Quantifying environmental indicators and assessing performance in tropical forest management

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it). The copyright of this thesis rests with the author. Quotation from it is permitted, provided that full acknowledgement is made. This thesis may not be reproduced without my prior written consent. I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party. As of submission, none of the work in the thesis has been published. I declare that my thesis consists of 71,670 words.

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46 R.Hijmans...................*For Dad.*

Glossary

- AGB: Above Ground Biomass
- ALOS-PALSAR: Advanced Land Observing Satellite - Phased Array type L-band Synthetic Aperture Radar
- AWGLCA: Ad Hoc Working Group on Long Term Cooperative Action
- BCI: Berbak Carbon Initiative. This is the case study for the thesis. It is comprised of Berbak national park and adjacent protected and production forests.
- COP: Conference of the Parties to the UNFCCC
- DEM: Digital Elevation Model: a representation of the height and structures of the surface of the earth
- Lidar: Light Detection and Ranging
- LULUCF: Land Use, Land Use Change and Forestry
- MODIS: The Moderate Resolution Imaging Spectroradiometer
- NASA: National Aeronautics and Space Administration
- REDD+: Reducing Emissions from Deforestation and Degradation in developing countries, and the sustainable management, conservation and enhancement of forest carbon stocks.
- VEM: Vegetation Elevation Model: an approximation of the vegetation across the surface of the earth; e.g. where SRTM data does not fully penetrate the forests canopy.
- SRTM: Shuttle Ranging and Topography Mission. NASA mission to map the Earth's topography.
- QANS: Quick Assessment and Nationwide Screening. A programme to model peatland extent and depth across Indonesia.
- UNFCCC: United Nations Framework Convention on Climate Change
- ZSL: Zoological Society of London

0.1 SI Units

SI Units are used throughout the thesis.

Pg Peta: 10^{15}

Mg Mega: 10^{6}

Gg Giga: 10^{9}

0.2 Assorted Indonesian terms used regularly

- Hutan lindung: Protected forest class managed by provincial forestry offices. Often used to protected ecosystem services e.g. watershed protection.
- Hutan produksi: production forests. Used for exploitation for timber or conversion to other land uses (which is called *hutan produksi konversi*). *Hutan produksi terbatas*is limited production forest, where conversion to other land use types is not permitted.
- TAHURA; Taman Hutan Raya: Forest Park. Another protected forest category.
- Suaka Margasatwa: Wildlife reserve.
- Taman Nasional: National Park.
- Uani piro (n.b. this is Javanese language rather than the Lingua Franca of Bahasa Indonesia): This means approximately 'money for looking the other way', ignoring illegal activity.
- Kabupaten: a spatial political division, a 'regency'. Several kabupaten make up one propinsi.
- Propinsi: a province. Multiple provinces constitute the Indonesian state.
- DINAS Kehutanan Propinsi: provincial forestry service.

Abstract

Tropical forests are being cleared rapidly, causing between 12 and 20% of all anthropogenic CO_2 emissions. This process drives climate change and biodiversity loss. A new mechanism called REDD+ is being developed to pay tropical forest countries to reduce deforestation, and thereby to reduce these negative externalities. To be able to do this, maps of forest carbon stocks and change are fundamental. Policy impact analysis is essential too since REDD+ payments are performance-based. Quantifying biodiversity benefits of REDD+ is important too for carbon credit buyers. This thesis addresses these needs on Sumatra. As of 2007, a 7.2Mha study area holds 503 $\pm$ 105 x 10^6 Mg of forest biomass, with the largest stocks in protected and production forests. Other land classes have much lower biomass, suggesting legally exploitable forests are already depleted. What forest remains is being cleared rapidly. Between 2007 and 2009, 229 x 10^3 ha of forest were cleared, a rate of 1.6% yr^{-1}, and loss of >6% of the 2007 forest biomass, creating emissions of 58 $\pm$12.1 x 10^6 Mg CO_2e. Yet the deforestation is not uniform. On average protected forests reduce deforestation. However at the extreme, one protected forest area had virtually no forest remaining at all by 2007. By contrast the Berbak Carbon Initiative REDD+ pilot project has significant stocks (34.7 $\pm$ 17.3 $\pm$3.5 x 10^6 Mg forest carbon; 380 x 10^6 Mg peat carbon). It also supports a population of critically endangered Sumatran tigers (occupancy Ψ=0.14; 95% CI= 0.05:0.33). The project developers hope to conserve tigers and carbon simultaneously. However, following the first year of project activities, compared against control sites, deforestation appears to have increased.

Chapter 1

Introduction

1.1 Policy background: Deforestation and degradation, climate change and biodiversity loss

Tropical forests provide multiple ecosystem services such as atmospheric regulation, carbon storage, biodiversity provision and fresh water supply. Yet they continue to be cleared and degraded. Deforestation and degradation in developing countries accounts for a large proportion of anthropogenic CO_2 emissions, estimated at between 7 and 20% of the total: 20% (Solomon et al., 2007); 15% with range 8-20% (van der Werf et al., 2009) 7-14% (Harris, 2012), ultimately with between 0.9 2Pg C yr^{-1} (Houghton, 2010) and 1.0 Pg C yr^{-1} (Baccini et al., 2012) being transferred to the atmosphere (Pg is petagrammes; 10^{15}grammes; see SI units section in glossary).

Preventing dangerous climate change will therefore be much more difficult if tropical deforestation is not reduced or reversed. This emphasises the importance of improved forest management, which is at the top of the list of global environmental concerns for reasons other than climate change. At the time of writing, news headlines globally are dominated by reports of Indonesian forest fires filling the air over Singapore with a pall of thick smog. Walking the island-state's streets has become hazardous: in June 2013 Singapore's Pollutants Standards Index rose to 370 thereby exceeding the "hazardous designation" of over 300 (Gaveau, 2013). Air transport has been hampered by reduced visibility leading to unquantified productivity losses. Whilst these stories make compelling headlines when rich countries are affected, the underlying processes which ultimately lead to these fires continue each year across the Indonesian archipelago, causing not just dangerous particulate pollution locally for Indonesians, but also a slew of other negative externalities across scales. Locally, the clearance of forest causes the loss of ecosystem services: Locally, reduced forest cover and fragmentation is associated with micro-climatic changes; the degradation of water supplies; and loss of biodiversity (Soares et al., 2006; Gibson et al., 2013; Koh and Sodhi, 2010). Globally, increased carbon emissions forces anthropogenic climate change. The effects of biodiversity loss are felt internationally too. In hypothetical markets at least, people in rich countries value the existence of forests and other species (Baranzini et al., 2010; Bienabe and Hearne, 2006). The Sumatran tiger *Panthera tigiris sumatrae* is now classified as Critically Endangered by the International Union for the Conservation of Nature (IUCN, 2013). Greater commitment at the government level e.g. Ministry of Forestry (2010) and more generally greater exploitation of non-use values (Alexander, 2000) are required to prevent their extinction, such as linking their conservation to carbon payment schemes (Dinerstein et al., 2013).

1.1.1 The significance of peat swamps for carbon storage and emissions

Tropical peat swamp forests are of crucial importance for REDD+ because they store huge quantities of carbon. Jaenicke et al. (2008) explains how this may be up to one order of magnitude more carbon than tropical forests on mineral soils (up to 10 x 10^3Mg C ha^{-1}) and therefore one of the richest terrestrial carbon stores (Jaenicke et al., 2008). Furthermore, in-tact peat swamps continually sequester carbon, meaning they are a natural net carbon sinks when undisturbed (Sorensen, 1993). Within the context of climate change, carbon storage is important to avoid future emissions, but the fact that peat swamps also sequester carbon means that if they were to be managed wisely, they could actually contribute to removing CO_2 from the atmosphere. The current potential annual carbon sequestration of tropical peatlands is estimated at 35 x $10^1$2 Mg yr^{-1}. However, the crucial caveat is 'if they are managed wisely'. However,under the pressures of growing, and more affluent populations, these peatlands are being rapidly drained and cleared of forest. Damage to the system undermines its stability, and the loss of the sequestration potential until the peat becomes a net source of emissions (Hooijer et al., 2010, 2012).

