugo. 2000. "The Potential for Carbon Sequestration Through Reforestation of Abandoned Tropical Agricultural and Pasture Lands." *Restoration Ecology* 8 (4): 394–407. doi:10.1046/j.1526-100x.2000.80054.x.

Steege, Hans ter, Nigel C. A. Pitman, Daniel Sabatier, Christopher Baraloto, Rafael P. Salomão, Juan Ernesto Guevara, Oliver L. Phillips, et al. 2013. "Hyperdominance in the Amazonian Tree Flora." *Science* 342 (6156): 1243092. doi:10.1126/science.1243092.

Stensgaard, Anna-Sofie, Christopher FL Saarnak, Jürg Utzinger, Penelope Vounatsou, Christopher Simoonga, Gabriel Mushinge, Carsten Rahbek, Flemming Møhlenberg, and Thomas K. Kristensen. 2009. "Virtual Globes and Geospatial Health: The Potential of New Tools in the Management and Control of Vector-Borne Diseases." *Geospatial Health* 3 (2): 127–141.

Swann, A. L. S., I. Y. Fung, and J. C. H. Chiang. 2012. "Mid-Latitude Afforestation Shifts General Circulation and Tropical Precipitation." *Proceedings of the National Academy of Science* 109 (January): 712–716. doi:10.1073/pnas.1116706108.

Travis, J. M. J. 2003. "Climate Change and Habitat Destruction: A Deadly Anthropogenic Cocktail." *Proceedings of the Royal Society B: Biological Sciences* 270 (1514): 467–473. doi:10.1098/rspb.2002.2246.

Turner, Will R., Michael Oppenheimer, and David S. Wilcove. 2009. "A Force to Fight Global Warming." *Nature* 462 (7271): 278–279. doi:10.1038/462278a.

UNFCCC. 2001. "Land Use, Land-Use Change and Forestry." In *Decision 11/CP.7*. Vol. FCCC/CP/2001/13/Add.1.

UNFCCC. 2009. *Decision 2/CP. 15 Copenhagen Accord*. FCCC/CP/2009/11/Add. 1.

Uriarte, María, Charles B. Yackulic, Yili Lim, and Javier A. Arce-Nazario. 2011. "Influence of Land Use on Water Quality in a Tropical Landscape: A Multi-Scale Analysis." *Landscape Ecology* 26 (8): 1151–1164. doi:10.1007/s10980-011-9642-y.

Verbesselt, Jan, Rob Hyndman, Glenn Newnham, and Darius Culvenor. 2010. "Detecting Trend and Seasonal Changes in Satellite Image Time Series." *Remote Sensing of Environment* 114 (1): 106–115. doi:10.1016/j.rse.2009.08.014.

Verbesselt, Jan, Achim Zeileis, and Martin Herold. 2012. “Near Real-Time Disturbance Detection Using Satellite Image Time Series.” *Remote Sensing of Environment* 123 (August): 98–108. doi:10.1016/j.rse.2012.02.022.

West, Thales A.P., Edson Vidal, and Francis E. Putz. 2014. “Forest Biomass Recovery after Conventional and Reduced-Impact Logging in Amazonian Brazil.” *Forest Ecology and Management* 314 (February): 59–63. doi:10.1016/j.foreco.2013.11.022.

Yu, Le, and Peng Gong. 2012. “Google Earth as a Virtual Globe Tool for Earth Science Applications at the Global Scale: Progress and Perspectives.” *International Journal of Remote Sensing* 33 (12): 3966–3986. doi:10.1080/01431161.2011.636081.

Zarin, Daniel J. 2012. “Carbon from Tropical Deforestation.” *Science* 336 (6088): 1518–1519. doi:10.1126/science.1223251.

Zhao, Kaiguang, and Robert B. Jackson. 2014. “Biophysical Forcings of Land-Use Changes from Potential Forestry Activities in North America.” *Ecological Monographs* 84 (2): 329–353. doi:10.1890/12-1705.1.

