Geographical Information Management and Applications

Characterising forest gain and related carbon sequestration using existing datasets

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Summary

Substantial areas of forest gain present worldwide are minimally explored in the field of remote sensing. Forest gain has a positive impact on many natural processes such as carbon sequestration, wildlife residence and ecological recycling of water and nutrients. This explorative study provides a characterisation of forest gain processes and related carbon sequestration in Indonesia from 1990-2015. Spatiotemporal information on forest gain is essential to make valuable judgements on forest change dynamics. The Indonesian government, among multiple other organisations, value accurate information on forest gain as highly relevant given the country's ecosystem and forest dynamics. Monitoring forest dynamics is an established research field that widely uses satellite data for analyses. Using satellite datasets is found to be a feasible approach to monitor forest gain processes in Indonesia.

Forest change dynamics are found to be the result of forest loss and forest gain. Forest gain is caused either by natural expansion or by planting forests. Forest loss is caused by deforestation and natural disasters. Forest gain and loss are defined according to the land-use definitions. Existing land-use and land cover datasets are used to identify areas of forest gain. The 2010 global Remote Sensing Survey of the United Nations Food and Agricultural Organisation (FAO) Forest Resource Assessment (FAO FRA-2010 RSS) on land-use change for the period 1990-2005 is used to identify polygons where forest gain occurs. The FAO dataset is compared with the tropical forest cover change assessment 1990-2010 (TREES-3 Project) from the Joint Research Centre (JRC) of the European Commission and the recently published high-resolution global maps of 21st-century forest cover change from Hansen et al. (2013).

Because forest gain processes are rather subtle and indistinct compared to forest loss, visual interpretation of satellite imagery is used to characterise forest gain as follows. The identified areas of forest gain are visually interpreted using satellite imagery to validate whether gain occurred and to characterise for relevant attributes such as origin, former coverage, tree canopy cover density and dispersion pattern. The characterised gain is used to quantify related carbon sequestration using biomass data from Langner et al. (2014) and IPCC (2006). The quantification derived from these biomass datasets distinguishes for actual and potential carbon sequestration. This is done for comparative purposes and to provide an indication of the extent to which forest gain areas reached their full potential. The sample-based results of the datasets are spatially extrapolated to the country and internal ecological zones using spatial extrapolation. In this way both the magnitude of the area and the related carbon sequestration are made comparable at the same spatial scale. Furthermore, the outputs are annualised to standardise the temporal scope.

Forest gain is found to be a small contributor to land-use change. The proportions of forest gain compared to all Indonesian territory are 0.4% for FAO, 0.6% for JRC and 3.1% for Hansen. One should consider that the Hansen land cover dataset is not characterised for land-use. The results thus reveal significant discrepancies between the existing datasets, both in magnitude and location of forest gain and related carbon sequestration. For FAO carbon sequestration due to forest gain is estimated at 698.6 tons C per km^2 per year. For JRC and Hansen this is 600.8 and 883.5 tons C per km^2 per year respectively. The origin of forest gain is predominantly natural gain, as can be derived from the related carbon sequestration of FAO and JRC. For FAO natural carbon sequestration is estimated at 5.2 times planted carbon sequestration. For JRC this ratio is 2.2 to 1.

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Table of contents

1 Problem and its context

This chapter forms the introduction to the carried out study. The chapter first defines the problem and its relevance. Secondly the research objectives are formulated. The chapter is concluded with the main research question and related sub-questions.

1.1 Problem definition

Worldwide there are substantial forest gain areas that are minimally explored in the field of remote sensing. Hence the related carbon sequestration tends to be overlooked and ignored (Pan et al., 2011; Gao & Yu, 2014; Bongers et al., 2015). These areas where forest gain occurs can have a positive impact on many natural processes including carbon sequestration, counteracting erosion, wildlife residence and ecological recycling of water and nutrients (Schroeder et al., 2007). Forest regrowth and afforestation projects on tropical latitudes are demonstrated to be highly effective in mitigating global warming, where indicated counterproductive on high latitudes and minimally effective on moderate latitudes (Bala et al., 2007). Around 18% of worldwide fossil fuel emissions each year are absorbed by tropical forests, functioning as a global buffer for climate change (Lewis, 2009). Forest gain in tropical areas results in significant carbon sequestration in the above ground biomass (AGB), below ground biomass (BGB) and soil, compensating for greenhouse gas emissions (Cook et al., 2013).

Valid measures of forest cover dynamics are critical to make valuable judgments on environmental sustainability (Grainger, 1993). Accurate, consistent and transparent information on the location and spatial extent of forests dynamics are therefore essential for the management of forests (Chaudhari et al., 2003). Spatiotemporal information on forest dynamics is especially valuable for achieving and improving national forest monitoring programs regarding the Reduction of Emissions from Deforestation and forest Degradation (REDD+) (Potapov et al., 2014). However, establishing efficient forest monitoring strategies to assess AGB is difficult for developing countries, due to the inaccessibility and large extent of tropical forests, the low quality of existing data, and the lack of resources to carry out these costly and time-consuming assessments (Houghton, 2005).

The assessment of satellite data to monitor forest cover on a large scale is a feasible and widely applied approach. Multiple previous works in this field delivered a consistent view on the dynamics of global forests, mostly from 1990 onwards using satellite data ranging from low to high resolution (Malingreau et al., 1995; Achard et al., 2002a; Hansen & DeFries, 2004; Hansen et al., 2013). To assess forest gain, different strategies are required for quantification compared to the strategies applicable to assess forest loss. This is due to the slow change rate of forest gain (Giree et al., 2013). Compared to manual classification, automatically classified land cover maps can be realised easily on a large scale to identify areas of land cover change that require further visual inspection to characterise the area for land-use change (FAO & JRC, 2012). Such identification filters for areas of interest that can be visually interpreted for characterisation. This approach is highly accurate and efficient, because change assessment is not required for the entire area (i.e. wall-to-wall) (Dymond et al., 2012). Visual interpretation and validation of automatically classified land-cover maps has led to revising over 20% of the data, providing a significant impact on results in former forest mapping studies (Raši et al., 2011). Since wall-to-wall mapping is not always feasible and practical, sampling of satellite imagery is commonly applied to monitor forest cover dynamics. The potency and adequacy of sampling is proved by Achard et al. (2002b), and multiple studies afterwards applied sampling-based estimations e.g. Duviller et al. (2008) and Potapov et al. (2008).

Due to the explorative nature of study and limited resources, the carried out research is narrowed down to a case study for the country of Indonesia. This thesis thus characterises and quantifies forest gain and related carbon sequestration in Indonesia. The analyses are carried out systematically and based on remote sensing satellite land-use data, land cover data and biomass data. The study investigates areas of forest gain in Indonesia as can be identified from the 2010 global Remote Sensing Survey of the United Nations Food and Agricultural Organisation (FAO) Forest Resource Assessment (FAO FRA-2010 RSS) for the periods 1990-2000 and 2000-2005 (FAO & JRC, 2012). A detailed characterisation of forest gain in Indonesia is carried out, to obtain a better understanding of the related processes. Hence Very High Spatial Resolution (VHR) satellite imagery is visually interpreted for the characterisation of forest gain. The FAO dataset is compared with the tropical forest cover change assessment 1990-2010 (TREES-3 Project) from the Joint Research Centre of the European Commission and the recently published high-resolution global maps of 21st-century forest cover change from Hansen et al. (2013). Biomass data is used to estimate carbon sequestration related to the characterised forest gain in Indonesia.

1.2 Research objectives

The main objective is to obtain a characterisation of forest gain and related carbon sequestration from 1990-2015 in Indonesia using existing datasets. To achieve this, the following sub objectives are formulated. First to estimate the extent of forest gain from 1990 – 2015 in Indonesia. Second to achieve a characterisation of forest gain in the study area for relevant attributes. And third to realise an integration of forest gain characterisation with biomass datasets to estimate forest gain and related carbon sequestration.

1.3 Research questions

How can forest gain and related carbon sequestration be characterised for Indonesia from 1990 to 2015 using existing datasets?

1. What processes cause forest gain?
2. How can forest gain be characterised using existing datasets (based on visual interpretation of satellite imagery)?
3. What is the magnitude of related carbon sequestration based on biomass datasets?

2 Study Area

In this chapter the studied country of Indonesia is introduced. First the relevance of studying Indonesia for forest gain is explained (2.1). Next the geography and biodiversity of the country are described (2.2). Finally, the Indonesian forest is examined (2.3).

2.1 Why Indonesia?

Indonesia is studied due to the importance of high quality information for the country's ecosystem, especially in the context of REDD+ (Langner et al., 2014). The shrinking size of the natural carbon stocks have impact on human and ecological life (World Resources Institute, 2013). In Indonesia around 50 – 60 million people directly rely upon the forest areas in their daily lives, both for the collection of forest products to meet daily requirements and as a working environment in the wood processing industry (World resources Institute, 2013). Worldwide approximately 240 million people reside in forest environments. In general, there is a relatively high dependence on forests for income amongst poor people, e.g. landless communities living or working in the forests. The World Bank estimates that there is a substantial dependency amongst 25% of the 'poor' and 90% of the 'very poor' worldwide (Chao, 2012). Furthermore, in Indonesia thousands of animal and plant species are domestically present in the forest areas. The Indonesian authorities acknowledge the relevance to protect these tropical areas and aim to act accordingly (World Resources Institute, 2013).

Due to the high forest degradation rates and general lack of management of forests in Indonesia, it is relevant to take measures to preserve and restore forest cover. Intervening measures can counterbalance the decline of utilities, non-wood forest products and natural timber supplies (FAO, 2009; FAO, 2010a). Restoration of forests and the development of forest plantations is therefore of crucial importance for the forestry sector of Indonesia (FAO, 2009). Enlarged international awareness of carbon sequestration caused by forest gain pushed towards policy formulation that is aimed at inducing regrowth processes (OECD, 2014). The related policy making processes to reduce carbon emissions need accurate information on the past, current and future dynamics of carbon emissions and carbon sequestration in planted and natural forests (Pan et al., 2011). For Indonesia the aim is to restore forest with an annual rate of 500,000 hectares (OECD, 2014). Indonesia's national development plan also addresses sustainable forest management as a strategy to mitigate climate change. Reforestation is supported by the plan to reinforce mutual effort and enlarge reforestation funds (OECD, 2014).

2.2 Geography Indonesia

The Republic of Indonesia is a sovereign country in Southeast Asia. The nation is an archipelago of 17,508 islands located amidst the Indian Ocean and the Pacific Ocean. The country is centred around the geographic coordinates 5º00´ South of the Equator and 120º00´ East of Greenwich. The country has land both North and South of the equator. With 257.4 million inhabitants, Indonesia is the fourth country worldwide regarding population size (Worldometers, 2016). The majority of Indonesia's land-use is tropical forest (52%), and secondly agriculture (31%) according to 2011 estimations (The World Factbook, 2015).

Table 2.1 Area per ecological zone

Ecological Zone	**Km²**	**%**
Tropical rainforest	1,627,576	86.8%
Tropical moist deciduous forest	63,702	3.4%
Tropical dry forest	43	0.0%
Tropical shrubland	7,993	0.4%
Tropical mountain system	175,837	9.4%
Total Indonesia	1,875,151	100.0%

Indonesia is identified as a megadiverse country, making it one of the 17 countries with the highest biodiversity worldwide. Some estimations even rank Indonesia second worldwide with regards to biodiversity and endemic species (Brown, 1997; Lambertini, 2000). The country is divided in five ecological zones. All ecological zones fall within the tropical domain. The largest ecological zone is tropical rainforest, the second-largest ecological zone tropical mountain system (Table 2.1). The spatial distribution of ecological zones is depicted in Figure 2.1. This map also depicts the sample tiles of the systematic sampling design used by FAO and JRC to monitor land-use and land cover change.

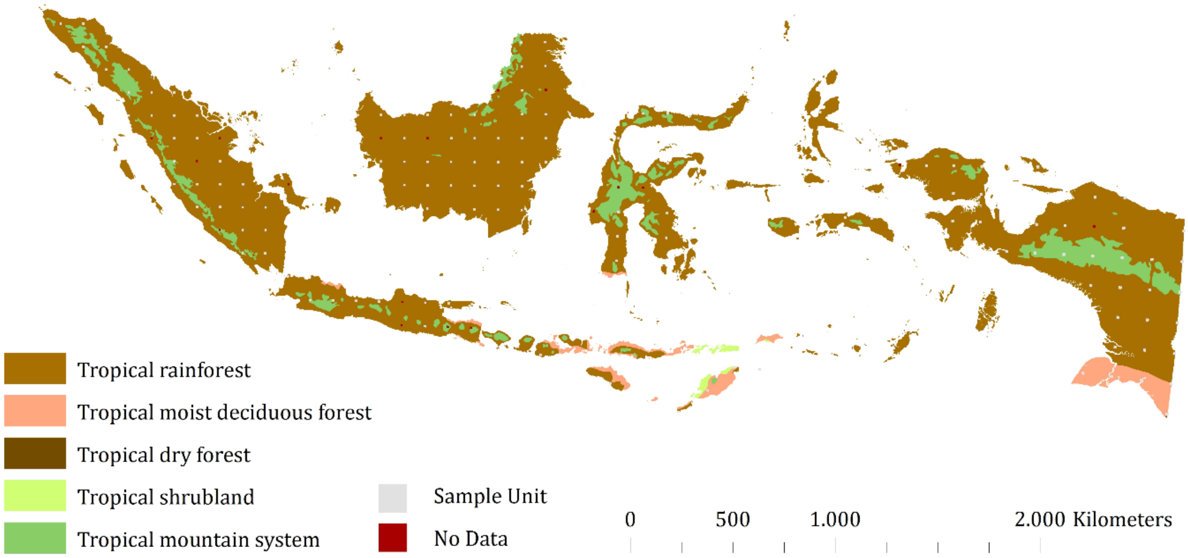


Figure 2.1 Map of sample units (FAO & JRC. 2012) and ecological zones (FAO, 2001a) in Indonesia

2.3 Forest area Indonesia

Indonesia is the 5th largest carbon emitting country in the world, predominantly caused by the transformations of forest land due to deforestation and peatlands due to drainage (World Resource Institute, 2013). The Indonesian Carbon Accounting System estimates that between 2001 and 2012 an area of 12,402 Km² of land is converted into forest land, thus identified as forest gain. In the same time span a cumulative area of 43,475 Km² of forest land has been subject to deforestation (Table 2.2) (INCAS Indonesia, 2015). Forest is defined as areas larger than 0.25 Ha, with a minimum tree canopy cover of 30% that are capable of reaching a minimum height of 5 m at maturity (INCAS Indonesia, 2015). Over the last 30 years crop plantations were the main driving force behind deforestation (Forest Watch Indonesia, 2011). Peatlands and forest areas account for major carbon storages in Indonesia.

Table 2.2 Forest gain and loss area estimates INCAS from 2001 – 2012

Year	**Forest gain in Km²**	**Forest loss in Km²**
2001	1,238	586
2002	1,377	2,385
2003	1,216	3,744
2004	1,018	3,438
2005	922	3,641
2006	921	4,954
2007	996	4,670
2008	1,004	5,184
2009	1,159	5,128
2010	1,424	4,244
2011	771	3,343
2012	356	2,157
Total	12,402	43,475

3 Theoretical Framework

This chapter provides the theoretical background to forest gain and related carbon sequestration. The first section defines forest gain and directly related processes, functioning as the framework of definitions. The second section discusses the accuracy of monitoring forest gain processes. Thirdly forest gain is related to climate change mitigation. Finally, carbon sequestration related to forest gain is investigated.

3.1 Defining forest gain and directly related processes

This section provides definitions on forest gain and related processes. To define forest gain, first forest land-use has to be delineated. Forest land-use is defined as tree covered land areas with a minimum size of 0.5 hectares. Tree covered land-use is operationalised as land with 30-100% forest canopy cover of trees that are above 5 meters in height (Eva et al., 2012; FAO & JRC, 2012). Forest canopy cover concerns the portion of land covered by the tree crowns as can be observed from a vertical projection of the tree canopy (Jennings et al., 1999). Tree canopy cover is a measure found to be linked to the growth and survival of trees (Jennings et al., 1999). For some tree species there is an almost linear relationship between their canopy cover and biomass volume (Dawkins, 1963). The canopy cover volume is demonstrated to be a solid indicator to enhance predictions on tree growth (Ahmad Zuhaidi, 2009). The above specified thresholds must be met or exceeded to let the area qualify as forest gain. This definition also includes areas where through natural processes or human influences the tree cover will re-establish in the future, which has to do with the difference between land-use and land cover as is discussed below.

Land cover delineates the physical land coverage of the surface (e.g. forest, wetlands), where land-use portrays how people use the land area or what the intentional land-use is (Lambin et al., 2001). Land-use can be derived automatically from imagery acquired through remote sensing, though the resulting classification generally still requires expert human interpretation for verification and revision (FAO & JRC, 2012). Information on land-use is crucial to correctly interpret land cover change and to realise or strengthen the influence of political strategies for forest management purposes (FAO & JRC, 2012). Precise measurements of land-use changes are complex because the land must be examined given its ecological context and post data acquisition changes such as regeneration and afforestation (Kurz, 2010). Due to the complex nature of the land-use definition, the practical consequence is that human expert interpretation is required to classify land-use change properly (FAO & JRC, 2012).

Forest gain is defined as both the consequence of planting and natural expansion that transforms previously non-forest land into forest land (FAO, 2010a; FAO & JRC, 2012). Forest dynamics consists of forest gain that transforms other land into forest and forest loss that transforms forest into other land (Figure 3.1).

Figure 3.1 Forest change dynamics (adopted from FAO, 2010a, p.17)

Natural expansion is defined as the areal increase of natural forests. Boundary conditions are that this expansion is not influenced by human planting and that the trees are of a primary nature (FAO, 2001b). On the other hand, forest plantations are influenced by human cultivation (planting and seeding). Forest plantations can be identified from their structure. A forest plantation can be recognised by a systematic distribution, the presence of one or two species, and a similar maturity. The plantations can consist of imported species or domestic species (FAO, 2001b). Generally natural regeneration is characterised with a random pattern, where plantations are characterised with a uniform pattern (Corbin & Holl, 2012), as illustrated through the growth processes in Figure 3.2.

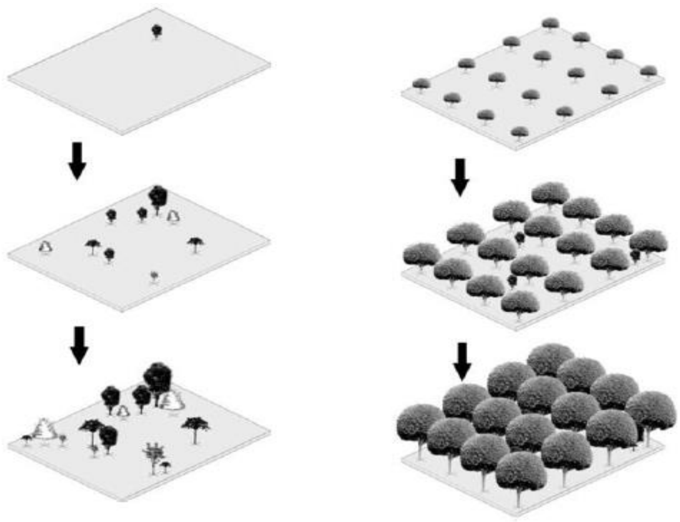


Figure 3.2 Forest gain processes from natural expansion and forest plantations (Corbin & Holl, 2012)

The dominant approach to define forest gain is the assessment of land-use change (Watson et al., 2000). The definition chosen for this study follows this approach. More extensive measures to assess land-use change related to forest gain include increasing canopy cover, increases in biomass and increases in carbon density (Watson et al., 2000).

Afforestation and reforestation are defined by the transformation from non-forest land to forest land, however with a different duration of the non-forest state of the land before transforming into forest. Where reforestation concerns the re-establishing of former land cover either naturally or through forest plantation, afforestation refers to the artificial establishment of trees in areas where no forest was present (SAFnet Dictionary, 2008a; SAFnet Dictionary, 2008b; Moon & Farmer, 2012). The definition of forest gain used in this thesis comprises land-use change from non-forest to forest. Due to limited availability of satellite imagery available from the 1970s onwards it is generally not (yet) attainable to assess whether forest gain concerns afforestation or reforestation (Moon & Farmer, 2012). The REDD+ definition on afforestation stresses this drawback, by describing that afforestation is only valid if a non-forest to forest conversion has not been carried out over the past 50 years (The Redd Desk, 2013).

3.2 Monitoring forest gain processes

Detecting forest expansion is possible using change detection and satellite data (Rosenqvist et al., 2003). Analysing digital imagery to detect change and classify land-use over time is a common method applied for change detection in the field of remote sensing (Mas, 1999; Rosenqvist et al., 2003). Analysing forest dynamics and specifically forest gain is ideally observed with high data frequencies, e.g. on a yearly basis. However, data is not always available in sufficient quality due to limited satellite coverage and erroneous data, a problem that is enlarged by visual barriers such as cloud cover (Akiyama & Kawamura, 2003).

Global forest monitoring projects contribute to knowledge on the structure and dynamics of the earth, generally using satellite data with a rather coarse resolution. Furthermore, due to the scale of these projects, the contributed knowledge is mostly rather rough. Information from global forest monitoring assessments is therefore often too inexact to characterise local processes in detail (Herold et al., 2008; Fritz et al., 2011; Dong et al., 2012; Leinenkugel et al., 2013; Kuenzer et al., 2014; Leinenkugel et al., 2015).

