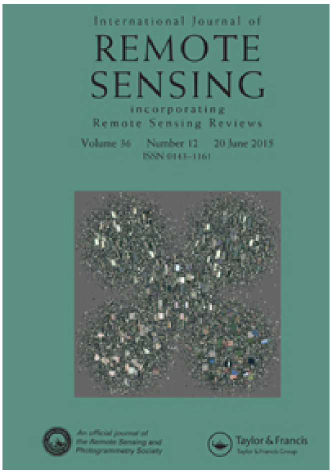

International Journal of Remote Sensing
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tres20

Tropical forest cover dynamics for Latin America using Earth observation data: a review covering the continental, regional, and local scale

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Published online: 30 Jun 2015.

To cite this article: E. Da Ponte, M. Fleckenstein, P. Leinenkugel, A. Parker, N. Oppelt & C. Kuenzer (2015) Tropical forest cover dynamics for Latin America using Earth observation data: a review covering the continental, regional, and local scale, International Journal of Remote Sensing, 36:12, 3196-3242, DOI: 10.1080/01431161.2015.1058539

To link to this article: http://dx.doi.org/10.1080/01431161.2015.1058539

International Journal of Remote Sensing, 2015
Vol. 36, No. 12, 3196–3242, http://dx.doi.org/10.1080/01431161.2015.1058539

REVIEW ARTICLE

Tropical forest cover dynamics for Latin America using Earth observation data: a review covering the continental, regional, and local scale

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(*Received 10 April 2015; accepted 31 May 2015*)

The tropical forest cover has varied greatly over the last few decades. The rapid advance of agricultural crops and illegal clearings in natural areas has resulted in the conversion of the majority of the world's forest into desolated patches. Although rates of deforestation have decreased compared to previous years, forest loss still remains a crucial concern. Latest studies conducted on a global scale identified the Latin American continent as one of the regions exhibiting the highest rates of deforestation in the world. The dynamics of forests over the past 40 years has attracted numerous remote-sensing-based studies to monitor forest loss, analyse patterns, and understand the drivers of land conversion. This review article provides a comprehensive overview of the remote-sensing-based studies of tropical forest dynamics in Latin America. Following an introduction with respect to global forest mapping products, a general outline of tropical forest ecoregions and drivers of deforestation in Latin America is provided. Subsequently, a review and categorization of the existing studies is presented, where focus is laid on selected sensors and data analysis methodologies apply. Furthermore, a case study for the whole of Paraguay is presented; Paraguay is a region which contains highly diverse ecosystems that have been ravaged as a result of deforestation over the past 40 years. The main results, challenges, and future needs are discussed.

1. Introduction

Tropical forest ecosystems around the world are immensely important. Their unquestionable role as a key component of climate regulation, biochemical cycles, and biological diversity (Joseph, Murthy, and Thomas 2011) has led to concerns about their future and protection. The rapid advance of deforestation over recent decades has resulted in the conversion of the majority of the world's tropical forest into isolated patches, endangering not only their continuity but the biodiversity within them. Deforestation has been defined by FAO (2007) as the decrease of the tree canopy below 10% boundary, due to the conversion of forests to another land use such as farms, ranches, mines, or urban sites. Degradation, on the other hand, is described as the decrease of the canopy cover within the forest, provided that the canopy stays above 10% (FAO 2001). Between the years 1990 and 2005, Latin America lost 69 Mha of forest, which is equivalent to 7% of the forest cover of the region. Moreover, this region contains one of the highest numbers of endangered tree species worldwide (FAO 2007). The latest

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studies conducted on a global scale identified Argentina, Paraguay, and Brazil as the regions exhibiting the highest rates of deforestation in Latin America (Hansen et al., 2008). Although rates of deforestation have decreased in comparison with previous years, the process still remains an ongoing threat. In order to halt the predation of forest, several strategies, decisions, conventions, and monitoring programmes were carried out in an international context. The Millennium Development Goals (MDGs), the UN Convention on Biological Diversity (CBD), the UN Convention to Combat Desertification (UNCCD), UN Forum on Forests (UNFF), UN Global Compact (UNGC), the Global Environment Facility (GEF), the United Nations Framework Convention on Climate Change (UNFCCC), and the mechanism for Reducing Emissions from Deforestation and Degradation (REDD+) are some of the programmes and strategies implemented (Rautner, Leggett, and Davis 2013). For instance, the international REDD+ negotiations sponsored by the UNFCC have provided methodological guidance on the REDD+ programme since 2005 through conservation of forest carbon stocks, sustainable forest management, and improvement of the carbon stocks in developing countries (Potapov et al. 2014). Following this, efforts of governmental and non-governmental institutions in Latin America such as the Instituto Nacional de Pesquisas Espaciais (INPE), Universidad Federal de Paraná, Universidad de Buenos Aires (UBA), Sistema de Información Ambiental de Colombia (SIAC), Centro Agronómico Tropical de Investigación y Enseñanza (CATIE), World Wildlife Fund (WWF), Guyra Paraguay, Red Agroforestal Chaco Argentina (Redf), and the Proyungas have all contributed over the years to monitoring and, where necessary, informing the relevant bodies of illegal deforestation activities (Sesnie et al. 2008; Hutchison and Aquino 2011). Numerous approaches were developed over the last few decades to understand the current dynamics of forests. The use of Earth Observation (EO) data to monitor forest has supported other methodologies such as ground forest inventories, primarily due to their lower cost and easier accessibility (Fagan and Defries 2009). Satellite-based measurements offer monthly or daily data, unbiased measurements, and the capability to synthesize large amounts of data. For example, the inclusion of remote-sensing technologies has more recently become crucial in the support and assessment of environmental programmes such as REDD+, an initiative which endeavours to protect the integrity of remaining forests (Fagan and Defries 2009; Gebhardt et al. 2014; Hosonuma et al. 2012; Kuenzer, Ottinger, et al. 2014; Potapov et al. 2014).

This article provides a comprehensive review of the approaches that have been implemented to study the changes in tropical forests in Latin America using remote-sensing technology. The context of the articles reviewed varies in scale from the continental to the local scale, covering almost all the countries in Latin America. A particular focus was given to the Atlantic Forest in Paraguay, which is considered to be one of the most threatened rain forests in the world; this is a highly diverse ecosystem that unfortunately has been ravaged over the past 40 years (Huang et al. 2007, 2009). Considerations are given to variations solely induced by anthropological activities, with particular emphasis on the deforestation and degradation process. The goal of this review article is to assess, analyse, categorize, and discuss all the studies which have integrated EO data to study the dynamics of tropical forests in Latin America, and to present how the studies are distributed, which sensors have been applied at which spatial and temporal resolution, which are the most prominent forest cover change detection techniques, and which variables are employed to reach high-accuracy results. Furthermore, current needs, challenges, research gaps, and future trends are discussed.

2. Global forest cover mapping approaches

Remote-sensing data have been crucial in numerous studies to obtain especially accurate information about the distribution, state, and composition of forests at a global scale (Hansen et al. 2002, 2008; Mayaux et al. 2005; Fagan and Defries 2009). Tucker, Townshend, and Goff (1985) created the first continental map of land cover applying 4 km satellite imagery from the Advanced Very High Resolution Radiometer (AVHRR). Loveland et al. (2000), under the funding of the International Geosphere–Biosphere Programme (IGBP), delivered the first pan-continental map at 1.1 km for the period between 1992 and 1993; different from Tucker, Townshend, and Goff (1985) forest covers that were stratified according to their leaf type. A following study conducted by Hansen et al. (2000) applied the same data to produce a new legend. Additionally, the European Commission's Joint Research Center (JRC), in cooperation with several other institutions, generated the 'GLOBAL Land Cover 2000' (GLC2000) product by using Satellite Pour l'Observation de la Terre (SPOT)-4 Vegetation data from the year 2000 (Bartholomé and Belward 2005). This product identified multiple forest classes and densities. Moreover, under the initiative of the GLOBCOVER programme, a higher-resolution land-cover map of 300 m was obtained by means of Europe's Medium Resolution Imaging Spectrometer (MERIS) data for 2005–2006, which contains several global classes at the global scale (Arino et al. 2007).

Subsequently, additional efforts were put into the global mapping of forest cover, specifically. Hansen et al. (2004) produced a global subpixel tree cover map and vegetation continuous field (VCF) using Moderate Resolution Imaging Spectroradiometer (MODIS) data, with a spatial resolution of 500 m × 500 m. Consequently, international programmes such as The Global Forest Resources Assessments (FRA) 2000 and TREES were carried out to assess tropical forest cover extent and dynamics with a special focus on the humid tropical forest. Both programmes used National Oceanic and Atmospheric Administration (NOAA)-AVHRR data with a spatial resolution of 1 km × 1 km and Landsat images as sample frames for forest cover characterization. While the FRA programme aimed to identify forest cover and forest cover change globally, the TREES programme targeted deforestation hotspots within humid tropical forest (Mayaux et al. 2005).

The results obtained by the FRA 2000 initiative were improved in a following programme called FRA 2010, which considered deforestation hotspots in a preliminary step in order to determine deforestation rates (Pacheco, Aguado, and Mollicone 2014), applying the same systematic sampling methodology developed by TREES II (FAO 2012).

Later investigations have yielded more accurate data than previous global maps, owing primarily to the increased spatial resolution of imagery such as Landsat and the Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar sensor (PALSAR), which offer a better understanding of forest cover change over time. For instance, a team of researchers from the University of Maryland generated a global forest cover map using Landsat images with a resolution of 30 m (Hansen et al. 2013). The study processed over 650,000 images using the computing power of the Google Earth Engine in order to quantify forest gain and loss over the entire globe between the years 2000 and 2012 (see Figure 1; Hansen et al. 2013). Similar to Hansen et al. (2013), Gong et al. (2013), under the Finer Resolution Observation and Monitoring of Global Land Cover (FROM-GLC) project, produced the first global land-cover map with a resolution of 30 m based on Thematic Mapper (TM) and

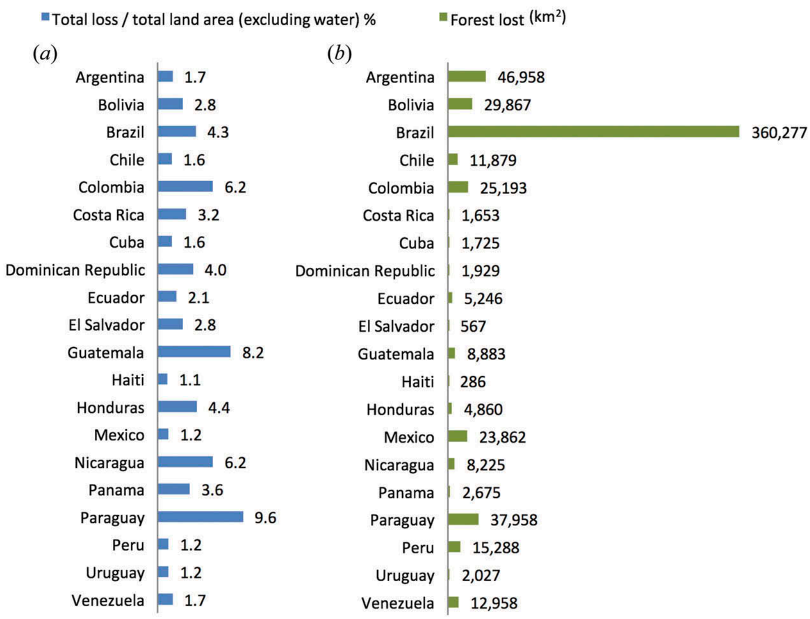

Figure 1. (*a*) Deforestation rates in Latin America based on the total surface of the country (2000–2012). (*b*) Total area deforested in Latin America between 2000 and 2012 (Hansen et al. 2013).

Enhanced Thematic Mapper Plus (ETM+) data derived from Landsat satellites. The global data produced in the most recent years (FAO 2012; Hansen, Stehman, and Potapov 2010) have been used extensively by policymakers, non-governmental organizations (NGOs), and scientists as a baseline tool for forest cover estimation around the world (Puyravaud 2003; Mather 2005; Mayaux et al. 2005; Achard et al. 2007, 2010). This information allowed the authors to discuss policies, environmental programmes such as the Payment for Ecosystem Services (PES) under REDD+, and conservation initiatives which aim to promote the protection of the remaining forests. Even though the accuracy of the global products was widely discussed by several authors (Steininger, Tucker, Townshend, et al. 2001; Sánchez-Cuervo et al. 2012; Kuenzer, Leinenkugel, et al. 2014; Brovelli et al. 2015; Leinenkugel et al. 2015), a general overview of the distribution of forests around the globe can be obtained from these products. An overview of the products is presented in Table 1.

3. Tropical forest cover change in Latin America

According to FAO (2010), taking into account reforestations, the world's entire forest cover area, has an extent of 4000 Mha – corresponding to almost 31% of the global land surface. Latin America and the Caribbean possess 22% of the world's forest, with an approximate area of 860 Mha. A further breakdown of these figures shows that 831.5 ha are located in South America (97%), 22.4 Mha in Central America, and 5.9 Mha in the Caribbean region (Pnuma and Cathalac 2010). This region is considered to be one of the most bio-diverse areas on the planet containing 33% of the world's total mammals, 35% of the reptile species, 41% of avian species, and 50% of amphibians. The vast majority of forest cover is distributed throughout South America. This includes the Amazonian Basin

Table 1. Main global land-cover maps derived from remote-sensing data 1 km to 25 m spatial resolution.