Zhu, Zhe, and Curtis E. Woodcock. 2012. “Object-Based Cloud and Cloud Shadow Detection in Landsat Imagery.” *Remote Sensing of Environment* 118 (March): 83–94. doi:10.1016/j.rse.2011.10.028.

Appendices

Appendix A – Contributions of tropical reforestation to climate change mitigation

Appendix B – Processing of the data by JRC and FAO

Appendix C – Hansen forest gain map for 2000 – 2012

Appendix D – JRC land cover and FAO land use classes

Appendix E – Detailed overview of added information to JRC and FAO dataset

Appendix F - Validation JRC dataset

Appendix G – Validation FAO dataset

Appendix H - Hansen forest gain calculation

Appendix I - Overlap JRC and FAO polygons

Appendix J - Forest gain Hansen with JRC sampling sites

Appendix A – Contributions of tropical reforestation to climate change mitigation

*Appendix A – Contributions of tropical reforestation (TR) to climate change mitigation (Locatelli et al. 2015). Examples with a * are not specific to reforestation but general to forests.*

Type of Contribution	Description of Contribution	Example Reference
Mitigating climate change globally and regionally		
Carbon capture and storage	TR has a high carbon sequestration potential	(Silver, Ostertag, and Lugo 2000)
Bioenergy and products	TR can reduce emissions by substituting plantation wood for fossil fuels or carbon-intensive materials	(Righelato and Spracklen 2015)
Reduced pressure on forests	TR reduces harvesting pressure on remnant older growth forests and their carbon stocks	(Carnus et al. 2006)
Biophysical cooling	TR creates regional cooling as a result of changes in evapotranspiration, surface roughness and albedo	(Anderson et al. 2011)
Regional climate regulation	TR reduces warming and drying in arid regions	(Oguntunde et al. 2014)
Protecting rural economies from impacts of climate variation		
Livelihood diversification	Livelihood diversification with forest products is an anticipatory strategy used by communities to reduce their sensitivity to climate variations	(Paavola 2008)*
Safety nets	Forest products are used by communities during and after extreme events to cope and recover	(McSweeney 2005)*
Microclimate and agriculture	TR improves the resilience of crop production to climate variations	(Sendzimir, Reij, and Magnuszewski 2011)
Reducing impacts of climatic variation on the water cycle and associated human uses		
Base flow conservation	TR increases dry season flow of streams and reduces impacts of drought	(Scott et al. 2005)
Flood control	TR reduces frequency and severity of flood-related catastrophes	(Bradshaw et al. 2007)*
Reducing local impacts of extreme weather events on society and ecosystems		
Heat waves	Urban trees moderate the health impacts of heat waves	(Bowler et al. 2010)
Coastal protection	Planted mangroves protect coastal settlements against storms and waves	(Adger 1999)
Landslide protection	Forest regeneration stabilizes hillsides and reduces landslides	(Robledo, Fischler, and Patiño 2004)
Reducing impacts of climate change on biodiversity		
Landscape connectivity	Forested habitat corridors facilitate species dispersal under climate change scenarios	(Imbach et al. 2013)*
Refugia and habitat provision	TR provides habitat refugia for climate-sensitive species of conservation significance	(Shoo et al. 2011)

Appendix B – Processing of the data by JRC and FAO

Appendix B – In this section the processing method of the JRC and FAO is discussed. It provides an insight into the main processing steps that were used by each dataset. It gives information regarding the source of the original data, the pre-processing, the classification procedure and the validation.

The majority of imagery used for classification and interpretation is derived from the United States Geological Survey's (USGS) Landsat Global Land Survey (GLS) (Gutman et al. 2008). Landsat imagery provides global coverage, a long time series of acquisitions and spatial and spectral characteristics that are desirable for detecting changes in tree cover (FAO and JRC 2012).