More than half the world's tropical peatlands are found in S.E.Asia (Hooijer et al., 2012). An estimated 65% (22 million ha) of S.E. Asia's peatland is found in Indonesia in coastal and sub-coastal regions on Sumatra, Borneo and West Papua. It covers 13.9% Indonesia's land area (Page et al., 2007, 2011). In an assessment of the entire archipelago Jaenicke et al. (2008) estimated that Indonesia's peatlands together store 55 x 10^6 Gg carbon. However, with the pressures of the world's fourth-largest population of at least 230 million people (World Bank, 2011), and a growing economy based on the mass exploitation of its natural resource base, Indonesia's remaining peat forests are being extensively cleared for their timber and for land to create new palm oil and pulpwood plantations (Hansen et al., 2009). Hooijer et al. (2010) highlights that as of 2006, approximately half of all Indonesia's peatland forest had been cleared. What remains is largely degraded and being cleared at an

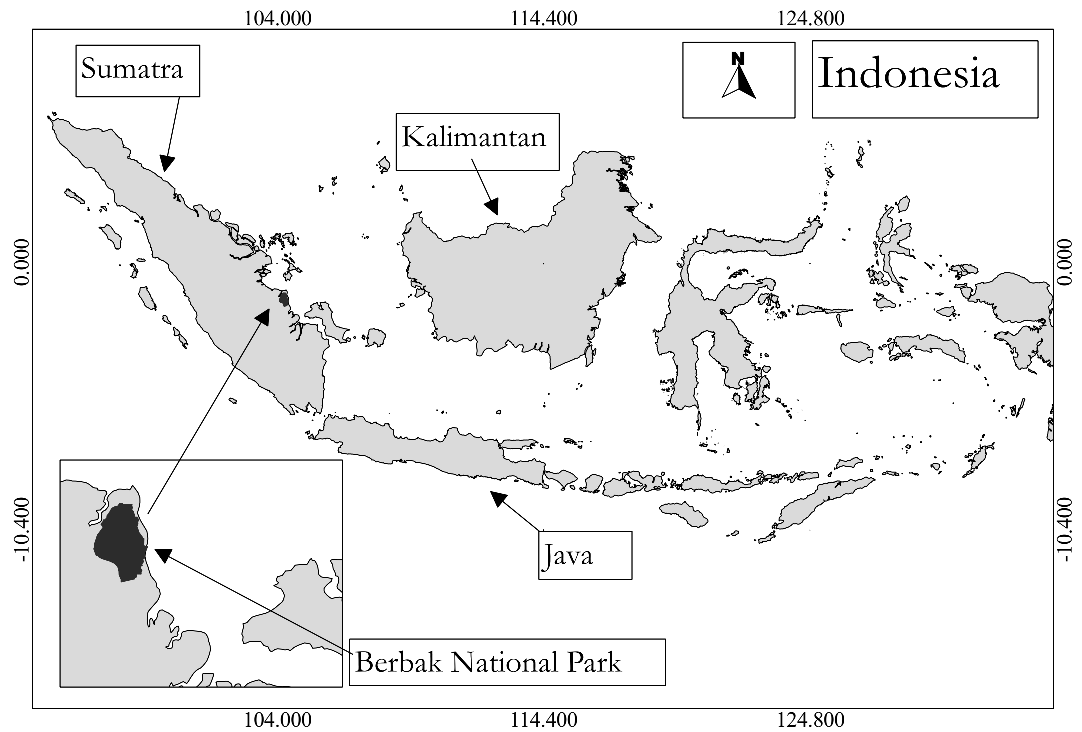


Figure 1.1: A map of Indonesia showing the main islands, and highlighting the position of Berbak National Park. This is the site of the Berbak Carbon Initiative, a pilot REDD+ project developed by the Zoological Society of London.

extremely fast pace. Miettinen et al. (2011) describes how even with a part of the world renowned for its rapid land cover change, the changes in areas where peat is found are very high. By 2010, the eastern lowlands of Sumatra had lost half of the peatland forest cover that they had in 2000 (Miettinen et al., 2011), a loss rate of 5% yr^{-1} over the ten year period.

Whilst peatland conversion produces short term financial benefits for land owners, it creates negative externalities. Specifically, the conversion process involves the construction of canals to drain the waterlogged peat and to provide land access. This causes consolidation and compaction of the peat. As the drained peat dries, the constituent part-decayed organic matter oxidises due to microbial activity. Oxidation of the carbon releases CO_2 to the atmosphere and causes subsidence as the organic material decomposes. In coastal swamps subsidence may even lead to sea water intrusion. Evidence suggests that these changes occur even if the water table is maintained at a high level by land managers. This means that subsidence and greenhouse gas (GHG) emissions from peat is an inevitable consequence of converting tropical peat swamp forests to other land uses even with management programme in place (Hooijer et al., 2012). Drying caused by drainage also increases peat's flammability. So when fires are used by land owners to clear the above ground vegetation, the peat also ignites. The peat may then burn for extended periods, and can even continue to smoulder underground during the wet season, and reignite in the following dry season. This further accelerates carbon emissions.

The huge size of these peat carbon stocks, and the pace of their destruction paints a dire picture for the global climate. Even if a land manager attempts to maintain high water levels in peatlands that are being used for plantations, the evidence shows that it will still collapse and cause emissions (Hooijer et al., 2012). There is therefore a need to manage peat to mitigate damage from these processes. In the context of REDD+ and climate change this is even more important.

At its most basic, peat management requires information on the depth and distribution of peat. Yet whilst peat distribution maps do currently exist globally (Joosten, 2009) and for Indonesia (Jaenicke et al., 2008) the accuracy of these has been contested and therefore need to be critically examined (Stahlhut and Rieley, 2007). Peat swamps are extremely hard to access, so estimations of peat extent and volume are made with limited field data sets. In addition to this lack of detailed information on peat thickness, there is variation in definitions of peat, leading to greater uncertainty in the quantity of peat in a given location (Page et al., 2007).

1.1.2 The development of REDD+ as a climate change mitigation mechanism

Forests have historically been excluded as a means to mitigate climate change for several reasons. Rich countries have questioned whether reductions in deforestation could be secured over the long term (permanence); and whether the interventions and payments made to forested countries would lead to reductions in deforestation over and above the changes that might have been expected to occur anyway (additionality) (Baker et al., 2010a; Santilli et al., 2005). Poor countries with large forests have expressed concern that new finance for forest management would lead to a loss of sovereignty over their land, resources and development strategies. A further concern raised was that paying poorer unindustrialised countries to reduce deforestation would simply become a huge multi-lateral carbon offsetting project that would crowd out efforts to reduce carbon emissions in rich industrialised countries instead of supplementing them (supplementarity). Finally, one of the main concerns of trying to implement spatially explicit programmes to reduce deforestation is that in a dynamic international market, reductions in deforestation in one area would simply be met with equivalent increases in deforestation in another area (leakage).

Consequently only re-forestation and afforestation were incorporated into the Clean Development Mechanism of the Kyoto Protocol as valid activities to generate carbon credits from forestry under the umbrella category of Land Use, Land Use Change and Forestry (LULUCF). The reduction of deforestation and degradation or the conservation of standing forests was excluded. However in 2007 the idea of compensated reductions in emissions from deforestation (RED) as a climate change mitigation strategy was established. This followed the 13th Conference of the Parties to the United Nations Framework Convention on Climate Change (UNFCCC) in Bali (COP13) and the development of the Bali Action Plan. Here, a group of forested tropical countries calling themselves the Coalition for Rainforest Nations (CfRN) lobbied for the inclusion of RED as a way for them to meaningfully participate in climate change mitigation and to access funds from the international community. This mirrored continued academic proposals for forests' inclusion under the UNFCCC and a post-Kyoto Protocol climate change agreement (Santilli et al., 2005). RED is a climate change mitigation strategy to address the failure of markets to price the negative externality of carbon emissions from deforestation, involving international transfers from rich country governments and private sector actors, to forest-rich but financial resource-poor countries. The definition of RED subsequently expanded to include degradation, that is Reduced Emissions from Deforestation and Degradation (REDD). Then, at the 15th conference to the parties of the United Nations Framework Convention on Climate Change (COP15, UNFCCC) the Ad Hoc Working Group on Long Term Cooperative Action (AWG-LCA) expanded the definition to include the Sustainable Management of Forests and the Conservation and the Enhancement of Forest Stocks, which gives the acronym its '+'. In summary, REDD+ includes (a) Reducing emissions from deforestation (RED); b) Reducing emissions from forest degradation (REDD); c) Conservation of forest carbon stocks (REDD+); d) Sustainable management of forests(REDD+); e)Enhancement of forest carbon stocks (REDD+) (AWG-LCA, 2009).