Rates of forest removal and area of net forest loss are typical numbers that are reported in forest change assessments. Subsequently these statistics are receiving a lot of attention, both in the scientific community as in public debate, overestimating the value of these indicators to understand forest dynamics according to FAO (FAO, 2001b; FAO, 2006). The FAO (2010a) advocates to include forest features that characterise the areas more extensively, describing that quantitative data on carbon sequestration and biomass volumes are often disregarded and undervalued. Merely reviewing the area of forest gain provides limited information on the health of the forest and to what extent these areas are managed (FAO, 2010a). There are various sustainable benefits to well-managed forests from the global to the local scale. Current accurate information on forest dynamics and related carbon stocks is vital to support the management of forests and the design of sustainable forestry policies (FAO, 2010b).

Monitoring large areas of forest using satellite data can be made cost-effective by applying automated mapping. This can result in an automatic classification of satellite imagery that is accurate enough to give an indication of single-date land-use. The precision of an automated approach is however not sufficient to produce reliable land-use change maps, especially when there is small change (Dymond et al., 2008). Forest gain is characterised by modest change over long-time spans (Fragal et al., 2016). Forest cover loss is the result of abrupt changes compared to forest cover gain. Loss can be detected relatively simple using the spectral reflectance of the surface, where gain is the result of a long-term series of gradual developments. Thus, opposing to forest loss, forest gain results generally in indistinct subtle changes in the spectral reflectance of the surface (Potapov et al., 2015). Characterising the gradual change of forest expansion can therefore often not be realised using automated mapping products. To make relevant estimations of forest gain more refined assessment approaches are needed (Dymond et al., 2008; Giree et al., 2013). An established method to detect processes of forest expansion uses visual interpretation of satellite imagery. When reviewing simple change detection methods, comparing two images of the same area over time for differences is proved to be highly accurate (Dymond et al., 2008).

The high accuracy that is reached with visual interpretation has the following consequences. First satellite imagery shows land cover instead of land-use, meaning that visual interpretation could bring inaccuracies in detecting land-use change. Second, the quality of multiple images over time is different, which affects the accuracy of detecting forest gain (e.g. different resolution imagery due to technical advancements in satellite sensors launched into space later in time) (Hori et al., 2007). Combining Landsat data with VHR imagery is a useful and inexpensive strategy for analyses of forest dynamics. VHR data is easily accessible and freely available in Google Earth, but also has its limitations as discussed below (Olofsson et al., 2014).

First, the available imagery is not equally allocated through space, which can cause errors due to differences in quality of imagery available for multiple areas. Second, the high temporal resolution (revisits of the same location at multiple points in time) is often achieved by adjusting the viewing angle of the satellite sensors. This can have the implication that an object (e.g. a tree) cannot be identified clearly in all images over time, while it is actually present. Finally, and obviously the VHR data is a relatively new development, with the consequence that high quality VHR data is generally not available before ca. 2005 (Olofsson et al., 2014).

3.3 Forest gain in relation to climate change mitigation

Forest gain provides multiple benefits to the environment, as demonstrated by the revival of vegetation and animal life, the renewal of land and carbon sequestration (Green Collar Association, 2014). Global forests store around 30% of terrestrial CO_2, sequestered through photosynthesis in trees and plants, serving as carbon sinks (Houghton et al., 2009). Forest gain therefore contributes to climate change mitigation, by storing considerable volumes of CO_2 (Canadell & Raupach, 2008). Furthermore, forest gain generally causes increases to the water cycle, boosting the flux of heat into the atmosphere and thereby cooling the earth's surface. These processes are comprised by the concept of evaporative cooling (Kleidon et al., 2000; Govindasamy et al., 2001; Bounoua et al., 2002; Bala et al., 2007; Bonan, 2008). Favourable conditions for forest gain are found in Indonesian peat swamp forests and mangrove forests. The above mentioned forest areas are typically inundated with freshwater or tidal areas such as marine shorelines and estuaries. These forest areas have substantial land coverage on the Indonesian archipelago and are characterised by their high productivity in generating biomass (The Jakarta Post, 2011).

Carbon storage in forests can properly be approximated based on the amount of biomass per area, using a 0.5 conversion factor that is commonly applied (e.g. Silver et al., 2000; Achard et al., 2014). Carbon stocks can be used to estimate the amount of carbon that is emitted after forest clearing (e.g. through fires) or to measure carbon sequestration related to forest regrowth (Cook et al., 2013). The definition used for biomass is the cumulative oven-dry weight of natural vegetation per unit area. Field assessments often only measure the oven-dry weight of AGB. Subsequently estimates of the total biomass are derived using conversion formulas applied to the measured amount of AGB (Gschwantner et al., 2009).

Climate change mitigation through forest management has successfully been achieved using the following approaches. The first method is to scale down deforestation and forest degradation. Secondly forest density can be enlarged to increase carbon storage. Thirdly forests can be used as a supplier of resources, replacing CO_2 emitting alternatives. Finally, forest areas can be expanded via reforestation (Canadell & Raupach, 2008).

Reforestation strategies can provide a significant contribution to carbon uptakes, despite the small scale occurrence (Silver et al., 2000; Thomson et al., 2008). An example is the successful application of reforestation in China, where the trend of forest carbon emissions is reversed towards carbon sequestration (Wang et al., 2007). The Intergovernmental Panel on Climate Change (IPCC) regards human-induced forest expansion as a leading approach of forest management to mitigate climate change (Nabuurs et al., 2007).

Especially in the tropical climates reforestation projects cause biophysical change that fosters climate mitigation, e.g. as is the case for the accumulation of clouds that reflect sunlight (Canadell & Raupach, 2008). Trees in tropical climates with wet seasons have a quicker growth rate because they can grow year-round. The trees in the tropical climates are generally larger, brighter, and have more abundant leaves than non-tropical climates. An investigation of 70,000 trees across Africa indicates that tropical forests are absorbing relatively high levels, circa 18%, of global carbon dioxide pollution (Lewis, 2009). Thus, forest gain in the tropics has a relative large potential to sequester high volumes of carbon compared to forest gain in non-tropical climates.

The presence of forest areas, including expanding biomass through forest gain, has some associated carbon emission risks. Despite the great potential of the forests to sequester carbon, forest interruptions may rebound carbon storage. This can be the consequence of climate extremes, climate change, fire outbreaks and insect epidemics. The mentioned circumstances could possibly cause negative effects due to a reversal of carbon storage into carbon emission (Westerling et al., 2006; Kurz et al., 2008).

3.4 Understanding carbon sequestration due to forest gain (in study areas)

Forest regeneration in the tropics is a long-term process that can take centuries to widely re-establish the former forest cover (Liebsch et al., 2008). A large scale study in tropical forests found that one to three centuries are needed to achieve a comparable forest quality as found in fully grown forests with regards to non-pioneer species, understory species and animal-dispersed species (Liebsch et al., 2008). Furthermore, thousand to four thousand years are needed to recover to the stage of endemism, where native species specific for the location are settled in mature forests (Myers et al., 2000; Liebsch et al., 2008).

Worldwide carbon sequestration related to tropical forest regrowth is estimated on 1.6 ± 0.5 Petagrams (Pg, i.e. 10^{15} grams) of carbon per year in the period 1990-1999 and 1.7 ± 0.5 Pg carbon per year in the period 2000-2007 (Pan et al., 2011). These estimates also indicate that forest regrowth sequesters more carbon compared to existing forest, because of higher growth rates found in the forest regrowth (Pan et al., 2011). The quantity of carbon sequestration in forests depends on multiple conditions including forest density, the size of trees, the range of tree species, forest diversity and locational factors such as fertility and humidity (Gorte, 2009). Further ambiguity exists due to a lack of standardisation and resources to carry out biomass assessments in the field (Silver et al., 2000, Chave et al., 2005). The estimations on carbon sequestration dynamics for tropical Asia from Pan et al. (2011) are based upon the mean change rate of two satellite monitoring networks across Africa and South America. Therefore, there is high uncertainty especially for tropical Asia due to the low amount or lack of longstanding measurements and data on regrowth rates (Pan et al., 2011). However, solid estimates are needed to assess the effect of tropical forest regrowth on the changing environment. Especially in the REDD+ context stable methods are a precondition for estimating national dynamics of carbon sequestration (Houghton, 2005). Oven-dry measuring of harvested trees requires a large amount of resources. Some global assessments have been carried out using a relatively low amount of trees for the purpose of allometric models. These global models provide an acceptable indication of carbon sequestration because the inconsistencies even out over larger areas. On the other hand, the models are proved to be too generic, prone to errors and most likely unrepresentative for the areal distribution of the assessed forest structures (Chave et al., 2005; Melson et al., 2011).

Study area

The Indonesian government is committed to report on carbon sequestration related to forest dynamics, however largely lacks the resources (Romijn et al., 2012). Rutishauer et al. (2013) reviewed existing estimates of forest related carbon sequestration in Indonesia. They found that the existing estimates are generally based upon global biomass assessments combined with a low amount of local biomass measurements in the field. Only two allometric biomass models are realised based on natural forests in Borneo. For these models the applicability on a national scale is questionable (Yamakura et al., 1986; Basuki et al., 2009).

4 Research phases

This chapter describes the steps taken to realise the research objectives. The relevance and contents of the used datasets and required software for analyses are explained in chapter 5 Data software and research material.

This study applies a similar approach as the monitoring and mapping framework (MMF) introduced by Falkowski et al. (2009). The MMF utilises VHR remote sensing imagery for forest inventory mapping and monitoring on a large-scale using a sampling strategy. The MMF consists of four stages. The first is an automated determination of perimeters that delineates deviating areas. Second, a computerised characterisation is used to assign attributes to the delineated areas. Third, human visual interpretation techniques using VHR remote sensing imagery are applied to add attributes that could not be generated automatically from the imagery. The fourth stage supplements related data for additional information, validation and comparison of stages one, two and three (e.g. biomass data). This thesis builds upon the FAO dataset - that already applied stages one and two of MMF - by adding additional information using visual interpretation and other datasets. The following conceptual framework is developed to illustrate the data, methods, steps and questions involved in this thesis (Figure 4.1).

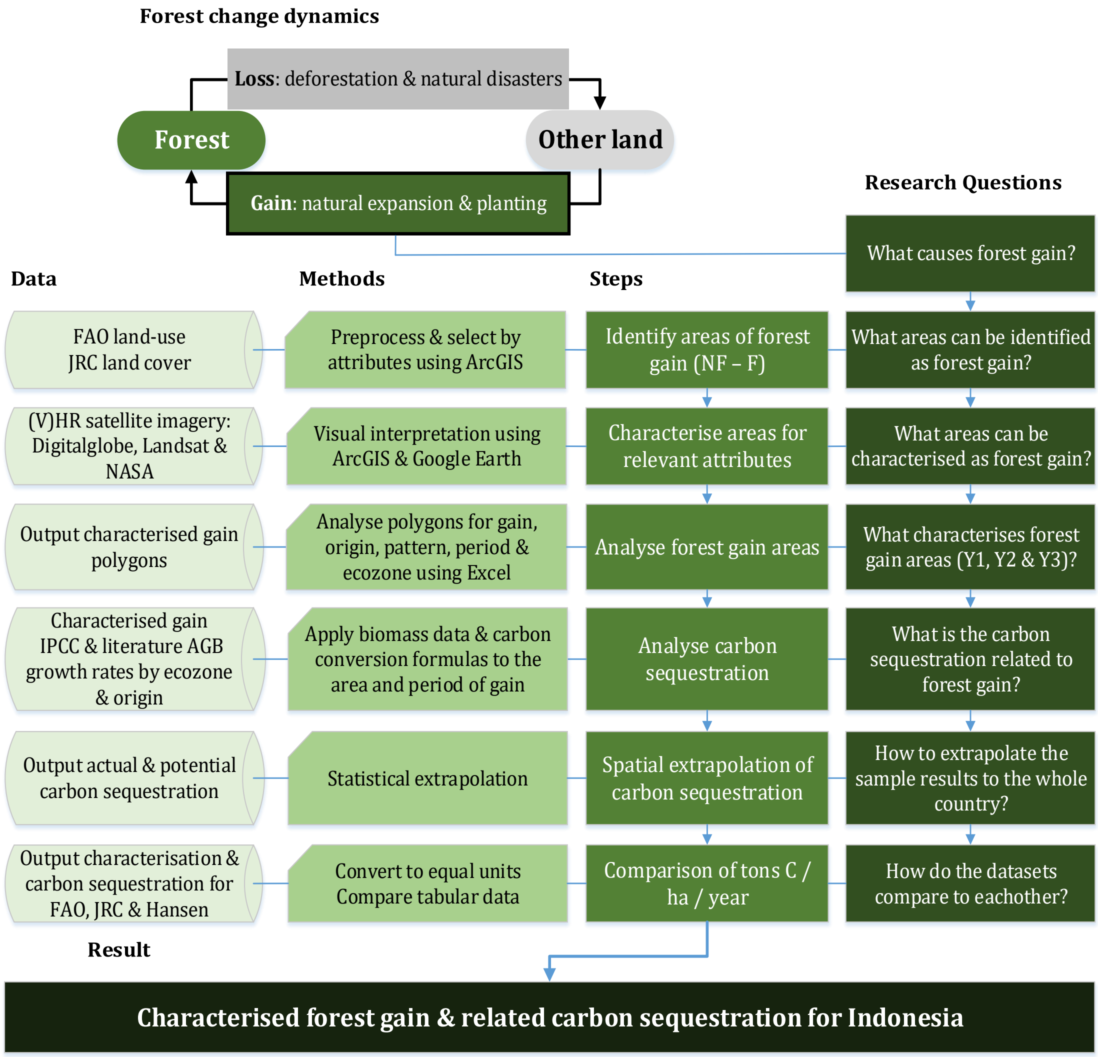


Figure 4.1 Conceptual framework

The FAO FRA-2010 RSS land-use dataset is used to identify areas of forest gain (4.1). The structure of the FAO dataset is discussed in section 5.1 and 5.2. To validate and further characterise the land-use change of these areas, visual interpretation is carried out using VHR satellite imagery (4.2). Next the characterisation is validated with the aid of an external expert (4.3). Subsequently the characterised gain is compared to other datasets (4.4). Next a quantification of actual and potential carbon sequestration related to forest gain is approximated using biomass values per ecological zone and annual biomass growth rates (4.5). Finally forest gain and related carbon sequestration are estimated on a national scale using statistical extrapolation (4.6), because the used dataset applies a sample-based approach.

4.1 Identify areas of forest gain

The identification of the areas of forest gain is carried out using SQL selection. The classified FAO dataset is used to select the areas of forest gain, i.e. the areas where the land-use changed from non-forest (NF) to forest (F) in the time interval 1990-2005. This land-use dataset of FAO is based upon an automatically mapped JRC land cover dataset. The dataset is constructed by the FAO in two phases, meaning that the land-use change of 1990–2000 was assessed independently from the land-use change for 2000–2005. This distinction made by FAO is also applied in this study by separately selecting forest gain polygons for both periods.

The areas that are reported as changed from non-forest to forest and back to non-forest for 1990, 2000 and 2005 respectively are excluded from further assessment. The size of these areas is computed as additional information, because these areas do not meet the forest gain definition used. The land cover change of these areas is expected to be the result of shifting cultivation. The focus of the study is on the areas that changed from non-forest to forest either in the period 1990-2000 or 2000-2005. These are the areas that can clearly be identified as forest gain.

4.2 Characterise areas by visual interpretation of satellite imagery

To characterise the identified polygons a classification is carried out using expert visual interpretation to add information to the dataset. Characterising land-use change is challenging compared to determining land cover. This is because satellite imagery captures land cover with related spectral signatures, where land-use requires supplementary human interpretation (e.g. shifting cultivation will be classified as land cover change, but not as land-use change). Therefore, visual interpretation is required to distinguish multiple forest characteristics (Hori et al., 2007; De Sy et al., 2015) as discussed below.

4.2.1 Satellite imagery used

The identified polygons are first characterised using a range of satellite imagery, mainly available from Landsat satellite data on a 30-meter pixel resolution, for year 1 (Y1). This Y1 is the reference year where the land is non-forest according to the dataset of FAO, thus circa 1990 or circa 2000. Next, the second year indicated by the dataset period is assessed to validate whether the dataset provides reliable indications of forest gain. This is done using a similar approach as in year 1. The data that is used is predominantly Landsat satellite data for year 2 (Y2), i.e. the year where the land is forest according to the FAO dataset, thus circa 2000 or circa 2005. Thirdly, VHR imagery interpretation is applied using the best quality and most recent Google Earth imagery available from circa 2015, from here referred to as year 3 (Y3).

Google Earth is a collection of multiple remote sensing datasets that displays high quality VHR imagery available for free. Historical satellite data available in Google Earth for Indonesia roughly ranges from 2005 to 2016. For this study higher quality imagery surpasses lower quality imagery that is more recent, because it provides the possibility for a higher level of detail in characterisation. This choice introduces some inconsistencies in the time that the data is acquired. These inconsistencies are corrected for using annual forest gain rates for comparison. The acquisition date of the imagery that is used to characterise Y1, Y2 and Y3 can variate due to data availability. For Y1 and Y2 it is aimed to use data as close as possible to the reference year. For Y3 it is aimed to use high quality imagery acquired as recent as possible.

4.2.2 Attributes for characterisation

Monitoring forest gain requires a strategy that identifies increases and differentiates for natural recovery and the expansion of planted trees (Achard & Hansen, 2012). For this prime characteristic or origin, visual interpretation is applied to separate natural forests and forest plantations. This distinction is realised using the visually attainable characteristics related to the origin of forest as recapped here based on section 3.1. Where natural forests generally have a high variety, forest plantations are typically even-aged, consist of one or two species and have consistent tree density over the plot. This means that there is high resemblance and relatively low variety in canopy cover found on forest plantations (FAO, 2001b).

Next to defining the origin of the forest gain, established methods to characterise forest areas in geographical patches aim to define the structure, canopy cover, distribution and the density of forest (Matveev, 2012). The canopy cover is estimated as a percentage in Y1, Y2 and Y3 to assess for the forest gain. The assigned percentages are estimates based on visual interpretation. Because single-percentage classes are not perceived to be realistic, the choice is made to arrange the coverage using 10% classes. Figure 4.2 is used to approximate the canopy cover percentage, following Terry & Chillinger (1955). The distribution of the trees over the polygon are typified (e.g. clumped), and the coverage of the land is estimated with regards to multiple coverages to assess for the diversity of forest land (e.g. percentage of herbaceous land on the forest gain area). Comparing forest areas in the tropics for these characteristics can help understand the distribution and relationship between the land-uses over variating geographical areas, also known as the study of floristics. Comparing these characteristics over time is highly relevant in understanding the structure and floristics of the forest area. This understanding is meaningful to manage forest gain processes effectively (Meng et al., 2011).

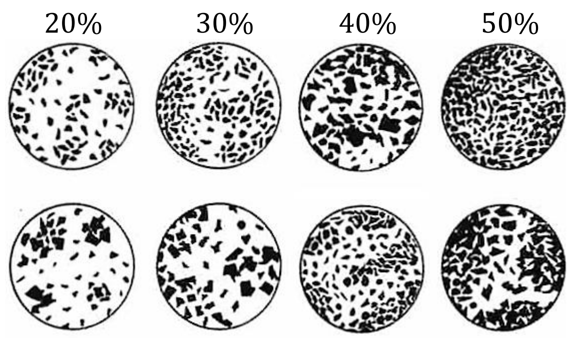


Figure 4.2 Tree canopy cover percentage examples ranging from 20% to 50%

Forest structures are commonly characterised for patterns of species dispersion. There are three main types of species dispersion: clumped, uniform and random (Figure 4.1). A clumped dispersion refers to a distribution of individual trees

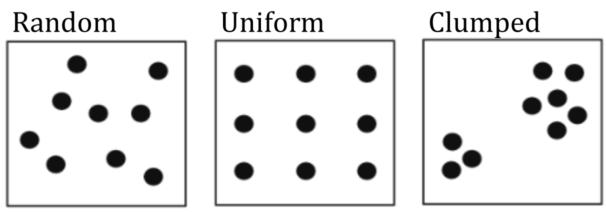


Figure 4.3 Characterising species dispersion patterns

that are clustered in patches. Random dispersion is observed when no clear pattern is apparent, i.e. the trees show autonomous separate distribution. Uniform dispersion means a distribution where individuals are more widely separated from each other compared to random distribution (Russel et al., 2013). Uniform dispersion patterns are generally the result of forest plantations (FAO, 2001b). Therefore, the uniform dispersion pattern is used in addition to the visually attainable characteristics as derived from section 3.1.

Determining a dispersion pattern depends on the spatial scale of the analysis and spatial resolution of the imagery (Russel et al.,2013). In this study the classification is based on a viewing distance of circa 250 meters. At this viewing distance the identified polygons with a mean size of 18 hectares were properly visible. The resolution used for analyses deviates from high resolution Landsat imagery for the reference years 1990, 2000 and 2005, to VHR imagery for the year of forest gain interpretation.

Classifying the coverage of land is a common approach to typify forest areas for land-use change (Batra & Pirard, 2015). Typologies of forests are culturally subjective and are difficult to define. This difficulty is enlarged due to varying natures of forests across the planet (Batra & Pirard, 2015). A precondition for typifying forests is that mutually exclusive categories must be established, that asses the complete coverage (Batra & Pirard, 2015). Therefore, the coverage of land with multiple land cover components (e.g. different types of vegetation) must add up to 100% for all polygons. The dominant coverage and related percentage that are used in the characterisation are solely applied to non-tree coverages within the identified forest gain polygons. This is done to understand the nature of the forest gain polygons more thoroughly. The coverage classes are derived from the IPCC good-practice guidelines (IPCC, 2006).