Title	Source	Domain	Sensor	Resolution	Forest classes assessed
International Geosphere–Biosphere Programme (IGBP) Discover	Loveland et al. (1999)	Global	AVHRR	1 km	Evergreen needle leaf forests, evergreen broadleaf forests, deciduous needle leaf forests, deciduous broadleaf forests, and mixed forests (IGBP classes).
Global land-cover classification 1 km spatial resolution. University of Maryland (UMD)	Hansen et al. (2000)	Global	AVHRR	1 km	IGBP classes.
TREES	Mayaux, Richards, and Janodet (1999)	Humid Tropics	AVHRR	1 km	Lowland moist forests, submontane forests, montane forests, secondary forests, and deciduous forests.
FRA-2000	FAO (2001)	Global	AVHRR	1 km	Tropical rain, moist, deciduous, and dry forests. Subtropical humid and dry forests. Temperate oceanic and continental forests. Boral coniferous forests.
MODIS land cover	Friedl et al. (2002)	Global	MODIS–Terra	1 km	IGBP classes.
Global land cover (GLC)	Eva et al. (2004) Mayaux et al. (2004)	Global	SPOT–VEGETATION	1 km	IGBP classes.
Vegetation continuous field (VCF)	Hansen et al. (2003)	Global	MODIS–Terra	500 m	No differentiation among forest classes. Percentage of forest in every pixel.
GlobCover	Arino et al. (2007)	Global	Envisat MERIS	300 m	IGBP classes.
Forest cover loss (2000–2012)	Hansen et al. (2013)	Global	Landsat	30 m	Tropical, subtropical, temperate, and boreal forests.
Finer-resolution observation and monitoring a global land cover: first mapping results with Landsat TM and ETM+ data	Gong et al. (2013)	Global	Landsat	30 m	Broadleaf forests, needle leaf forests, mixed forests, and orchards grouped as a single forest class.
New global forest/non-forest map	Shimada et al. (2014)	Global (Tropical forest)	ALOS PALSAR	25 m	No differentiation among forest classes (forest or non-forest).

Source: Adapted from Achard and Hansen (2012).

– the world's largest rain forest, with over 20 types of rainforest ecosystems (Pnuma and Cathalac 2010). Furthermore, the Coordinator of Indigenous Communities from the Amazonian Basin (COICA) estimates that almost 390 indigenous communities with 2.78 million inhabitants are residing in the area (Cordero 2011).

Despite high levels of biodiversity and its importance in terms of ecological resources, the humid tropical forest in Latin America still remains under threat. Internal and external drivers, which include the constant increase in global population and consumption per capita, have direct effects on the forest (Morton et al. 2006). Large multinational companies, land grabbing, and lack of polices and law enforcement are some of the most prominent drivers in tropical deforestation (Rautner, Leggett, and Davis 2013).

3.1. Forest ecoregions and drivers of deforestation

The following characterization of tropical forest in Latin America is based on FAO (2001) terrestrial ecoregions, generated predominantly through a collection of data provided by each country. The FAO 2000 product provides not only a general overview of the distribution of the various forest types throughout Latin America (see Figure 2) but also a general description of each ecoregion. Moreover, the current work only considers

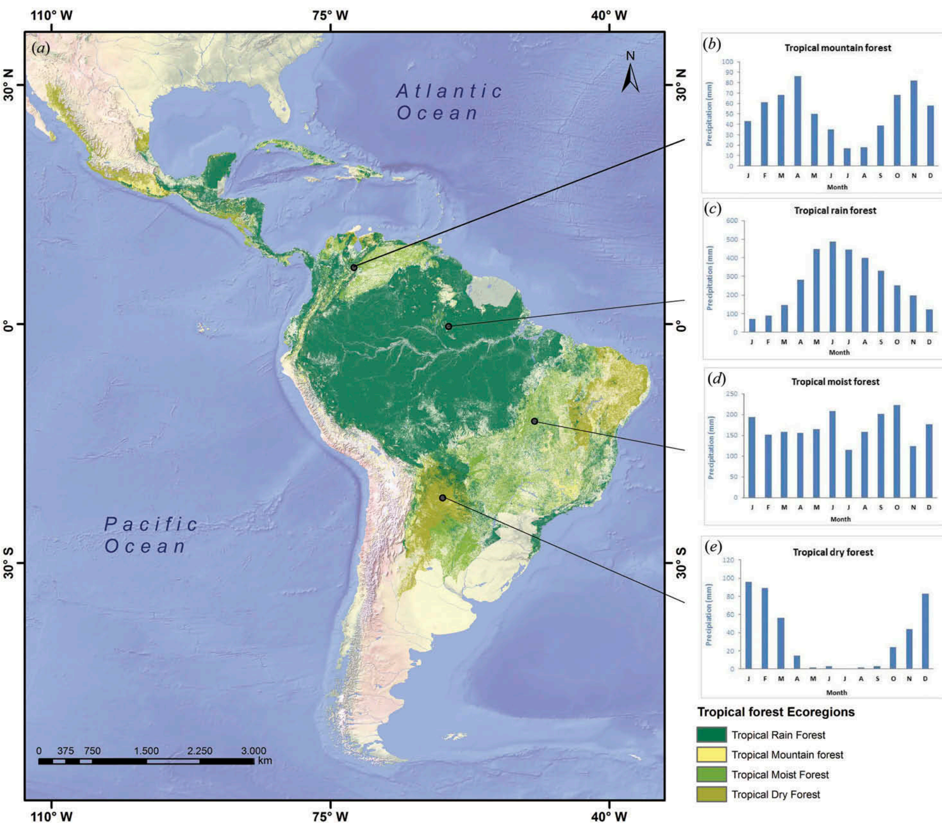

Figure 2. (*a*) Tropical forest cover distribution of Latin America (source: base layers adapted from MERIS GlobCover Project (v.2.2), 2008, FAO FRA 2000 Program (Fao 2001) and Natural Earth (2014)). (*b*)–(*e*) Precipitation diagrams for selected locations (Hijmans et al. 2005).

tropical forest ecoregions: tropical rain forests, tropical moist deciduous forests, tropical dry forests, and tropical mountain domains (see Figure 2).

The largest ecoregion in Latin America is represented by tropical rain forest, which extends to approximately 37% of the South American territory and which covers 2% of Central America (FAO 2001). The Latin American climate varies considerably from south to north. Whilst annual temperatures range from 20°C to 30°C in the south, further north it only reaches a maximum of 26°C. Rainfall, on the other hand, is more frequent in South America, especially in the Amazonian region, varying from 1500 to 3000 mm per year. Vegetation is dominated by evergreen and semi-evergreen trees; uneven age forest stands with canopies reaching almost 40–50 m and a dense sublayer containing trees varying from 5 to 25 m tall. Tree species such as *Cedrela* spp., *Cordia* spp. *Ceiba* spp., *Cordia* spp., and *Swietenia macrophylla* are distributed from north to south. In spite of recent efforts from governmental and non-governmental agencies, the tropical rain forests remain threatened. Illegal logging, agricultural expansion, mining activities, and clearing for pasture are some of the main deforestation drivers identified (Ichii, Maruyama, and Yamaguchi 2003; Ferraz, Capão, and Vettorazzi 2006; Matricardi et al. 2007; Hutchison and Aquino 2011; Aide et al. 2012). For instance, Nicaragua, Honduras, and Peten Guatemala have been historically exploited, especially their semi-green and ever-green forests characterized by valuable hard wood species, such as *Swietenia macrophylla*, *Manilkara*, *Haematoxylum*, and *Red Cedar* (FAO 2001). Further to the south, Morton et al. (2006) documented the conversion of 540,000 ha of forest into croplands during 2001–2004 in the state of Mato Grosso, Brazil.

Following the stratification of FAO (2001), tropical moist deciduous forest is the second largest ecoregion in Latin America. The climate here has similar rates of precipitation; however, it differs from rain forest because of longer periods of dryness (FAO 2001; Olson and Dinerstein 2002). Evergreen seasonal or semi-deciduous forest can be found in drier parts within the outskirts of the Amazonian Basin, Argentina, and Paraguay which even includes tree species up to 30 m tall. Nevertheless, no continuous forest stands along the continent, but indeed in patches along with tree savannahs and shrub lands (FAO 2001). *Aspidosperma polyneuron*, *Balfourodendron riedcianum*, *Cedrela* spp., and *Eschweilera calyculata* are prevalent among tree vegetation. Similar to the ecoregions described above, deciduous forests are highly threatened. In South America, several authors identified that in Bolivia's Tierras Bajas region, 20,000 km^2 of deciduous forest was converted into croplands from the 1980s to the late 1990s (Steininger, Tucker, Ersts, et al. 2001; Killeen et al. 2007). Lack of policies and pressure on food production were identified as the main causes of forest loss during this period.

The FAO ecoregions of mountain forest systems cover over 11% of the Latin American continent (FAO 2001). Variations in altitude and wind direction within mountainous regions result in diversity in both climate and vegetation. For instance, in the highlands of Mexico, broad-leaf forests are more frequent, while in the mountains of Guatemala, where precipitation is well below 1000 mm annually, tree species formations including *Pinus pseudostrobus* and *Quercus* dominate. Furthermore, dense tall forests characterized by Oak or *Lauraceae* species can be found in Costa Rica and Panama at altitudes ranging from 1600 to 3500 m. Further south in the central and northern Andean regions, evergreen seasonal forests are spread within altitudes of 3200–3800 m (FAO 2001). Tree species such as *Alchornea bogotensis*, *Burnellia comocladifolia*, and *Cinchona cuatrecasasii* are common in the Colombian Andes, where the upper montane forest starts at 1800 m and extends up to 3400 m (FAO 2001). The vast tree species

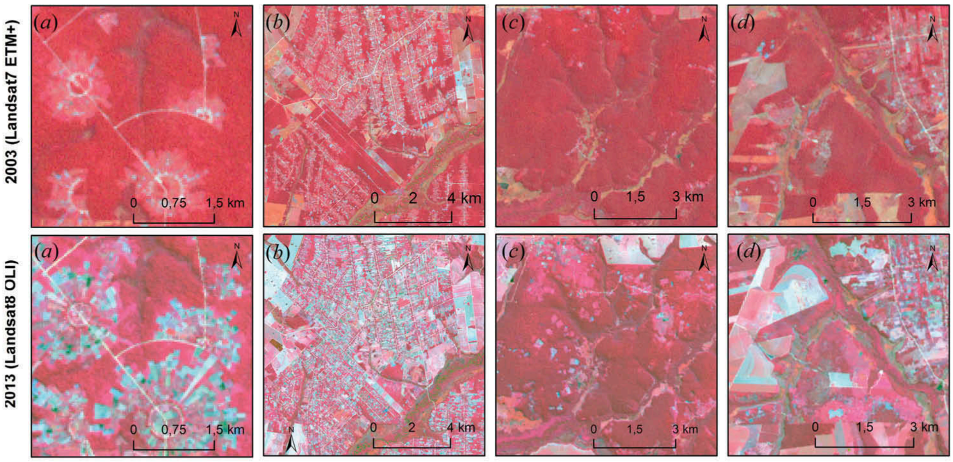

Figure 3. Deforestation pattern examples from the Atlantic Forest in Paraguay based on Landsat images from 2003 to 2007. (*a*) Circle clearing, (*b*) fishbone clearing, (*c*) small-scale clearings, and (*d*) compact clearings. Patterns were based on Roberts et al. (2002), Huang et al. (2009), and Souza and Verburg (2010).

diversity and the richness of the soil of mountainous systems result in different drivers of deforestation. Besides agro-industrial expansion and the illegal logging of valuable tree species, the forest is under intense pressure by human colonization that goes along with illegal cropping activities (Viña, Echavarria, and Rundquist 2004; Armenteras et al. 2006; Etter et al. 2006; Sanchez-Cuervo and Aide 2013). For example, high deforestation rates were experienced between 2002 and 2007 in the northern Andes Chaco and Amazon Forest of Colombia, resulting in a loss of 27,952 and 1160 km^2, respectively. This was primarily due to coca plantations (Dávalos et al. 2011). Figure 3 depicts examples of different patterns of deforestation resulting from different drivers of forest loss.

Extended dry and rainy seasons characterize climate conditions of the last ecoregion: tropical dry forests. Short and semi-deciduous forest dominates the main stratus of vegetation formed by leguminous tree species, such as *Mimosa*, *Caesalpinia*, and *Acacia* (FAO 2001). Alternatively, the Chaco area of South America is characterized by *Schinopsis*, *Aspidosperma*, *Chorisia speciosa*, *Tabebuia impetiginosa*, and *Ruprechtia triflora* originating from a xerophilous forest (FAO 2001). According to Hansen et al. (2013), from 2000 to 2012, tropical dry forests in Paraguay, Argentina, and the Bolivian Chaco were affected by the highest deforestation rates among tropical forest remnants around the world. This is caused by poor soil conditions and a lack of precipitation coupled with agricultural practices that have turned many tropical dry forest areas into focus regions for cattle and ranching activities (Killeen et al. 2007; Gasparri and Grau 2009; Caldas et al. 2013; Mereles and Rodas 2014).