1.1.3 REDD+ activity

Following the development of the Bali action plan there has been extensive development of REDD+ action, at both national and international levels. This includes passing of laws and developments of policies in tropical forest counties to facilitate the development of REDD+, including in national plans and laws in Indonesia, Ghana, Brazil and Vietnam, (Townshend et al., 2013). These laws and policies have been developed in order to enable the development of both small scale project development and national schemes which can access funds available from the international community. Of the multilateral projects the United Nations Programme on Reducing Emissions from Deforestation and Degradation (UN REDD Programme) scheme has been important in bringing together forested countries and supporting national REDD+ schemes, drawing on the experience of work of the Food and Agriculture Organisation and the UN Environment and Development Programmes (UNEP;UNDP). Currently the UN-REDD programme has 47 partner countries with 16 receiving direct support to their National Programmes. In particular it has been instrumental in orchestrating the development of the National Forest Monitoring, Reporting and Verification systems (MRV); the development of Free, Prior and Informed consent for people upon whom REDD will impact, such as subsistence users of forest products ('local people'); and the development of REDD+ Safeguards and Social and Environmental Standards (REDDStandards.org, 2012).

In addition, the World Bank has its own mechanism, called the World Bank Forest Carbon Partnership Facility (FCPF) which has selected six partner countries in Africa (Democratic Republic of Congo, Gabon, Ghana, Kenya, Liberia, Madagascar); five in Latin America (Bolivia, Costa Rica, Guyana, Mexico, Panama); and three in Asia (Nepal, Lao PDR, and Vietnam). The goal of the partnership is to build the capacity of each of the partner countries to implement activities to reduce deforestation and forest degradation; monitor, report and verify these activities; and participate in nascent carbon markets.

1.1.3.1 REDD+ and biodiversity conservation

The possibility of carbon-based financing for forest conservation has lead to a great deal of excitement in the academic conservation biology literature at least, with carbon credits being perceived as a new way to fund conservation activities, particularly in places where there is overlap between high biodiversity and carbon values e.g. Venter et al. (2009a,b) though there has been concern that the focus on carbon values will lead to the bias in the conservation of peat swamp forests which are less biologically diverse and have lower abundance of threatened (and charismatic) mammal species than forests on mineral soils (Paoli et al., 2010).

One such charismatic species is the Sumatran tiger. Indeed the funding and opportunity for this PhD research derived from the establishment of the Berbak Carbon Initiative in Jambi province, the case study for the thesis. The initiative is a pilot REDD+ project established by the Zoological Society of London to explore whether REDD+ could contribute to tiger conservation. In Jambi, some of Indonesia's and indeed the world's last tigers remain in increasingly isolated blocks of forests. These forests are the target of exploitation by plantation and logging companies on the one hand, and the focus of carbon mitigation and biodiversity conservation schemes on the other. Some of these forests have been included in a forest logging moratorium imposed by the Indonesian government as a part of a bilateral deal with the Government of Norway under the banner of Reduced Emissions from Deforestation and Degradation (REDD+) (Murdiyarso et al., 2011a).

1.2 Problem statement

There are significant data and methodological requirements for the implementation of REDD+. At the most fundamental level it is required to know the location and amount of biomass across the landscape, in both the above (vegetation) and below-ground (soils) stores. Since there is interest in exploring whether the implementation of REDD+ can simultaneously address climate change and biodiversity loss, it is also required to estimate the biodiversity attributes of forests under REDD+ schemes. Whilst this information is necessary, it is not sufficient. REDD+ implementation requires an understanding of the socio-economic, political and legal conditions which regulate land use. This requires not only qualitative understanding, but also the quantification both of the drivers of deforestation, and the impact of past policies designed to reduce deforestation such as national parks. Finally, when new policies are created, there is a need for causal inference in order to be able understand what works in forest conservation, and where it works.

1.3 Aims of the data chapters

Three natural science chapters form the first half of the data-driven component of the thesis. The aims of these were to estimate the occupancy of tigers and their potential prey species (chapter 5); estimate biomass and carbon stocks below-ground in the peat soils (chapter 6) and above-ground in the forest (chapter 7. Next, three social science chapters complete the data-driven section of the thesis. The aims of these were to analyse the patterns of biomass distribution estimated for 2007 with reference to institutional conditions, specifically the official land use designations (chapter 8). Then, by exploiting the estimation of the change in forest cover over time, the next aim was to assess the impact of protected areas on forest loss (chapter 9. For the final data chapter of the thesis, the aim was to assess the impact of one year of REDD+ project activities on deforestation rates at Berbak national park. The specific objectives of each chapter are discussed in the following section.

1.4 Objectives of the data chapters

1.4.1 Establishing a biodiversity baseline: tiger and prey occupancy analysis using camera trap data

Since the Berbak Carbon Initiative (BCI) was initiated in order to conserve tigers, a crucial piece of research is to quantify aspects of the tiger population at the site. The objective of this chapter was therefore to estimate tiger occupancy at Berbak, using camera trapping data. A second objective was to use the same camera-trapping estimate the occupancy of the tiger's prey at the site.

1.4.2 Estimating the quantity of peat biomass and carbon at the Berbak Carbon Initiative

The BCI project site is important for Indonesian REDD+ because it is largely comprised of peat swamp forest, which is known to store huge quantities of carbon

(Page et al., 2002). A nationwide-wide effort was recently conducted to estimate the quantity of peat, but for an unknown reason the models developed could not deal with the data gathered at Berbak, rendering the area a 'blank spot' on the peat map. This presents a significant problem for the project, and an interesting applied research question. The aim was therefore to use geo-spatial methods to quantify the volume of below-ground biomass at the site, and from this to estimate the quantity of carbon stored.

1.4.3 Estimating above ground biomass using integrated L-band Radar and Lidar data

The objective of this chapter was to provide the most accurate estimation possible of the biomass in the forests of the study area surrounding the Berbak project site. A secondary objective was to quantify the changes of the biomass over time.

1.4.4 An analysis of forest biomass with respect to Indonesian land use classes

The purpose of this chapter was to take the findings of the forest biomass estimation, and to explore these in the context of Indonesia's official land use classes. This was done in order to understand which land use classes still held the largest amounts of forest biomass and as such which would potentially contribute the most to the conservation of forest carbon stocks, and which had already lost their forest. It asks: what are the relationships between the levels biomass and the land use classes in the study area? Are there significant differences between the distributions of biomass in each forest class? Which forest class had the lowest mean forest biomass per hectare, and which the highest?

1.4.5 Assessment of the impact of protected areas on deforestation between 2007 and 9

The purpose of this chapter is to understand to what degree the protected areas have reduced deforestation during the study period. Specifically, did the protected areas provide additional forest protection when contrasted with the other land use classes in the study area?

1.4.6 Seeking additionality: an impact assessment of the impact of a year of REDD+ intervention

The objective of this chapter was to quantify the impact of one year of the implementation of conservation activities under the name of REDD+. Specifically, how did the risks of deforestation inside the protected area change after the project began conservation activities there? This was in response to the challenge set out in the literature for the impact of projects to be rigorously assessed. Additionally it sought to test a hypothesis that the mere presence of researchers in the field was sufficient to reduce the risks of deforestation.