Confidence levels are added to provide ground for the accuracy of the characterisation assessment. The confidence levels are applied to (1) whether there is forest gain, (2) what the origin is and (3) what the proportions of multiple coverages in Y3 are. The level of confidence is expressed as low, medium or high. Low confidence is assigned when there is almost no certainty about the change based on the visual interpretation of the data, e.g. when the only imagery available depicts cloud coverage. Medium confidence is assigned to reasonable quality imagery available that provides a tolerable level of detail, e.g. when only Landsat 30m resolution imagery is available to assess the coverage in Y3. High confidence is given as label to the areas with (very) clear imagery, e.g. when individual trees can be identified on the image in Y3.

Given the theory and research objectives, the characterisation of forest gain is operationalised using multiple attributes. To correct for errors and ensure consistency, all areas are double checked by the expert. To assess for the identified change from non-forest to forest, the polygons of forest gain are characterised for the following attributes.

1. *Julian data of acquisition satellite imagery first year (Y1)*
2. *Source of image Y1*
3. *Julian date of acquisition satellite imagery second year (Y2)*
4. *Source of image Y2*
5. *Julian date of acquisition satellite imagery last year (Y3)*
6. *Source of image Y3*
7. *Gain (Y/N) (Y1-Y2)*
8. *Confidence of gain (low, medium, high)*
9. *Gain (Y/N) (Y1-Y3)*
10. *Confidence of gain*
11. *Canopy cover % (Y1)*
12. *Canopy cover % (Y2)*
13. *Canopy cover % (Y3)*
14. *Dispersion Y1 (Clumped, Uniform, Random)*
15. *Dispersion Y3*
16. *Natural / plantation*
17. *Confidence of Natural/Plantation*
18. *Dominant coverage Y1 (Crops / Shrubs / Herbaceous / Wetlands / Settlements / Bare land / Other land)*
19. *Dominant coverage %*
20. *Dominant coverage Y2*
21. *Dominant coverage %*

Coverage of (sum=100%) (Y3):

22. *Trees % (= canopy cover % Y3)*
23. *Crops %*
24. *Shrubs %*
25. *Herbaceous %*
26. *Wetlands %*
27. *Settlements %*
28. *Bare land %*
29. *Other %*
30. *Confidence of coverage*
31. *Remarks*

After characterisation of the dataset, it appeared from the remarks that four additional patterns frequently occurred on the identified forest gain polygons. Therefore, these remarks were transformed into the following supplementary attributes.

32. *Crop cover is palm oil plantation*
33. *Forest gain on (former) roads*
34. *Forest gain on (former) water*
35. *Settlement cover is road*

4.2.3 Methodology tested on subset of data

To get acquainted with the dataset and data entry methods, the methodology is tested for a subset of the data. The first 30 polygons were characterised as a test. The test data entrance was erased and carried out again. The test subset can be perceived as a repetition to ensure consistent data entrance, using the test outcomes to improve the data quality. The main test outcomes are briefly discussed.

The automated classification of FAO and JRC is predominantly based on Global Land Survey (GLS) data. These datasets are constructed to support scientific research and data users in accessing historical satellite imagery through a dependable, consistent, terrain rectified and coordinated data collection (USGS, 2015). In this thesis satellite imagery is used from GLS1990, GLS2000, GLS2005 and GLS2010. GLS1990 uses Landsat 4-5 Thematic Mapper (TM) data. GLS2000 uses Landsat 7 Enhanced Thematic Mapper Plus (ETM+) data. GLS2005 and GLS2010 use a combination of Landsat TM and ETM+ data. An improvement was made for the entered time of acquisition. Originally it was chosen to use the year of image acquisition, however it was found that it can be defined as Julian date with minimum incremental effort, providing higher accuracy in the characterisation, compared to the original approach. Next a duplicate characteristic present in the research proposal is removed (Canopy cover % Y3 & Tree cover % Y3). Finally, the sequence of attributes for characterisation was rearranged to facilitate a more convenient and structured data entrance procedure.

4.3 Validate characterisation

Validation is carried out with the aim to correct for subjectivity in characterisation of the author. Another expert visual interpreter is asked to characterise a sample of the identified gain in the FAO dataset for forest gain. This sample is chosen using a simple random sampling strategy. The resemblance of the characterisation from the external expert compared to the characterisation of the author serves as quality indicator for the visual interpretation carried out by the author.

The sampling frame used is a list frame, i.e. the list of all identified gain polygons. The sampling units used are the identified gain polygons. These classified polygons represent the two-dimensional spatial coverage of the area on the earth surface. To avoid bias, a simple random sampling strategy is chosen. This strategy has a common inclusion probability design that is typically used to ensure that each polygon in the population of identified gain has equal chance of being present in the sample (Stehman & Czaplewski, 1998). A large-scale study that assessed the accuracy of thematic maps computed from ETM and IKONOS satellite imagery compared simple random sampling, systematic sampling and stratified sampling for validation of land cover classification in China (Xulong et al., 2005). The authors found that both points and polygons are valid sample units. The accuracies of the three methods that Xulong et al. (2005) studied were found to be rather similar. Hence, the easiest to implement method was applied; the method of simple random sampling.

Due to practical reasons the other expert was only willing to characterise a small part of the data. Therefore, the tolerated error level is set to 10%. Because the dataset was already characterised at this stage, the estimated percentage in the population of gain polygons is known to be 90%. This leads to a sample size of 32 (31.3) polygons to be analysed for validation, using the formula below. In the formula n = sample size, z = confidence level (95% confidence gives z = 1.96), N = population size, p = estimated percentage in population, q = 100 – p, and e = tolerated error level (%).

$$n = \frac{z^2 \times N \times (pq)}{e^2 \times (N-1) + (z^2 \times (pq))} \quad 32 = \frac{1.96^2 \times 319 \times (90 \times 10)}{10^2(319-1) + (1.96^2 \times (90 \times 10))}$$

Random selection of 32 from the 319 polygons is applied to extract the desired sample size. The 32 samples are randomly selected by first assigning a random number to each polygon, second the polygons are sorted from low to high by random number, and finally the first 32 polygons are selected.

The attributes are prioritised to minimise the amount of attributes and time required for validation. The most important attributes assess whether there is gain, the origin, the tree canopy cover and the dominant cover next to trees. The resulting list of attributes is partially filled out in advance to ensure that the same imagery is used for validation. Another eleven attributes need data entrance for each polygon. An overview of all attributes for validation is provided below.

Provided in advance:

1. Year of acquisition satellite imagery first year (Y1)
2. Source (Y1)
3. Year of acquisition satellite imagery second year (Y2)
4. Source (Y2)
5. Year of acquisition satellite imagery last year (Y3)
6. Source (Y3)

Requires data entrance:

7. Gain Yes / No (Y1-Y2)
8. Confidence of gain: low, medium, high
9. Gain Yes / No (Y1-Y3)
10. Confidence of gain: low, medium, high
11. Natural / plantation (Y3)
12. Tree canopy cover % (Y1)
13. Dominant coverage Y1
14. Tree canopy cover % (Y2)
15. Dominant coverage Y2
16. Tree canopy cover % (Y3)
17. Dominant coverage Y3
18. Remarks

4.4 Compare results with other datasets

This section discusses the methods used to compare the output of FAO with other datasets. Two comparable datasets are found and analysed. The datasets vary for land-use vs. land cover, forest definitions and the assessed periods. These differences are outlined in Table 4.1 and are further explained below.

Table 4.1. Definitions FAO, JRC and Hansen compared

Subject	FAO	JRC	Hansen
Land cover / land-use	Land-use	Land cover	Land cover
Tree canopy cover threshold	≥ 30%. Except for urban & agricultural tree cover ≥ 30%	≥ 30%	≥ 50%
Height threshold	≥ 5 m trees	≥ 5 m trees	≥ 5 m vegetation
Minimum mapping unit	0.5 Ha	0.5 Ha	0.09 Ha (due to $30m^2$ pixels)
Time period(s)	1990 – 2000, 2000 - 2005	1990 – 2000, 2000 - 2010	2000 - 2012

4.4.1 Dataset from the Joint Research Centre (JRC)

For the JRC land cover dataset a visual interpretation and characterisation is carried out to compare with the FAO dataset. Details on the JRC dataset can be found in section 5.2. The majority of attributes used to characterise the FAO dataset are used to characterise the JRC dataset. Because the aim of characterising the JRC dataset was to assess the quality of the FAO dataset, an exception is made for the coverage in Y3. This attribute is characterised less extensively for the JRC dataset. However still the dominant cover and related percentages are characterised for Y1, Y2 and Y3. This means that 24 attributes used for FAO as listed in section 4.1.2 are used, however with two items on dominant coverage in Y3 that replace the items 22-30 used for FAO.

The JRC dataset is used for comparison with the FAO dataset. Because the identified gain in the JRC dataset is rather large and the emphasis of study lies on studying the FAO dataset, a sample is taken that functions as a representation of the JRC dataset. Since all identified gain polygons of the datasets are known, it is possible to apply a random sampling strategy to test the quality of the JRC dataset. The tolerated error level is set to 5% and the confidence level to 95%. The size of the sample is determined using random sampling with an estimated distribution of 50% gain and 50% no gain. This estimated distribution is the default distribution of the formula. There is a 90% gain and 10% no gain distribution found in the FAO dataset. However due to the large variation in both datasets with regards to definitions used, amount and location of polygons, no reliable initial estimate can be used as input for the formula. With the population of 632 polygons, this leads to a sample size of 240 (239.2) polygons. This amount of polygons is determined using the following formula (the same formula as in section 4.3).

$$\mathrm{n} = \frac{z^2 \times N \times (pq)}{e^2 \times (N-1) + (z^2 \times (pq))} \quad 240 = \frac{1.96^2 \times 632 \times (50 \times 50)}{5^2(632-1) + (1.96^2 \times (50 \times 50))}$$

This formula can be used to determine the appropriate sample size for research activities with a known population size (Krejcie & Morgan, 1970). The 240 sample polygons are randomly selected by first assigning a random number to each polygon, second the polygons are sorted from low to high by random number, and finally the first 240 polygons are selected.

4.4.2 Dataset from Hansen et al. (2013)

The Hansen dataset is a global dataset on forest gain and forest loss between 2000 and 2014. The data on forest gain is only available for the period 2000-2012. This Hansen forest gain data is used for comparison to the extrapolation of the FAO dataset on forest gain. Due to the fact that the dataset spans over all Indonesian land and the total area of forest gain in the indicated period is

69701.1 Km^2, it was not found feasible to visually interpret this dataset for forest land-use gain. The outputs of this dataset should be dealt with precaution, because different definitions are used compared to FAO and JRC. Furthermore, the product is automatically classified and it is not a land-use but a land cover dataset (see Table 4.1 for comparison of FAO, JRC and Hansen). Hansen et al. (2013) define forest gain as the opposite of forest loss. Forest gain regards to the formation of tree canopy on a location that originally was in a non-forest condition. Conditions for gain are related to the definition of forest, such as tree canopy cover density of ≥ 50%.

To determine the actual carbon sequestration related to the Hansen dataset, the same growth rates are applied as with the FAO and JRC dataset. The growth rates are applied for twelve years from 1-1-2000 up to 1-1-2012. This is further explained below in section 4.5.

4.5 Determine carbon sequestration

Biomass data is used to determine carbon sequestration related to forest gain. A distinction is made in assessing actual carbon sequestration and potential carbon sequestration, where the latter is relatively uncertain because it is unknown whether the potential carbon sequestration will be achieved in the future. The actual carbon sequestration divided by the potential carbon sequestration provides an indication to what extent the full potential of the forest is reached, i.e. the maturity of forest gain. Both actual and potential sequestration are assessed, taking into account that the former realises more realistic outputs and higher accuracies in time i.e. biomass change rates for Asia are linearly applied to the period from Y1 to Y3. Where the latter achieves higher accuracy in space, because data is available for Indonesia divided per ecological zone. Due to limited availability of biomass data and satellite imagery, the forest gain processes are assumed to be linear. This means that constant annual growth rates are applied to forest gain. The method used to derive the moment that forest gain starts is explained in between actual and potential carbon sequestration, because this is only relevant for the former.

To enlarge confidence in carbon sequestration estimates, IPCC (2006, 4.29, p. 29) recommends making subdivisions in forest regrowth. IPCC encourages using classes to subdivide planted and natural forests, ecological zones and crown cover proportions present in the study area. Hence data from IPCC is also conveniently separated for natural forests and forest plantations. Due to the nature of study and the advice of IPCC the results will be analysed using multiple classes to assess the forest gain from deviating viewpoints.

4.5.1 Actual carbon sequestration

Growth rates

To determine the carbon sequestration related to forest gain between Y1 and Y3, biomass growth rates are used. In spite of the search for country specific growth rates (in English and Indonesian), the only AGB growth rates applicable to the study area were found as Tier 1 values on the continental scale of Asia. These annual AGB growth rates from IPCC (2006) are assumed to be the only estimate of AGB increases attainable for Indonesia (Table 4.2). These growth rates provide information on natural forests and planted forests.

Table 4.2 AGB growth of natural & planted forests

Ecological zone	**Natural (t/ha/y)**	**Planted (t/ha/y)**
Tropical rainforest	13.0	5.0
Tropical moist deciduous forest	11.0	8.0
Tropical dry forest	7.0	7.0
Tropical shrubland	2.0	6.0
Tropical mountain systems	7.5	5.0

Calculate start date of forest gain

The moment when forest regrowth starts is somewhere in between 1990-2000 or 2000-2005, with a situation changing from non-forest to forest. The moment when forest gain starts is of course related to the definition of forest gain, where certain thresholds function as a requirement for an area to be classified as forest (e.g. ≥ 30% tree canopy cover). There are multiple options to derive this forest gain starting date. The most straightforward option is using the intermediate year. A more advanced option would be to use growth curves, however the data used for this study is not available at a high enough frequency to realise this approach. The chosen approach in this study is to use the tree canopy cover % to derive the forest gain threshold date, from here referred to as "Start gain". This approach is perceived as the proper balance regarding the data availability, ambitions and realism, e.g. when the canopy cover increase in 10 years from 20% to 80%, it is perceived likely that the ≥ 30% threshold is reached in the first half of these 10 years. These calculations are carried out using the image acquisition dates and provided tree canopy cover percentages of Y1 and Y2.

To correct for variations throughout the dataset the intermediate date is chosen based on the date where the canopy cover reaches 30%, assuming linear canopy cover gain. E.g. the image acquisition date of Y1 is 1-1-1992 with a 20% canopy cover and for Y2 the date is 1-1-2001 with 40% canopy cover. The date that the 30% threshold is reached (in the example 2-7-1996), serves as the start for determining carbon sequestration related to forest gain.

The robustness of the method used to determine the start of forest gain is tested with a sensitivity analysis applied to the FAO dataset. In this thesis the time of forest gain is determined using the 30% canopy cover threshold date as start of forest gain. This date is derived assuming a linear canopy cover growth. Forest gain starts somewhere between Y1 and Y2, determined using this threshold date calculation method. Furthermore, for Y1 and Y2 the actual measurements are used, i.e. the image acquisition dates are taken as Y1 and Y2. This means in practice that there can be deviation of circa five years between Y1 for the same forest gain period between multiple polygons, e.g. Y1 can variate from 1988 to 1993. The other approach to determine the start of forest gain – used for sensitivity analysis - is to use the intermediate year and not take into account canopy cover growth. This approach simply uses the time period of regrowth and the intermediate year. This method is applied by means of sensitivity analysis of the results. For this analysis the nominal dates are used. Thus for Y1 this means either 1-1-1990 or 1-1-2000, depending on whether gain occurs from 1990 to 2000 or 2000 to 2005. The related intermediate dates are 1-1-1995 or 2-7-2002. Using this method, it is assumed that forest gain starts at these intermediate years.

4.5.2 Potential carbon sequestration

The maximum value of long-term carbon sequestration, i.e. when the forest gain reaches maturity, is studied. The methods used are partly derived from De Sy et al. (2015). Langner et al. (2014) recommend to use a combination of the two pantropical biomass maps created by Baccini et al. (2012) and Saatchi et al. (2011). This combination achieves an alternative to the IPCC Tier 1 AGB values, which can be used to provide estimates at the country level and make distinction for ecological zones. Country specific AGB values are derived from Langner et al. (2014) for Indonesia, with a distinction for five ecological zones. These biomass values for Indonesia are compared with IPCC (2006) biomass values on the continental scale (Table 4.3). Two equations are used to convert AGB to carbon. Total biomass values are determined using the following formula.

Total Biomass = AGB + 0.489 × AGB$^{0.89}$ (Saatchi et al., 2011). Total carbon sequestration is defined as 50% of total biomass following Achard et al. (2014) (amongst others).

Table 4.3 AGB by ecological zone in tons per hectare for Indonesia (Langner et al., 2014, appendix Table 3) and Asia split to natural forests & forest plantations (IPCC, 2006, vol 4.4.29, pp. 54-56)

Ecological zone	**Langner et al. (2014) applicable to Indonesia**	**IPCC (2006) applicable to Asia**	
	AGB (t/ha)	**AGB in natural forests (t/ha)**	**AGB in forest plantations (t/ha)**
Tropical rainforest	245	350	220
Tropical moist deciduous forest	136	290	180
Tropical dry forest	135	160	90
Tropical shrub land	175	70	40
Tropical mountain systems	254	205	95

4.6 Extrapolate results to the national scale

To extrapolate the results of the actual and potential carbon sequestration to a national scale, a similar approach is used as in De Sy et al. (2015), that was based on the FAO FRA-2010 RSS (FAO & JRC, 2012). In the FAO & JRC (2012) sampling grid, each tile has a total area of land of 10 x 10 km, that is excluded from areas with water and no data (e.g. due to cloud cover). To correct for inconsistencies between tiles (e.g. due to earth curvature) all tiles are converted using the Equal Area Mollweide projection, resulting in the total assessable land area for each tile (ti).

The proportions of forest area gain and carbon sequestration both per ecological zone and per dominant coverage in Y1 are extrapolated to the country of Indonesia. This is done using the Horvitz-Thompson direct estimator (Särndal et al., 1992).

$$\bar{x}_c = \frac{1}{F} \times \sum_{i=0}^{n} (t_i \times x_{ic}), \qquad \text{where} \qquad F = \sum_{i=0}^{n} t_i$$

In the formula xic is the proportion of forest gain or carbon sequestration in the ith tile, and ti is the area of the ith tile. In combination with the total assessable land area of the dataset for Indonesia (F), ti functions as a weight factor for the proportions found in each tile. Next the total area of forest gain or amount of carbon sequestration ($Gain_{subset}$) is calculated using the total assessable land area of Indonesia (A) as follows.

$$Gain_{subset} = A \times \bar{x}_c$$

To derive the standard error (SE) of the extrapolation, the variance of the mean (s^2) is estimated. This variance is used to calculate the standard error. The SE is used to determine the precision of the forest gain estimations and expresses the sampling error. The used equations for the SE are displayed below.

$$s^2 = \frac{1}{F} \times \sum_{i=0}^{n} t_i \times (\bar{x}_c - x_{ic}), \qquad \text{and} \qquad SE = A \times \frac{s}{\sqrt{n}}$$

5 Data, software and research material

The following chapter describes the data, software and related research material used for research. The chapter is structured as follows. First the FAO dataset is introduced (5.1). Secondly the FAO dataset is compared to the JRC dataset that is used (5.2). Next the global dataset of Hansen is introduced (5.3). Section 5.4 describes the biomass data exploited for this study. Finally, the software packages used for research are specified (5.5).

5.1 FAO dataset with sample-based approach

The FAO dataset is described here because it served as the main input for identifying forest gain in this study. The FAO product contains estimates of forest land-use change between 1990, 2000 and 2005, serving as reference years (FAO & JRC, 2012). FAO used a systematic sampling design that covers around 1% of the total land area on earth. This is done using 10km by 10 km tiles that are located on all degree latitude-longitude confluence points (Achard et al., 2014; Eva et al., 2012; FAO & JRC, 2012). This approach was chosen over stratified sampling. Despite the potential higher accuracy for this single study, stratified sampling is favoured because of easier follow-up research and better alignment with national forest inventories. Especially in tropical countries forest inventories are often aligned with this systematic sampling approach (Mayaux et al., 2005; FAO & JRC, 2012). The dataset used medium resolution satellite imagery that is acquired as close to the reference years as possible. The tiles were divided based on spectral information of the land cover through an automated method that results in segments with a minimal size of 5 hectares. Next this automated land cover classification was visually interpreted by country experts and classified for land-use in the reference years. The prime classes are forest, other wooded land and other land, that are demarcated following existing FAO definitions (FAO, 2010a).

For Southeast Asia the dataset consists of 418 sample sites. The coverage of Indonesia comprises 158 sample units, from which 18 sample units are unavailable in the FAO dataset used due to insufficient satellite imagery data coverage in 1990, 2000 and 2005 (Achard et al., 2014), resulting in 140 assessable sample units. The missing tiles are the result of bad quality imagery, erroneous data and weather conditions.

This dataset is used because it provides a systematic sample from which appropriate estimations can be derived for Indonesia. The FAO dataset has a limited temporal coverage from 1990 to 2005. More recent datasets are available from which forest gain can be estimated that have temporal coverage up to 2012 (e.g. Hansen et al., 2013). However, the FAO dataset is favoured above these more recent datasets, because of the land-use definition applied. A similar dataset to FAO is available from JRC. This dataset automatically classified land cover, but did not assess for land-use. The FAO dataset provides a land-use classification that is more feasible to use given the research objectives to characterise forest gain and related dynamics such as origin and dominant coverage. Using the JRC dataset in Indonesia would mean that a substantial share of the classified forest cover is not of interest given the forest land-use definitions.