4. Categorization of tropical forest studies employing EO data

For Latin America, a total of 137 articles were found that employed remote-sensing data to derive tropical forest dynamics. The articles focus on major themes such as global and continental characterization (19), deforestation (88), degradation (17), and fragmentation (13). Figure 6(*c*) presents the percentage of articles which included either degradation or deforestation processes; studies related to fragmentation were counted as deforestation studies since fragmentation itself is a negative effect of the deforestation process. The publication period of articles investigated covered time frames from 1989 to 2015. Whereas the number of articles related to deforestation and fragmentation commenced to appear in the late 1980s, articles which studied forest degradation did not appear before the late 1990s. For instance, Skole and Tucker (1993), Alves (2002), Lu, Batistella, and Moran (2004), Southworth, Munroe, and Nagendra (2004), and Ferraz, Capão, and Vettorazzi (2006) assessed deforestation and change patterns over the Brazilian Amazon, focusing on the Rondônia state based on Landsat imagery spanning the years 1978–2002. Souza et al. (2003, 2005), Matricardi et al. (2005), and Wang, Qi, and Cochrane (2005) analysed the degraded forest consequence of selected logging operations in Mato Grosso Brazil using Landsat, SPOT, and IKONOS images covering the years from 1988 to 2006. It is important to remark that degradation studies increased considerably over the years, apparently following the initial stages of development of the REDD programme. The constant difficulties experienced in the definition and detection of degraded forests are often discussed in these articles (Asner et al. 2002; Souza et al. 2003, 2005).

4.1. Spatial patterns

The focus regions of the articles reviewed are presented in Figure 4, in which the numbers of investigations are represented for each country. Nineteen articles were found regarding the global and continental scale. However, most of the studies were carried out at a regional and local level. Almost 84% of the articles were concerned with studies carried out within the South American region. The majority of studies centred on Brazil, with 62 studies focusing on the topics of deforestation, degradation, and fragmentation. Most of these focused on the Brazilian Amazon, particularly in Rondônia and Mato Grosso states, where the majority of the disturbances occur. Other regions of South America, on the other hand, were the subjects of far fewer studies, even though countries such as Paraguay (four articles), Argentina (three articles), and Bolivia (nine articles) still demonstrated remarkable rates of deforestation (Hansen et al. 2013). Further north in Central America, Costa Rica is the subject of the majority of studies (12 studies), many of which focus especially on dry forest ecosystems. Fewer articles were conducted for other countries from the same region such as Mexico (4), Guatemala (2), and Honduras (3). The present review article includes all the countries of Latin America. However, no articles were found for the regions of El Salvador, Panama, Nicaragua, or Cuba. The general trend identified is that the distribution of studies could be related either to the availability of information or to the importance given by the scientific community to a specific region. While Costa Rica and the Amazon Basin have been specified as main sources of biodiversity, carbon stocks, and natural resources, other similar regions have not been given the same importance.

4.2. Applied sensors used to assess forest dynamics

Overall, 17 different satellite sensors were employed by the 137 studies reviewed. The Landsat sensor appears to be the most frequently used satellite in these studies with 66 articles, followed by MODIS (18 studies) and then AVHRR (12 studies). In addition, 20 articles were gathered which implemented other sensors such as SPOT-4 Vegetation, MERIS, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), The China–Brazil Earth Resources Satellite (CBERS), SPOT (high resolution visible, high

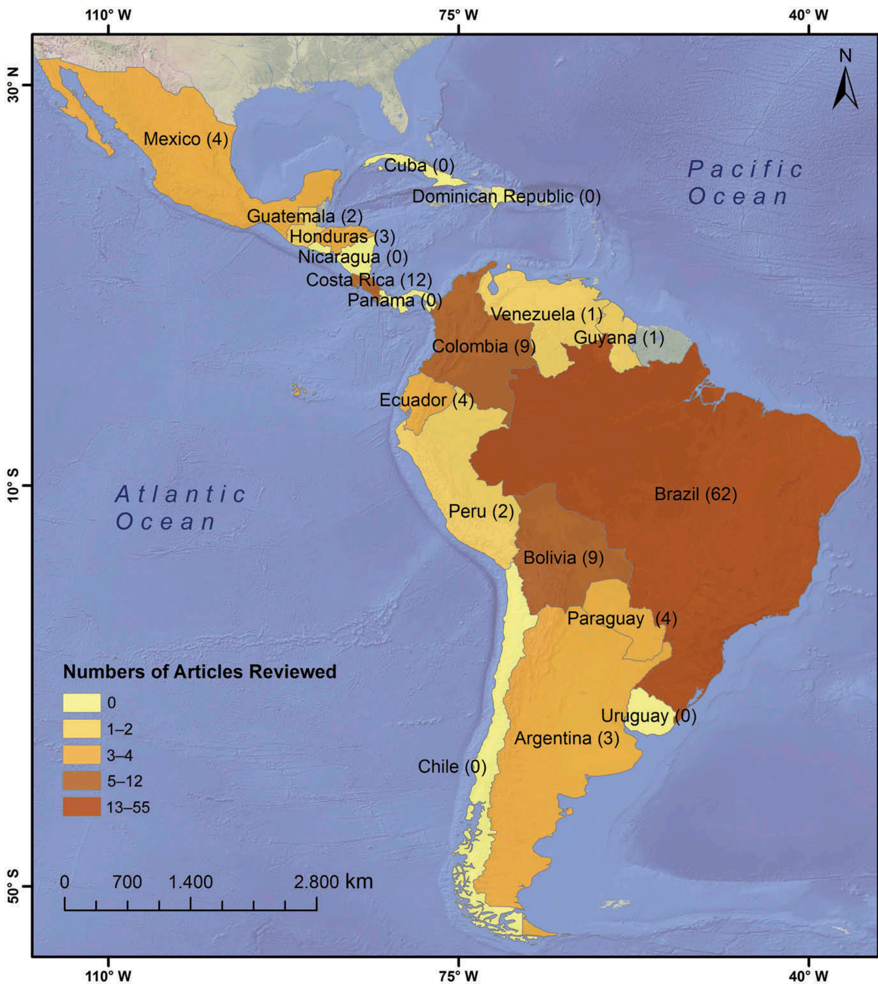

Figure 4. Country focus of studies reviewed. The number of studies per country is represented in parentheses (base layer source: Natural Earth 2014).

resolution geometrical), IKONOS, and QuickBird, which were used less frequently either as a single data set or in conjunction with Landsat imagery. Furthermore, 20 studies applied radar sensors such as European Remote Sensing Satellite (ERS)-1/ERS-2, Japanese Earth Resources Satellite (JERS)-1, Spaceborne Imaging Radar (SIR)-C/X, ALOS PALSAR, RADARSAT 2, and COSMO Sky Med to assess deforested areas principally in the Brazilian Amazon (see Figure 5(*b*)). Since the Amazonian region is characterized by high cloud cover, radar sensors that can penetrate clouds have been favoured in many cases. Most of the studies which evaluated the dynamics of forests at a continental or global scale were based on coarse-resolution data (MODIS and AVHRR) (DeFries, Hansen, and Townshend 2000; FAO 2001; Hansen et al. 2003; Clark et al. 2010), whereas only a few recent studies (Hansen et al. 2013; Shimada et al. 2014) integrated medium-resolution data (Landsat, ALOS PALSAR) to assess changes in the forest at a global scale. For example, Clark, Aide, and Riner (2012) produced an annual land-cover map to analyse the changes exhibited in the dry Chaco ecoregion of South

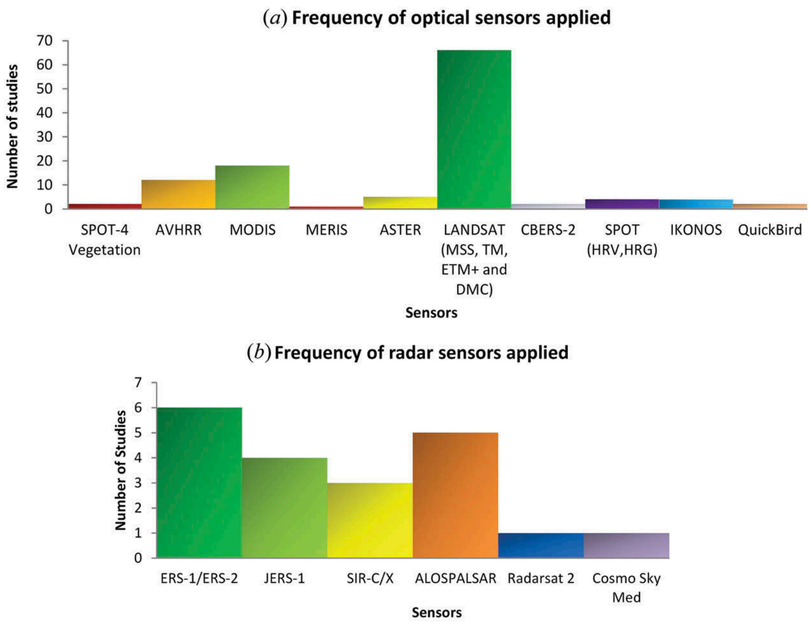

Figure 5. (*a*) Frequency of optical sensors applied in the reviewed studies. (*b*) Frequency of radar sensors applied in the reviewed studies.

America (Paraguay, Argentina, and Bolivia) based on MODIS imagery from 2001 to 2007.

As demonstrated in Figure 5(*a*), the dominant sensor applied in the majority of the studies is the Landsat sensor including the Multi-Spectral Scanner (MSS) sensor, the TM sensor, the ETM+, and the Operational Land Imager (OLI). The Landsat programme started as a joint initiative of the United States Geological Survey (USGS) and the National Aeronautics and Space Administration (NASA). The sheer volume of data available (since 1972), free acquisition, and the favourable spatial (79–30 m), temporal (16 days), and spectral resolution (0.45–0.90 μm) have turned the Landsat sensors into the main source of information for numerous monitoring programme studies (Fagan and Defries 2009). According to the articles reviewed, Landsat images were mostly applied in studies focusing on the monitoring of deforestation (Van Laake and Sánchez-Azofeifa 2004; Hayes and Cohen 2007; Alves et al. 2009), followed by studies focusing on degradation (Almeida-Filho and Shimabukuro 2002; Souza, Roberts, and Monteiro 2005; Matricardi et al. 2005) and fragmentation (Steininger, Tucker, Ersts, et al. 2001; Hansen et al. 2000; Cayuela, Benayas, and Echeverría 2006). Additionally, some studies integrated Landsat imagery with different sensors such as IKONOS, CBERS, ALOS PALSAR, and SPOT in the case of validation, shortage of free-cloud data, or to increment the temporal resolution. For instance, Vollmar et al. (2013) and Ichii, Maruyama, and Yamaguchi (2003) integrated ALOS AVNIR 2 (10 m resolution) and AVHRR (1 km) images to perform multi-temporal cover change analysis, at both regional and continental levels. Both studies intended to fill the missing data from Landsat ETM+. Wang, Qi, and Cochrane (2005) used IKONOS 1-m pansharpened imagery to validate canopy fractional cover maps resulting from ETM + Landsat data. Redo (2012) applied Landsat series data in conjunction with Chinese–

Brazil Earth Resources Satellite (CBERS-2 and CBERS-2B) in order to correct the residual banding distortion from Landsat 7 data and to map land use and land cover change (LULCC) from 1975–2008 in Tierras Bajas, Bolivia. Other approaches combined active and passive sensors as an alternative in obtaining information *not affected* under atmospheric conditions (Salas et al. 2002; Zaloti et al. 2006; Lu et al. 2011; Gutiérrez-Vélez and DeFries 2013; Nascimento et al. 2013). As presented in Figure 5(*b*), the dominant sensor among the radar studies was ERS-1/ERS-2 with six studies, followed by ALOS PALSAR (five studies), JERS-1 (four studies), and SIR-C/X (three studies). A small number of articles were found for the sensors RADARSAT 2 and COSMO Sky Med, with only one study for each sensor. For instance, Reiche et al. (2013) integrated ALOS PALSAR with Landsat images to monitor tropical and forest degradation in the central part of the South American Republic of Guyana. SAR and optical medium-resolution subpixel fraction information were analysed independently and fused with a decision tree classifier to detect tropical deforestation and degradation from 2007 to 2010 (Reiche et al. 2013).