1.5 Novelty and research contributions of the thesis

The research provides novel contributions to the literature on monitoring of tropical forests and the impact of policies to conserve them. At the most basic level, the research provides novel **baseline information** about a data poor region which has enormous potential to contribute to climate change mitigation and biodiversity conservation. It then provides new **methodological contributions** through the development of forest monitoring technologies, and new **policy contributions** through the assessment of forest conservation activities. These are discussed in turn:

1.5.0.1 Baseline data

1. To the knowledge of the author, this is the first study to have quantified peat volume and carbon stored in the Berbak ecosystem. A recent collaboration between multiple NGOs led by an international environmental consultancy tried to develop a nation-wide model of peatland distribution, but the model did not fit the Berbak region. As such the estimate provided here is the sole estimation to date of the huge quantities of carbon stored.

2. This is the first study to provide systematic baseline information on the mammal fauna at Berbak; and to quantify this biodiversity in a robust ecological monitoring framework that accounts for detectability and the environmental co-variates of site occupancy. The development of population statistics will allow future analysis to assess not only the state of tiger prey at a given point, but also the change in the status of the prey since 2009.

3. The baseline biomass estimation for 2007 across the 7.2Mha study area provides a rich data set to explore the relationship between land use classes and forest biomass and carbon stocks.

1.5.1 Methodological contributions

1. The main methodological contributions were made in the work to calculate the forest biomass and the change in that biomass over time. The value of a method was demonstrated for the first time in Indonesia, showing how the

perennial problem of cloud and smoke obscuring forest could be overcome using a combination of active radar and lidar sensing. It further showed how by using relative normalisation and threshold-limited differencing of annually gathered radar data, it was possible to measure change against the baseline of forest biomass. This allowed estimates not only of the total area cleared during the study period, but also of the total emissions arising from the process.

1.5.2 Policy contributions

1. The assessment of the impact of protected areas during the study period provides important contribution to the understanding of land use change in a region undergoing some of the fastest change in the world. Only one other analysis has addressed this question before on Sumatra but using a much older data set. Nonetheless, this more recent analysis supports the conclusions of the earlier work, and suggests that even matching pixels for the predictors of deforestation, that the protected areas are contributing to forest conservation. This has important implications for the way in which forest is managed in Indonesia and particularly for how REDD+ is implemented: empirical assessments of what actually works in conservation interventions has increasingly been called for in the literature.

2. It was increasing demand to see quantitative assessment of the policy interventions that also motivated the final empirical chapter, which provides the *first quantification of the performance of one year of a REDD+ pilot project*. This provides the most significant policy contribution.

1.5.3 Interdisciplinarity

This thesis represents the first institutional collaboration between the Institute of Zoology at the Zoological Society of London, and the London School of Economics and Political Science in order to develop a PhD. As such it incorporates a range of ideas, research methodologies and concepts.

1.6 Overview and structure of the thesis

The thesis is broken down into 1. a background section, 2. a data-driven section and 3. a discussion. The data-driven section is in turn divided into three natural science and three social science chapters. An outline of the thesis is provided at the beginning of each chapter, highlighting the reader's position in the text.

The thesis begins with a review of the methodological context that reviews the key relevant literature (chapter 2). The next chapter then reviews the literature of the history of the socio-economic conditions which led to contemporary patterns of

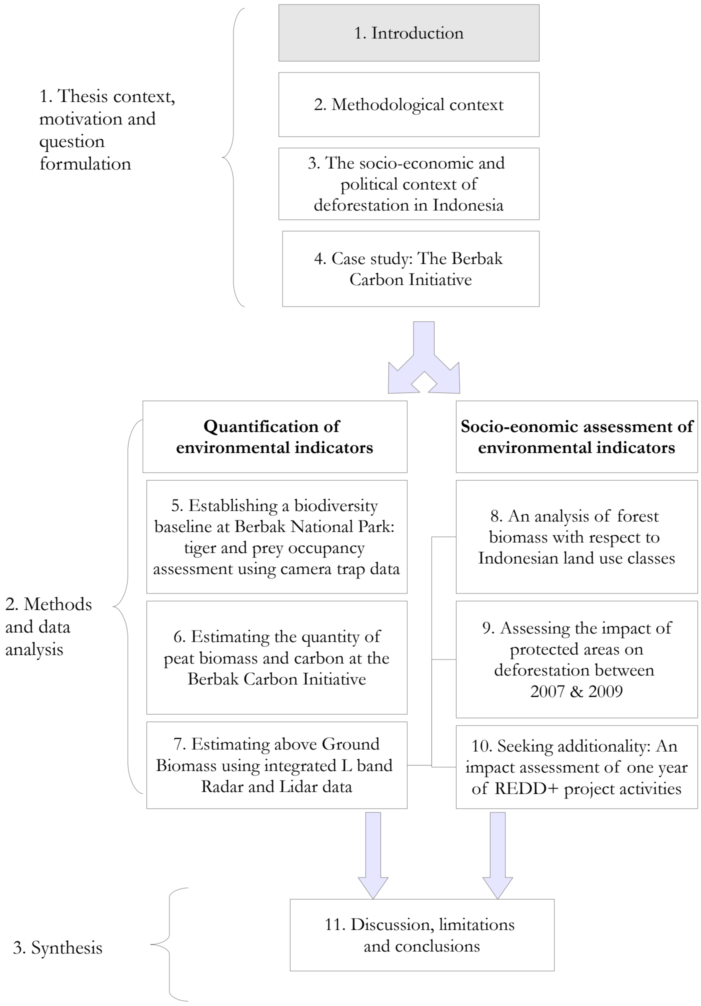


Figure 1.2: An outline of the PhD thesis, with the reader's current position highlighted.

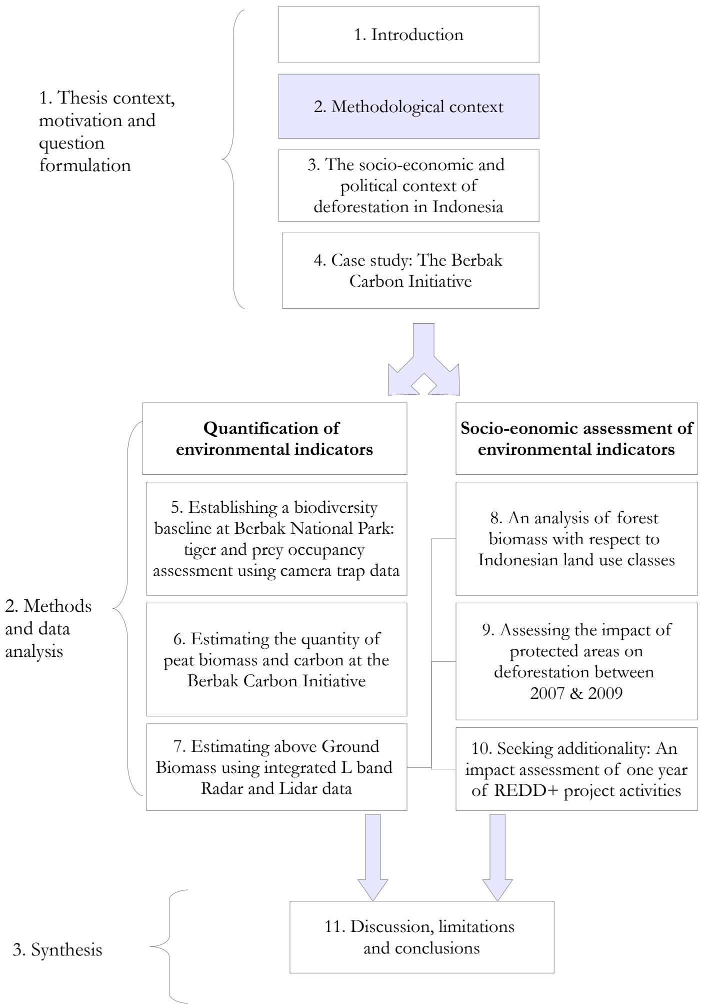
forest distribution and deforestation (chapter 3). In particular it focuses on land use policy and governance, and the trend towards the centralisation and monopolisation of resources. This begins with the Dutch colonial period, through to independence and more recently *reformasi* and multi-party democracy. Following this, chapter (4) draws on this background but focuses on Jambi province in Sumatra, where the general patterns described across Indonesia are grounded in case study of the Berbak Carbon Initiative (BCI). This is a REDD+ pilot project centred on Berbak National Park and established by the Zoological Society of London to support the conservation of the Critically Endangered Sumatran Tiger. This concludes the background information section.