5.2 FAO land-use dataset & JRC land cover dataset compared

The emphasis of study is to characterise and quantify the identified gain from the FAO dataset. The global database of multi-temporal sample tiles produced for the FAO dataset is based on the USGS GLS archives. The same dataset is used by JRC for the TREES-3 dataset. Additionally, JRC filled the missing tiles and areas with high cloud cover present in the FAO dataset with other Landsat imagery and alternative remotely sensed datasets. The processes of producing the FAO and JRC datasets were a joint venture of the two organisations. Because the datasets have slightly different purposes (e.g. land-use vs. land cover), the resulting datasets are somewhat dissimilar.

Because the JRC dataset has a high spatial and temporal resemblance compared to the FAO dataset a sample of this dataset is also characterised for forest gain. The identified gain from the Hansen dataset has a relatively low spatial and temporal resemblance compared to the FAO dataset and is therefore only used for comparison at the national scale. For comparison of the used dataset, the classified land cover dataset of JRC is used. The same sample grid is used in a collaborative approach of FAO & JRC (2012) to assess both land-use and land cover dynamics. This resulted in the same sample tiles, with equal names and comparable inner polygons. Each tile is saved as shapefile with a name that indicates the latitude and longitude of the sample unit centre, e.g.: N30_E110.shp. Basically the land-uses assigned in the FAO dataset are converted land covers from the JRC dataset, with additional expert classification (FAO & JRC, 2012, p. 9). The areas that

Table 5.1 Conversions of JRC land cover to FAO land-use

JRC		**FAO**	
Land cover code	**Explanation**	**Land-use code**	**Explanation**
10	≥ 70% tree cover	11	Forest ≥ 30% tree cover*
12	≥ 30% tree cover		
20	Shrub cover	12	Other wooded land
30	Other land cover	13	Other tree cover
		14	Natural herbaceous
		15	Agriculture
		16	Built-up
		17	Bare
		19	Wetland
		30	Other land-use
60	Water	18	Water
90	No data	99	No data

* The FAO definition of forest excludes "land predominantly under agricultural or urban use", such as oil palm plantations (FAO, 2000)

are defined forest in FAO are the tree cover and tree-cover mosaic land cover classes from JRC, with the only difference that FAO filters forest cover for the exceptions of urban and agricultural land-use. This difference has a substantial impact on the output. In Indonesia substantial non-forest areas are transformed to palm-oil plantations. These palm-oil plantations are often erroneously classified due to the land-use and land cover definitions. Within the land cover definition palm-oil plantations are often found within the identified gain, while this is not an appropriate result for characterising forest land-use gain. The identified areas of forest gain of the FAO dataset are intersected with the JRC dataset to assess for overlap and differences between the data. An overview of conversions is provided in Table 5.1. The JRC dataset provides land cover codes for 1990, 2000 and 2010. The FAO dataset provides land-use codes for 1990, 2000 and 2005.

5.3 Hansen dataset

The Hansen dataset is available in square tiles of 10 by 10 degree granules in .tiff format. The pixel resolution of the Hansen dataset is 30 meters (i.e. each pixel represents an area of 30m^2). First all tiles with Indonesian territory were downloaded for processing in ArcGIS. Second the tiles were merged. Third the gain pixels were clipped to the relevant ecological zone within Indonesian territory. Here also non-Indonesian territory is further excluded from analysis. The clipping is done using a conditional statement with raster calculator, where all pixels that are both present as gain in the Hansen data and as location in the ecological zone are classified as gain for that ecological zone. All raster conversions and calculations are executed using the same spatial resolution. Fourth, the resulting pixels for Indonesia were measured. Here it was found that the pixel size is 27.8 m^2 when projected using the Equal Area Mollweide projection. The pixel count per ecological zone are multiplied with this average pixel size to determine the area of forest gain for Indonesia and its inner ecological zones.

5.4 Biomass datasets

The 2006 IPCC Guidelines for National Greenhouse Gas Inventories are used to determine the actual carbon sequestration related to forest gain between Y1 and Y3. In these guidelines there are annual biomass growth rates available for forests in Asia, separated for ecological zone and origin. The guidelines provide internationally agreed upon estimates of greenhouse gas sequestration, emissions and storage (IPCC, 2006). As discussed in section 4.1.3 these growth rates are the only estimate attainable for Indonesia.

Next to the growth rates used from IPCC, other biomass data is used to estimate potential carbon sequestration. First IPCC has potential carbon sequestration estimates available for Asia (IPCC, 2006). Secondly Langner et al. (2014) provide spatially explicit information on a subnational scale, i.e. countries subdivided into ecological zones, in tons of dry matter per hectare (t / ha). The authors use the combination of the Saatchi and Baccini pantropical AGB datasets. This is encouraged to use in estimating biomass and related carbon sequestration in the REDD+ context, because it reduces a large share of uncertainty compared to former Tier 1 values (Langner et al., 2014).

The chosen approach is favourable compared to the alternative of using Forest Resource Assessment reports of FAO that also provide forest biomass estimates. This data is generally adopted from the information provided by national authorities. Using this data has multiple drawbacks; it is often incomplete, outdated, unreliable and / or collected for other goals. Furthermore, these national estimates are generally not subdivided into smaller regions within the country, thus excluding spatially explicit information within the country, making this approach less suitable for realising REDD+ objectives (Avitabile, 2013).

5.5 Software

Multiple software packages are used for this study. First SQL querying within ArcGIS (model builder) is used for selecting and editing the polygons of forest gain. Second, recent VHR and Global Land Survey (GLS) data accessed with Google Earth and ArcGIS Online are used for visual interpretation of satellite imagery. Analyses of the visually interpreted polygons are done using Microsoft Excel and ArcGIS. Third, biomass determination is done using ArcGIS and Microsoft Excel.

6 Forest gain in existing datasets

This chapter describes the results of identifying forest gain from the compared datasets (6.1). After identification of the gain polygons, the areas are characterised using visual interpretation as described in section 6.2. The result of validating the results with the help of another expert interpreter is presented in section 6.3.

6.1 Identified forest gain

Substantial differences are found between the FAO, JRC and Hansen datasets for the quantity and locations of forest gain (Table 6.1). For the FAO dataset 6,031 Ha is identified as forest gain, representing 296 polygons. In the JRC dataset an area of 19,736 Ha is identified as forest gain, the sum of 632 polygons. For this study the areas of interest are those that change from non-forest to forest without shifting cultivation, from here referred to as identified forest gain. Shifting cultivation is excluded because of the forest land-use definition. According to this definition the intentional use of the land defines the land-use applied to the area. When shifting cultivation occurs, the intentional land-use remains forest.

The results indicate that the majority of identified forest gain in the FAO and JRC datasets are not even in close proximity to each other. After spatially comparing the datasets it was found that there is relatively little overlap for the identified gain. Just 9 of the 319 identified gain polygons are geometrically identical, i.e. identical in location and boundaries. This low output is possibly caused by the slightly different methods used to build the datasets as described in section 5.2. The results of intersecting both datasets were somewhat higher, but still rather low. The identified gain of both datasets is intersected to check if the low overlap is caused by the differences that exist between FAO and JRC. In the first period (1990-2000) the share of intersection is substantial with 42.5%, however for the second period (2000-2005) the intersection is very low with 6.6%. For the second period the low share of intersecting polygons can also be caused by the difference in temporal scope. Applying an additional search distance of 1,000 meters resulted in a small increase of selected areas, i.e. this lets the shares rise to 55.2% and 14.8% respectively. An intersect occurs when a polygon from one of the datasets shares a common part with a polygon in the other dataset. Due to data gaps in the FAO dataset only 140 of the intended 158 tiles were available. In the JRC dataset all the intended tiles are available. It is chosen to only compare for the same 140 tiles as can be found in both datasets. By only assessing the overlapping tiles the datasets are compared for the same areas and differences are reduced to the nature of the dataset only.

Comparing the entire datasets of FAO and JRC stresses the result that the areas of identified gain in both datasets are completely different. Almost all FAO polygons intersect with the JRC polygons 98.9% (45,184/45,695). The majority of polygons are found to be somewhat different regarding geometry. Just 8.3% of the FAO polygons have identical geometry compared to the polygons present in the JRC dataset. In number of polygons this percentage equals 3971 polygons from the totals of 45,695 FAO polygons and 51,349 JRC polygons. The abbreviations used in Table 6.1 are explained here. (1) ≥0.5 Ha = polygons that have a minimal area of 0.5 hectare. (2) F = forest. (3) NF = non-forest. (4) NSC = no shifting cultivation, meaning that in the period 1990–2000-2005 the pattern is NF–F-F. NF-F means a transition from non-forest in the first year of the time period to forest in the final year of the time period. The FAO dataset consists of 45,695 polygons, from which 44,075 meet the minimum mapping unit requirement of ≥ 0.5 Ha. Polygons that are classified as no data are regarded as an unbiased loss of information. All areas provided from the dataset where no data was present are therefore excluded from further analysis.

Table 6.1 Comparison of FAO and JRC data for identified forest gain polygons

What	**FAO**		**JRC**	
Time period	90 - 00	00 – 05	90 - 00	00 - 10
Amount of polygons	45,695		50,923	
Area in Km^2	14,129.0		15,884.1	
Amount of polygons (≥0.5 Ha)	44,075		49,868	
Amount of 10x10 km tiles	140		158	
Average amount of polygons (≥0.5 Ha) per tile	315		316	
Polygons NF–F (≥0.5 Ha)	178	145	482	336
Area in ha of polygons NF–F (≥0.5 Ha)	3,791	2,897	13,657	10,614
Shifting cultivation (NF-F-NF)	4		114	
Shifting cultivation area in Ha	13		2,186	
Identified NF–F NSC (≥0.5 Ha) polygons	**174**	**145**	368	336
Identified NF–F NSC (≥0.5 Ha) in ha	**3,778**	**2,897**	11,471	10,614
Total NF–F NSC (≥0.5 Ha)	319		704	
Total NF–F NSC (≥0.5 Ha) in ha	6,676		22,085	
Comparison of NF-F NSC for the same 140 tiles				
Identified NF–F NSC (≥0.5 Ha) polygons	**174**	**145**	342	290
Identified NF–F NSC (≥0.5 Ha) in Ha	**3,778**	**2,897**	10,505	9,231
Identical NF–F NSC (≥0.5 Ha) polygons	7 (4.0%)	2 (1.4%)	7 (2.0%)	2 (0.7%)
Intersection between NF–F NSC (≥0.5 Ha) polygons	71 (40.8%)	8 (5.5%)	71 (20.8%)	8 (2.8%)
Total NF–F NSC (≥0.5 Ha)	**319**		632	
Total NF–F NSC (≥0.5 Ha) in Km^2	**66.8**		197.4	
Area NF–F NSC (≥0.5 Ha) / area dataset	**0.47%**		1.24%	

Hansen dataset

Next to the datasets of FAO and JRC that apply a sample-based approach, the Hansen dataset with full land coverage is also used for identification of forest gain. Within this dataset an area of 69701.1 Km^2 is identified, representing 90.1 million forest gain pixels. The gain identified from Hansen is not characterised, but it is used for comparison to the other datasets. Therefore, the results from the Hansen dataset are discussed more extensively in section 8.4, where the extrapolated results from the FAO and JRC datasets are used for comparison.

Sample JRC

From the 632 identified gain polygons (>0.5 ha) present in the JRC dataset, a random sample was taken that resulted in 240 polygons, with a total area of 6925 Ha. For these areas the overlap with the FAO dataset is assessed. One should bear in mind that the JRC sample is not directly comparable to the identified gain present in FAO dataset, because the sample excludes 62% of identified gain.

A large share of the identified overlap for all identified gain polygons of the JRC dataset is also present in the sample (Table 6.2). It was found that 7 polygons are geometrically identical to the identified gain areas in the FAO dataset. Furthermore 56 of the 240 identified polygons intersect with the FAO dataset.

Table 6.2 Comparison of polygons used for visual interpretation

What	**FAO**		**JRC**	
Time period	90 - 00	00 – 05	90 - 00	00 - 10
Identified NF–F NSC (≥0.5 Ha) (sample) polygons	174	145	128	112
Identified NF–F NSC (≥0.5 Ha) in Ha	3,778	2,897	3,783	3,142
Identical NF–F NSC (≥0.5 Ha) polygons	5 (2.9%)	2 (1.4%)	5 (3.9%)	2 (1.8%)
Intersection between NF–F NSC (≥0.5 Ha) polygons	50 (28.7%)	6 (4.1%)	50 (39.1%)	6 (5.4%)

6.2 Characterised forest gain

6.2.1 Main results characterisation

For both datasets the majority of identified forest gain is characterised as forest gain (Table 6.3). Characterised gain refers to the identified gain areas that are confirmed as forest gain using visual interpretation of satellite imagery. For the FAO dataset 90.3% of identified gain is characterised as forest gain, for the JRC dataset 58.2% of identified forest gain was characterised as forest gain for the analysed sample of JRC polygons.

Table 6.3 Comparison of FAO and JRC data for characterised forest gain polygons

Characteristic	**FAO**	**JRC***
Characterised gain area / identified gain area	90.3%	58.2%
Characterised gain area in ha	6,031	4,031
Natural gain area / characterised gain area	71.5%	45.2%
Planted gain area / characterised gain area	28.5%	54.8%
Dominant ecological zone area	Tropical rainforest (69.4%)	Tropical rainforest (91.6%)
Dominant cover of characterised gain areas in non-forest state in Y1	Shrub land (70.6%)	Shrub land (68.4%)
Dominant dispersion pattern area in Y3	Random (64.6%)	Random (48.3%)
Average increase in canopy cover % from Y1-Y3	39.2% ± 17.1%	33.1% ± 11.1%

* The characterised gain of JRC is based on a 38% sample of the identified gain

The characterised no gain areas of the FAO dataset are for 83.1% of the area caused by the presence of crop palm-oil plantations in Y3, however one should note that these crop areas are for 89.9% initiated after Y2. The relatively low confirmation of the JRC dataset is for 72.0% caused by polygons that were already forest in Y1, however classified as non-forest in the dataset. The other major cause is the presence of crop palm-oil plantations. These crop areas are present at 23.5% of the characterised no-gain areas.

Regarding the origin of characterised gain both datasets provide quite some deviating results. For the FAO dataset 71.5% of the area is reported as natural gain, where in the JRC dataset this share is only 45.2%. Concerning the distribution of the dominant coverage in Y1, the dispersion patterns and the canopy cover increase percentages, the results are comparable for both datasets.

Next to the attributes characterised, also the location of characterised gain is compared for the FAO and JRC datasets (Table 6.4). The majority of the intersect of the identified gain polygons (as presented in Table 6.2) is also found for characterised gain. The largest shift is found for the period 1990-2000 where the amount of intersecting polygons dropped from 50 to 42.

Table 6.4 Comparison of characterised gain polygons

What	**FAO**		**JRC**	
Time period	90 – 00	00 – 05	90 - 00	00 - 10
Characterised NF–F NSC (≥0.5 Ha) (sample) polygons	164	122	128	112
Characterised NF–F NSC (≥0.5 Ha) in ha	3,663	2,368	2,058	1,973
Identical NF–F NSC (≥0.5 Ha) polygons	5 (3.0%)	2 (1.6%)	5 (3.9%)	2 (1.8%)
Intersection between NF–F NSC (≥0.5 Ha) polygons	42 (25.6%)	5 (4.1%)	42 (32.8%)	5 (4.4%)

Besides the tabular information on the characterised forest gain as portrayed in Table 6.4, the characterised gain is visualised in maps. These maps can be found in Figures A.1 – A.4 of the appendix of this thesis. Four maps are generated in total. For both datasets two maps are made for the two periods that are assessed. The total area of characterised forest gain is summed per tile and depicted as proportional symbol for the quantity of gain in hectares.

6.2.2 Forest gain FAO

The identified FAO gain polygons are characterised for the attributes described in section 4.1.2. The results presented in this section are separately discussed based on origin, period, dispersion pattern and ecological zone. First the general outcomes are discussed. To evaluate the quality of the dataset a distinction is made between identified forest gain and characterised forest gain, in the general outcomes. In the subsequent paragraphs "forest gain" refers to characterised forest gain, unless stated otherwise.

General outcomes

From the identified gain a share of 90.3% of the area and 89.7% of the polygons is characterised as forest gain. Put exact, for the total identified gain area of 6,676 Ha, an area of 6,031 Ha is characterised as gain (and 286 of the 319 polygons) in Y3. This result indicates that the majority of the identified polygons continued regrowth after Y2 from the forest gain periods of FAO (1990-2000 or 2000-2005). Furthermore, the identified share of forest gain compared to the entire dataset of 0.47%, slightly declined to 0.43% as characterised forest gain.

The characterised no gain areas of the FAO dataset are for 83.1% of the area caused by the presence of crop palm-oil plantations and for 10.9% by the fact that the identified non-forest state in Y1 is found to be forest using visual interpretation of Y1.

The polygons are interpreted for Y1, Y2 and Y3. All identified areas are analysed in Y2 to check for the accuracy of the dataset – i.e. to check to what extent the identified gain is correct - and to investigate resemblance to the forest gain or loss result found in Y3. From the characterised forest gain areas in Y3, 99.1% (5,975 Ha) is characterised as gain in Y2 and 0.9% (57 Ha) as no gain in Y2. The validated no gain areas in Y3 are analysed in Y2 to verify the no gain result found in Y3. From the no gain areas in Y3, 91.7% (591 Ha) is confirmed to be no gain in Y2 and 8.3% (54 Ha) is characterised as gain in Y2. This results in 6,028.2 Ha of land that is characterised as forest gain in Y2, representing a share of 0.43% of the area of the FAO dataset. These results indicate that a commission error of 9% is present in the dataset for the identified forest gain. Based on the characterisation a canopy cover gain percentage is determined, by subtracting the canopy cover in Y3 from the canopy cover in Y1. The average canopy cover gain for all gain polygons is 39.2% ± 17.1%.

All 319 identified gain polygons (≥0.5 Ha) have a cumulative size of 6,676 Ha. The average size of these polygons (≥0.5 Ha) is 20.9 ± 25.3 Ha. The smallest polygon has a size of 0.5 Ha and the largest is 210.4 Ha. The majority of polygons of forest gain were classified with high confidence for forest gain (Table 6.5). A minor share of gain was classified with medium certainty. Zero gain polygons are classified with low certainty. The no gain polygons were classified with a relatively low certainty compared to the gain polygons. One third of the polygons is characterised with low confidence and two third with medium confidence.

Table 6.5 Confidence levels of visual interpretation

Confidence	**Gain polygons**		**No gain polygons**	
	Count	**%**	**Count**	**%**
High	252	88%	0	0%
Medium	34	12%	22	67%
Low	0	0%	11	33%

Origin

The majority of forest gain is natural forest gain. From the 286 polygons 80.1% is characterised natural forest gain and 19.9% as planted forest gain. When looking at the related areas, the difference gets smaller with 71.5% (4,312 Ha) natural and 28.5% (1,720 Ha) planted forest gain. The average canopy cover gain found for natural gain is 37.7% ± 17.1%. For planted gain the average canopy cover gain is found to be 20.1% higher compared to natural gain, with an average increase of 45.3% ± 19.8%.

The land coverage of natural forest gain and planted forest gain areas vary substantially (Table 6.6). The tree cover on planted forest gain is higher compared to natural gain. Crop land and settlements represent a relative large proportion of land on planted forest gain compared to natural forest gain. It was expected that the planted forests would be characterised by a higher rate of human involvement, because these trees are planted by humans. This is confirmed by the higher presence of crop land and settlements, indicating that more human activity is taking place in the planted forest gain areas. From the crop land on the planted gain polygons 50.0% are palm oil plants, compared to 14.3% for natural gain. The

Table 6.6 Coverage forest gain polygons Y3 by origin

What	**Natural gain**	**Planted gain**
Tree cover	57.0%	64.8%
Crop land	2.2 %	4.4 %
Shrubland	23.1 %	9.6 %
Herbaceous	11.4 %	15.6 %
Wetlands	2.8 %	0.2 %
Settlements	1.4 %	3.5 %
Bare land	2.1 %	1.4 %
Other land	0.0 %	0.5 %
All cover	100%	100%

settlements surrounding planted gain are for 79.7% predominantly roads, for natural gain this fraction is 62.1%.

During visual interpretation remarks were provided to polygons where relevant. This resulted in the addition of four new attributes assigned to the polygons. These attributes are found to be rather different for natural forest gain opposing planted forest gain (Table 6.7). On natural gain there is a relatively high percentage of gain on (former) roads or water compared to planted gain. Multiple times it was observed that in Y1 there was clearly a road structure, where in Y3 this road was overgrown with natural forest regrowth. Another interesting output is that about a quarter of the planted forest gain polygons have road structures amidst. A possible explanation is that there needs to be accessibility to land via roads as a precondition for human-induced forest plantations. Next there is also a substantial share of polygons where gain on (former) water occurred. These forest gain polygons were often found next to meandering rivers or shorelines.

Table 6.7 Portion of additional attributes by origin

Attribute	**Natural**	**Planted**
Gain on (former) roads	3.9%	3.5%
Gain on (former) water	3.9%	1.8%
Settlement is road	7.9%	24.6%
Crop is palm oil plantation	3.5%	5.3%

Pattern

The majority of forest gain is characterised with a random dispersion pattern. Clumped gain occurred at 37 of the polygons with a total area of 890 Ha. Random gain was found at 211 of the polygons with a total area of 3,899 Ha. Finally, for 38 of the polygons uniform gain was determined, representing a total area of 1,243 Ha.