For each sample unit, medium resolution satellite imagery was acquired for the reference years. The JRC team processed sites within the tropics, sub-Saharan Africa and western Europe (Beuchle et al. 2011; Seebach, Strobl, and Vogt 2010). Although the JRC and FAO team processed particular regions, their processing methods consisted of the following common components (FAO and JRC 2012):

- Data acquisition
- Data pre-processing and image normalisation
- Image segmentation
- Image classification

The automated segmentation and classification of land cover types has two main goals. First, it supports the design of a spatially and temporally consistent dataset. Second, it avoids manual delineation, which helps to reduce complications with the visual review and revision of land-cover and land-use labels. The land cover segmentation and classification consisted of four main steps:

- Image segmentation at level 1 (no minimal mapping unit) and level 2 (minimal mapping unit of 5 hectares).
- Collection of training data from representative sites
- Construction of a model for land cover classification
- Assigning land cover classes at level 2 products

These four steps were carried out using eCognition[5] image segmentation and processing software. Image segmentation groups similar pixels into patches (i.e. segments or polygons) based on spectral similarity and spatial distinctions. The land cover classification was executed on the level 1 segments, which are spectrally homogeneous. For the tropics, the land cover classification at level 1 was based on a spectral library (Raši et al. 2011). The assigning of the labels was then done on the level 2 segments, based on the underlying percentage

[5] http://www.ecognition.com/suite/ecognition-developer

composition of level 1 (Appendix B - 1). For the classification of the sample sites, a supervised automatic classification was selected as the preferred processing option.

Appendix B - 1 Land cover classes with percentage forest cover for assigning level 2 labels (FAO and JRC 2012).

Level 1 segment	Percentage composition	Level 2 land-cover label
Tree cover	≥ 30	Tree cover
Other wooded land	≥ 70	Other wooded land
Other land cover	≥ 70	Other land cover
Water	≥ 70	Water

JRC

Appendix B - 2 Detailed definition of the land cover classes used by JRC (Beuchle et al. 2011).

Tree cover	▪ 70% or more of a mapping unit is covered by a continuous layer of trees, the tree canopy can be closed or open ▪ The tree layer density is at least 10% or more, ▪ Tree height is ≥ 5m
Tree cover mosaic	▪ The tree layer in a mapping unit is discontinuous ▪ The tree layer covers 30% to 70% of the mapping unit ▪ Tree density ≥ 10% ▪ Tree height ≥ 5 m (as required for the definition of 'Tree Cover')
Other wooded land	▪ A mapping unit is covered to 70% or more of by a layer of shrubs, tree re-growth, or mixed vegetation with a mainly woody component (including village complexes) ▪ The height of the layer is mainly < 5 m
Other land cover	▪ Land cover other than tree cover or other wooded land, including e.g. herbaceous cover, non-woody agricultural crops and mosaics, bare soils, built-up or urban areas ▪ A potential tree cover component covers less than 30% of a mapping unit and / or the tree density is less than 10%
Water	▪ Inland and sea water
Clouds	▪ Cloud and cloud shadow
No data	-

FAO

With the land cover classes, a conversion to the land use classes was made for the FAO dataset. The first step consisted of an automatic conversion of land cover classes to preliminary land use labels. With this method, the majority of the polygons is converted. The second step requires expert knowledge to accurately quantify the true land use changes. This complicated step requires an examination of the area in an ecological context, which not only determines the vegetation that is present, but also entails knowledge about how the land will respond in the future through process of regeneration and afforestation (Kurz 2010). For the conversion from land cover to land use, expert human interpretation was necessary for the categorisation of land use. The JRC land cover classes 'tree cover' and 'tree cover mosaic' were converted to 'forest' land use. The 'other wooded land' cover received the same class name in the FAO dataset. 'Other land cover' was converted to the 'other land use' class.