The following chapters are empirical, and based on the analysis of a series of different data sets. First (chapter 5) is the quantification of attributes of biodiversity at the project site using a six month camera trapping survey analysed in an occupancy modelling framework. This ultimately provides an occupancy estimate for both tigers and their prey at the study site, which is an estimate of the probability of occurrence of a species, accounting for detection probability. Next, chapter 6 quantifies the below ground biomass stocks within the boundaries of the Berbak project site using spatial statistics (kriging). This provides a total volume estimation for the amount of peat biomass and carbon at the site. The following chapter 7 quantifies a) a baseline of the forest biomass in a 7.2 M ha swathe of Jambi and South Sumatra provinces, and b) the changes in this biomass and the associated emissions between 2007 and 2009. Next, chapter 8 explores the distribution of the forest biomass in 2007 with respect to the government's land use classes, and explores whether there are any differences between the different designations in order to provide a descriptive analysis of the study area.

The next section of the thesis examines the deforestation data. First, the entire 7.2Mha study area is examined in chapter 9 in order to test whether protected area status had any effect on the risk of deforestation between 2007 and 2009. Once again, this study then focusses down onto the case study area surrounding Berbak National Park (chapter 10). Deforestation in Berbak is compared with the deforestation in control sites before and after the implementation of one year of REDD+ pilot project activities. The final chapter summarises the key findings of the thesis and discusses the limitations of the work, before providing suggestions for future research.

Chapter 2

Methodological context



This thesis is multidisciplinary, drawing on both the natural and social sciences in order to make a contribution to understanding changing patterns of forest cover in Indonesia: why deforestation is occurring; how to measure deforestation; establishing indices of forest biodiversity; and assessing the impact of policies designed to reduce deforestation. As such, a review of the literature is challenging in that it must span several disciplines, and broach multiple topics. Because of this the review is broken down as follows. First there is a review of the state of the art in the quantification of environmental indicators. These are the quantification of peat carbon stocks; the quantification of forest biomass and carbon stocks and change over time; and options for measuring biodiversity. Second, there is a review of impact assessment evaluation to measure the performance of policy interventions.

2.0.1 Quantification of environmental indicators

The environmental indicators of concern to this thesis are first, the biomass and hence carbon stored in a) peat and b) in forests; and second, the biodiversity of those forests. These are now addressed in order.

2.0.1.1 Peat volume estimation

Peat soils form in shallow basins on the landscape over thousands of years when the production of organic matter exceeds the decomposition rate in waterlogged anaerobic conditions (Stahlhut and Rieley, 2007). The soil accumulates faster at points furthest from rivers in what is termed an 'accumulation zone'. Near major rivers, and near the shallow margins of the depression which it forms, the accumulation rate decreases and the peat becomes shallower. This leads to the formation of the classic peat dome shape, which forms the core of the physical geography theory (Moore and Bellamy, 1947). This theory underpins the analysis used by contemporary researchers to estimation peat dome volume.

S.Page in particular has been influential in highlighting the importance of peat for ecosystem service provision and its potential to adversely affect the climate when damaged. Probably the single most important research finding in this regard was the calculation that between 2.4 and 6.8 M ha peatland burned in Indonesia during the el nino 'fire seasons' of 1996 and 1997; and that as a consequence which between 0.81 and 2.57 x 10^6 Gg C were released to the atmosphere(Page et al., 2002). This finding was more remarkable though when put into context: the authors claim that these ***emissions from just two years of fires in Indonesian peatlands are equivalent of 18-57 years of successful Kyoto climate change protocol implementation***. However this research came on the back of a historical dearth of work on peatlands. The authors of an albeit grey literature review for an EU project called Carbopeat (Page et al., 2007) lament that in the two decades after 1985 when relative ignorance of tropical peatlands was raised as a concern, research had still not greatly progressed. Page et al. (2007) explain how fundamental concepts like precisely what constitutes 'peat' and 'tropical peat' are still being contested, with the main issues of concern being the proportion of organic matter, and the thickness of the peat itself. If today there is still a lack of consensus even over what constitutes peat, then it is perhaps less surprising that research did not progress during those twenty years after 1985.

Page et al. (2007) highlight the problems of determining the extent of peatland in Indonesia. This country has the single largest store of peat carbon in the tropics (Page et al., 2011). Sari et al. (2007) highlight how the destruction of peatland ecosystems has brought Indonesia the dubious distinction of being the third largest emitter of CO_2 and other greenhouses gases (GHGs) after the mass energy consumers USA and China. However these emissions are not constant; they tend to occur in quite dramatic events. Gaveau (2013) explains how the fires of 2013 caused enormous forest losses in peatland areas, recording 140,000 ha burned down in a 3.5M ha study area in the month of June alone. In 2008 Indonesia was by far the largest emitter of CO_2 from degrading peat of any country, releasing some 500 x 10^6 Mg CO_2 from the process. This is over three times more than the next largest source of emissions, Russia, at 139 x 10^6 Mg CO_2 (Joosten, 2009). However at least prior to 2007 estimates of the extent of the peatland varied significantly, from a minimum of 160,000km^2 to a maximum of 270,000km^2. Evidently there are significant problems in being able to measure the distribution of, and the quantity of carbon in, peatlands. In particular, their extent is huge, and they are found in remote locations, which means it is difficult to get into the field and take direct measures of thickness using drilling equipment (Page et al., 2011). A large problem in trying to resolve these differences in estimates of peatland extent is the fact that during the same period that the estimates were being made, huge land cover changes occurred in Indonesia (Miettinen et al., 2011). This is important since when the forests covering peat are cleared, and the land drained, large amounts of the peat is lost through oxidation of the organic material. So these systems are rapidly changing under anthropogenic pressure even as researchers attempt to define and measure them.

A further variable is that both the carbon and bulk density of peat varies across different peat ecosystems (Page et al., 2007). So even when the extent, depth and hence peat volume can be estimated, the final carbon stock ultimately estimated depends on bulk density and carbon content. These uncertainties in each of these values contribute to the propagation of errors that together lead to great uncertainty in the estimations of peat volumes and in turn emissions (Shimada et al., 1999).

The most widely-cited estimate is that emissions from tropical peat leads to approximately 3% of all emissions from anthropogenic activity (van der Werf et al., 2009). The combination of the huge emissions but with large uncertainties means that there is a great need for research in this area, to better characterise peat and estimate storage and emissions. This is all the more pressing in the context of REDD+, as policy makers seek to meet commitments to reduce emissions (e.g. Indonesia has committed to reduce emissions by 26% by 2020, see chapter 3 for details), there is a need to identify the most effective and efficient means to do this.

A recent approach has been to use three dimensional modelling to estimate peat volumes. This was driven by the PhD research of Jaenicke et al. (2008), subsequently published as Jaenicke et al. (2010). The essence of this technique is to focus on a specific peatland area, and integrate various pieces of data in order to estimate a) the surface and b) the base of the peat deposit. In theory the peat should be shallower at its margins, and then get deeper further towards the centre of the zone of accumulation (Moore and Bellamy, 1947). This depth should be reflected both in the depth of the deposit (deeper areas forming in the centre of a river basin), but also in terms of the height of the peat. Whereas the depth of the dome has to be measured by going into the field and drilling into the ground - a laborious process - the height of the land can be measured using remote sensing data. If the relationship suggested from theory between the height of the peat dome and the sampled depth of the deposit is sufficiently strong, then the depth can be modelled across the entire deposit without need for further depth samples. Jaenicke et al. (2008, 2010) successfully exploited this relationship to create a 3D model for several Indonesian peat domes and estimate a total peat carbon stock of 55Gt for all of Indonesia.