4.3. Spatial scale

Throughout the studies reviewed, different spatial scales have been used to assess changes in forests at local, regional, and global levels (Figure 6(*a*)). Whereas local (65%) and regional (26%) scale studies were found to be more frequent, only a few articles assessed forest variations at a global scale (9%). The majority of articles which fall into this category focused on detecting changes only, as is regularly done for tropical forests around the world (Achard et al. 2002, 2001; Hansen et al. 2004, 2008, 2010, 2013; Huang and Friedl 2014; Shimada et al. 2014). Commonly, this has been done using either wall-to-wall coverage or statistical sampling strategies from medium-resolution (30 m) to

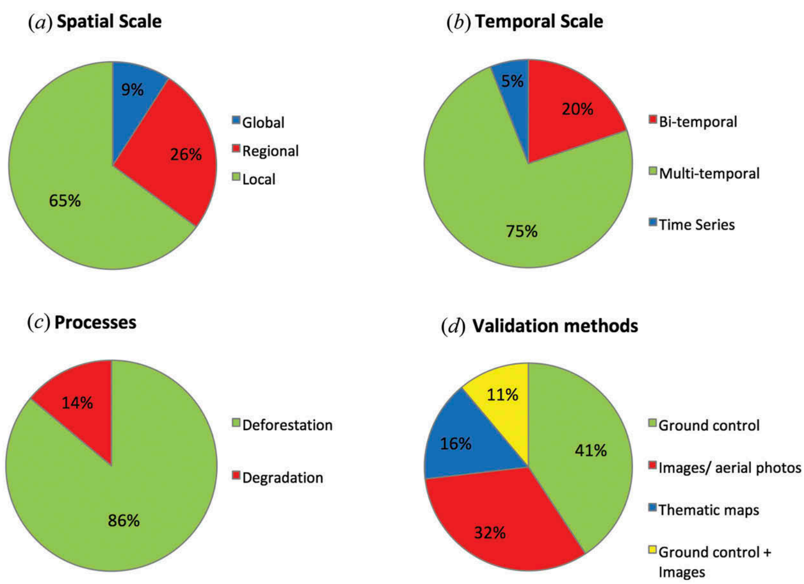

Figure 6. (*a*)–(*d*) Categorization of the studies with regard to spatial and temporal scales, process, and validation methods.

coarse-resolution (1 km) data designed to evaluate global land-cover changes. For instance, a stratified sampling design was implemented by the Forest Resources Assessment (1990) and the Global Resource Assessment 2000 (FAO 2001) to estimate forest cover and deforestation. Remote-sensing surveys in the context of the Forest Resources Assessments for 1990 and 2000 were based on a stratified design which applied predicted deforestation rates to assign further samples into locations where higher deforestation activities were expected. Hansen et al. (2008) employed a stratified sampling design to estimate deforestations from 2000 to 2005 in the pan-humid tropical forest biome applying MODIS (500 m) imagery based on deforestation data extracted from Landsat images to quantify the deforestation per sample block. Recently, Hansen et al. (2013) developed global wall-to-wall forest coverage with a resolution of 30 m by combining the computing power of the Google Earth Engine and the extensive Landsat data archive to process over 650,000 images in order to estimate forest variations in the tropics from 2000 to 2012. Following this effort, a global forest or non-forest map was generated by Shimada et al. (2014) at a resolution of 25 m using annual data sets from 2007 to 2010 based on ALOS PALSAR horizontal transmitting, horizontal receiving (HH) and horizontal transmitting, vertical receiving (HV) polarized L-band data; just like Hansen et al. (2013), the global product aimed at estimating gain and loss of the forest in the tropics.

Assessments performed at the regional scale generally monitored coarser changes in forests, variation patterns, and few studies on degradation. Regional studies vary in scale, considering not only broader areas such as the entire Amazon in Brazil (Alves 2002; Matricardi et al. 2007; Broich et al. 2009) but also the entire country or continent of Latin America (Huang et al. 2007; Killeen et al. 2007; Clark, Aide, and Riner 2012; Sanchez-Cuervo and Aide 2013; Vollmar et al. 2013; Gebhardt et al. 2014). A good example of forest change detection at a continental level is provided by Aide et al. (2012) which implemented a wall-to-wall approach to assess deforestation and reforestation rates over the Latin American continent from 2001 to 2010, using coarse-resolution MODIS data on board Aqua and Terra (250 m). Huang et al. (2007), Killeen et al. (2007), Pacheco, Aguado, and Mollicone (2014), and Sanchez-Cuervo and Aide (2013) studied the natural forest cover lost country-wide for Paraguay, Bolivia, Venezuela, and Colombia by implementing coarse (MODIS) and medium resolution (Landsat) data spanning the years from 1975 to 2010. More centralized regional assessments were often settled over the Brazilian Amazonian region; especially in the states of Rondônia and Mato Grosso (Alves 2002; Carreiras and Pereira 2005; Matricardi et al. 2007; Egler et al. 2013). Principally, medium spatial resolution (30 m) data were applied to identify the patterns which led to the deprivation of forest.

Sixty-five per cent of the articles reviewed (Figure 6(*a*)) were carried out at a local level. Similar to regional studies, the majority of the articles were carried out within the Brazilian region (75% of the studies), mainly covering the states of Mato Grosso, Rondônia, Pará, and Paraná (Di Maio Mantovani and Setzer 1997; Alves et al. 1999; Ichii, Maruyama, and Yamaguchi 2003; Ferraz et al. 2005; Morton et al. 2006; Zaloti et al. 2006; Brown et al. 2007; Wynne et al. 2007; Souza and Verburg 2010; Yoshikawa and Sanga-Ngoie 2011). Local studies were often aiming at understanding the influences of anthropological activities impacting the forest, giving particular attention to agricultural expansion and urbanization (Sierra 2000; Nagendra, Southworth, and Tucker 2003; Armenteras et al. 2006; Morton et al. 2006; Alves et al. 2009; Pinto-Ledezma and De Centurión 2010; Dávalos et al. 2011; Rodríguez et al. 2012). Unlike the global and regional scale, local studies more often address forest degradation (Almeida-Filho and Shimabukuro 2002; Souza et al. 2003, 2005; Souza and Roberts 2005; Matricardi et al.

2005; Wang, Qi, and Cochrane 2005; Maurício et al. 2015) (15% of the studies); smaller study areas permit a finer distinction of the disturbances occurring in the forest. In terms of EO data applied, not only the trend of using medium spatial resolution data (Landsat) prevails, but also the majority of the studies which incorporated radar data (Van Der Sanden and Hoekman 1999; Salas et al. 2002; Zaloti et al. 2006; Servello, Kuplich, and Shimabukuro 2010; Liesenberg and Gloaguen 2013; Rahman and Sri Sumantyo 2012; Reiche et al. 2013; Nascimento et al. 2013; De Azevedo et al. 2014) were carried out at a local level. For instance, Ferraz et al. (2005) used Landsat imagery from 1984 to 2002 to monitor deforested areas in Rondônia state, Brazil. Furthermore, deforestation drivers and patterns were assessed by Cayuela, Benayas, and Echeverría (2006), and Armenteras et al. (2011) covered the Mexico and Colombian highlands based on Landsat images, covering the years 1975–2000 and 1985–2005. Schmidt et al. (1997), on the other hand, applied ERS-1 data to monitor forest dynamics in the Brazilian Amazon spanning the years 1992–1994. More recently, Rahman and Sri Sumantyo (2012) used Shuttle Imaging Radar (SIR – C) and ALOS PALSAR L-band data to quantify deforestation from 1994 to 2004 within the state of Mato Grosso in Brazil.

4.4. Temporal scales

As presented in Figure 6(*b*), variations in forest cover were studied through bi-temporal, multi-temporal, or time-series analysis. Studies which encompassed bi-temporal assessments (Saatchi, Soares, and Alves 1997; Alves et al. 1999; Strozzi et al. 1999; Van Laake and Sánchez-Azofeifa 2004; Shimabukuro et al. 2007; Sesnie et al. 2008; Redo, Joby Bass, and Millington 2009; Mello et al. 2011) basically estimated changes in the forest by comparing TMs previously generated from two satellite images obtained at different points in time. The time span of the majority of the studies varied from 1 to 10 years locally focusing on the Amazonian region and applying medium-resolution data (Landsat). Representative examples are the deforestation maps provided by Skole and Tucker (1993), Alves et al. (1999), and Souza and Verburg (2010) using Landsat images from 1978 to 1988, 1985 to 1995, and 2000 to 2008 to assess deforestation in the state of Rondônia, Brazil. Unlike the studies conducted with medium-resolution imagery, some studies which included radar data assessed changes in the forest considering monthly spans among the images. For instance, Eva, Conway, and D'Souza (1995) and Strozzi et al. (1999) applied ERS-1/ERS-2 sensors to discriminate deforested areas in the Amazon region from May to June (1992) and March to April (1996), with a spatial resolution of 26 m. Recently, Servello, Kuplich, and Shimabukuro (2010) compared TMs obtained from classified RADARSAT-2 polarimetric images acquired in 2008 and 2009 to detect forest conversion in the Pará region of Brazil.

Studies which incorporated multi-temporal analysis made up almost 75% of the studies (see Figure 6(*b*)). Different from bi-temporal assessments, multi-temporal evaluations cover longer time periods not only permitting the quantification of the changes in the forest cover (Alves and Skole 1996; Guild, Cohen, and Kauffman 2004; Sanchez-Azofeifa, Harriss, and Skole 2001; Salas et al. 2002; Viña, Echavarria, and Rundquist 2004; Arroyo-Mora et al. 2005; Cayuela, Benayas, and Echeverría 2006; Etter et al. 2006; Reyes Hernández et al. 2006; Renó et al. 2011; Lima et al. 2012) but also providing information related to the status of the forest (Almeida-Filho and Shimabukuro 2002; Souza et al. 2003; Matricardi et al. 2007; Reiche et al. 2013; Maurício et al. 2015). Overall, the focus of the studies varied with the three main applications: identification and analyses of deforestation patterns (Cayuela, Benayas, and Echeverría 2006; Lira et al.

2012; Rodríguez et al. 2012; Bianchi and Haig 2013; Egler et al. 2013; Bonilla-Bedoya et al. 2014), quantification of forest cover increase and decrease (Tucker and Townshend 2000; Viña, Echavarria, and Rundquist 2004; Cayuela, Benayas, and Echeverría 2006; Michalski, Peres, and Lake 2008; Redo 2012), and assessment of forest degradation (Souza and Roberts 2005; Broadbent et al. 2008; Joseph, Murthy, and Thomas 2011). Similar to the bi-temporal analysis, Landsat imagery was identified as the dominant sensor applied in almost 88% of the studies, whereas MODIS and radar sensors were used less frequently. With regard to the time steps used to distinguish changes between images, different temporal patterns were observed. For instance, some studies evaluated changes in the forest considering regular time intervals between the images (Hayes and Sader 2001; Alves et al. 2003; Ferraz et al. 2005; Shimabukuro et al. 2006; Killeen et al. 2007; Michalski, Peres, and Lake 2008; Marsik, Stevens, and Southworth 2011; Beuchle et al. 2012; Lira et al. 2012; Pessoa et al. 2013; Schmitt-Harsh 2013). For example, annual data from MODIS were used by Hansen, Stehman, and Potapov (2010) to produce global forest change maps covering the years 2000–2005; a quantification of the global gross forest loss was derived from the results. Matricardi et al. (2005) assessed selective logging operations in Mato Grosso, Brazil, by applying annual time-series analysis based on 11-year series of Landsat imagery (30 m) from 1992 to 2002. The authors concluded that multi-temporal analysis made it possible to estimate not only the dynamics of deforested and logged areas but also the interaction among them. Michalski, Peres, and Lake (2008) analysed changes in the landscape of Alta Floresta (Mato Grosso), Brazil, based on a biennial sequence of 11 Landsat images from 1984 to 1998 and 2000 to 2004 with 30 m resolution in order to compare deforestation rates over the years and to estimate the influence of human intervention. Souza et al. (2013) assessed degradation and deforestation rates in the Brazilian amazon over a period of 10 years using annual Landsat imagery from 2000 to 2010. The results obtained from the study demonstrated a significant decline of annual deforestation rates by 46% at the end of 2005 and a 20% increment of annual forest degradation. Based on radar sensors, Filho et al. (2005) evaluated the use of multi-temporal JERS-1 synthetic aperture radar (SAR) images from 1994, 1995, and 1996 in order to assess deforestation by comparing forest covers obtained for every year. Shimada et al. (2014) applied PALSAR images to assess annual rates of deforestation at a global level covering 2007 to 2010. Different from regular temporal intervals, other studies applied irregular time intervals between images acquired. Imagery was selected according to the aim of the study including up to seven time steps over the analysis (Sanchez-azofeifa et al. 2002; Ichii, Maruyama, and Yamaguchi 2003; Armenteras et al. 2006; Rodríguez et al. 2012; Bianchi and Haig 2013; Lu et al. 2013). For example, Viña, Echavarria, and Rundquist (2004) analysed deforestation drivers and rates over the Colombian and Ecuadorian Amazon using Landsat images from 1973, 1985, and 1996, thereby comparing the deforestation rates obtained for each of these years. Also, Reyes Hernández et al. (2006) studied the changes over the forest cover in San Luis Potosí, Mexico, using Landsat data from 1973, 1985, 1990, and 2000 comparing cover maps generated for each year. Sánchez-Cuervo et al. (2012) evaluated the use of multi-temporal ALOS PALSAR data for monitoring the Brazilian Amazon rainforest in the Mato Grosso state based on non-continuous monthly imagery acquired from 2009 to 2011.