Land use classes used for classification are based on the FAO forest definition (FAO 2010b):

- *Forest* – land covering at least 0.5 hectares, with trees higher than 5 metres and a canopy cover exceeding 10 percent, or trees should be able to reach this threshold *in situ*. Land that is mainly under agricultural or urban use is not included.
- *Other wooded land* – land that is not classified as forest, covering more than 0.5 hectares. Trees must be higher than 5 metres and have a canopy cover of 5 to 10 percent, or should be able to reach these thresholds *in situ*. A combined cover of scrubs, bushes and trees above also allows for classification in this group. Land that is mainly under agricultural or urban use is not included.
- *Other land* – all land that is not classified as forest or other wooded land.

Appendix C – Hansen forest gain map for 2000 – 2012

Appendix C – Hansen forest gain map for the study area for 2000 – 2012

Appendix D – JRC land cover and FAO land use classes

Appendix D – Land cover and land use classes as used by the JRC and FAO, respectively (Simonetti et al. 2011).

LAND COVER	CLASS	CODE
	TREE COVER	10
	TREE COVER MOSAIC	12
	OTHER WOODED LAND	20
	OTHER LAND COVER	30
	BURNT	50
	WATER	60
	CLOUD & SHADOW	80
	NO DATA	90
	UNCLASSIFIED	99

LAND USE	CLASS	CODE
	FOREST	11
	OTHER WOODED LAND	12
	OTHER LAND USE	30
	WATER	18
	NO DATA	99

Appendix E – Detailed overview of added information to JRC and FAO datasets

Appendix E Elaboration of added information to JRC and FAO datasets.

Date of the first observation (i.e. around 2000)
For this column the date (month and year) of the first observation is recorded. The first observation is selected to be as close to the start year as possible for the JRC / FAO datasets, in order to allow for an effective comparison between the classification of the JRC / FAO and the newly created validation dataset.

Date last observation (i.e. around 2005 / 2010)
The last observation date (month and year) is also recorded, which is as close as possible to the year 2010 for JRC or 2005 for the FAO.

Regrowth or not (yes / no)
The next step is to note down if reforestation has occurred or not. This information is gathered as a dummy variable i.e. either true / yes (1) or false / no (0). This information may be used to test the agreement between the validation dataset and the JRC / FAO dataset.

Confidence of regrowth (low, medium, high)
With regard to the occurrence of reforestation, the confidence level of the presence of regrowth is noted down. This is done by assigning one of the following three levels: low, medium or high. Situations with a medium or low level of confidence could be the result of e.g. low quality imagery due to resolution or clouds, or a validation date in Google Earth that deviates largely from the dataset date.

Type of regrowth (natural / plantation / mixed)
Once the regrowth has been identified, the next step is to identify whether natural regrowth or a plantation is present within the polygon, or a mix of these.

Confidence type of regrowth (low, medium, high)
The confidence level for the presence of being natural regrowth or a plantation in noted down, using three levels: low, medium and high. Situations with a medium or low level of confidence could be the result of e.g. low quality imagery due to resolution or clouds, or a validation date in Google Earth that deviates largely from the dataset date.

Canopy cover first observation (in percentages, arranged deciles)
The canopy cover for the first observation (around the year 2000) is recorded. With this part of the visual analysis, the canopy cover is divided into 10 equally sized groups, giving ten deciles, which is used to do an estimate of the canopy cover for each polygon.

Canopy cover last observation (in percentages, arranged in deciles)
Similar for the last observation around the year 2010 (JRC) or 2005 (FAO). Canopy cover is likewise divided into 10 equally sized groups, giving ten deciles.

Regrowth pattern (random, uniform or clustered, or any combination of these)
For reforestation in the polygon, the pattern of regrowth is documented. There several levels: random, uniform or clustered, or any combination of these. A combination of a regrowth pattern may occur when within one polygon both natural regrowth and plantation regrowth are present.

Number of historical images in Google Earth
Google Earth has a collection of historical imagery, with a varying number and quality of images, depending on the location. The number of historical images is useful for a comparison between the sample sites. Each sample site has a different amount of historical imagery. The number of images is used during the time series for the selection of the Landsat tile that is best covered by historical imagery from Google Earth.