Yet there are some problems with this approach. One is arbitrariness when identifying peatland margins from space: it is surprising that the state of the art in estimating this huge stock of terrestrial carbon ultimately comes down to drawing a line by hand around a satellite photograph of the study site. Yet the problems of working in these remote environments are huge. A further problem is that the remote sensing technology (C-band radar from the Shuttle Ranging and Topography Missions; SRTM) used to estimate the terrain (which is called a Digital Elevation Model; DEM) does not fully penetrate the forest canopy. This is because the radar interacts with the tree limbs and trunks. Hence the SRTM-derived DEM is accurate on bare land but overestimates height in areas with in-tact forest. Jaenicke et al. (2010) resolved this problem by using a different remote sensing technology (a laser pulsing system called Light Detection and Ranging; Lidar) to estimate forest height across the study sites. These forest height estimates can then be subtracted from the DEM, to create a 'virtual deforestation' model. However, Lidar data is very expensive to gather and process, requiring commissioning an aeroplane with the specialised equipment mounted to fly over the study area. One of Jaenicke's co-authors runs a remote sensing consultancy and had access to such a data set. However, most REDD+ project developers, NGOs and government bodies managing these resources would likely struggle fund this expensive data collection and processing. This sets a research challenge: **are there ways of developing virtual**

deforestation digital elevation models for peat modelling without needing to commission Lidar overflights? This was the first research motivation for chapter 6.

Even where this problem can be resolved, the extent of tropical peatlands means that there is an urgency to develop methods to develop peatland models on a landscape scale without having to take a case-by-case approach. One means to do this is to model the peat depth against the geomorphological features which are theorised to determine peatland depth, such as distance from rivers. This approach was set out on a local scale by Shimada et al. (1999). To take such an approach on a nationwide basis would however require a huge amount of data for the entire area for which modelling were to be attempted. This, along with the accelerating destruction of Indonesia's peatlands, but the promise of at least a partial solution via REDD+, was behind a recent large collaboration of NGOs in Indonesia to try to and develop the best model possible for peatland development. This effort was called Quick Assessment and Nationwide Screening for REDD+ (QANS). Data from sites across the archipelago was gathered together for the first time, providing a data set that would be extremely expensive for any one organisation to gather. As of the time of writing, the results of this assessment are not officially available. However, the headline results are that the project has been successful in modelling peat distribution and depth across the archipelago but crucially not for the Berbak peninsular. This is the location of ZSL's REDD+ pilot project called the Berbak Carbon Initiative, which is the case study for this thesis. The lack of success with the QANS model at the Berbak site therefore provided an interesting applied research problem: **what other methods could be used to estimate peat volume at the site to help with the REDD+ project**. This was the second motivation for undertaking research in this area.

2.0.2 Spatial statistics

The below ground biomass chapter draws heavily on spatial statistics, and particularly on kriging (it is important to note that these statistical techniques are not unique to the analysis of peat). The fundamental assumption behind kriging is that is that things which are closer together are more similar than things which are further apart, that is they are spatial auto-correlated. In some cases this can prove a problem. For instance in chapters 9 and 10, spatial correlation in regression model error terms violates assumptions about error distribution, and so needs to be controlled for. However, spatial correlation can also be useful: where a parameter is sampled across a landscape (e.g. peat depth), the degree of spatial correlation can be used to make estimates of that parameter between sampled sites and at unsampled sites. This idea underpins kriging, which derives from regionalised variable theory, which was originally developed for use in mining (Matheron, 1971). Kriging models estimate the relationship between values based both in the distance and direction between sampled points.

The first stage in kriging is to construct a semivariogram. This provides information on the spatial auto-correlation of the data, which is how much the difference in the data varies with distance. It is measured in the terms of half the distance squared, hence 'semi-variogram'. Kriging takes spatial autocorrelation information from the sampled sites and uses this to create the weights used to created predicted values at unsampled sites as a function of distance and direction from sampled sites. In the production of the semi-variogram, pairs of sampled sites are binned together to reduce the number of combinations of different data points measuring variation. A regression model is then estimated for the semi-variance and distance. This is best understood with reference to figure 2.1.

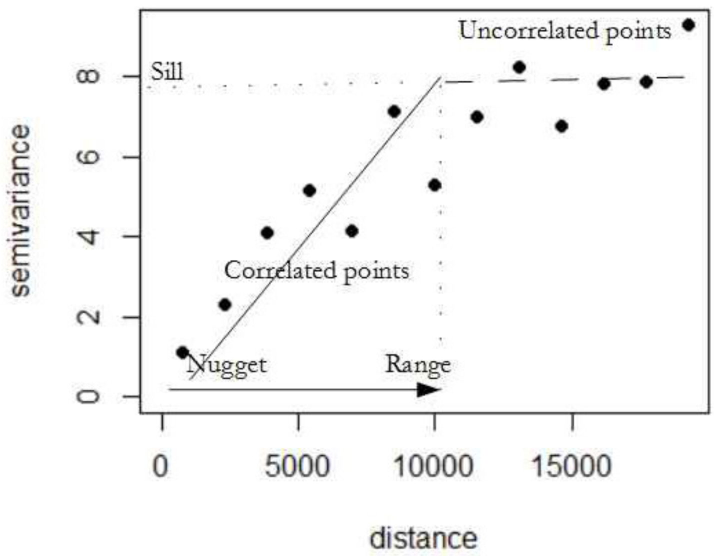


Figure 2.1: A semivariogram showing the range,sill and nugget. The data taken from the peat depth kriging exercise.

The larger the first derivative of the semi-variogram nearer the origin, the larger the influence the nearest data point will have on the value of the prediction of a value for the unknown point. Other key properties of the semi-variogram which affect the ultimate outcome of the kriging exercise are the range, the nugget and the sill. The range is the point in the variogram where the fitted model line flattens out i.e. where the first derivative approaches zero. Any samples separated by a distance greater than the range are not spatially autocorrelated. The sill is the value on the y axis which the variogram reaches at the range (see figure 2.1). In theory points which are separated by 0 units distance have 0 difference (because they are at the same location) however in reality the difference is greater than 0 due to measurement errors either in the sampling device, in the methods (e.g. peat core sampling may involve hitting still-hard trees in the mire and provide false bottoms (Page et al., 2011), or variations in measurements at finer resolution than the units of measurement in the production of the semi-variogram. For instance one may consider peat depth at 1000m intervals across the landscape, and whilst the mean difference indeed changes as a linear function of distance from rivers, the first data bin of 0-1000m might itself contain a large degree of variance. This could be because, for instance, of the nature of the bedrock on which the peat forms; anthropogenic disturbance of the peat; and finally simply because there is more unexplained variation in reality than idealised models of the formation of the ombrogenous peat dome would suggest. The difference (as measured on the Y axis) found at the variogram's nominal distance of zero is called the nugget. A final issue regards trends in the data. Ordinary kriging assumes that the constant mean of the data is unknown, or, that there is no trend in the data. Where there are theoretical geophysical reasons for a trend, trends can be estimated (through a polynomial function in universal kriging) and subtracted from the data, leaving the deterministic element to be calculated from the random errors.

2.0.2.1 Forest biomass quantification

Emissions from tropical peat are extremely important, but carbon stores in forests are in aggregate even more important to the global climate, hence the development of REDD+. Measuring above ground biomass (AGB), the carbon within it, and changes over time is a central challenge for REDD+ implementation. Remote sensing using satellite data is absolutely fundamental to be able to do this. Satellite data allows the observation of huge areas of land and the development of relationships with other data sets, such as data from field measurements, like direct measurement of trees (Woodhouse, 2013; Mitchard et al., 2009b). This allows the modelling and estimation of forest attributes across the landscape in a way which would not be possible using field data alone. For the assessment of AGB and change for REDD+, researchers would ideally have high resolution maps made for each year, allowing assessments of the impact of policies to reduce deforestation and forest degradation. Yet there are major challenges to doing this since no satellite sensor directly measures biomass (Woodhouse et al., 2012). Further, the relationships between remote sensing data and biomass tend to break down at medium to high biomass levels. This means there is a loss of sensitivity for high biomass forest (Mitchard et al., 2009a). However, direct calibration from optical imagery has been performed by Baccini et al. (2012). Detecting biomass change is a more sophisticated challenge still, since this requires repeat estimates across time with well-understood uncertainties and error propagation.