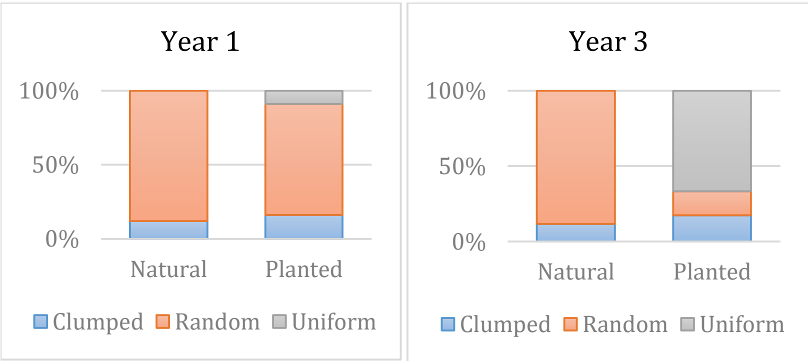


Figure 6.1 Dispersion pattern per origin for Y1 & Y3

The dispersion patterns for natural and planted forest gain are rather similar for Y1 (Figure 6.1). In Y1 there is 9% uniform forest on planted gain, indicating that some of these polygons were already plantation in Y1. In the time between Y1 and Y3 there are large shifts mainly from the random pattern to the uniform dispersal pattern. These shifts are predominantly caused by forest plantations.

The areas with uniform gain are characterised by the highest canopy cover gain percentage of 53.7% ± 17.5%. A boxplot of the results is presented in Figure 6.2. The areas with clumped forest gain are characterised by their relatively low gain percentage of 29.5% ± 10.3%. The random gain polygons are in between with an average increase of 38.3% ± 16.4%.

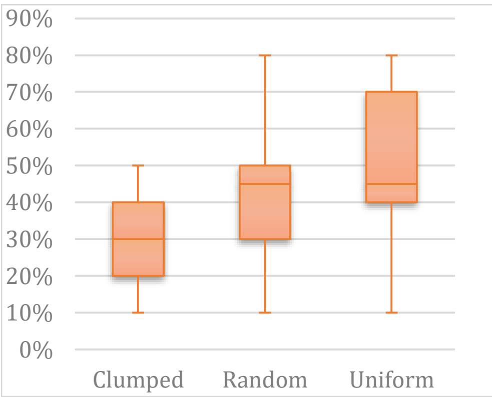


Figure 6.2 Boxplot of canopy cover gain percentages per dispersion pattern

Period

The majority of the forest gain area is characterised in the first period. From the 6031 Ha of forest gain 60.7% is found for the period 1990-2000 and 39.3% for the period 2000-2005. However, given the temporal scope of the periods, the forest gain per year is 29% higher for the second period (474 ha / year) compared to the first period (366 ha / year).

Overall there is a weak positive linear relationship found between the time in years (Y3 - Y1) and canopy cover gain percentage: R = 0.39 (Figure 6.3). The results indicate that the time of regrowth has some positive correlation with the proportion of canopy cover gain.

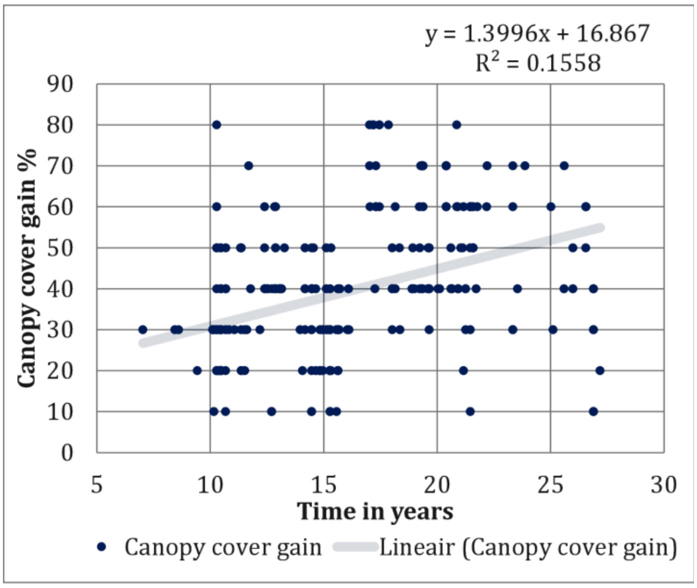


Figure 6.3 Correlation time and canopy cover gain

The dominant coverage in year 1 is predominantly shrubland for 63.4% of the polygons where gain occurred between 1990 and 2000 and 80.3% for gain between 2000 and 2005 (Figure 6.4). For both periods the second largest coverage in Y1 was herbaceous land.

The canopy cover gain is higher for the polygons where forest gain took place between 1990-2000, compared to the polygons where gain took place between 2000-2005. The former has an average canopy cover gain of 44.9% ± 17.8%, where the latter has an average canopy cover gain of 31.6% ± 12.7%.

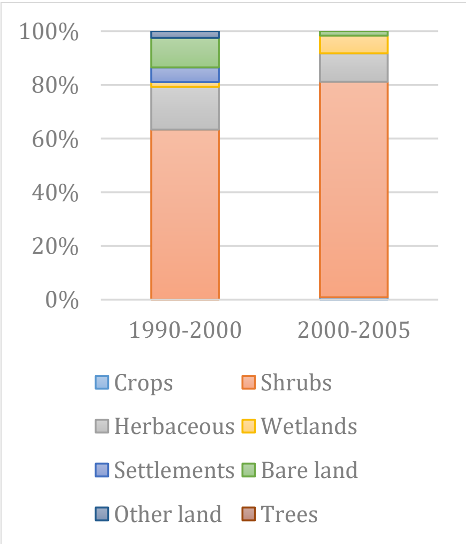


Figure 6.4 Distribution of dominant coverage Y1 for 1990-2000 & 2000-2005

The share of polygons with crops is 3.7% (6 polygons) for gain between 1990-2000 and 19.7% (24 polygons) for gain between 2000-2005. Over one third (36.7%) of the crop land is palm oil plantation, 2 out of 6 and for 1990-2000 and 9 out of 24 for 2000-2005.

From the 286 gain polygons, 164 polygons are identified for the period 1990 – 2000 and 122 polygons for the period 2000 – 2005. For gain in the period 1990-2000 the average Y1 date of acquisition is 4-8-1991 ± 2.1 years. In Y2 the average date is 8-5-2001 ± 0.8 years. For Y3 the average date is 28-4-2013 ± 1.6 years. The images used for gain in the period 2000-2005 are closer to the reference years compared to the images used for gain in the period 1990-2000. For gain between 2000 and 2005 the average Y1 date of acquisition is 12-10-2000 ± 0.4 years. For Y2 the average date is 9-7-2005 ± 0.5 years and for Y3 the average date is 12-10-2013 ± 1.1 years.

Ecological zone

The distribution in forest gain areas per ecological zone is as follows. Tropical rainforest represents 69.4%, tropical moist deciduous forest 25.9% and tropical mountain systems 4.7%. The canopy cover gain percentages are highest for tropical rainforest with 42.2% ± 18.0%, in between for tropical moist deciduous forest with 34.4% ± 11.5% and lowest for tropical mountain system with 30.8% ± 11.4%.

6.2.3 Forest gain JRC

The identified JRC polygons are characterised for the attributes described in section 4.1.3. The section is constructed as follows. First the general outcomes are reviewed, second the results are presented for the origin, period and ecological zone. To evaluate the quality of the dataset a distinction is made between identified forest gain and characterised forest gain, in the general outcomes. In the subsequent paragraphs "forest gain" refers to characterised forest gain, unless stated otherwise.

General results

The characterised gain that verified the identified gain resulted in a share of 58.2% of the area and 62.5% of the polygons. Thus 150 of the 240 polygons are characterised as forest gain in Y3, representing 4031 Ha.

The relatively low confirmation of the JRC dataset is for 72.0% caused by polygons that were already forest in Y1, however classified as non-forest in the dataset. It was found that the JRC dataset often erroneously classifies the Y1 values in the dataset. For 72.0% of the characterised no gain areas it was found that the non-forest state identified in Y1 actually is a forest state. The other major contributor to the relatively low characterised gain compared to identified gain is the presence of crop palm-oil plantations. These crop areas are present at 23.5% of the characterised no-gain areas.

Generally, the identified forest gain polygons continued regrowth after Y2 from the forest gain periods of the JRC dataset (1990-2000 and 2000-2010). Only 3 polygons deviate in Y2 from Y3 with respect to whether there is forest gain. For these 3 polygons there was forest gain between Y1 and Y2, however the land is transformed into palm oil plantation between Y2 and Y3. Meaning that the identified gain was valid for characterisation of the assessed period by JRC, however the land-use changed after the assessed period by JRC.

The majority of forest gain polygons are classified with high confidence. A small share was classified with medium certainty. A minority is classified with low certainty (Table 6.8). The polygons with low confidence are not taken into account for analysis.

Table 6.8 Confidence levels of visual interpretation

Confidence	Gain polygons		No gain polygons	
	Count	%	Count	%
High	129	86	66	73
Medium	19	13	22	25
Low	2	1	2	2

Period

The characterised forest gain is found to be quite equally distributed over the identified gain periods. For the JRC period the periods of identified gain both have a temporal scope of 10 years. For the first period of 1990-2000 a share of 51.1% of the area of characterised gain is found. For the second period of 2000-2010 a portion of 48.9% of the area is found.

There is no correlation found between the time of regrowth and canopy cover gain (Figure 6.5). After plotting the data practically no relationship (R = 0.01) is found between time of regrowth and canopy cover gain. When plotted only for the identified gain that started between 1990 and 2000, the correlation between time and canopy cover gain is still found to be low at R = 0.14. Plotted for gain that started between 2000 and 2010, the relationship is found to be somewhat higher with a positive R of 0.22. Despite the increases when dividing in sub groups, no clear relationship can be derived from the results.

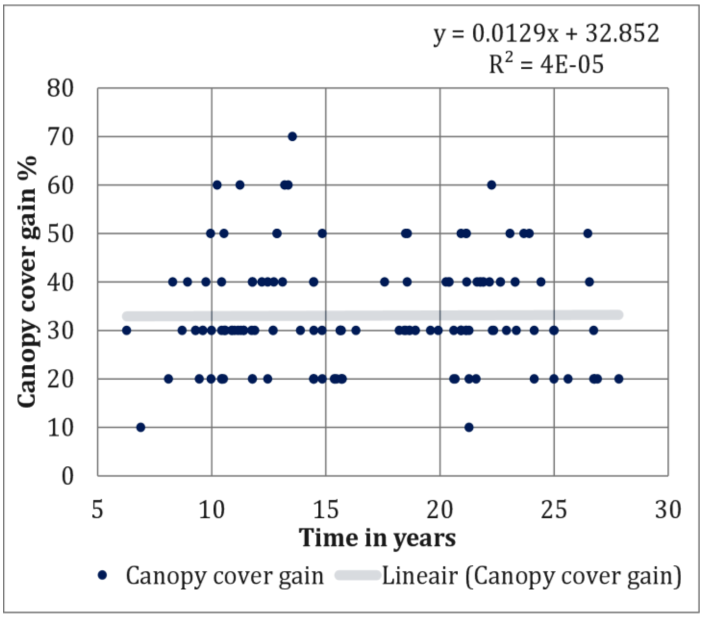


Figure 6.5 Correlation time and canopy cover gain

Origin
The distribution in origin is fairly equal, regarding the size in hectares the distributions is 45.2% (1,821 Ha) natural gain and 54.8% (2,209 Ha) planted gain. Concerning the amount of polygons 55.3% is characterised natural forest gain and 44.7% as planted forest gain. The average canopy cover gain found for natural gain is 31.2% ± 9.8%. For planted gain the average canopy cover gain is found to be 13.5% higher compared to natural gain, with an average increase of 35.4% ± 12.2%.

Ecological zone
From the total characterised gain area of 4031 Ha, the distribution in forest gain per ecological zone is as follows. Tropical rainforest represents 91.6% (3,691 Ha), tropical moist deciduous forest 8.0% (323 Ha) and tropical mountain systems 0.4% (17 Ha).

6.3 Characterisation validated

For the purpose of validating the results of the visual interpretation, another expert characterised a subset of the FAO dataset. The tested subset is compared to the data entered by the author. The results of this comparison are discussed in this section.

The validation provided an **agreement of 91%** to the data characterised by the author, i.e. 29 of the 32 polygons received the same result with regards to whether there is forest gain between Y1 and Y3 or not. Furthermore. a high resemblance is found with regards to the origin, with a similarity of 94%. With regards to the dominant coverage in Y1 the correspondence was 75%. This relatively low correspondence is probably caused by the medium resolution of the GLS data used for Y1, making the classification somewhat imprecise.

Thanks to one expert reviewer with sufficient knowledge and the willingness to carry out this visual interpretation voluntarily, the validation is part of this thesis. The expert reviewer is a Dutch student in the final stage of the MSc Geo-Information Science at Wageningen UR. The reviewer gained expertise in tropical forestry at a BSc level. Furthermore, the subject of his master thesis is characterising forest regrowth in Brazil, for which he used a similar characterisation approach as applied in this thesis.

In comparison to the author, the expert reviewer found it somewhat difficult to interpret the tree canopy cover in Y1 and Y2. This experienced difficulty was predominantly caused by the relatively low spatial resolution of the datasets for these years. For example, in the remarks a statement is made about the ability to distinguish herbaceous land from shrub land. Furthermore, a misunderstanding in definition caused that the expert reviewer defined palm oil cover as forest land-use at two polygons. This was corrected for in the final output.

The validation confirms that the visual interpretation carried out by the author is of high quality. It is assumed that the correspondence between the output of the validator and the output of the author are a good indicator of visual interpretation quality. Since the validation did not provide 100% agreement, it is assumed that about 9% of visual interpretation could provide an ambiguous output. Here one should consider that the validation is only carried out by one person for a relatively small subset of the characterised data. However due to the high correspondence of validation, the output by the author is overall assumed to be fairly reliable.

7 Carbon sequestration related to characterised forest gain

This chapter provides the carbon sequestration result for the characterised forest gain of the FAO and JRC datasets. The estimates address the carbon sequestration without spatial extrapolation. For JRC the characterised gain is based on a 38% sample of the identified gain. The carbon sequestration estimates refer to the total amount of carbon, i.e. the sum of AGB and BGB. To facilitate simple comparison, the carbon sequestration related to the dataset is normalised to tons C per hectare per year.

7.1 General

Carbon sequestration is determined using the time between the start of gain and 31-12-2015 for each polygon, from here referred to as “start gain – 2015”. If a polygon is confirmed to be forest gain, the annual growth rate is applied and multiplied with the area in hectares and the time in years between the start of gain and 31-12-2015.

The carbon sequestration results of the characterised forest gain are presented in Table 7.1. The average carbon sequestration rate found in the FAO dataset is 16.3% higher compared to the average carbon sequestration rate derived from the JRC dataset, indicating a moderate difference.

Table 7.1 Actual carbon sequestration FAO and JRC compared by origin (start gain - 2015)

Dataset	**All**		**Natural**		**Plantation**	
	Tons C	**Tons C / Ha / Y**	Tons C	% / All	Tons C	% / All
FAO	682,273	**6.99**	571683	**83.8**	110,590	**16.2**
JRC*	399,133	**6.01**	274856	**68.9**	124,277	**31.1**

* The characterised gain of JRC is based on a 38% sample of the identified gain

For the distribution in origin large differences are found between the datasets. For FAO the large majority of 83.8% is natural gain, where in the JRC dataset this share is only 68.9%. In both characterised datasets the proportion of carbon sequestration related to natural forest gain is found to be higher than the share of carbon sequestration related to planted forest gain. The carbon sequestration by natural gain was not only in absolute terms higher than the planted forest gain, but also relatively by evaluating the carbon rates per hectare per year. The carbon sequestration rates found for planted gain were 46% of the rates found for natural gain for FAO. For JRC this the planted gain rates are 40% of the rates found for natural gain.

7.2 FAO

This section quantifies the characterised forest gain derived from the identified gain polygons present in the FAO dataset. The estimates are provided for actual carbon sequestration and potential carbon sequestration. For actual carbon sequestration a sensitivity analysis is executed to enlarge robustness of the method used for determination of the start of forest gain.

7.2.1 Actual carbon sequestration

The actual carbon sequestration due to characterised forest gain is divided based on location (ecological zones), origin (natural / plantation) and previous land-use (dominant cover Y1). When assessing the spatial component, 74.8% of the carbon sequestration is located in tropical rainforest, 21.1% in tropical moist deciduous forest, and 4.1% in tropical mountain systems (Table 7.2). With regards to the origin 83.8% is carbon sequestration related to natural gain and 16.2% is the result of planted forest gain. The relatively small area of forest gain in tropical mountain systems deviates from the other ecological zones in the proportion of carbon sequestration with regards to origin. In the tropical mountain systems 95% is found as natural gain and 5% as planted gain.

Table 7.2 Actual carbon sequestration by origin and ecological zone (tons C start gain - 2015)

Region	**Natural**		**Plantation**		**All**	
	Tons C	% / Origin	Tons C	% / Origin	Tons C	% / Region
Total Indonesia	571,683	**83.8**	110,590	**16.2**	682,273	100.0
Tropical rainforest	424,902	83.2	85,750	16.8	510,653	74.8
Tropical moist deciduous forest	120,554	83.7	23,450	16.3	144,005	21.1
Tropical mountain systems	26,226	95.0	1,389	5.0	27,615	4.1

The actual carbon sequestration is separately assessed for the dominant cover in the non-forest year (Y1) (Table 7.3). The dominant coverages are unevenly distributed with regards to area and carbon sequestration. The majority of forest gain took place in areas with shrubland as dominant coverage in Y1. The second largest dominant coverage is herbaceous, with 10.4% of the area and 10.0% of the carbon sequestration. The proportions of area and related carbon sequestration are rather similar, though there are larger variations for the dominant coverages with a relatively small area. These variations are caused by the fact that these small subgroups are formed of a relatively low amount of polygons, that have a non-representative distribution of carbon sequestration rates compared to the average of all forest gain. The biggest relative difference in proportion of area compared to proportion in tons C is found at other land. For this dominant coverage the share in tons C is 89.7% larger than the share of the gain in Ha.

Table 7.3 Forest gain related area (Ha) and actual carbon sequestration (tons C) per dominant coverage in Y1 from start gain – 2015

Dominant coverage Y1	**Area gain polygons**		**Actual Carbon sequestration**	
	Ha	%	Tons C	**%**
Crop land	6	0.1	588	0.1
Shrubland	4,750	78.8	531,395	77.9
Herbaceous	625	10.4	67,941	10.0
Wetlands	95	1.6	9,998	1.5
Settlements	87	1.4	13,491	2.0
Bare land	432	7.2	51,601	7.6
Other land	35	0.58	7,260	1.1
Total	6,031	100.0	682,273	100.0

7.2.2 Sensitivity analysis

The impact of the method for determining the start of forest gain on the carbon sequestration rates is assessed with a sensitivity analysis on the output of the FAO dataset. The results of this method can be found in Table 7.4.

Based on the low difference in the total output of 11% it is concluded that there is relatively low sensitivity to the method used. When assessing subcategories minor shifts are found regarding the internal distributions.

Table 7.4 Actual carbon sequestration compared for start gain – 2015 and intermediate date

Region	**Actual Carbon sequestration (start gain - 2015)**		**Actual Carbon sequestration (intermediate date)**		**Δ carbon sink**	**Δ internal distribution**
	Tons C	%	Tons C	%	%	%
Indonesia	682,273	100.0	757,154	100.0	11.0	0.0
Natural	571,683	83.8	632,726	83.6	10.7	-0.2
Planted	110,590	16.2	124,428	16.4	12.5	1.2

In general, the results provide a higher output compared to the initial method used. For Indonesia as a total, the growth in actual carbon sequestration is only 11%. When it comes to distribution the differences are relatively small. The origin is for 83.6% natural and 16.4% plantation, a marginal shift compared to the output of the initial method used (83.8% natural and 16.2% plantation). Furthermore, there are some minor shifts in distribution of carbon sequestration between the ecological zones. The largest relative changes are found at the tropical mountain systems and the tropical moist deciduous forest. Planted forest gain at tropical mountain systems increases with 33% due to using this method, however the absolute change is rather small due to the minor presence of this subset compared to all gain. The second largest increase is found at forest gain in tropical moist deciduous forest, with a gain of 18%. Overall it is found that the approach used for sensitivity analysis shows an increase in all categories, though the relative distribution between internal categories is rather stable.

To increase the thoroughness of the sensitivity analysis, the impact of using the intermediate year to calculate carbon sequestration is also applied to the dominant coverage in Y1. In Table 7.5 this comparison is done using both the absolute distribution and the relative distribution. Additionally, the Δ carbon sink and Δ internal distribution are provided. The Δ carbon sink reports changes between the tons C of the threshold date method and the intermediate date method. The top three largest relative changes are increases of 31%, 28% and 30% for crop land, herbaceous land and wetlands respectively. The other land coverage is the only category with a decrease in carbon sequestration. The internal distribution, i.e. the shares of each category relative to the total of the used method are relatively stable. The largest relative shifts occur at herbaceous land, bare land and other land with 15%, 13% and -18% respectively.