Quality of historical Google Earth imagery (low, medium, high)
Likewise, the quality of the Google Earth imagery is recorded. This is done using three levels: low, medium and high.

Source of quality error in historical Google Earth imagery (clouds, resolution, image colouring)
In case of a medium or low quality of the Google Earth imagery, the source of this error is documented. Errors such as clouds, low spatial resolution or colouring of the image can occur.

Source of imagery for first observation (Google Earth / Landsat)
Finally, the imagery is derived from either Google Earth or Landsat for the first observation year; for the final observation year around 2010 or 2005, all imagery is obtained from Google Earth. The notation of the source can give an indication of the accuracy of the validation dataset.

Appendix F – Validation JRC dataset

Appendix F is divided into three tables, one for each JRC forest regrowth change type. Each table displays information about the amount and type of regrowth, as validated using visual analysis. Percentages are given between brackets if applicable.

Appendix F - 1 Validation of JRC dataset for change type 'other land cover to tree cover'.

Total nr. of polygons within change type	278		
Sum (km^2)	60.86		
Mean (km^2)	0.22		
Nr. of regrowth polygons (Yes / No)	225 / 53 (80.9 / 19.1)		
Confidence regrowth	**Low**	**Medium**	**High**
Nr. of polygons	15 (5.4)	11 (4.0)	252 (90.6)
Type of regrowth	**Natural**	**Plantation**	**Mixed**
Nr. of polygons	17 (6.1)	201 (72.3)	60 (21.6)
Confidence type of regrowth	**Low**	**Medium**	**High**
Nr. of polygons	5 (1.8)	15 (5.4)	258 (92.8)
Canopy cover year 2000 (%)	14.96		
Canopy cover year 2010 (%)	85.14		

Appendix F - 2 Validation of JRC dataset for change type 'other wooded land to tree cover'.

Total nr. of polygons within change type	57		
Sum (km^2)	10.36		
Mean (km^2)	0.18		
Nr. of regrowth polygons (Yes / No)	4 / 53 (7.1 / 92.9)		
Confidence regrowth	**Low**	**Medium**	**High**
Nr. of polygons	17 (29.8)	7 (12.3)	33 (57.9)
Type of regrowth	**Natural**	**Plantation**	**Mixed**
Nr. of polygons	16 (28.0)	27 (47.4)	14 (24.6)
Confidence type of regrowth	**Low**	**Medium**	**High**
Nr. of polygons	2 (3.5)	1 (1.8)	54 (94.7)
Canopy cover year 2000 (%)	42.98		
Canopy cover year 2010(%)	85.26		

Appendix F - 3 Validation of JRC dataset for change type 'tree cover mosaic to tree cover'.

Total nr. of polygons within change type	107		
Sum (km^2)	22.69		
Mean (km^2)	0.21		
Nr. of regrowth polygons (Yes / No)	60 / 47 (56.1 / 43.9)		
Confidence regrowth	**Low**	**Medium**	**High**
Nr. of polygons	14 (13.0)	25 (23.4)	68 (63.6)
Type of regrowth	**Natural**	**Plantation**	**Mixed**
Nr. of polygons	41 (38.3)	12 (11.2)	54 (50.5)
Confidence type of regrowth	**Low**	**Medium**	**High**
Nr. of polygons	2 (1.9)	14 (13.1)	91 (85.0)
Canopy cover year 2000 (%)	45.89		
Canopy cover year 2010 (%)	81.96		

Appendix G – Validation FAO dataset

Appendix G is divided into two tables, one for each FAO forest regrowth change type. Each table displays information about the amount and type of regrowth, as validated using visual analysis. Percentages are given between brackets if applicable.

Appendix G - 1 Validation of FAO dataset for change type 'other land use to forest'.