Mitchard et al. (2012) characterized the options available for AGB mapping as (a) the classification of forest into landcover types, which are then attributed a mean AGB value based upon field or remote sensing measurements; or (b) the direct regression between AGB measurements from the field and a remote sensing variable.

There are different standards for monitoring established under the UNFCCC for reporting carbon emissions reduction activities, which have varying levels of rigour. These standards are called Tiers and numbered 1 to 3, where 1 is the least rigorous and 3 the most. Tier 1 involves the use of default parameter values such as global or country-level land cover maps. Tier 2 requires country-level data at a higher resolution, whilst tier 3 involves the use of high resolution country or region-specific data and models. Approach (a) largely maps onto the less rigorous Tier 1 and Tier 2 approaches, whilst Tier 3, involving local modelling, probably requires approach (b) (Arino et al., 2009). In Indonesia, approach a) has been followed most often in efforts to map deforestation and degradation. Most of the current research in this area uses optical imagery to do this, which involves the detection of visible wavelengths of the sun's light reflected from the surface of vegetation. Since it relies on reflected light, it is referred to as passive sensing.

The most commonly-used sensors to do this have been on NASA satellites, namely LANDSAT and MODIS (Moderate Resolution Imaging Spectroradiometer). For instance, in an assessment of the projected impacts of REDD+ in northern Sumatra, Gaveau et al. (2009c) used composite LANDSAT images to estimate forest loss. More recent for forest monitoring on Sumatra efforts integrate MODIS data in addition to LANDSAT. Broich et al. (2011a) used this combination to map forest change across both Sumatra and Kalimantan. However the latter work highlighted one of the central challenges of identifying forest type from remote sensing imagery: in areas with persistent cloud cover like the humid tropics, it is rare for the satellite sensors to record completely cloud free images. This means that images from several years often have to be stitched together in composites in order to provide the final images for analysis. This is a frustrating challenge in itself. However, a more substantive problem is that multi-year composites mask deforestation and regrowth occurring during the time period over which the composite was created (Hansen et al., 2009). This is a major concern in Indonesia where forest is cleared very rapidly (Miettinen et al., 2011) and being replaced with plantations: forest that appears not to have changed in the few years during which the maps are produced could in fact have been cleared in that time and replaced with a fast growing plantation e.g. *Acacia*, or an oil palm plantation. The implication is that loss of the original forest cover and associated emissions is underestimated in the subsequent analysis. One solution to this was developed by Broich et al. (2011b) who used algorithms to develop pixel forest histories. However this still only measures biomass indirectly. In an island-wide study of Sumatra using LANDSAT and LiDAR, Margono et al. (2012) re-iterate these monitoring challenges of high cloud cover and rapid regrowth.

Change is occurring very rapidly in Indonesia and particularly in Sumatra (Miettinen et al., 2011), cloud cover is high, and smoke from the fires plagues Sumatra and Kalimantan, which causes extensive damamge to forest and peat and obscures optical remote sensing imagery (Page et al., 2002). Somewhat ironically this makes the areas experiencing the most dramatic environmental change the most difficult to monitor. The need for high temporal resolution forest biomass and change data for REDD+ implementation presented an interesting research gap for the PhD research: what other technologies could measure both forest cover and changes in a way that would not be affected by cloud cover and smoke?

The only operational technology that can do this in high biomass tropical forest is LiDAR, which can produce maps of AGB (Lefsky, 2010; Asner et al., 2010). Other operational sensors, such as radar, saturate at some level of biomass (Lu, 2006; Mitchard et al., 2009b). So Lidar data across the entire landscape is the ideal data set in principle. However, coverage of the landscape is only available from aircraft (Asner et al., 2010). As noted with respect to peatland analysis, both this and the data processing requirements make Lidar data acquisition prohibitively expensive for REDD+ projects and government agencies managing natural resources. Yet there are limited Lidar data samples from the Ice, Cloud and land Elevation Satellite (ICESat). The Geoscience Laser Altimeter System (GLAS) sensor provided dispersed Lidar transects across the earth's surface, which serendipitously included tropical forests. Crucially these data are available to researchers without charge, and in Sumatra have already been exploited by Margono et al. (2012). These Lidar data do not span the landscape, and it is little use to have estimates of biomass in transects across a study area. However, Shugart et al. (2010) explained how these transect data *can* can be statistically related to, and used in conjunction with, other freely-available remote sensing data which do provide full coverage of the landscape, like radar. This relationship can be extrapolated across the second data set with full coverage in order to provide a landscape-wide estimate of Lidar readings.

Mitchard et al. (2009b) showed that whilst the relationship between radar and biomass does saturate at high biomass levels, a crucial advantage is its long wavelength relative to visible light penetrates cloud and smoke. This means that each data set collected can be used without needing to create composites with other images. This is a huge advantage, because in principle it allows the production of annual maps of forest cover which can be differenced to produce deforestation maps: precisely the kind of data that would be required for REDD+ assessment. Moreover radar relies upon the reflection of energy emitted (and is thus active sensing) for sensing purposes rather than passive reflected light from the sun (Woodhouse, 2013). Synthetic Aperture Radar (SAR) sends out a beam of energy from a sensor mounted on a satellite, and then measures the intensity of echoes returning to that sensor (Ryan et al., 2012). This backscattered energy detected at the sensor is a ratio of the power of the energy returned to the energy emitted to the ground. The medium wavelength (λ=0.23 m) of L-band radar used by the Japanese Space Agency's ALOS-PALSAR is of the same order of magnitude as the limbs and trunks of forest trees (Woodhouse, 2005). This results in more diffuse scattering than would be the case if the emitted energy were incident with bare ground, and so results in higher backscatter (*ibid.*). This means that in principle it is possible also to make estimates of biomass per pixel, rather than classifying forest into different type (primary, secondary etc.) and then attributing a mean value of biomass per forest class. Nonetheless radar technology is no silver bullet, due to changes in backscatter caused by seasonal variations in moisture in the study scene independent of real changes in the condition of the forest, and steep terrain causing radar 'shadows' on hill and mountainsides facing away from the sensor (Mitchard et al., 2012). This is clearly a major issue in rainforests and swamps. In addition there are problems associated with sideways-looking radar and topography. Radio 'shadows' appear over steep terrain, meaning that the far side of steep slopes from the sensor cannot reflect the emitted energy (negative bias), whilst the slopes facing the sensor reflect larger amounts than would otherwise be expected (positive bias). These challenges and opportunities provided the central motivation for the remote sensing component of the thesis: **could freely-available data be integrated for Indonesia in order to provide per-pixel estimates of biomass, and change detection unencumbered by cloud cover and the problems of terrain in the study site in Sumatra**?

2.0.3 Forest biodiversity estimation

Tropical deforestation is probably the most important driver of biodiversity loss globally (Koh and Sodhi, 2010). Because of this, REDD+ has been seen as having the potential to address climate change and biodiversity conservation. As such there has been a profusion of research which explores the potential synergies and tradeoffs between the two objectives (Harvey et al., 2010; Phelps et al., 2012a; Grainger et al., 2009), and even new financial mechanisms deriving from carbon credits to generate conservation funding (Busch et al., 2011; Dinerstein et al., 2013). In particular the spatial relationships between carbon stocks and biodiversity has been widely explored. Strassburg et al. (2010) found high spatial congruence between carbon stocks and species diversity globally; and Venter et al. (2009a) highlighted that in Asia, it was actually more cost effective to undertake REDD+ activities in areas with higher abundance of threatened mammals. More recently, De Barros et al. (2013) have identified locations in Brazilian municipalities which appear to offer large additional benefits to both carbon emissions reductions and the conservation of Jaguar conservation. Some authors have sought to emphasise that more biologically diverse forests will probably be more resilient and so provide more permanence of carbon stocks, especially in the face of continuing environmental change (Miles et al., 2010).