Real time-series analyses are less frequent over the literature reviewed (5%), covering local and regional assessments. In the studies reviewed, change detection assessments were conducted in daily, monthly, and yearly intervals (Aide et al. 2012; Clark, Aide, and Riner 2012; Sanchez-Cuervo and Aide 2013; Huang and Friedl 2014). Different from bi-temporal analysis, time series can provide a quasi-continuous history of forest disturbances and regeneration processes. In terms of the sensor applied, time-series analysis was mostly based on MODIS data with near-daily global coverage. A good example is provided by Clark, Aide, and Riner (2012), who assessed land-cover changes (focusing on deforested areas) within all the municipalities in Latin America spanning the years 2001–2010. The authors applied 39 MODIS tiles which cover all the study area calculating annual statistics (minimum, maximum, mean, standard deviation, and range) for three 4-month periods, two 6-month periods, and monthly intervals throughout the 9-year observation period. Similar to Clark, Aide, and Riner (2012), Sanchez-Cuervo et al. (2012) and Sanchez-Cuervo and Aide (2013) conducted a time-series analysis to estimate deforestation hotspots and forest recovery in Colombia based on the same MODIS data set and time intervals applied by the previous study, thereby incorporating annual statistics for the red, near-infrared (NIR), and mid-infrared (MIR) reflectance bands as well as for the enhanced vegetation index (EVI) from 2001 to 2010.

4.5. Methods employed to map and characterize forest cover

Most approaches for the detection of forest cover dynamics require the initial mapping or characterization of forests based on satellite data acquired at the beginning and at the end of the respective period of investigation. Particularly, the early studies thereby delineated forest areas based on visual photointerpretation of satellite imagery and geographic information systems (GISs) as seen in Skole and Tucker (1993), who characterized the forests in the Brazilian Amazon based on photo interpretation of 210 panchromatic photographic images from the Landsat TM from 1978 to 1988 to assess the quality of forests including deforestation and fragmentation processes. The majority of studies, however, use automated, statistical classification approaches of satellite data to identify and differentiate between individual land-cover classes, thereby taking into account their respective spectral properties, textural features, and object characteristics (e.g. size, texture, shape, and context). Particularly useful for the classification and characterization of forests, and vegetation in general, are the contrasting spectral characteristics of photosynthetically active vegetation in the red (from 0.4 to 0.7 μm) and NIR (from 0.7 to 1.1 μm) portion of the spectrum, which forms the basis of nearly every vegetation index. This is why vegetation indices, such as the normalized vegetation index (NDVI), soil-adjusted vegetation index (SAVI), modified soil-adjusted vegetation index (MSAVI), and EVI are, besides the sensor's reflectance bands, the most used input features for classifying forest ecosystems based on optical sensors. But, also the outputs of image transforms such as the higher-order components of principal component (PC) analyses (Hayes and Sader 2001; Hartter et al. 2008; Guild, Cohen, and Kauffman 2004; Yoshikawa and Sanga-Ngoie 2011) or the indices of brightness, greenness, and wetness resulting from a tasselled cap (TC) linear transformation (Crist and Cicone 1984; Schowengerdt 1997; Guild, Cohen, and Kauffman 2004; Hayes and Cohen 2007; Beuchle et al. 2012) are used for improving forest differentiation in advance of change detection studies. Guild, Cohen, and Kauffman (2004), for instance, applied a TC prior to the classification of forest and forest change in Rondônia, Brazil, based on Landsat 5 and Landsat 4 TM data. The TC thereby not only reduced the spectral redundancy of the visible and infrared bands but also enhanced the contrast between intact forests, cleared areas, and regrowth.

Forest classification approaches based on radar sensors differ by bands and polarization. The most frequent bands encountered over the articles reviewed were the L-band (from 15 to 30 cm), C-band (from 4 to 8 cm), and the X-band (from 2.5 to 4 cm) along with HH and HV polarization. The application of different wavelength bands not only results in different spatial resolutions but also shows effects on the capacity to penetrate the land surface and cloud cover. Higher penetration occurs when the wavelength increases, meaning that the L-band is less sensitive to cloud cover and can penetrate deeper into the forests than the C- or the X-band. Generally, forest characterization can be performed by any band available in radar. Overall, shorter wavelengths (2–6 cm) are applied best for detecting tree leaves (canopy). At these lengths, the surface scattering from the soil is minimal and volume scattering prevails. Furthermore, shorter wavelengths are more sensitive to small changes in the surface (e.g. regrowth) and offer more information related to vegetation classes (e.g. forest types). Longer wavelengths (10–30 cm), on the other hand, are more suitable to differentiate forest from non-forest cover due to their deeper penetration into surfaces and less impact by vegetation covers (Achard and Hansen 2012). Particularly, in radar-based studies, textural characteristics of the land surface, i.e. the spatial variation of the image tone as a function of the scale, are important features for the identification and characterization of forests (Servello, Kuplich, and Shimabukuro 2010; Filho et al. 2005; Salas et al. 2002; Shimada et al. 2014; Cutler et al. 2012). Particularly, the well-known occurrence and co-occurrence measures, such as range, mean, variance, homogeneity, dissimilarity, contrast entropy, skewness, second moment, and correlation, are among the most often used texture metrics for classifying radar images (Haralick, Shanmugam, and Dinstein 1973). For instance, Cutler et al. (2012) applied a grey level co-occurrence matrix (GLCM) on JERS-1 (L-band) and Landsat images obtained in 1992 and 1995, respectively, to estimate tropical forest biomass in Manaus Brazil. In this study, the texture measures calculated from the GLCM were entropy, energy, correlation, contrast, dissimilarity, homogeneity, second moment, and variance, which were shown to be very useful to differentiate tropical forest types.

Additional popular features used for classifying forests in Latin America were information on topography, such as elevation, azimuth, slope, or solar duration as derived from digital elevation models (DEMs), first and foremost originating from the Space Shuttle Radar and Topography Mission (SRTM) (Di Maio Mantovani and Setzer 1997; Guild, Cohen, and Kauffman 2004; Sesnie et al. 2008; Yoshikawa and Sanga-Ngoie 2011; Egler et al. 2013; Sanchez-Cuervo and Aide 2013; Souza et al. 2013; Leinenkugel et al. 2014).

Among the reviewed studies, 20% of all studies used unsupervised classification approaches (Tucker and Townshend 2000; Hayes and Sader 2001; Ichii, Maruyama, and Yamaguchi 2003; Souza et al. 2003; Wang, Qi, and Cochrane 2005; Anand 2006; Huang et al. 2007; Killeen et al. 2007; Michalski, Peres, and Lake 2008; Bianchi and Haig 2013; Caldas et al. 2013), whereby the ISODATA clustering algorithm was more popular than the basic *k*-means optimization algorithm. Among the supervised classification approaches (Sánchez-Azofeifa et al. 1999, 2001; Sierra 2000; Nagendra, Southworth, and Tucker 2003; Armenteras et al. 2006; Cayuela, Benayas, and Echeverría 2006; Rodríguez et al. 2012; Lu et al. 2013; Paneque-Gálvez et al. 2013), most studies applied the traditional maximum likelihood classification (Alves and Skole 1996; Sanchez-Azofeifa, Harriss, and Skole 2001; Ferraz, Capão, and Vettorazzi 2006; Redo 2012) followed by conventional non-parametric decision tree algorithms (Roberts et al. 2002; Morton et al. 2006; Marsik, Stevens, and Southworth 2011; Reiche et al. 2013; Pacheco, Aguado, and Mollicone 2014; Sun et al. 2014). Later, with increasing popularity of more-sophisticated machine learning algorithms, Random Forests classifiers (Clark et al. 2010; Aide et al. 2012; Sánchez-Cuervo et al. 2012; Gutiérrez-Vélez and DeFries 2013) were also applied; however, no study on forest cover dynamics for Latin America used modern non-parametric classifiers, such as support vector machines (SVMs) or artificial neural networks (ANNs).

Besides the traditional pixel-based approaches, object-based classification approaches for forest mapping have been used in Latin-America, however only since the beginning of 2010 (Renó et al. 2011; Beuchle et al. 2012; Nascimento et al. 2013; Vo et al. 2013; Gebhardt et al. 2014). Object-based approaches first aggregate image pixels into spectrally homogenous image objects using an image segmentation algorithm and then classify the individual objects. The generation of meaningful objects makes it possible not only to integrate additional spectral information compared to single pixels, but also to include complementary spatial, textural, and contextual object properties to potentially improve the classification accuracy (Blaschke 2010). Nascimento et al. (2013), for instance, used criteria, such as the minimum area of objects, as well as contextual information, such as the distance to the coast or to other classes, to improve the mapping of mangrove forests along the Brazilian coastline. Also, Gebhardt et al. (2014) used a set of object metrics (minimum, maximum, average, and standard deviation) calculated for multi-temporal NDVI metrics, elevation, slope, and aspect, resulting in a total set of more than 200 features per object, which were used for classifying forest-cover and other land-cover classes for the whole of Mexico.

Both pixel- and object-based classifications assume that forest classes are mutually exclusive with discrete boundaries separating each other. Forest ecosystems, though, may vary in space in a continuous manner; this can be observed for example in the gradual transition from forests over woodlands to woody grassland, with the consequence that traditional maps with discrete boundary provide an unrealistic representation of such ecosystems (Foody 1999). Furthermore, particularly when using coarse-resolution sensors, such as MODIS, MERIS, or SPOT-vegetation, for the mapping of heterogeneous and complex forest mosaics, mixed pixels may emerge, where multiple land-cover types occur within the extent of the sensor's projected instantaneous field of view. It has been shown that upon assigning mixed pixels to a specific single type of land cover, results of inferior mapping performance are being obtained (Fernandes et al. 2004; Foody et al. 1997; Friedl et al. 2000; Leinenkugel et al. 2013) and in particular gives rise to an overall underestimation of non-dominant land-cover types (Nelson and Holben 1986; Braswell et al. 2003). Moreover, the classification of continuous quantitative information into discrete labels is implicitly accompanied by information degradation. For most algorithms, this leads to an increase in uncertainty that often remains hidden in the output maps and thus cannot be accounted for during further analysis (Rocchini et al. 2013). In this respect, the use of continuous variables, such as fractional forest cover estimates or biophysical properties such as tree cover at the subpixel level, has proved to be more effective in the quantification and characterization of forest ecosystems, particularly in the case of gradients and mosaics in the landscape (Adams et al. 1995; Carpenter et al. 1999; DeFries et al. 1997; DeFries, Hansen, and Townshend 2000; Fernandes et al. 2004; Hansen et al. 2002, 2005; Tottrup et al. 2007; Gessner et al. 2013). Methods to derive these continuous variables include linear mixture models (Adams et al. 1995; DeFries, Hansen, and Townshend 2000; Scanlon et al. 2002; Lu, Moran, and Batistella 2003; Kuenzer et al. 2008; Kumar, Kerle, and Ramachandra 2008), fuzzy membership functions (Foody and Cox 1994), neural networks (Foody et al. 1997; Carpenter et al. 1999; Braswell et al. 2003; Liu et al. 2004; Liu and Wu 2005), SVMs (Esch et al. 2009; Leinenkugel, Esch, and Kuenzer 2011), and regression trees (DeFries et al. 1997; DeFries, Townshend, and Hansen 1999; Hansen et al. 2002; Gessner et al. 2013). The use of continuous variables for the analysis of forest cover and their dynamics in Latin America however is almost limited to the physically based linear mixture models, such as those applied by Wang, Qi, and Cochrane (2005), Souza et al. (2003, 2005), or Filho et al. (2005). Souza et al. (2003, 2013), Filho et al. (2005), and Roberts et al. (2002), for instance, applied linear spectral unmixing to separate subpixel fractions of green vegetation (GV), non-photosynthetic vegetation (NPV), soils, and shades for studying forest degradation and deforestation in the Brazilian Amazon. Wang, Qi, and Cochrane (2005) by contrast applied a two-component linear model based on the assumption that logged areas consist of only two components, i.e. tree canopies and open areas. The resulting forest canopy fractional cover was then used for identifying forest degradation caused by selective logging in the Amazonian state of Mato Grosso, Brazil. Ichii et al. (2003) in contrast used a multi-scale regression approach to derive continuous forest cover fraction from monthly Pathfinder AVHRR Land (PAL) NDVI layers at 8 km resolution. Therefore, higher-resolution Landsat MSS, TM, and ETM+ data were classified and aggregated to AVHRR resolution to derive Landsat-based forest cover fractions for calibration. A logarithmic relationship between the AVHRR-derived NDVI and Landsat-based forest cover fractions could then be examined, which was finally utilized to estimate the forest cover fraction from the AVHRR-based NDVI data. Also, Hayes and Cohen (2007) used an approach for estimating proportional forest change as a continuous variable for a study site in Central America based on a regression model that relates multispectral, multi-temporal MODIS data to reference change data sets derived from a Landsat analysis.

4.6. *Methods employed to assess forest cover dynamics*

Forest dynamics are defined as the change in the shape and structure of a forest, related to its underlying physical and biological forces. For forest cover dynamics, two main elements are recognized: forest disturbance and forest succession. Forest disturbances are caused by changes induced primarily by fire, flood, human influence (logging), and diseases, whereas forest succession is characterized by the recovery of the vegetation after a disturbance event (GOFC 2010). Several methods have been applied to monitor the dynamics of tropical forests; a summary of the main change detection approaches is presented in Tables 2 and 3.