Table 7.5 Actual carbon sequestration per dominant coverage in Y1 compared for start gain – 2015 and intermediate date methods

Dominant coverage Y1	**Actual Carbon sequestration (start gain - 2015)**		**Actual Carbon sequestration (intermediate date)**		**Δ carbon sink**	**Δ internal distribution**
	Tons C	**%**	**Tons C**	**%**	**%**	**%**
Crop land	588	0.1	771	0.1	31.2	0.0
Shrubland	531,395	77.9	571,235	75.4	7.5	-3.2
Herbaceous	67,941	10.0	86,707	11.5	27.6	15.0
Wetlands	9,998	1.5	13,006	1.7	30.1	13.3
Settlements	13,491	2.0	15,163	2.0	12.4	0.0
Bare land	51,601	7.6	63,688	8.4	23.4	10.5
Other land	7,260	1.1	6,583	0.9	-9.3	-18.2
Total	682273	100.0	757154	100.0	11.0	0.0

7.2.3 Potential carbon sequestration

The potential carbon sequestration is estimated to provide insight in the extent to which the forest gain areas reached their full potential (Table 7.6). On average the actual carbon sequestration amounts found are 61.5% of the potential carbon sequestration. For natural gain this percentage is somewhat higher, where for planted gain this percentage is somewhat lower. The average time of forest gain is provided to put the estimated percentage of potential in perspective. This period is based on start gain - 2015. Because the actual carbon sequestration is based upon IPCC (2006) data, the comparison with potential carbon sequestration is based on the same data source. IPCC default AGB values (t/ha) are used to derive total carbon. Next these carbon values per hectare are applied to the polygon areas as described in section 4.5.2.

Table 7.6 Actual (start gain – 2015) and potential carbon sequestration compared

Area	**Actual sequestration**	**Potential sequestration**	**% of potential**	**Time of forest gain in years**
Indonesia	682,273	1,109,195	61.5	16.2
Natural gain	571,683	879,530	65.0	15.9
Planted gain	110,590	229,666	48.2	16.8

Next to IPCC (2006), Langner et al. (2014) also provide estimates on potential carbon sequestration (Table 7.7). The potential carbon sequestration derived from Langner et al. (2014) is 75.0% of the estimate derived from the potential carbon sequestration indicated by IPCC. This lower estimate of potential carbon sequestration is spatially more specific compared to IPCC (2006) data for potential carbon sequestration. Therefore, the output of IPCC is only used to estimate the extent to which the full potential of the forest gain polygons is reached. The data of Langner et al. (2014) does not align with the IPCC (2006) data used for actual carbon sequestration, where the IPCC (2006) data for potential carbon sequestration is derived from the same product.

The IPCC biomass density values are provided by ecological zone and separately for natural and planted forests. The distribution of carbon sequestration is 79.3% natural and 20.7% planted, a substantial difference compared to the distribution found using the carbon growth rates that are separately provided by IPCC (2006) to derive actual carbon sequestration. When comparing the distributions in ecological zones for actual and potential of carbon sequestration quite some differences become apparent. When comparing for IPCC (2006), the proportional differences for the ecological zones are relatively small. Using Langner et al. (2014) the proportions found are higher for tropical rainforest and tropical moist deciduous forest and somewhat lower for tropical moist deciduous forest.

Table 7.7 Potential carbon sequestration by origin and ecological zone (start gain – 2015) (FAO dataset)

Ecological zone	Langner et al. (2014)		IPCC (2006)					
	All forest gain		Natural		Planted		All forest gain	
	Tons C	%	Tons C	%	Tons C	%	Tons C	%
Tropical rainforest	648,619	78.0	621,784	70.7	188,876	82.2	810,659	73.1
Tropical moist deciduous forest	136,320	16.4	223,220	25.4	39,109	17.0	262,329	23.7
Tropical mountain systems	46,954	5.6	34,526	3.9	1,681	0.7	36,207	3.3
Total Indonesia	**831,893**	100.0	879,530	100.0	229,666	100.0	**1,109,195**	100.0

7.3 JRC

This section analyses the carbon sink results related to characterised forest gain found in the JRC dataset (Table 7.8). The majority of the carbon sequestration has a natural origin. This is predominantly due to the high presence of natural gain in tropical rainforest. There is only a small amount of carbon sequestration found in tropical moist deciduous forest. For this ecological zone only natural gain is characterised. Noteworthy is the deviation in the tropical mountain systems from the other ecological zones regarding the origin, where the majority of the carbon sink is found for planted forest gain, rather than for natural forest gain.

Table 7.8 Actual carbon sequestration by origin and ecological zone (start gain - 2015)

Ecological zone	Natural		Plantation		All	
	Tons C	% / Origin	Tons C	% / Origin	Tons C	% / Region
Tropical rainforest	269,924	72.8	100,747	27.2	370,671	92.9
Tropical moist deciduous forest	1,988	100.0	0	0.0	1,988	0.5
Tropical mountain systems	2,944	11.1	23,530	88.9	26,474	6.6
Total Indonesia	274,856	68.9	124,277	31.1	399,133	100.0

The bulk of the characterised forest gain areas had shrubland coverage in the non-forest state in Y1 (Table 7.9). The second largest dominant coverage in Y1 is found to be herbaceous land. Remarkable is the carbon sequestration output found for wetlands. The carbon estimate represents a 50.0% larger proportion compared to the related proportion this land cover has when assessed for the gain area.

Table 7.9 Forest gain area and related actual carbon sequestration per dominant coverage in Y1 (start gain – 2015)

Dominant coverage Y1	Area		Carbon sequestration	
	Ha	**%**	**Tons C**	**%**
Crop land	0	0.0	0	0.0
Shrubland	**2,673**	**68.0**	**248,667**	**64.9**
Herbaceous	**954**	**24.2**	**106,553**	**27.8**
Wetlands	85	2.2	12,561	3.3
Settlements	0	0.0	0	0.0
Bare land	222	5.6	15,090	3.9
Other land	0	0.0	0	0.0
Total	3,934	100.0	382,871	100.0

8 Carbon sequestration Indonesia

This chapter provides the main results of this study. To make appropriate comparisons the datasets used are compared at the same spatial scale. Therefore, the FAO and JRC datasets are extrapolated to the country of Indonesia. This makes it possible to compare the characterised gain of FAO and JRC to the identified gain present in the Hansen dataset. First the general results are discussed, afterwards the individual datasets are elaborated on separately.

8.1 General

This section discusses and compares the extrapolated results for FAO, JRC and Hansen (Table 8.1) To put the results into perspective of the impact on national scale, the estimations of FAO and JRC are extrapolated to Indonesia. The Hansen dataset does not need any extrapolation and is therefore merely used for comparison with the extrapolated outputs of FAO and JRC.

The estimated gain areas form a relatively low percentage of the countries territory. For FAO in total just 0.4% ± 0.1% of Indonesian land is classified as forest gain. For JRC 0.6% ± 0.1% of Indonesian land is classified as forest gain. And finally the non-characterised Hansen dataset identifies 3.1% of Indonesian land is identified as forest gain.

Next to the absolute output of the gain area, the relative outputs of the datasets are compared. The three datasets all have a different gain area and a different temporal scope for forest gain. For valid interpretation of the results the column "Tons C / Km^2 / Y" is added to Table 8.1, to standardise the output. The standardised FAO dataset estimate of 698.6 tons C per km^2 per year sequestered due to forest gain is found to be in between the JRC and Hansen datasets. The highest carbon sequestration is found for the Hansen dataset, with a carbon sequestration of 883.5 tons C per km^2 per year. The JRC dataset indicates a carbon sequestration rate of 600.8 tons C per km^2 per year, the lowest result of the three datasets used for comparison. Total carbon sequestration is here expressed in teragrams (Tg, i.e. 10^{12} grams). The majority of the carbon sequestration is caused by natural gain as indicated by the output of FAO and JRC. For the FAO dataset carbon sequestration related to natural and planted gain is found to be 71.5% and 28.5% respectively of the total estimate. For JRC the natural gain is 68.9% of the total and planted gain 31.1%.

Table 8.1 FAO, JRC and Hansen compared forest gain area and related carbon sequestration in teragrams per dataset & origin, including standard error

Dataset	**Origin**	**Gain area**			**Carbon sequestration (C)**				
		Km^2	**% SE**	**% of gain**	**Tg C**	**% SE**	**% of total C**	**Years (Y)**	**Tons C / Km^2 / Y**
FAO	All	**8,004.1**	17.1	100.0	90.5	16.8	100.0	16.2	**698.6**
	Natural	5,722.0	16.2	**71.5**	75.9	14.0	**83.8**	15.9	**831.9**
	Planted	2,282.1	19.1	**28.5**	14.7	31.5	**16.2**	16.8	**382.0**
JRC	All	**12,970.5**	19.2	100.0	128.4	19.8	100.0	16.5	**600.8**
	Natural	5,860.7	22.8	**45.2**	88.4	16.1	**68.9**	17.1	**881.9**
	Planted	7,109.8	16.3	**54.8**	40.0	28.0	**31.1**	16.0	**352.4**
Hansen	All	**69,701.1**	-	100.0	739.0	-	100.0	12.0	**883.5**

8.2 FAO

This section describes the extrapolated areas and carbon sequestration related to the FAO dataset (Table 8.2). Interesting to compare is to what extent the proportions of forest gain area match the proportions of carbon sequestration. The natural gain area is found to have a lower proportion of the total area, compared to its related carbon sequestration proportion of the total carbon sequestration for natural gain. This difference predominantly occurs because of the high carbon sequestration rate for natural gain (889.7 Tons C / Km^2 / Y) compared to the relatively low carbon sequestration rate for planted gain (352.4 Tons C / Km^2 / Y) in the tropical rainforest. One should note the relatively high standard error for the planted gain within the tropical mountain systems.

Table 8.2 FAO forest gain area and related carbon sequestration in teragrams per ecological zone & origin, including standard error (start gain - 2015).

Origin	**Ecological zone**	**Gain area**			**Carbon sequestration**			
		Km^2	**% SE**	**% of gain**	**Tg C**	**% SE**	**% of total C**	**Tons C / Km^2 / Y**
Natural	Tropical rainforest	3,752.0	12.0	46.9	56.4	9.0	0.1	889.7
	Tropical moist deciduous forest	1,618.7	15.3	20.2	16.0	17.5	77.9	756.6
	Tropical mountain systems	351.4	66.6	4.4	3.5	77.1	10.0	521.9
All Natural		*5,722.0*	16.2	*71.5*	*75.9*	14.0	*83.8*	*831.9*
Planted	Tropical rainforest	1794.0	19.0	22.4	11.4	33.3	11.4	352.4
	Tropical moist deciduous forest	451.9	8.9	5.6	3.1	12.9	3.1	555.6
	Tropical mountain systems	36.2	150.3	0.5	0.2	200.0	0.2	352.4
All planted		*2,282.1*	19.1	*28.5*	*14.7*	31.3	*16.2*	*382.0*
All		8,004.1	17.1	100.0	90.5	20.0	100.0	698.6

Next to comparing for the division for origin and ecological zones, the characterised gain areas and related carbon sequestration are compared for the dominant coverage in Y1 (Table 8.3). The large majority of the forest gain area (78.8%) and related carbon sequestration (70.5%) is estimated for shrub land. The second largest dominant coverage in Y1 is herbaceous land, representing 10.4% of the area and 9.0% of the carbon sequestered. One should bear in mind that the standard errors for the subdivided categories are relatively high for crop land, wetlands, settlements and other land. This high standard error is predominantly caused by the small proportion of the category represented compared to the total.

Table 8.3 FAO forest gain area and related carbon sequestration in teragrams per dominant coverage in Y1 & standard error (start gain – 2015)

Dominant coverage Y1	**Gain area**					**Carbon sequestration**		
	Km²	**% SE**	**% of gain**	**‰ of country**	**‰ of country SE**	**Tg C**	**% SE**	**% of total C**
Crop land	8.5	96.5	0.1	0.005	0.004	0.1	100.0	0.1
Shrub land	6,304.0	7.0	78.8	3.362	0.235	70.5	7.1	77.9
Herbaceous	829.5	35.9	10.4	0.442	0.159	9.0	36.7	10.0
Wetlands	126.1	209.6	1.6	0.067	0.141	1.3	230.8	1.5
Settlements	115.4	180.6	1.4	0.062	0.111	1.8	133.3	2.0
Bare land	573.7	42.0	7.2	0.306	0.128	6.8	41.2	7.6
Other land	46.8	292.1	0.6	0.025	0.073	1.0	160.0	1.1
All	8,004.1	19.9	100.0	4.269	0.851	90.5	20.0	100.0

8.3 JRC

In this section the results of the extrapolated areas and related carbon sequestration related of the JRC dataset are presented (Table 8.4). The larger part (68.9%) of carbon sequestration is found for natural gain. In contrast the majority (54.8%) of the forest gain area is found for planted gain. Within both the natural as the planted gain areas, the dominant ecological zone is tropical

Table 8.4 JRC forest gain area and related carbon sequestration in teragrams per ecological zone & origin, including standard error (start gain - 2015)

Origin	**Ecological zone**	**Gain area**			**Carbon sequestration**			
		Km²	**% SE**	**% of gain**	**Tg C**	**% SE**	**% of total C**	**Tons C / Km² / Y**
Natural	Tropical rainforest	5,725.8	14.9	44.1	86.9	9.7	67.6	889.7
	Tropical moist deciduous forest	55.0	90.7	0.4	0.6	266.7	0.5	756.6
	Tropical mountain systems	79.9	540.2	0.6	0.9	477.8	0.7	521.9
All Natural		*5,860.7*	22.8	*45.2*	*88.4*	16.1	*68.9*	*881.9*
Planted	Tropical rainforest	6,153.0	13.0	47.4	32.4	23.8	25.2	352.4
	Tropical moist deciduous forest	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Tropical mountain systems	956.8	37.2	7.4	7.6	46.1	5.9	352.4
All planted		*7,109.8*	16.3	*54.8*	*34.0*	39.7	*31.1*	*352.4*
All		12,970.5	19.2	100.0	128.4	19.8	100.0	600.8

rainforest. Especially for the carbon sequestration related to natural gain this dominance is really high with 98.1% (67.6%/68.9%). The difference in distribution for gain area compared to carbon sequestration is a noteworthy item. In the JRC dataset these distributions are rather different. This difference is predominantly caused by the high carbon sequestration rates for the tropical rainforest areas. Within this ecological zone the majority of the gain area is found to be natural gain. The natural gain areas in this ecological zone have a carbon sequestration rate (Tons C / Km^2 / Y) that is 0.4 times the magnitude of the planted gain areas.

The characterised gain areas and related carbon sequestration are also divided for the dominant coverage in Y1 (Table 8.5). Similar to the FAO dataset the largest dominant coverage in Y1 is shrub land and the second largest herbaceous land. From the characterised gain of the JRC dataset, no crop land areas are found in Y1. For this subdivision in dominant coverage the distribution of gain area compared to the distribution of carbon sequestration is rather similar. Again the standard error percentages are rather high for the categories with low proportions (wetlands, settlements and other land).

Table 8.5 JRC forest gain area and related carbon sequestration in teragrams per dominant coverage in Y1 & standard error (start gain – 2015)

Dominant coverage Y1	**Gain area**					**Carbon sequestration**		
	Km^2	**% SE**	**% of gain**	**‰ of country**	**‰ of country SE**	**Tg C**	**% SE**	**% of total C**
Crop land	0.0	0.0	0.0	0.000	0.000	0.0	0.0	0.0
Shrub land	8,603.1	9.6	66.3	3.856	0.369	80.0	9.6	62.3
Herbaceous	3,069.5	23.2	23.7	1.376	0.319	34.3	23.0	26.7
Wetlands	273.7	215.8	2.1	0.123	0.265	4.0	217.5	3.1
Settlements	250.6	150.8	1.9	0.112	0.169	4.5	157.8	3.5
Bare land	713.4	20.1	5.5	0.320	0.064	4.9	20.4	3.8
Other land	60.2	422.4	0.5	0.027	0.114	0.8	412.5	0.6
All	12,970.5	22.4	100.0	5.813	1.301	128.4	27.9	100.0

8.4 Hansen

The Hansen dataset uses a similar definition for forest compared to the JRC dataset. This dataset is only used for comparison to the FAO and JRC datasets. The Hansen dataset is used to provide estimates only for identified gain and related carbon sequestration. Therefore, there are no quantifications of characterised gain derived from the related estimates.

To compensate for this lacking characterisation, the dataset is briefly examined using visual interpretation. By shortly panning through the dataset in map view, substantial wrongly indicated areas of forest gain are found.

These erroneously indicated areas are often no forest gain, but instead crop plantations. This is exemplified in Figure 8.1. At the satellite image on the left a palm oil plantation is identified, the same area on the right is indicated as forest gain according to the Hansen dataset.

Compared to the FAO and JRC datasets, the forest gain estimate derived from Hansen is high both absolutely as relatively (Table 8.6). The estimated area of forest gain is 69,701.1 Km^2. This area estimate is 8.7 times higher compared to FAO and 5.4 times the area of JRC. When comparing for carbon sequestration similar ratios are found. The Hansen carbon sequestration estimate is 8.2 times the magnitude of FAO and 5.8 times the magnitude of JRC.

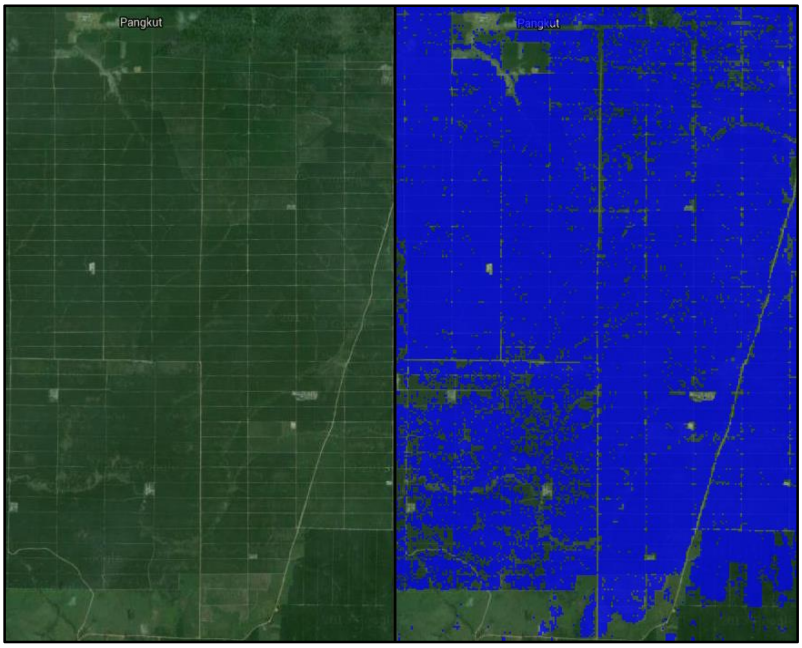


Figure 8.1 Forest gain example Hansen dataset (blue: forest gain)

The carbon sequestration rates depend on the ecological zone. The relatively high carbon sequestration per kilometre per year is found due to the 98.9% presence of forest gain within the tropical rainforest, the ecological zone where the highest carbon sequestration rates are found.

Table 8.6 Hansen dataset estimates of forest gain areas and related carbon sink per ecological zone (2000-2012)

Ecological Zone	**Forest gain Km^2**	**Forest gain / area ecological zone %**	**Tg C**	**Tons C / Km^2 / Y**
Tropical rainforest	68,457.4	3.6	730.9	0.89
Tropical moist deciduous forest	166.2	0.2	1.5	0.76
Tropical dry forest	0.2	0.3	0.0	0.49
Tropical shrub land	41.8	0.4	0.1	0.15
Tropical mountain system	1,035.5	0.5	6.5	0.52
Total Indonesia	69,701.1	3.1	739.0	0.88

9 Conclusion

This chapter answers how forest gain and related carbon sequestration can be characterised for Indonesia over 1990-2015 using existing datasets. The chapter is structured by the formulated research questions as formulated in section 1.3. First the main question is answered (9.1). Next the sub-questions are answered in section 9.2 – 9.4. Section 9.2 answers what processes cause forest gain. Section 9.3 explains how forest gain can be characterised using existing datasets. And finally section 9.4 reports the magnitude of carbon sequestration related to forest gain according to biomass datasets.

9.1 Main conclusion

The estimated area of forest gain in Indonesia is 8004.1 Km^2 ± 17.1%. The related carbon sequestration is approximated at 90.5 Tg ± 16.8%. Forest gain in Indonesia is found to be a small contributor to land-use change according to the FAO dataset. Only 0.43% of Indonesian territory is characterised as forest gain. The forest gain area estimate derived from the FAO dataset is the smallest area of the three datasets compared. The Hansen dataset provides the highest estimate; however, this is only deduced from identified forest gain. The majority of this characterised forest gain is caused by natural regrowth. A high resemblance of 90.3% is found for characterised gain (visual analysis of very high resolution satellite images) compared to identified gain in the FAO dataset. For the JRC dataset this resemblance is found to be 58.2%. This relatively low resemblance is primarily caused by wrongfully classified areas in year 1 of the JRC dataset and by the forest gain classification assigned to palm-oil crop plantations, which are not perceived forest gain areas according to the land-use definition.

Furthermore, the identified gain in the studied datasets provides completely different outputs with respect to amount and location. This indicates substantial omission errors present in both datasets. This is because substantial areas of characterised gain derived from the FAO and JRC datasets do not overlap. The low overlap was expected based on the relatively low intersection found for the identified gain areas. These considerable sources of uncertainty could also be caused by differences in land-use versus land cover definitions, the variation in temporal scope of identified gain, errors in automatic classification, errors in human interpretation and errors in the underlying satellite data used for classification.

9.2 Processes that cause forest gain

Forest gain is a part of forest change dynamics. These dynamics include forest loss and forest gain. Forest gain is induced by natural regrowth and forest plantations. Forest change dynamics are defined using land-use definitions. The processes that cause forest gain have a nature that is fairly subtle and hard to distinguish compared to forest loss, therefore satellite imagery is visually interpreted to characterise forest gain.