Total nr. of polygons within change type	11		
Sum (km^2)	2.56		
Mean (km^2)	0.23		
Nr. of regrowth polygons (Yes / No)	8 / 3 (73.73 / 27.27)		
Confidence regrowth	**Low**	**Medium**	**High**
Nr. of polygons	7 (63.6)	1 (9.1)	3 (27.3)
Type of regrowth	**Natural**	**Plantation**	**Mixed**
Nr. of polygons	5 (45.5)	2 (18.2)	4 (36.3)
Confidence type of regrowth	**Low**	**Medium**	**High**
Nr. of polygons	0 (0)	2 (18.2)	9 (81.8)
Canopy cover year 2000 (%)	60.0		
Canopy cover year 2010 (%)	60.0		

Appendix G - 2 Validation of FAO dataset for change type 'other wooded land to forest'.

Total nr. of polygons within change type	11		
Sum (km^2)	1.84		
Mean (km^2)	0.17		
Nr. of regrowth polygons (Yes / No)	5 / 6 (45.5 / 54.5)		
Confidence regrowth	**Low**	**Medium**	**High**
Nr. of polygons	7 (63.6)	0 (0)	4 (36.4)
Type of regrowth	**Natural**	**Plantation**	**Mixed**
Nr. of polygons	5 (45.4)	3 (27.3)	3 (27.3)
Confidence type of regrowth	**Low**	**Medium**	**High**
Nr. of polygons	1 (9.1)	3 (27.3)	4 (63.6)
Canopy cover year 2000 (%)	22.73		
Canopy cover year 2010 (%)	50.0		

Appendix H – Hansen forest gain calculation

Appendix H shows the calculation of Hansen forest gain for 2000 – 2012, for the entire study area (H – 1), and for the forest gain within the JRC / FAO sample sites (H – 2) . The forest gain is simply the number of pixels showing 'forest gain' divided by the total number of pixels in the study area and within the tiles, respectively.

Appendix H – 1 Pixel based analysis of forest gain from the Hansen dataset for the entire study area.

Pixels showing 'forest gain'	6027882
Pixels showing 'no forest gain'	156486773
Total number of pixels in study area	162514655
Forest gain in study area (%)	3.71
Total forest gain 2000 – 2012 (km^2)	15642.66

Appendix H – 2 'Sampled' Hansen forest gain percentage and total forest gain within JRC / FAO sample sites.

Pixels showing 'forest gain'	263662
Pixels showing 'no forest gain'	6394317
Total number of pixels in study area	6657979
Forest gain in study area (%)	3.96
Total forest gain 2000 – 2012 (km^2)	16447.62

Appendix I – Overlap JRC and FAO polygons

Appendix I Overlap between JRC and FAO polygons. The table is sorted on percentage of overlap, and the area size.

Tile Name	Change type JRC	Area polygon JRC (km^2)	Change type FAO	Area polygon FAO (km^2)	Overlap (km^2)	Overlap (%)
S27_W050	Tree Cover Mosaic to Tree Cover	0.130	Other Wooded Land to Forest	0.130	0.130	100.00
S26_W053	Other Land Cover to Tree Cover	0.285	Other Wooded Land to Forest	0.084	0.084	100.00
S25_W053	Other Land Cover to Tree Cover	0.064	Other Land Use to Forest	0.064	0.064	100.00
S26_W053	Other Land Cover to Tree Cover	0.285	Other Wooded Land to Forest	0.046	0.046	100.00
S26_W053	Other Land Cover to Tree Cover	0.285	Other Wooded Land to Forest	0.040	0.040	100.00
S29_W052	Tree Cover Mosaic to Tree Cover	0.119	Other Land Use to Forest	0.325	0.113	34.75
S26_W053	Tree Cover Mosaic to Tree Cover	0.083	Other Land Use to Forest	0.193	0.024	12.56
S27_W050	Other Wooded Land to Tree Cover	0.004	Other Wooded Land to Forest	0.227	0.004	1.59

Appendix J – Forest gain Hansen with JRC sampling sites

Appendix J – The forest gain map of Hansen with JRC / FAO sampling sites.