Early studies (Skole and Tucker 1993; Alves and Skole 1996; Alves et al. 1999; Alves 2002) assessed forest changes by delineating logged areas through on-screen digitalization of disturbed areas based on medium- (Landsat, SPOT) to high- (IKONOS) spatial resolution imagery and GIS. For instance, Alves (2002) assessed the spatial patterns of deforestation in the Brazilian Amazon by manual interpretation of forest clearings based on Landsat MSS and TM images from 1991 to 1997. Manual interpretation has been used not only to quantify clearings in natural forest but also to identify degraded areas resulting from selected logging operations (Matricardi et al. 2005; Souza et al. 2003). While manual interpretation works particularly well for spatial assessments, including geometric, textural, and contextual characteristics of deforestation patterns, and for the general interpretation of direct deforestation drivers, this approach is rather time-consuming and less effective in quantitative, wall-to-wall assessments of forest cover dynamics. Matricardi et al. (2007) tested the performance of an automatic textural algorithm against manual interpretation to identify selective logging operations in the Brazilian Amazon based on multi-temporal analysis of Landsat images obtained in 1992, 1996, and 1999. The author concluded that visual interpretation (92.8%) and automated techniques (90.2%) were equally effective in detecting selectively logged areas. However, visual interpretation

Table 2. Summary of main forest change detection methodologies applied for Latin America.

Location	Purpose	Forest change	Methodology	Study area (ha)	Platform	Resolution	Author
San Luis Potosí, Mexico	Land-cover change from 1973 to 1983, 1985 to 1990, and 1990 to 2000.	Almost 88,055 ha were deforested between 1973 and 2000.	Maximum likelihood supervised classification. Post-classification comparison.	305,600	Landsat MSS, ETM+	60 and 30 m	Reyes-Hernandez et al. (2006)
Northern Guatemala (part of the Maya Biosphere Reserve)	Distinction of spectral change patterns from year to year in response to possible forest disturbance.	Between 2000 and 2003, 187,399 ha cleared.	Visual interpretation and clustering of multi-date NDVI composite imagery. Linear regression analysis.	n/a	MODIS	500 and 250 m	Hayes and Cohen (2007)
Colombian Andes	Estimate deforestation in lowlands and highlands.	Between 1985 and 2005, 1,477,932 of forest cover lost.	Mixed digital supervised classification with on-screen visual interpretation. GIS overlay.	28,772,000	Landsat MSS, ETM	60 and 30 m	Armenteras et al. (2011)
Machadinho d'Oeste, Northeastern Rondônia state, Brazilian Amazon basin	Explore the application of linear spectral mixture analysis to detect land-cover changes.	Changes from 1994 to 1998 are mainly from the mature forest deforestation; 56.93% (14.63% from mature forest to successional vegetation and 42.3% from mature forest to crop lands).	Fractional images based on spectral mixture models tree decision tree classifier. From–to change detection using pixel-by-pixel comparison.	100,000	Landsat TM	30 m	Lu, Batistella, and Moran (2004)

(*Continued*)

Table 2. (*Continued*).

Location	Purpose	Forest change	Methodology	Study area (ha)	Platform	Resolution	Author
Paraguay	Forest loss assessment for the entire Paraguayan region.	Between 1970 and 2000, the Atlantic Forest ecoregion lost almost 75% of the cover. Between 1990 and 2000, Chaco area lost 16.23%.	Hybrid method applying iterative clustering-supervised labelling method (including unsupervised ISODATA clustering and supervised). Systematic sampling approach to assess changes from 1970 to 1990. Final wall-to-wall change map.	40,675,200	Landsat TM MSS	30 m	Huang et al. (2009)
San Julian District, Santa Cruz, Bolivia	Deforestation and fragmentation patterns assessed by satellite images.	Between 1976 and 2006, the forest lost around 382,276 ha.	Unsupervised ISODATA clustering for classifying the images. Relationship of Puyravaud (2003) to estimate deforestation rates.	n/a	Landsat TM, ETM	30 m	Pinto-Ledezma and De Centurión (2010)
Southeast to Amazon River, São José Bay, Brazil	Inclusion of SAR data and object-based approach to assess changes along the Brazilian coastline.	Between 1996 and 2008, the area of mangroves decreased by 121,300 ha.	Object-based segmentation and classification. Comparison of the resultant maps.	759,100	JERS-1 SAR and ALOS PALSAR	18 and 20 m	Nascimento et al. (2013)

Ji-Paraná Rondônia state, Brazil	Combination of Landsat and NOAAVHRR data to assess deforestation.	Around 30% of the study area was deforested between 1973 and 1999.	Unsupervised classification, forest fraction cover analysis. Change detection assessed based on image comparison.	3,422,500	Landsat MSS, TM ETM+. and NOAA/ AVHRR	30 m and 8 km	Ichii, Maruyama, and Yamaguchi (2003)
Mato Grosso, Brazil	Integration of GIS and NOAA/AVHRR to assess deforestation dynamics.	The study demonstrates that 76.1% of the changes in the forest occur 30 km from the paved roads.	Extraction of the dominant characteristics of the vegetation distribution by PC analysis. Unsupervised classification and GIS overlay to assess the changes.	90,338,600	NOAA/ AVHRR	8 km	Yoshikawa and Sanga-Ngoie (2011)

Table 3. Summary of main methodologies to assess forest degradation for Latin America.

Mapping approach	Studies	Sensor	Location	Objective	Advantages	Disadvantages
Visual interpretation	Stone and Lefebvre (1998).	Landsat TM	Pará state, Brazil	Mapping the total area logged	No complex image processing methodologies required.	The intensive work required when dealing with larger areas might bias the results.
Combination sensing with GIS (detection of logging areas and buffer zones)	Souza and Barreto (2000), Matricardi et al. (2001)	Landsat TM and ETM +	Pará state, Brazil. Brazilian Amazon	Mapping the total area logged (clearings, canopy damage, and untouched forest)	Easy to apply. Provides a satisfactory estimation of the total area logged.	The actual shape of the logged area has been accurately represented by the buffer zones.
Textural analysis	Asner et al. (2002), Matricardi et al. (2007)	Landsat TM and ETM +	Pará state, Brazil. Brazilian Amazon	Assessing selective logging	Fully automated process and easy to implement.	Canopy damage caused by tree falling is difficult to detect.
Decision tree	Souza et al. (2003)	SPOT 4	Pará state, Brazil.	Assessing canopy damage caused by logging and burning	No complex classification rules.	Classification rules may differ along the landscape. It has not been tested in larger areas.
Change detection	Souza and Roberts (2002)	Landsat TM and ETM+	Brazilian Amazon	Assessing canopy damage caused by logging and burning	Improves the detection of canopy-damaged areas.	Anthropogenic and natural forest changes are considered to be together. Two pairs of images are required
Image segmentation	Graça et al. (2005)	Landsat TM	Mato Grosso region, Brazil	Mapping the total area logged (clearings, canopy damage, and untouched forest)	Easy to apply. Provides a satisfactory estimation of the total area logged.	Classification rules may differ along the landscape. It has not been tested in larger areas.

CLAS	Asner et al. (2005, 2006)	Landsat TM and ETM+	Brazilian Amazon	Mapping the total area logged (clearings, canopy damage, and untouched forest)	Standardized for large areas and highly automated.	Intensive computation processing and pair images required.
NDFI	Souza and Roberts (2005)	Landsat TM and ETM+	Brazilian Amazon	Mapping the total area logged (clearings, canopy damage, and untouched forest)	Improves the detection of canopy-damaged areas.	Anthropogenic and natural forest changes are considered together. Has not been tested in larger areas.

approaches were considered to involve a far greater workload and the precision of the final product was associated with the skills of the interpreter.

A rather simple but very effective approach to identify and evaluate forest cover dynamics is the post-classification comparison. The post-classification approach is performed by generating independent classification results from two images obtained in different time periods and subsequently compared pixel-by-pixel or object-by-object (Sesnie et al. 2008; Hayes and Sader 2001; Van Laake and Sánchez-Azofeifa 2004; Arroyo-Mora et al. 2005; Huang et al. 2007; Pinto-Ledezma and De Centurión 2010; Servello, Kuplich, and Shimabukuro 2010; Souza and Verburg 2010; Lira et al. 2012; Bianchi and Haig 2013; Caldas et al. 2013; Pessoa et al. 2013). By effectively tagging the classification results, a comprehensive matrix of change is generated and change classes can be labelled by the expert. The strength of this approach lies in its capacity not only to identify change but also to gain specific information on what has changed, e.g. forest to grassland (from–to change). However, this approach can only be applied in a bi-temporal manner and therefore requires multiple bi-temporal comparisons when more than two time points are compared. As an example, Reyes Hernández et al. (2006) studied the changes in forest cover and land use in San Luis Potosí, Mexico, from 1973 to 2000. The study applied a multiple bi-temporal comparison of paired Landsat images from 1973 to 1985, 1985 to 1990, and 1990 to 2000 to obtain changing rates from forest cover and land use over time.

However, this approach requires highly accurate base maps, since errors caused from misclassifications of the individual maps will multiply in the final change map (Hussain et al. 2013); particularly in land-cover maps derived from low-resolution sensors, uncertainty levels often are higher than levels of area changes. As a consequence, post-classification comparisons based on low-resolution sensors frequently result in large proportions of spurious change (Achard and Hansen 2012; Herold et al. 2008; Kuenzer, Leinenkugel, et al. 2014), hampering the identification or real changes in the ground. Furthermore, traditional classification, where each pixel belongs to the class it most closely resembles, prohibits the identification of gradual processes over time, as evident in the case of forest degradation or selective logging or when forest cover within a coarse-resolution pixel is successively converted or removed over periods of several years. By contrast, change detection approaches based on continuous variables permit the differentiation of gradual changes at a pixel level and incorporate information associated with the quality of the stand. Recent change detection approaches on continuous variables identify change by the well-established image algebra approach (Borak, Lambin, and Strahler 2010; Haertel, Shimabukuro, and Almeida-Filho 2004; Hansen and DeFries 2004; Leinenkugel, Esch, and Kuenzer 2011), whereby a difference image is calculated from the data sets of two respective dates and a threshold is set to differentiate between significant and insignificant changes. Typically, the threshold is based on a multiple of the difference image standard deviation, based on the assumption that change pixels generally represent outliers within the difference image (Hansen and DeFries 2004). Greenberg et al. (2005) applied image differencing over the neo-tropical rain forest in the National Park Yasumi located in the eastern region of Ecuador based on multi-temporal analysis of seven Landsat scenes between 1993 and 2002. As continuous variables, the authors derived shadow fractions from the Landsat data being more sensitive for vegetation-to-vegetation and vegetation-to-non-vegetation changes in comparison to ordinary vegetation indices. Lighter regions (less shadow) were indicative of anthropogenically disturbed areas while darker regions (more shadow) were indicative of late successional forest. Finally, the individual shadow fraction images were pairwise compared and a deforestation occurrence was identified on a pixel basis when more than three standard deviations of the shadow fraction difference image were observed.

Besides the simple image-differencing technique also more complex relative change detection methods were developed for the identification of forest dynamics that are applied directly on the surface reflectance bands. Spectral–temporal transform approaches, such as PC analysis (Hayes and Sader 2001; Guild, Cohen, and Kauffman 2004), for instance, were applied to multi-temporal image stacks in order to extract patterns indicative of change over time. Guild, Cohen, and Kauffman (2004), for instance, tested three methods of change detection to map deforestation and land-cover change among 1984, 1986, and 1992 in Rondônia, Brazil, based on three Landsat 4 and Landsat 5 TM scenes. The three indices of brightness, greenness, and wetness resulting from a TC transform formed the basis for a nine-layered multi-date TC data stack. Furthermore, a PC transform was applied on this data stack to further highlight land-cover changes evident in the resulting component layers. Finally, the multi-temporal TC data stack, a manual selection of three PC layers, as well as two difference images of the TC image date pairs were each classified based on a maximum likelihood classification for the identification of land-cover changes. The authors conclude that the multi-date TC composite classification had the best accuracy in identifying forest dynamics.