9.3 Characteristics of forest gain

The origin of the characterised forest gain areas in the FAO dataset is for 71.5% natural and for 28.5% plantation. For the JRC dataset the forest gain is found to be quite equally divided for natural and planted gain, with a somewhat larger area of planted gain representing 54.8% of the total. The majority of forest gain areas can be typified by the following characteristics. The forest gain is located within the tropical rainforest, the dominant coverage in year 1 was shrub land and the dispersion pattern in year 3 is random.

Based on the weak relationships found between time of regrowth and canopy cover gain percentage across different sites (polygons), it is concluded that canopy cover change is not a good indicator of age. The found relationships are either very weak with R = 0.39 for FAO or not present at all with R = 0.01 for JRC. There is of course some uncertainty here, because the canopy cover gain percentages are based on visual interpretation. However, the relationship found contradict somewhat to the expectations derived from the theoretical framework, where it was found that increase in canopy cover is a legitimate sign of tree growth.

The results indicate that there is quite some forest gain next to water or on top of former water areas. These gain areas are expected to be amidst peat swamp forests or mangrove forests. As found in the literature these forest types are significantly present in Indonesia, have high productivity and are inundated with water.

The analyses of the FAO and JRC datasets indicate that Y2 is a good indicator for Y3 and vice versa with regards to whether there is forest gain or not. For the FAO dataset 91% of the identified gain is correct for the identified time period (Y1 – Y2) and a proper predictor for characterised forest gain in subsequent years (Y3). For FAO the highest forest gain per year is found for the period 2000-2005. For JRC the quantity of forest gain is rather similar for both the periods 1990-2000 and 2000-2010.

9.4 Carbon sequestration related to forest gain

Carbon sequestration is estimated for the FAO, JRC and Hansen datasets on the national scale. From the FAO dataset it is estimated that 698.6 tons C per km^2 (of Indonesian land area) per year are sequestered due to forest gain. The JRC dataset indicates a carbon sink of 600.8 tons C per km^2 per year, the lowest result of the three datasets used for comparison. The highest carbon sequestration is found for the Hansen dataset, with 883.5 tons C per km^2 per year sequestered. The majority of the carbon sequestration is caused by natural gain as indicated by the output of FAO and JRC. The ratio of carbon sequestration for natural : plantation is 5.2 : 1.0 for the FAO dataset and 2.2 : 1 for the JRC dataset.

10 Discussion

This chapter provides a review on the choices made, the methods used and the results derived from the executed steps. The chapter discusses the validity of the research approach (10.1), the limitations of the study (10.2) and provides recommendations for additional research (10.3).

10.1 Interpretation of results

The FAO dataset is found to be a reliable indicator to estimate characterised forest gain in Indonesia. The characterised no gain areas are predominantly found to be the result of palm-oil plantations initiated after Y2. The output of JRC indicates that results on forest gain merely based on the identified forest gain of this dataset should be dealt with precaution.

The differences between FAO and JRC are caused by multiple factors that impact the content of the datasets. The multiple aspects of deviation between the datasets are discussed here. The low overlap is partly caused by the difference in definitions of land-use and land cover. This could mean that a large share of identified polygons of interest in the JRC dataset are no forest gain, but something else e.g. palm oil plantation, thus excluded from the FAO land-use dataset. Furthermore, there is a relatively low overlap in period 2, partly caused by the deviation in time periods between FAO and JRC. Period 2 in FAO spans from 2000-2005, in JRC this temporal scale is double in time from 2000-2010. It could also be that there are automatic classification errors in the datasets. Another conceivable hypothesis is that there are human mistakes in the land-use classification of FAO, that is executed by expert interpreters from multiple countries.

Based on the relatively low presence of planted gain present in the FAO dataset compared to the presence in the JRC dataset, the author presumes that FAO unjustly eliminates planted forest gain areas from the automatically classified forest areas in the verification process.

One should consider that the method used for determining the start of forest gain is based upon the assumption of linear canopy cover growth. This method is applied to all characterised gain areas to derive carbon sequestration estimates. Because this method determines the time factor in the carbon sequestration estimate, it has a substantial impact on the results. Using a more sophisticated method could have resulted in a somewhat different carbon sequestration estimate.

The used methods and datasets are subject to errors of omission and commission. Omission errors are the consequence of data gaps, i.e. where areas that should have been classified are not taken into account. Errors of commission occur when a misclassification takes place. This can be through classifying into the wrong class or splitting classes with homogenous contents into multiple classes incorrectly (Short, 2005). The FAO dataset was first automatically classified using a computerised approach, next this classification is checked and where needed corrected for using visual interpretation. There are however also large data gaps in the FAO dataset, where a substantial share is classified as no data. In this part of the dataset there probably are areas of forest gain, omission errors not taken into account for further analysis. Errors of commission are the result of incorrect measurements or calculations. These errors are found in the identified forest gain of the FAO dataset, that has a share of 9% erroneously classified polygons.

Furthermore, the carbon sequestration estimates derived from the FAO and JRC datasets are subject to significant standard errors, especially for the smaller categories of dominant coverage in Y1, where the standard error exceeds 100% of the estimate. In these cases, the size of the investigated areas are most likely insufficient to make statements applied to the national scale.

10.2 Limitations of study

Datasets used

The FAO and JRC surveys are built upon a systematic sampling design with global coverage, covering roughly 1% of the earth surface. The consequence of using these datasets is that statistically valid results can only be obtained for ecological zones, or at a global or regional scale level. This limits the statistical validity of the obtained results to a national scale or to the ecological zone level.

This study is unable to encompass the entire availability of existing datasets. The most prominent datasets available for identification of forest gain are used to identify gain areas, and internationally accepted biomass data used for carbon sequestration. Additionally, other datasets also could have been used either with similar results or with supplementary insights, such as tree height data or canopy cover data based on MODIS satellite data.

The identified forest gain present within the temporal scope of the FAO, JRC and Hansen datasets are used to make statements about the research objective for 1990-2015. However, none of the datasets fully cover this temporal scope. This means that forest gain outside the temporal scope of the used datasets is not taken into account.

Attributes characterised

The visual interpretation process was a repetitive task that was essential for the purpose of the study to characterise the identified forest gain. This repetitive task is executed by an expert interpreter that will never be as consistent as a computerised application of characterising the same attributes for multiple areas. The consistency is however qualified with the help of expert validation. Due to practical reasons just one expert validator willing to characterise a subset of the identified forest gain was found.

The most relevant attributes deduced from literature are implemented to characterise forest gain. However, it was also found that forest typologies are culturally subjective and difficult to define, due to varying nature of forests. Therefore, the used typology cannot be perceived as blue print for future studies. The most relevant attributes used for characterisation are origin and canopy cover density. These attributes were generally found in studies similar to this thesis, thus are perceived somewhat more generic.

In the conceptual framework a distinction is made in origin for natural gain and planted gain. In reality this dichotomy is not that hard. Multiple forest restoration strategies are applied with a more intermediate approach, using a mixture of natural gain and planted gain. To improve for this dichotomy, a third hybrid category could be introduced. However, this can solely be done with knowledge of the local circumstances, which was not available for this study.

Another limitation that lacked sufficient local knowledge is the differentiation of tree species. When characterising forest gain, ideally the tree species and their related biomass values are known for carbon sequestration estimates. The available biomass data did however not differentiate for species; thus carbon sequestration estimates are not feasible at this level of detail. The limited knowledge of the author on tree species in combination with the used satellite imagery, made it impossible to make demarcations of tree species.

Furthermore, four data-derived attributes are introduced based on patterns found more often as perceived by the author. These attributes do not encompass the full range of possible additional attributes. For example, with the additional attribute for palm-oil crops, other crops also could have been characterised in more detail. Such a characterisation was however not feasible due to the lack of local knowledge by the author, where palm-oil crops reveal a clear pattern that is abundantly present in Indonesia.

Potential sources of error

To estimate the omission errors in the dataset the inclusion probability of the compared datasets need to be assessed. The inclusion probability is the chance of a gain area to be included in the sampling strategy applied by the different datasets. Extensive examination of the inclusion probability of forest gain areas is beyond the scope of this study.

Predominantly within the FAO dataset and to a smaller extent in the JRC dataset there are substantial data gaps in land-use classification for 1990, 2000 and 2005. These areas are now regarded as unbiased loss of data, however in reality this loss of data could have substantial impact on the quantity of forest gain. To correct for these data gaps, it is advised to characterise the no data polygons, with the condition that sufficient satellite imagery is available.

There are inconsistencies present in the used data due to variations in the image acquisition date of the satellite imagery. Two possible errors that cannot be completely ruled out are discussed here. First it could be that there are areas of forest gain that did not continue forest gain after the image acquisition date of Y3 (e.g. 1-1-2013). The carbon sequestration rates are applied from start gain – 2015. Here it is assumed that forest gain continues up to 31-12-2015, which cannot always be confirmed because the satellite image acquisition date for Y3 ranges from 2007-2015. Second it could be that there are some cases where forest gain is found using the image acquisition dates, where in reality no forest gain is present between the intended dates of Y1 (1-1-1990 or 1-1-2000) and Y3 (31-12-2015).

10.3 Recommendations

Despite the difficulties in implementing the land-use definition for automatization purposes it is recommended to investigate the possibilities to automate the characterisation process supplementary to the approaches used to construct the FAO and JRC datasets. It is advised to implement VHR imagery in the automatization process because it surpasses Landsat imagery with a lower resolution for the application of object recognition. Before implementing this approach, the introduced inconsistencies due to improving spatial resolution over time need to be considered thoroughly. It is advised to use available studies in time series analysis with varying resolutions (e.g. Wang et al., 2010) as a guideline. The benefits are found in decreased subjectivity, less errors due to human mistakes, higher consistency and scalability. As technology is ever improving, it is expected that the current VHR imagery will be perceived inferior in the future. Therefore, the scalability of varying image resolutions is highly relevant and is expected to remain relevant in the future.

Based on this case study research for the country of Indonesia it is found that the FAO dataset is quite a reliable indicator for forest gain. However, one cannot extrapolate results from this study to the entire FAO dataset without characterising (samples of) other countries. Therefore, it is advised to first characterise forest gain for other areas or to use the results of the current study merely as indicator in need of verification for forest gain in other areas.

For this study two random samples are taken from FAO for expert validation and from the identified gain of JRC for providing a reliable estimate of forest gain present in the dataset. The choice for random sampling strategy was made because in the literature it was found that there is small variation in output for different sampling strategies available. To check whether there is little variation in output, it is recommended to compare multiple sampling strategies before implementing one strategy at large scale.

This study characterised forest gain for the FAO and JRC datasets and used the identified gain from the Hansen dataset. A follow-up study is advised to characterise (a sample of) the Hansen dataset using land-use definitions. The Hansen dataset uses a smaller temporal scope compared to FAO and JRC, however the product has global coverage instead of sample coverage. To make valuable estimates on the forest change dynamics a characterisation of forest land-use change using this dataset is advised, because this is found to be a feasible approach in distinguishing for origin and identifying erroneously classified areas such as palm-oil plantations.

Appendix: maps of characterised forest gain FAO and JRC

Figure A.1 Characterised forest gain estimate Indonesia based on FAO for time period 1990-2000

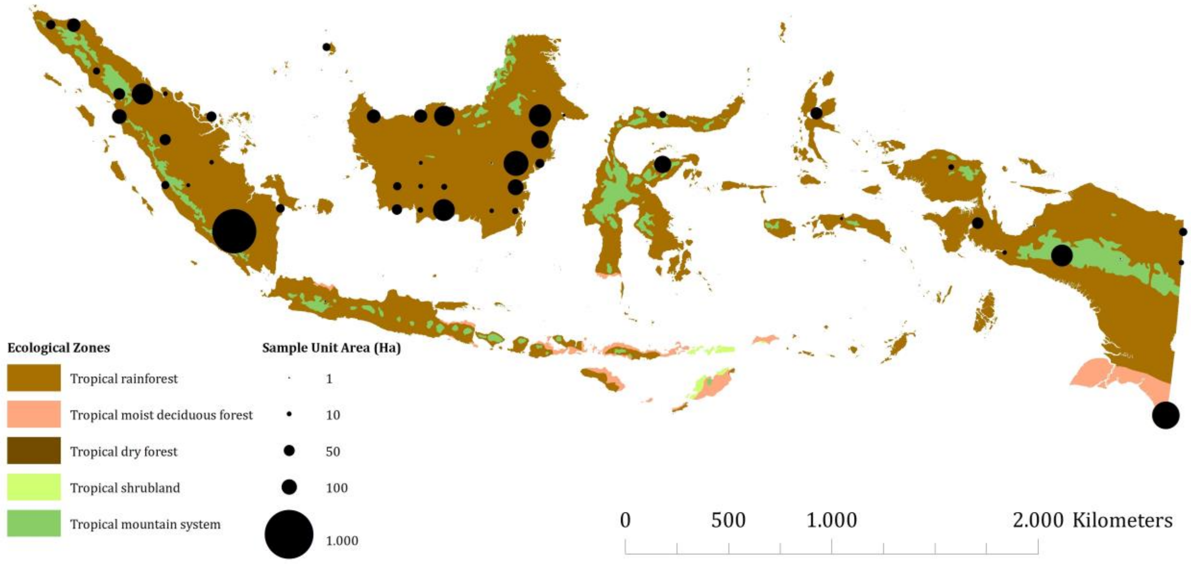


Figure A.2 Characterised forest gain estimate Indonesia based on FAO for time period 2000-2005

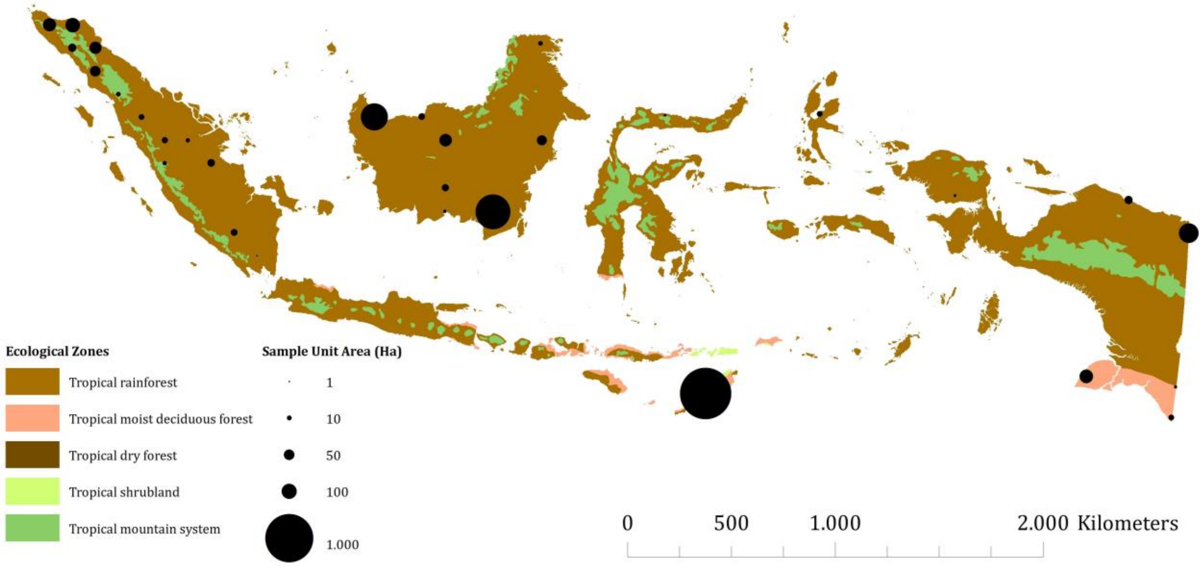


Figure A.3 Characterised forest gain estimate Indonesia based on JRC for time period 1990-2000

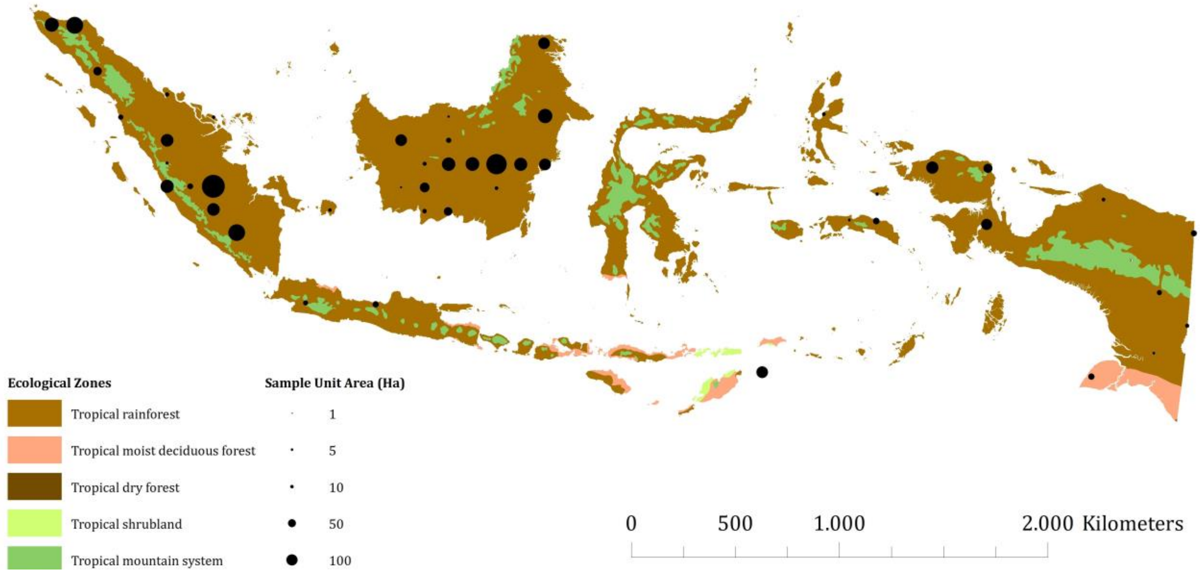
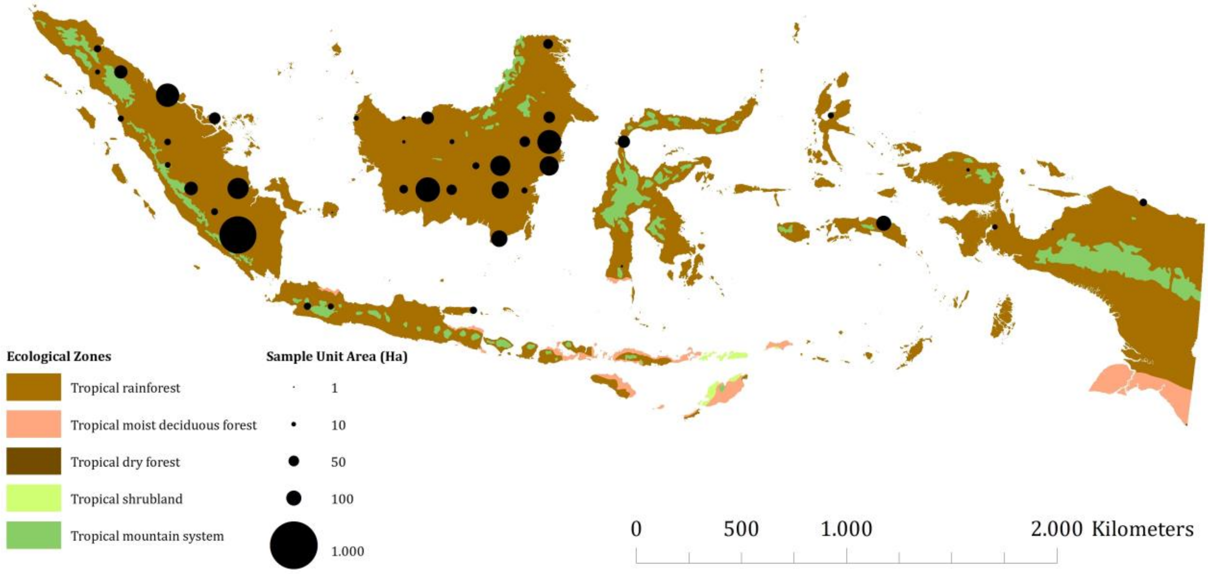


Figure A.4 Characterised forest gain estimate Indonesia based on JRC for time period 2000-2010



References

Achard, F. & Hansen, M.C. (2012). Global Forest Monitoring from Earth Observation. Taylor & Francis. New York, 18-20.

Achard, F., Beuchle, R., Mayaux, P., Stibig, H.-J., Bodart, C., Brink, A. & Simonetti, D. (2014). Determination of tropical deforestation rates and related carbon losses from 1990 to 2010. Global Change Biology, 20(8), 2540–2554. doi:10.1111/gcb.12605.

Achard, F., Stibig, H.J., Eva, H.,Mayaux, P. & Va, I.-I. (2002a). Tropical forest cover monitoring in the humid tropics — TREES project. Tropical Ecology, 43(1), 9–20.

Achard, F., Eva, H.D., Stibig, H.-J., Mayaux, P., Gallego, J., Richards, T. & Malingreau, J.-P. (2002b). Determination of deforestation rates of the world's humid tropical forests. Science 297, 999–1002.

Ahmad Zuhaidi Y. (2009). Local growth model in modelling the crown diameter of plantation-grown Dryobalanops aromatica. Journal of Tropical Forest Science 21, 66–71.

Avitabile, V. (2013). Measuring tropical forest carbon stocks. In Lyster, R., MacKenzie, C. & McDermott, C. (Eds.), Law, Tropical Forests and Carbon, 44–67. Cambridge: Cambridge University Press. doi:10.1017/CBO9781139236904.005.

Baccini A., Goetz S.J., Walker, W.S. et al. (2012). Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nature Climate Change 2, 182–185.

Bala, G., Caldeira, K., Wickett, M., Phillips, T. J., Lobell, D. B., Delire, C. & Mirin, A. (2007). Combined climate and carbon-cycle effects of large-scale deforestation. Proceedings of the National Academy of Sciences of the United States of America 104(16), 6550–6555. doi:10.1073/pnas.0608998104.

Basuki, T.M., van Laake, P.E., Skidmore, A.K. & Hussin, Y.A. (2009). Allometric equations for estimating the above-ground biomass in tropical lowland Dipterocarp forests. Forest Ecology and Management, 257(8), 1684–1694. doi:10.1016/j.foreco.2009.01.027.

Batra, P. & Pirard, R. (2015). Is a typology for planted forests feasible, or even relevant? Center for International Forestry Research (CIFOR), Bogor, Indonesia. doi:10.17528/cifor/005608.

Bonan, G.B. (2008). Forests and Climate Change: Forcings, Feedbacks, and the Climate Benefits of Forests. Science 320 (5882), 1444-1449.

Bongers, F., Chazdon, R., Poorter, L. & Pena-Claros, M. (2015). The potential of secondary forests. Science, 348(6235), 642–643. doi:10.1126/science.348.6235.642-c.

Bounoua, L., Defries, R., Collatz, G., Sellers, P. & Khan, H. (2002). Effects of land cover conversion on surface climate. Climate Change 52, 29–64.

Brown, L.R. (1997). State of the World 1997: A Worldwatch Institute Report on Progress Toward a Sustainable Society (14th edition). New York: W. W. Norton & Company, 7-8. ISBN 0-393-04008-9.

Canadell, J.G. & Raupach, M.R. (2008). Managing Forests for Climate Change. Science (AAAS) 320(5882), 1456–1457. doi:10.1126/science.1155458. PMID 18556550.

Chao, S. (2012). Forest Peoples: Numbers Across the World. Forest Peoples Program, Moreton-in-Marsh, UK.

Chave, J., Andalo, C., Brown, S., Cairns, M. A., Chambers, J. Q., Eamus, D. & Yamakura, T. (2005). Tree allometry and improved estimation of carbon stocks and balance in tropical forests. Oecologia, 145 (1), 87–99. doi:10.1007/s00442-005-0100-x.

Chaudhari, B.S., Beniwal A. & Arya V.S. (2003). Remote sensing applications in mapping of forest cover and potential afforestation sites for sustainable forest management. A case study of rewari district, haryana, india. XII. World Forestry Congress.

Cook, R.L., Stape, J.L. & Binkley, D. (2013). Soil Carbon Dynamics Following Reforestation of Tropical Pastures. Soil Science Society of America Journal 70(1), 290-296.

Corbin, J.D. & Holl, K.D. (2012). Applied nucleation as a forest restoration strategy. Forest Ecology and Management, 265, 37–46. doi:10.1016/j.foreco.2011.10.013.

Dawkins, H.C. (1963). Crown diameters: Their relation to bole diameter in tropical forest trees. Commonw. For. Rev. 26, 318–333.

De Sy, V., Herold, M., Achard, F., Beuchle, R., Clevers, J.G.P.W., Lindquist, E. & Verschot, L. (2015). Land-use patterns and related carbon losses following deforestation in South America.

Dong, J., Xiao, X., Sheldon, S., Biradar, C., Duong, N.D. & Hazarika,M. (2012). A comparison of forest cover maps in Mainland Southeast Asia from multiple sources: PALSAR, MERIS, MODIS and FRA. Remote Sensing of Environment, 127, 60–73.

Dymond, J.R., Shepherd, J.D., Arnold, G. & Trotter, C.M. (2008). Estimating area of forest change by random sampling of change strata mapped from satellite. Forest Science 54, 475–480.

Dymond, J.R., Shepherd, J.D., Newsome, P.F., Nelson Gapare, N., Burgess, Deborah W., & Watt, P. (2012). Remote sensing of land-use change for Kyoto Protocol reporting: the New Zealand case. Environmental Science and Policy 16, 1–8.

Eva, H.D., Achard, F., Beuchle, R., de Miranda, E., Carboni, S., Seliger, R. & Gallego, J. (2012). Forest Cover Changes in Tropical South and Central America from 1990 to 2005 and Related Carbon Emissions and Removals. Remote Sensing, 4(12), 1369–1391. doi:10.3390/rs4051369.

Falkowski, M.J., Wulder, M.A., White, J.C. & Gillis, M.D. (2009). Supporting large-area, sample-based forest inventories with very high spatial resolution satellite imagery. Progress in Physical Geography, 33(3), 403–423. doi:10.1177/0309133309342643.

FAO (2000). On Definitions of Forest and Forest Change, Forest Resources Assessment Programme Working Paper 33. Rome, Food and Agriculture Organisation of the United Nations.

FAO (2001a). Global Ecological Zoning for the Global Forest Resources Assessment 2000 Final Report Working paper 56. Rome, Food and Agriculture Organisation of the United Nations.

FAO (2001b). FRA 2000 Main Report. FAO Forestry Paper 140. Rome, Food and Agriculture Organisation of the United Nations.

FAO (2006). Global forest resources assessment 2005 – Progress towards sustainable forest management. FAO Forestry Paper 147. Rome, Food and Agriculture Organisation of the United Nations.

FAO (2009). Indonesia Forest Outlook Study. By Center for Forestry Planning and Statistics, Ministry of Forestry. Paper No. 13. Food and Agriculture Organisation of the United Nations Regional Office for Asia and the Pacific. Bangkok, Food and Agriculture Organisation of the United Nations.

FAO (2010a). Global Forest Resources Assessment 2010. Main report. Forestry Paper 163. Rome, Food and Agriculture Organisation of the United Nations.

FAO (2010b). Remote sensing survey: an outline of objectives, data and approach: forest resources assessment. Working paper 155. Rome, Food and Agriculture Organisation of the United Nations.

FAO & JRC (2012). Global forest land-use change 1990–2005, by Lindquist, E.J., D'Annunzio, R.. Gerrand, A., MacDicken, K., Achard, F., Beuchle, R., Brink, A., Eva, H.D., Mayaux, P., San-Miguel-Ayanz, J., & Stibig, H-J. FAO Forestry Paper No. 169. Food and Agriculture Organisation of the United Nations and European Commission Joint Research Centre. Rome, Food and Agriculture Organisation of the United Nations.

Forest Watch Indonesia (2011). Portret keadaan hutan Indonesia, periode tahun 2000-2009. FWI, Bogor, Indonesia.

Fragal, E.H., Silva, T.S.F. & Novo, E.M. (2016). Reconstructing historical forest cover change in the Lower Amazon floodplains using the LandTrendr algorithm. Acta Amazonica, 46(1), 13–24. doi:10.1590/1809-4392201500835.

Fritz, S., See, L., McCallum, I., Schill, C., Obersteiner, M., Van Der Velde, M., et al. (2011). Highlighting continued uncertainty in global land cover maps for the user community. Environmental Research Letters, 6(4).

Gao, Q., & Yu, M. (2014). Discerning fragmentation dynamics of tropical forest and wetland during reforestation, urban sprawl, and policy shifts. PloS One, 9(11), e113140. doi:10.1371/journal.pone.0113140.

Gschwantner, T., Schadauer, K., Vidal, C., Lanz, A., Tomppo, E., Di Cosmo, L.. & Lawrence, M. (2009). Common tree definitions for national forest inventories in Europe. Silva Fennica 43(2), 303–321.

Giree, N., Stehman, S.V., Potapov, P & Hansen, M.C. (2013). A sample-based forest monitoring strategy using Landsat, AVHRR and Modis Data to estimate gross forest cover loss in Malaysia between 1990 and 2005. Remote Sens 5, 1842–1855.

Gorte, W.R. (2009). Carbon Sequestration in Forests. Congressional Research Service, Natural Resources Policy, Report for Congress, 2-20.

Govindasamy, B., Duffy, P.B. & Caldeira, K. (2001). Land-use changes and northern hemisphere cooling. Geophysical Research Letters 28(2), 291–294.

Grainger, A. (1993). Rates of deforestation in the humid Tropics: Estimates and measurements. Geogr. J. 159, 33–44.

Green Collar Association (2014). Reforestation and Afforestation. Retrieved September 8, 2015, from http://www.greencollar.org/reforestation_afforestation.html.

Hansen, M. & DeFries, R. (2004). Detecting long-term global forest change using continuous fields of tree-cover maps from 8-km advanced very high resolution radiometer (AVHRR) data for the years 1982–99. Ecosystems, 7(7), 695–716.

Hansen, M., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., et al. (2013). High-resolution global maps of 21st-century forest cover change. Science, 342(6160), 850–853.

Herold, M., Mayaux, P., Woodcock, C.E., Baccini, A. & Schmullius, C. (2008). Some challenges in global land cover mapping: An assessment of agreement and accuracy in existing 1 km datasets. Remote Sensing of Environment, 112(5), 2538–2556.

Hori, S. Hayashi, M., Matsubara, Y., Awaya, Y. & Iehara, T. (2007). Detection of Afforestation, Reforestation and Deforestation (ARD) by Visual Photo Interpretation of High Spatial Resolution Images - A Fundamental Case Study. Journal of Forest Planning 13, 109-123.

Houghton, R.A. (2005). Aboveground Forest Biomass and the Global Carbon Balance. Global Change Biology, 11(6), 945–958. doi:10.1111/j.1365-2486.2005.00955.x.

Houghton, R.A., Hall, F. & Goetz, S.J. (2009). Importance of biomass in the global carbon cycle. Journal of Geophysical Research, 114, G00E03. doi:10.1029/2009JG000935.

INCAS Indonesia (2015). Indonesian national carbon accounting system: national data. Retrieved January 11, 2016, from http://www.incas-indonesia.org/data/national-data/#source-5.

IPCC (2006). 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Prepared by the National Greenhouse Gas Inventories Programme, Eggleston H.S., Buendia L., Miwa K., Ngara T. and Tanabe K. (eds). Published: IGES, Japan.

Jennings, S.B., Brown, N.D. & Sheil, D. (1999). Assessing forest canopies and understorey llumination: Canopy closure, canopy cover and other measures. Forestry 72(1), 59-73.

Kleidon, A., Fraedrich, K. & Heimann, M. (2000). A green planet versus a desert world: estimating the maximum effect of vegetation on the land surface climate. Climatic Change 44(4), 471–493.

Krejcie, R.V. & Morgan, D.W. (1970). Determining Sample Size for Research Activities. Educational and Psychological Measurement, 30(3), 607–610. doi:10.1177/001316447003000308.

Kuenzer, C., Leinenkugel, P., Vollmuth, M. & Dech, S. (2014). Comparing global land-cover products – implications for geoscience applications: an investigation for the transboundary Mekong Basin. International Journal of Remote Sensing, 35(8), 2752–2779.

Kurz, W.A., Stinson, G., Rampley, G.J., Dymond, C.C. & Neilson, E.T. (2008). Risk of natural disturbances makes future contribution of Canada's forests to the global carbon cycle highly uncertain. Proceedings of the National Academy of Sciences, 105(5), 1551–1555. doi:10.1073/pnas.0708133105.

Kurz, W.A. (2010). An ecosystem context for global gross forest cover loss estimates. Proceedings of the National Academy of Sciences, 107(20), 9025–9026. doi:10.1073/pnas.1004508107.

Lambertini, M. (2000). A Naturalist's Guide to the Tropics. University of Chicago Press.

Lambin, E.F., Turner, B.L., Geist, H.J., Agbola, S.B., Angelsen, A., Bruce, J.W., … Xu, J. (2001). The causes of land-use and land-cover change: moving beyond the myths. Global Environmental Change, 11(4), 261–269. doi:10.1016/S0959-3780(01)00007-3.

Langner, A., Achard, F. & Grassi, G. (2014). Can recent pan-tropical biomass maps be used to derive alternative Tier 1 values for reporting REDD+ activities under UNFCCC? Environmental Research Letters, 9(12), 124008. doi:10.1088/1748-9326/9/12/124008.

Leinenkugel, P., Kuenzer, C. & Dech, S. (2013). Comparison and enhancement of MODIS cloud mask products for Southeast Asia for Southeast Asia. International Journal of Remote Sensing, 34(8), 2730–2748.

Leinenkugel, P., Wolters, M.L., Oppelt, N. & Kuenzer, C. (2015). Tree Cover and Forest Cover Dynamics in the Mekong Basin from 2001 to 2011. Remote Sensing of Environment 158, 376–392. doi:10.1016/j.rse.2014.10.021.

Lewis, S.L. (2009). Widespread monitoring of African forests gives clues to carbon storage. Nature 457, 933. doi:10.1038/7232933a.

Liebsch, D., Marques, M.C.M. & Goldenberg, R. (2008). How long does the Atlantic Rainforest take to recover after a disturbance? Changes in species composition and ecological features during secondary succession. Biological Conservation, 141(6), 1717–1725. doi:10.1016/j.biocon.2008.04.013.

Malingreau, J. -P., Achard, F., D'Souza, G., Stibig, H. -J., D'Souza, J., & Estreguil, C., et al. (1995). AVHRR for global tropical forestmonitoring: The lessons of the TREES project. Remote Sensing Reviews, 12(1–2), 29–40.

Mas, J.F. (1999). Monitoring land-cover changes: a comparison of change detection techniques. Int. J. Remote Sensing 20(1), 139-152.

Matveev, N.M. (2012). Methodology of using the floristic structure of afforestation for characterisation of biotopes in the steppe zone. Biology Bulletin, 39(10), 794–799. doi:10.1134/S1062359012100020.

Mayaux, P., Holmgren, Achard, F., Eva, H., Stibig, H.-J. & Branthomme, A. (2005). Tropical forest cover change in the 1990s and options for future monitoring. Phil. Trans. Biol. Sci. 360, 373–384.

Melson, S.L., Harmon, M.E., Fried, J.S. & Domingo, J.B. (2011). Estimates of live-tree carbon stores in the Pacific Northwest are sensitive to model selection. Carbon Balance and Management, 6(1), 2. doi:10.1186/1750-0680-6-2.

Meng, J., Lu, Y., Lei, X. & Liu, G. (2011). Structure and floristics of tropical forests and their implications for restoration of degraded forests of China's Hainan Island. Tropical Ecology, 52(2), 177-191.

Moon, Z. K. & Farmer, F.L. (2012). Processes associated with afforestation near public lands. Advances Appl. Sociol. 2(1), 1–6.

Myers, N., Mittermeier, R.A., Mittermeier, C.G., da Fonseca, G.A. & Kent, J. (2000). Biodiversity hotspots for conservation priorities. Nature 403(6772), 853-858.

Nabuurs, G.J., Masera, O., Andrasko, K., et al. (2007). Forestry, in Metz, B., Davsion, O.R., Bosch, P.R., et al. (eds). Climate Change 2007 : Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, 541–584.

OECD. (2014). OECD Green Growth Studies Towards Green Growth in Southeast Asia. Retrieved from https://books.google.com/books?id=QehNBQAAQBAJ&pgis=1.

Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E. & Wulder, M.A. (2014). Good practices for estimating area and assessing accuracy of land change. Remote Sens. Environ. 148, 42–57. doi:10.1016/j.rse.2014.02.

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

Potapov, P., Hansen, M.C., Stehman, S.V., Loveland, T.R., & Pittman, K. (2008). Combining MODIS and Landsat imagery to estimate and map boreal forest cover loss. Remote Sens. Environ. 112, 3708–3719.

Potapov, P.V, Dempewolf, J., Talero, Y., Hansen, M.C., Stehman, S.V., Vargas, C. & Zutta, B.R. (2014). National satellite-based humid tropical forest change assessment in Peru in support of REDD+ implementation. Environmental Research Letters, 9(12), 124012. doi:10.1088/17489326/9/12/124012.

Raši, R., Bodart, C., Stibig, H.-J., Eva, H., Beuchle, R., Carboni, S., … Achard, F. (2011). An automated approach for segmenting and classifying a large sample of multi-date Landsat imagery for pan-tropical forest monitoring. Remote Sensing of Environment, 115(12), 3659–3669. doi:10.1016/j.rse.2011.09.004.

Romijn, E., Herold, M., Kooistra, L., Murdiyarso, D. & Verchot, L. (2012). Assessing capacities of non-Annex I countries for national forest monitoring in the context of REDD+. Environmental Science & Policy, 19-20, 33–48. doi:10.1016/j.envsci.2012.01.005.

Rosenqvist, A., Milne, A., Lucus, R., Imhoff, M. & Dobscon, C. (2003). A review of remote sensing technology in support of the Kyoto Protocol. Environmental Science and Policy 6, 441-455.

Russell, P., Hertz, P. & McMillan, B. (2013). Biology: The Dynamic Science. Cengage Learning, 1171-1175. Retrieved from https://books.google.com/books?id=dVIWAAAAQBAJ&pgis=1.

Rutishauser, E., Noor'an, F., Laumonier, Y., Halperin, J., Rufi'ie, Hergoualc'h, K. & Verchot, L. (2013). Generic allometric models including height best estimate forest biomass and carbon stocks in Indonesia. Forest Ecology and Management, 307, 219–225. doi:10.1016/j.foreco.2013.07.013.

Saatchi, S.S., Harris, N.L., Brown S. et al. (2011). Benchmark map of forest carbon stocks in tropical regions across three continents. Proceedings of the National Academy of Sciences, 108, 9899–9904.

SAFnet Dictionary (2008a). Definition for afforestation. Retrieved September 12, 2015, from http://dictionaryofforestry.org/dict/term/afforestation.

SAFnet Dictionary (2008b). Definition for reforestation. Retrieved September 12, 2015, from http://dictionaryofforestry.org/dict/term/reforestation.

Särndal C.E., Swensson, B. & Wretman, J. (1992). Model assisted survey sampling. New York: Springer.

Schroeder, T.A., Cohen, W.B. & Yang, Z. (2007). Patterns of forest regrowth following clearcutting in western Oregon as determined from a Landsat time-series. Forest Ecology and Management, 243, 59–273, doi:10.1016/j.foreco.2007.03.019.

Short, N.M. (2005). Collecting data at the surface: accuracy assessment. Retrieved January 11, 2016, from http://fas.org/irp/imint/docs/rst/Sect13/Sect13_3.html.

Silver, W.L., Ostertag, R. & Lugo, A.E. (2000). The potential for carbon sequestration through reforestation of abandoned tropical agricultural and pasture Lands. Restoration Ecology, 8(4), 394–407. doi:10.1046/j.1526-100x.2000.80054.x.

Stehman, S.V. & Czaplewski, R.L (1998). Design and Analysis for Thematic Map Accuracy Assessment. Remote Sensing of Environment, 64(3), 331–344. doi:10.1016/S0034-4257(98)00010-8.

Terry, R. & Chillinger, G. (1955). A Guide to Agroforestry in British Columbia (Small Woodlands Program of British Colombia). Sedimentary Petrology, 25(3), 229–234.

The Jakarta post (2011). 71% of Indonesian mangrove forests damaged. Retrieved January 15, 2016, from http://www.thejakartapost.com/news/2011/08/07/71-indonesian-mangrove-forests-damaged-minister.html.

The Redd Desk (2013). Afforestation definition. Retrieved September 15, 2015, from http://theredddesk.org/encyclopaedia/afforestation.

The World Factbook (2015). Indonesia. Retrieved January 4, 2016, from: https://www.cia.gov/library/publications/the-world-factbook/geos/id.html.

Thomson, A.M., César Izaurralde, R., Smith, S.J. & Clarke, L.E. (2008). Integrated estimates of global terrestrial carbon sequestration. Global Environmental Change, 18(1), 192–203. doi:10.1016/j.gloenvcha.2007.10.002.

USGS (2015). Global Land Surveys (GLS). Retrieved November 18, 2015, from https://landsat.usgs.gov/science_GLS.php.

Wang, Q., Megalooikonomou, V. & Faloutsos, C. (2010). Time series analysis with multiple resolutions. Information Systems, 35(1), 56–74. doi:10.1016/j.is.2009.03.006.

Wang, S., Chen, J.M., Ju, W.M., Feng, X., Chen, M., Chen, P. & Yu, G. (2007). Carbon sinks and sources in China's forests during 1901–2001. Journal of Environmental Management, 85(3), 524–537. doi:10.1016/j.jenvman.2006.09.019.

Watson, R., Noble, A., Bolin, B., Ravindranath, N.H. & Verado, D. (2000). Intergovernmental Panel on Climate Change Special Report; Land-use, Land-Use Change and Forestry. Cambridge University Press, Cambridge.

Westerling, A.L., Hidalgo, H.G., Cayan, D.R. & Swetnam, T.W. (2006). Warming and earlier spring increase western U. S. forest wildfire activity. Science 313(5789), 940–943.

World Resources Institute (2013). Forests and Landscapes in Indonesia. Retrieved October 26, 2015, from http://www.wri.org/our-work/project/forests-and-landscapes-indonesia.

Worldometers (2016). Indonesia Population. Retrieved January 7, 2016, from http://www.worldometers.info/world-population/indonesia-population/.

Xulong L., Chunyang H., Yaozhong P., Mingchuan Y. & Zhang, J. (2005). Accuracy assessment of thematic classification based on point and polygon sampling units. 2005 IEEE International Geoscience and Remote Sensing Symposium. IGARSS '05. 6, 3837–3840. doi:10.1109/IGARSS.2005.1525746.

Yamakura, T., Hagihara, A., Sukardjo, S. & Ogawa, H. (1986). Aboveground biomass of tropical rainforest stands in Indonesian Borneo. Vegetatio, 68(2), 71–82. doi:10.1007/BF00045057.