Most of the studies reviewed analyse forest dynamics on a bi-temporal basis or for only a few points in time. However, continuous time series of low- to medium-resolution sensors, such as MODIS or Landsat, theoretically allow for a quasi-continuous reconstruction of forest disturbance and regeneration histories over observation periods of several decades. However, only very few studies actually exploit the large potential of continuous spectral–temporal trajectories for the detection and analyses of forest dynamics, as seen in Huang et al. (2010), Kennedy, Yang, and Cohen (2010), Griffiths et al. (2013), and Leinenkugel et al. (2015). Among the studies reviewed, only four authors applied real trajectory-based or time-series-based analyses (Aide et al. 2012; Clark, Aide, and Riner 2012; Sanchez-Cuervo and Aide 2013; Huang and Friedl 2014). Clark, Aide, and Riner (2012) applied 250 m MODIS time-series data at 16-day intervals to produce annual land-cover maps for Latin America and the Caribbean between 2001 and 2010. Finally, land-cover proportions were calculated for individual municipality- and biome-zones and a linear regression model was applied to these statistics to identify trends in land cover over the 10-year observation period. Sánchez-Cuervo et al. (2012) and Sanchez-Cuervo and Aide (2013) applied the same data basis and methodological approach to statistically identify land-cover trends and hotspots of land-cover change at varying scales (country, biome, ecoregion, and municipality) over the same 10-year period for Colombia. Huang and Friedl (2014) tested a distance metric-based change detection method for identifying changed pixels at annual time steps using 500 m MODIS time-series data. The approach utilizes distance metrics to measure the similarity between a pixel's annual time series to annual time series for pixels of the same land-cover class as well the similarity between annual time series from different years at the same pixel. The developed method successfully identified pixels affected by logging and fire disturbance in temperate and boreal forest sites in Mato Grosso, Brazil. Hayes and Cohen (2007) by contrast performed an analysis to highlight the distinct spectral change patterns from year-to-year in response to the possible land-cover trajectories of forest clearing, regeneration, and changes in climatic and land-cover conditions through an analysis of six dates (2000–2005) of Landsat data for a study area located in northern Guatemala. Ferraz, Vettorazzi, and Theobald (2009) prepared an 18-year Landsat TM and ETM+ time series in biennial intervals to examine the aspects of tropical deforestation through rates and patterns of change. Furthermore, the authors developed four trajectory-based metrics, i.e. annual deforestation rate, secondary forest mean proportion, mean time since deforestation, and deforestation profile curvature, to measure historical changes. The authors concluded that the tested indicators were able to represent the main temporal land-use changes considered related to deforestation, cumulative effect, and forest regeneration. Others studies in Latin America also use continuous time series for analysing forest dynamics over long time periods, such as Roberts et al. (2002), Alves et al. (2009), Morton et al. (2006), Hartter et al. (2008), or Marsik, Stevens, and Southworth (2011). However, these studies actually do not apply trajectory-based methods for detecting forest dynamics at a pixel level. Instead, forest cover proportions for the study area are aggregated for each year and the long-term trajectory of forest cover proportions for the entire study area was interpreted by the authors.

5. Forest cover dynamics within the Atlantic Forest and Chaco areas of Paraguay

The following section provides a comprehensive overview of the deprivation of the forest in the Paraguayan region over the last 40 years. A closer look into the rates of deforested areas, importance of the ecosystems affected, and the scarce number studies which applied EO to analyse the changes is provided. The aim of this section is to emphasize the significance of spreading the study areas over the Latin American continent in regions equally important and threatened as the Amazonian rain forest.

Paraguay has lost the majority of its natural forest cover in just 40 years, presenting one of the highest rates of deforestation in the world. Annually, forest losses were estimated to be approximately 1.64% from 1984 to 1997 and 0.9% until 2011 (Hansen and DeFries 2004; FAO 2011). Recent estimations demonstrate the remaining forest cover in Paraguay at 17.58 Mha – spanning almost 44% of the total land area of the country. Further analysis revealed that 80% of the remaining forests were located within the western region of the country, an area characterized by poor soil conditions and extended dry seasons not suitable for agriculture, as it covers 60% of the country's surface but contains less than 5% of the population (Macedo and Cartes 2003). Unlike Paraguay's western region, the eastern area of the country possesses less than a quarter of the forest coverage, with the vast majority of the population and also includes the Atlantic Forest ecoregion. The following section provides a brief characterization of the Paraguayan regions, deforestation drivers, and a review of the approaches implemented in order to assess variation in the forest cover using optical data.

5.1. Site characterization

Paraguay is located in the heart of South America, located between 19º 18′ and 27º 36′ S and 54º 19′ and 62º 38′ W. The country has a total area of 406,752 km^2, neighbouring Brazil, Argentina, and Bolivia. Geographically, it is divided into two natural regions: the Oriental (eastern) region, which has a surface of 159,827 km^2, and the Occidental region (western), containing a total area of 246,925 km^2. The eastern part of the country is characterized by a high variety of physical and geographical aspects, containing forest, grasslands, and the vast majority of the country's croplands. Furthermore, it encompasses remnants of the Atlantic Forest ecoregion, one of the largest areas for biology conservation (Di Bitetti, Placci, and Dietz

2003). According to an analysis carried out by WWF based on data related to biodiversity, it is acknowledged that the Atlantic Forest is one of the most complete ecoregions in the world (Di Bitetti, Placci, and Dietz 2003), with around 20,000 plant species and almost 13,000 fish vertebrate species (Mittermeier et al. 1999). The Atlantic Forest is a combination of 15 ecoregions, starting from the Atlantic coast of Brazil, passing through the eastern region of Paraguay, and finally reaching the northwestern region of Argentina. Nevertheless, the Atlantic Forest is one of the most threatened tropical rain forests at the moment; only 7% of the original cover remains (Di Bitetti, Placci, and Dietz 2003). The biggest area of the forest within the 15 ecoregions is located in the Atlantic Forest of Upper Paraná, spanning an area of 471,204 km^2. One of the major aquifers in the world is located under the Atlantic Forest of Upper Paraná, almost 1.2 million km^2, which includes approximately 40,000 km^2 of freshwater (Di Bitetti, Placci, and Dietz 2003). By 1945, the Atlantic Forest of Upper Paraná in Paraguay covered almost 55% of the eastern region of the country (that is approximately 8.806 Mha); however, nowadays, only 13% of the forest cover remains (Fleytas 2007).

The Occidental region of Paraguay, also known as the Gran Chaco region, is well known for being one of the major wooded grasslands in central South America. The Gran Chaco is shared by four countries (Argentina, Brazil, Bolivia, and Paraguay) and is thus considered to be the second largest biome in South America, after the Brazilian Amazon. The general climate of the Chaco demonstrates a remarkable variation in precipitation and humidity, differing from east to west, resulting in higher humidity near Rio Paraná in Paraguay, Argentina, and Brazil (Mereles and Rodas 2014).

The aridity of the region increases towards the West, reaching the driest part along the Andean foothills. In spite of its dryness, the area is also known for its wetlands, which can be found in some parts of the Paraguayan Chaco. The precipitation of the region is rather low compared with the Oriental region of the country, varying from 600 to 1000 mm annually. The dominant vegetation throughout is woodland, also known as thorn forest and grassland. The most commonly found tree species within the area are *Prosopis* spp. *Parkinsonia* and *Tabebuia* spp. (FAO 2001). During the period from 1985 to 1990 and 1996 to 2001, around 9% (6858 km^2) of the original forest cover was lost. Although the rates of deforestation are less than that of the Oriental region, the loss was considered to be in relation to the population density; only 2% of Paraguay's inhabitants settle within the western region.

5.2. Deforestation drivers and the actual state of the forest

Between 1945 and 1975, intensive wood harvesting activities took place in the eastern region of Paraguay primarily due to the vast amount of forest concentrated there. Most of the harvesting activities were concentrated in the areas of Concepcion, Upper Paraná, Caaguazú, Amambay, San Pedro, and Itapúa (regions of the Atlantic Forest of Alto Paraná). The process of deforestation increased in the early 1950s, due to a process of agricultural expansion, human settlements, and especially colonization programmes (Fleytas 2007). During the government regime of General Alfredo Stroessner (1954–1989), intensive programmes for the agricultural development of the land were introduced which thus reduced pressure on the central areas of the Oriental region. The areas that were considered to be empty or without appropriate utilization were promoted by the state, in order to initiate the colonization, without consideration of the indigenous inhabitants of these areas. This programme was imposed without any consensus or participation of local communities (Fleytas 2007). Law 854 of the Agrarian Statute established in 1963 recognized the right to the exploitation of the lands for agricultural purposes – including lands with forest cover tagged under the name of 'wastelands'. The lack of appropriate definition of land that is indeed suitable for production or conservation was one of the main factors in deforestation over the years (Fleytas 2007). After the implementation of the colonization programmes and the agricultural expansion, the rates of deforestation in Paraguay were over 2000 km^2 per year and it thus became one of the countries with the highest rates of the deforestation at an international level (Macedo and Cartes 2003). The process of deforestation occurred in the Oriental region during the early 1940s until the late 1980s, resulting in the loss of 4,900,000 ha of forest (around 123,000 ha per year). During the 40-year span, the peak in deforestation (1968–1976) saw 212,000 ha of forest logged per year. Further studies demonstrated that the remaining forests were constituted by residual patches (32.2%) and low commercial value stands (68.8%). Although not as severe as in the Oriental region during this period, deforestation rates within western areas reached almost 45,000 ha per year (Mereles and Rodas 2014). Following the early 1990s, the forest continued to disappear at an alarming rate. By the end of 1991, 32% of the eastern region was covered by forest (45,000 km^2 approximately); however, by the end of 2001, this was reduced to 22%. Most of the forest loss was attributed to the conversion of forest to agricultural lands, timber harvesting, and small scale invasion into forests by rural settlers (Guyra study under the supervision of Maryland). More recent studies carried out by the Forest Engineering Faculty of the National University of Asuncion-Paraguay, in consortium with the Forestry and Forest Products Research Institute (FFPRI) from Japan, applied supervised classification over Landsat 5 images to estimate the forest cover of the Atlantic Forest region for the years 1990, 1995, 2000, 2005, and 2011 (Figure 7). The resultant analysis exhibited that approximately 1,550,000 ha of the forest was logged during the study period, whereas the Occidental region presented an annual rate of approximately 174,000 by 2008 (Caldas et al. 2013). According to several authors, it is important to establish not only the direct drivers affecting the forest, but also the external factors that are equally crucial, such as failures within the environmental policies, extensive corruption associated with lack of monitoring programmes and conservation laws (JICA 2002; Yanosky and Cabrera 2003; FAO 2004; Quintana and Morse 2005; Wright et al. 2007).

Only a few articles which encompassed the Paraguayan territory were found during the review. A total of four studies (Huang et al. 2007, 2009; Caldas et al. 2013; Mereles and Rodas 2014) were carried out in the country itself and three additional studies (Gasparri and Grau 2009; Clark et al. 2010; Hoyos et al. 2013) were conducted in the border between Argentina and Paraguay. Although variations in the forest cover have been assessed continuously by NGOs (WWF and Guyra Paraguay) and governmental institutions (National Forestry Institute and Ministry of Environment) no publications of the results were found within indexed journals. Most of the outcomes from the investigations are only available in internal reports of the institutions.

6. Discussions

In the previous sections, an overview of the remote-sensing approaches on tropical forest dynamics in Latin America was provided. In the following section, we summarize and discuss the main findings of this review article along with the resultant needs of further studies on the dynamics of tropical forest in Latin America. The emerging needs of studies are addressed not only to the scientific community dealing with innovative remote-sensing approaches, but also to environmental programmes, policymakers, and conservation institutions which rely on this valuable information to develop further strategies and policies.

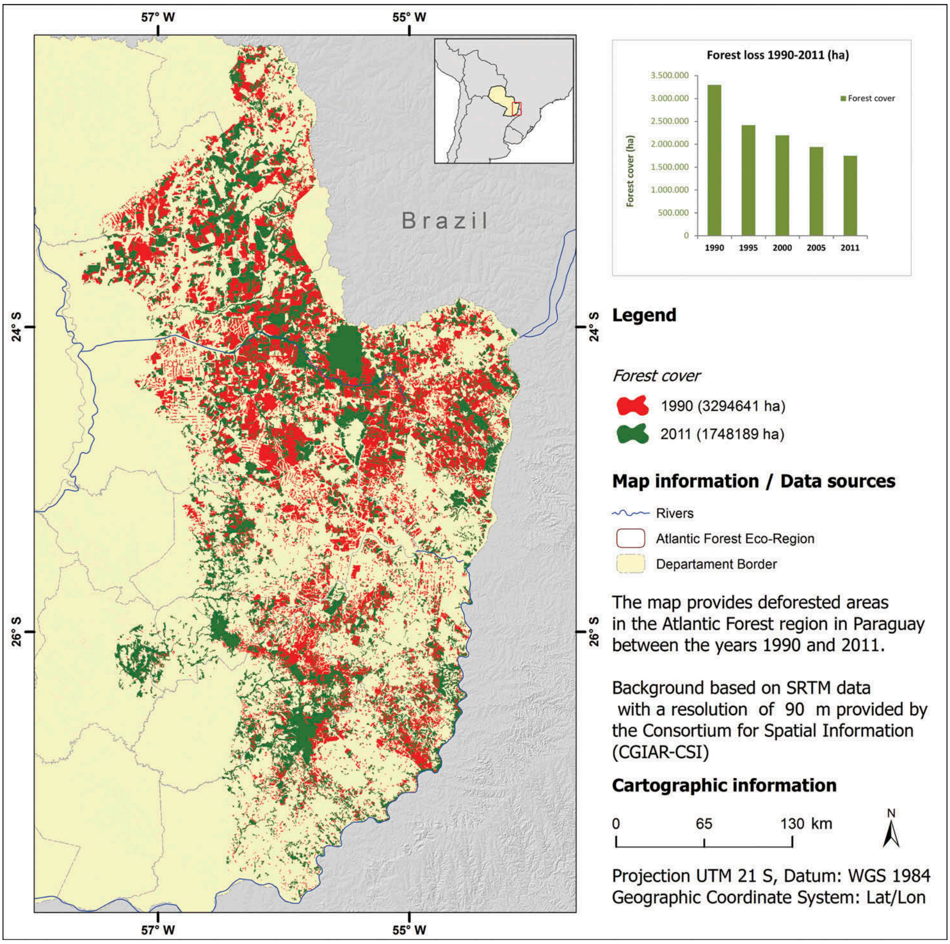

Figure 7. Atlantic Forest loss between the years 1990 and 2011 (Source for the forest cover layer for 1990 and 2011: FFPRI project and the Department of Statistics, Surveys and Census).

6.1. Summary of main findings and results

Within the articles reviewed, several products were obtained from the different approaches discussed previously. For instance, global forest products became available in the earliest 1990s from coarse-resolution imagery (MODIS, AVHRR, or MERIS) varying from 1 km to 300 m resolution. More recent improvements in change detection procedures allowed the generation of global forest change products with higher resolutions, varying from 30 to 25 m based on Landsat and ALOS PALSAR L-band HH and HV polarization data (Hansen et al. 2013; Shimada et al. 2014). The vast majority of the articles focused on the understanding of deforestation and degradation processes, identifying change patterns, hotspots, and drivers. As mentioned repetitively within several sections in this article (Sections 3.1, 4.3, 4.5, 4.6, and 5.2), the constant advance of agricultural crops over natural areas still remains as the main threat affecting the forest in Latin America. In terms of EO data applied, the Landsat satellite was by far the most used sensor (see Figure 6(*a*)). Other EO data less used such as ASTER, CBERS, IKONOS, QuickBird, and SPOT were incorporated primarily to fill in the gaps not covered by the Landsat satellites, or as means of validation. Similar to the sensors cited above, studies which applied radar data (ERS-1/ERS-2, JERS-1, SIR-C/X, ALOS PALSAR, RADARSAT 2, and COSMO Sky Med) were scarce and were mainly conducted in the Brazilian region. As observed in Figure 5(*b*), most of the radar studies were carried out with ERS-1/ERS-2 data at a local level based on bi-temporal approaches to identify forest cover changes.

Over the articles reviewed, deforestation and degradation maps were obtained by applying a variety of change detection methods (as described earlier in Section 4.6); the methodologies differed from each other according to the data available and the main objective of the research. The change detection technique is an inclusive procedure that requires the cautious consideration of each step: the objective of the change detection analysis, selection of remotely sensed data, image processing, extraction of variables from satellite imagery, selection of suitable change detection technique, and final evaluation of the results. Overall, deforestation maps were obtained through manual interpretation, TMs, or continuous variables conducting bi-temporal, multi-temporal, or real time-series analysis. The inclusion of continuous variables such as vegetation indices, subpixel vegetation fractions, continuous fields of tree cover, PCA components, or TC metrics has clearly improved classification accuracies and change detection precision.

Contrary to deforestation, degradation analysis was more difficult to accomplish. First, forest degradation must be mapped within a short period of time, since the spectral signatures of the disturbed forest becomes less distinct already after the first year. Second, forest degradation can be confused with natural disturbances such as seasonal changes or wind throws. Third, lack of economic resources designated for capacity building on the management and operation of algorithms and software's capability to detect degraded forest. Even though over the articles, a standardized protocol to assess forest degradation was not found, several methodologies which included fraction images (GV, NPV, soils, and shades) and other continuous variables (NDVI, SAVI, MSAVI, PC, and TC) as well as textural metrics successfully detected logged areas expanding the detection time up to 3 years after the disturbance occurrence.

Generally, the validation of classifications and the forest change maps was achieved through ground control data as presented in Figure 6(*d*). When true ground data were not available, alternative methods such as the use of high-resolution imagery (ASTER, IKONOS, Quickbird, SPOT), aerial photography, or previous knowledge from experts of the area were often applied. Even though these substitution methods were shown to improve the accuracy of the results, some authors agreed that ground control data remain as the most effective method (Wang, Qi, and Cochrane 2005; Achard et al. 2010).

6.2. Current needs and challenges

Presently, there is an ongoing necessity for more accessible, fast, and precise information on the world's forest dynamics among the scientific community, environmental institutions, monitoring programmes, and governmental entities. The vast majority of the articles reviewed responded to at least one of the following questions: Which type of vegetation cover is changing and at what rate? What are the causes and factors of deforestation? Are these causes natural or anthropological (Yoshikawa and Sanga-Ngoie 2011)? Despite constant advances in remote-sensing technologies, the data generated so far appear not to be sufficient to satisfy the growing demand for information in terms of spatial extent, temporal resolution, and availability. For instance, deforestation and degradation processes occur on a daily basis and on different scales all over Latin America; yet many countries do not have the economical means or governmental support to introduce monitoring programmes addressed to assess disturbances of the forest. An exception is the Brazilian governmental project 'Programa Despoluição de Bacias Hidrográficas or Basin Restoration Program' (PRODES), carried out through INPE, which monitors the forests over the Legal Amazon region (GOFC-GOLD 2010). The programme produces annual wall-to-wall forest cover maps based on Landsat imagery (GOFC-GOLD 2010), covering an area of approximately 5 M km^2 using a minimum unit area of 6.25 ha. Complementary to PRODES, since May 2005, the Brazilian government implemented a near real-time monitoring system called Detecção de Desmatamento em Tempo Real (DETER), capable of detecting forest disturbances larger than 25 ha (GOFC-GOLD 2010) in a 15-day interval on the basis of MODIS and CBERS satellite data. In addition, in 2008, a new programme was introduced, called Mapeamento da Degradação Florestal na Amazônia Brasileira (DEGRAD), to assess degradation particularly from selectively logged operations by using Landsat images and CBERS. Even though these programmes have been successfully monitoring the forests for over 15 years (PRODES), the large amount of data, human resources, and financial resources required to operate such a system is far beyond affordability for other Latin American countries.

With regard to the spatial resolution of current satellite sensors, coarse-resolution data have been successfully applied to estimate large-scale forest losses not lesser than 25–100 ha in size. However, since human-induced change processes frequently result in much smaller spatial patterns, a major part of these changes remain undetected at coarse resolution even when change detection approaches based on continuous variables are implemented. This particularly applies for the detection of forest degradation processes that do not result in forest clearance but only modify the structure of the canopy. Nevertheless, only coarse-resolution sensors possess the ability to continuously monitor forest changes in a wall-to-wall manner at regional and global scales. Such detected deforestation hotspots can subsequently be analysed in detail on the basis of high-resolution imagery. Additionally, coarse-resolution sensors offer the only opportunity for almost real-time monitoring of the forest, a service growing on demand by a diverse range of forest stakeholders. Besides the Brazilian near real-time system DETER, Global Forest Watch, an open online platform for forest monitoring, also provides almost near real-time information on forest loss based on 500 m MODIS data at 16-day intervals. On the other hand, the use of high- to medium-resolution data, originating from RapidEye, SPOT, Landsat, or the upcoming Sentinel-2 satellite, offers greater opportunities for the detailed analyses of deforestation patterns, including those of forest degradation processes. In this respect, these sensors are the most important means in terms of satellite-based monitoring as part of the REDD+ programme.

With respect to change detection methods, most forest change studies so far have been based on comparisons of bi-temporal remotely sensed information products. Bi-temporal approaches, however, only provide a static depiction of land-cover change occurring between two particular time points, giving no scope for an evaluation of land cover between these dates, meaning that temporary disturbances occurring between these dates remain undetected. Furthermore, by only analysing changes at a bi-temporal basis, the temporal patterns of specific change processes, such as those of cyclical forest harvesting, e.g. shifting-cultivation practices, cannot be accounted for. With respect to the estimation of carbon emissions, however, the detection of cyclical forest losses and their differentiation from permanent losses is highly relevant (Leinenkugel et al. 2015). Houghton (2012), for example, estimated that globally, the harvest of timber and shifting cultivation adds 32–35% more to the net emissions calculated on the basis of deforestation alone. Also, gradual, long-term degradation or regeneration processes of forests that may result in subtle trends within a satellite data time series remain undetectable when data are compared only at a bi-temporal basis. Trajectory-based change detection approaches based on long-term time series, in contrast, provide excellent means to reconstruct and to analyse a quasi-continuous history on forest cover and their disturbances over periods of several decades. While some studies have already been performed based on continuous time series, thereby also taking into account temporal disturbance profiles, considerable potential still exists in the field of trajectory-based change detection approaches.

The scope for further development in this field has to be seen in view of the extensive archives holding historic satellite data from low-resolution sensors, such as MODIS, SPOT vegetation, or AVHRR, spanning time periods up to 40 years and are continuing to grow. In addition, access policies for high- to medium-resolution data have changed recently, particularly since the USGS released for free to the public its Landsat archive in 2008. Landsat 8 meanwhile collects more than 700 images per day – 14 times as much as in the 1980s (Wulder and Coops 2014). Future global coverage as well as free and open data access are continuing to improve with the European Union's free Copernicus data policy for the use of the European Space Agency (ESA) Sentinel satellites. The ESA Sentinel 1 radar satellite currently provides an all-weather day-and-night supply of imagery at a 12-day repeat cycle and will be joined by the Sentinel-2 satellite in 2015, which will map the Earth's land area every 10 days at a maximum of 10 m resolution.

6.3. Uneven distribution of the studies

Regarding the distribution of the studies (see Figure 4), the vast majority of the investigations were carried out within the Brazilian region, particularly in the Brazilian Amazon (Rondônia and Mato Grosso states). The rapid advances of agricultural crops, illegal operations, and land grabbing have been common drivers of deforestation in these areas. However, other countries in Latin America are affected by these land-use and land-cover transformations to the same degree, often showing deforestation trends much more severe than observed in the Amazonian region (see Figure 1). The case study over the Paraguayan region in this review article demonstrates a clear example of how the forests have been devastated over the years and only a scarce number of studies have been undertaken to observe the dynamics in this area. The same applies to Peru, Argentina, or Bolivia, which have been already identified among the regions with the highest rates of deforestation in the world (Hansen et al. 2013, Shimada et al. 2014). It can be inferred that the shortage of the studies in these areas is related to a lack of expertise in the area, a lack of governmental concern, a lack of international interest from the scientific community, and a lack of financial support for local studies. However, it is important to mention that several institutions (NGOs) within the Latin American continent are currently involved in private monitoring programmes and forest assessments at the regional scale; nevertheless, the data generated are frequently classified as sensitive data not available for public use.

7. Conclusions

In this review article, a complete overview of the studies of tropical forest dynamics in Latin America based on EO data was given. A comprehensive categorization of the reviewed studies with respect to the spatial distribution and areal coverage, the sensors applied and their spatial and temporal resolutions was provided. Furthermore, forest classification and change detection methodologies and their applications in detecting different forest processes were presented. Finally, a summary of the main results was discussed along with gaps and current research needs. Based on the findings and discussion in this review article, the major conclusions are:

(1) Studies relating to tropical forest dynamics are mainly centred on the Brazilian region, especially on the states of Mato Grosso and Rondônia. In view of this, there is a necessity to expand the study areas to other regions in Latin America, which are equally important, particularly in the context of the REDD+ programme. The Paraguayan case study presented in this article served as an example to show how forests have been massively devastated over the years and yet only a scarce number of studies were conducted for this region.
(2) Concerning the scale and sensors used, the majority of the studies were carried out at a local level applying medium-resolution imagery from the Landsat sensor. The studies carried out at regional and global levels were mostly based on coarse-resolution MODIS and AVHRR data. Moreover, only a few studies included SAR imagery, all of which were performed exclusively for Brazil.
(3) Multi-temporal and bi-temporal studies were often conducted to detect degradation and deforestation processes, covering almost 95% of the studies reviewed. Change detection methods were mostly based on comparisons of TMs derived from Landsat imagery or based on image differencing approaches. Also, the use of continuous variables such as vegetation indices or the outputs from PC or TC analyses were regularly applied to increase the accuracy of detected changes.
(4) Studies based on continuous time series of satellite data were less frequent in the reviewed studies (5% of the studies). Most of these studies applied MODIS time series spanning observation periods of up to 10 years, thereby also utilizing intra-annual statistics. Trajectory-based change detection methodologies that analyse the entire disturbance history of a forest on a pixel basis were rare. In view of this, more sophisticated change detection approaches are needed that are capable of utilizing the open data archive of the Landsat sensor or the high-spatial and temporal resolution of the upcoming Sentinel satellites.
(5) While most studies demonstrate high capabilities for the detection of deforestation processes, forest degradation was more difficult to identify and remains a challenge to be mapped even from high- to medium-resolution sensors such as SPOT or Landsat. Particularly, the rapid advance of secondary vegetation formations over logged and small cleared areas presents a major constraint on the detection procedures. Nevertheless, continuous variables for forest characterization, such as fraction images, were shown to be highly useful for the mapping of degraded areas even up to 3 years after the actual disturbance event.
(6) All scientific studies focus on the detection of historic forest dynamics. In view of this, the development of real-time change detection approaches capable to be implemented in monitoring programmes at national levels have to be further promoted. The extent of Latin America's forests declines on a daily basis, but no monitoring programmes are being implemented with the exception of INPE in Brazil and some operated by NGOs without any governmental support.

With the continuous expansion of agricultural land, the illegal extraction of timber, and the increasing demand for natural goods, tropical forest stands remain threatened. In view of these developments, there is a necessity to continue the development of methods and information products in the field of EO, which facilitate the implementation and enforcement of laws, environmental programmes, and policies in order to prevent the depredation of the remaining natural forest stands on the continent.

Acknowledgements

This work was conducted under the Paraguay Land Use (PARLU) 'Protecting Forest for the Benefit of Climate, People and Nature in Paraguay' project.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the German Federal Ministry of Education and Research (BMBF).

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