However despite the positive potential of identifying sites where in principle carbon and biodiversity could be conserved together, there are substantial concerns about tradeoffs (Phelps et al., 2012a). For instance Paoli et al. (2010) explained how REDD+ development in Indonesia was focussing on peatland areas due to the amount of carbon stored in this ecosystem, and the huge potential environmental benefits of improving management here. However, the authors provide data that suggest that these swamps are not as important for threatened mammals as dry forests on mineral soils, and that as such there is a potential tradeoff between biodiversity and carbon management. There is possibly a degree of taxonomic chauvinism underlying this, since peat swamp forests contain interesting species in their own right such as highly specialised peat swamp fish (stenotopic acidophilic icthyofauna). Nonetheless, for the purposes of mammal conservation, the data do seem to suggest that peatlands are probably less important for biodiversity conservation. Worse is that the authors hypothesised that restricted development in peatlands will simply displace activities into forests on mineral soils which are highly threatened (few such forests now remain in lowland Sumatra) but which support a higher abundance of endangered mammals. This is the problem of 'leakage', where deforestation reduced in one place simply increases elsewhere. However this argument about whether or not there is an overlap between biodiversity and carbon misses the point that REDD+ was never designed to be a biodiversity conservation scheme: it is a climate change mitigation scheme that could also provide positive externalities for biodiversity. Moreover, Collins et al. (2011b) pointed out that even if there there is a simple spatial relationships between high biodiversity and high carbon values in areas facing deforestation, REDD+ alone is not sufficient for biodiversity conservation: wildlife can be hunted to extinction in perfectly in-tact forests, leading to 'empty forest syndrome'. As such, they proposed that the idea of supplementary funding for carbon credits generated from REDD+ implemented in places which are particularly important for biodiversity. However, Phelps et al. (2012b) warned that internalising the costs of biodiversity within REDD+ risks raising the costs of REDD+ and ultimately undermining its chances of implementation at all. The same author has warned that there are more general risks with linking so much of the future of biodiversity conservation with carbon finance (Phelps et al., 2011), especially if it does not ever materialise on the scale anticipated. Moreover, these discussions about biodiversity and conservation often ignore the institutional conditions which are likely to be required to actually implement REDD+ in a given country (Collins et al., 2011a). In addition, there has been a strong focus on the opportunity costs of land use as a measure of the cost of REDD+ implementation, however this approach may fail to account for what Ghazoul et al. (2010) call downstream effects, such as the wealth generated through employment and associated service industry demand generation i.e. multiplier effects.

These are broader and fundamental questions about the development of REDD+. They could themselves be the focus of several PhD theses. For the purposes of the present thesis, it is an important motivation that within existing voluntary carbon markets there are certification schemes that assure credit buyers that forest carbon credits are real and provide additional benefits against the business-as-usual scenario. This certification therefore provides a 'badge of quality', and is carried out by independent auditors using the criteria of certification organisations, such as the Verified Carbon Standard (www.v-c-s.org). In addition to these standards, biodiversity conservation organisations have created standards that aim to ensure that forest carbon projects also provide biodiversity benefits (economists call these benefits positive externalities, but they are called 'co-benefits' in REDD+ jargon). Most prominent of the biodiversity certification schemes is the Climate, Community, and Biodiversity Alliance standard (CCBA)(Niles et al., 2005). These standards require the quantification of forest biodiversity, and evidence of its change over time. One of the reasons carbon credit buyers choose forest carbon credits is that expect they biodiversity benefits to be generated by conserving forest. As such they often require CCBA certification to ensure the credits do generate these benefits (See Diaz et al. (2011) for a full report of the voluntary carbon marketplace, and the current evidence for demand for biodiversity conservation within forest carbon schemes). This provided the motivation for the biodiversity component of the thesis: how can a REDD+ pilot project in a remote tropical swamp forest that supports a crucial tiger population demonstrate a positive biodiversity impact? Because from the project principal's perspective (ZSL) the focus of the project is on tiger conservation the options for monitoring forest mammals are now reviewed.

Monitoring forest mammals In forests where animals use trails and leave impressions in the substrate, presence/absence data can be generated by repeatedly walking transects and recording whether the footprints of the target species are found in an area (Wibisono et al., 2011). However, in environments where access is limited and long transects not possible, or where the substrate is too wet, this record of presence is obscured. This is the case in tropical peat swamp forest. The forest floor is regularly inundated, or otherwise the substrate is deep and footprints of animals are impossible to identify. The problem of recording species in such environments has increasingly been solved by using camera traps (O'Brien et al., 2003; Wibisono et al., 2009; Rowcliffe and Carbone, 2008; Ahumada et al., 2013). These are cameras with a sensor unit that is triggered by body heat and/or motion. These are set up in the forest and left running for weeks at a time. The resulting data can be interpreted in different ways. At the most basic level, species lists can be compiled for rapid biodiversity assessments. This provides rudimentary baseline information, but it would not be possible to attribute the presence of an additional species new to the activities of the project (it may have previously been present but undetected). As such it would be unlikely an auditor would deem this sufficient evidence for certification.

Another approach is to examine species richness across the different types of environments at the site, which serve as quasi-treatments. For instance, analyses of the rates of photographs of each species can be used to make Relative Abundance Indices (RAI), a measure of how relatively common species are. For an impact assessment, these could be used to measure the differences between mature and degraded forest at the site. Then, if an intervention were able to ensure that the degraded forest regenerated, it might be reasonable to hypothesise that during the lifetime of the project the mature forest species would begin to recolonise the degraded forest. This may demonstrate some biodiversity co-benefit against the original conditions. However, the use of camera trap rate derived analysis and RAI has become one of the most contentious issues amongst wildlife researchers (O'Connell et al., 2011; Jennelle et al., 2002; Carbone et al., 2002, 2001). This is largely because a researcher must make the assumption that species detectability is constant across the variable of interest, such as habitat condition. Yet detectability varies across such dimensions (Sollmann et al., 2013). As a simple example, consider that it is more likely that a researcher is able to observe a deer crossing a patch of open grassland between patches of forest, than in the thick undergrowth of a swamp forest: this is the essence of heterogeneous detectability. The fundamental problem arising is that failing to account for detectability conflates variation in the ecosystem with variation in the system used to observe it (Archaux et al., 2012). Ultimately, apparent changes in a simple RAI may therefore be attributable to changes in detectability rather than changes in abundance of the species under study. This can cause large differences in RAI for a species even from the same study site. One experiment showed that a detectability difference of 4-8% can create a 50-90% risk of falsely concluding there was a real difference between treatments (Archaux et al., 2012), depending on survey details. However, non-calibrated RAI is still often applied because of the ease of the calculations involved. This is despite the risk of erroneous conclusions from intra and inter-specific comparisons for which constant detection and abundance is implicitly assumed (Archaux et al. 2012). Because of these uncertainties, this approach is similarly unlikely to convince a project auditor.

A different method is to take presence and absence data for target species and explore these against environmental variables using binary logistic regression modelling. This is more sophisticated than the previous approach because it acknowledges that abundance is spatially heterogeneous. This approach would allow for predictive species modelling across the site. The probability of presence could be then used as baseline data, and if the data collection were repeated at a later date, it may be possible to show how the probability of occurrence of target species changed following the implementation of the project. However, establishing sufficiently strong and precise relationships with environmental variables is a challenge in macro-ecology since the relationships are complex (Karanth et al., 2004). Moreover, simple logistic regression still assumes constant detectability of species across space. However a solution to this problem arises where researchers undertake repeated detection/non-detection surveys. These time series data can be exploited to calculate the detectability $\hat{p}$ of species at a site (MacKenzie et al., 2002). This is used in conjunction with the records of presence or absence to generate the probability $\hat{\Psi}$ that a species is present at any site. This approach is called occupancy modelling *(ibid.)*. The ultimate aim is to produce an estimate of the occupancy of the target species across the study site, where occupancy is an estimate of probability of the presence of a species, accounting for heterogeneous detectability. As such occupancy modelling actually involves the specification of two sub-models: 1. a model for the the probability of detection given the species is present, and 2. the probability of presence. The two parameters are estimated simultaneously using Maximum Likelihood Estimation (MLE). Ahumada et al. (2013) recently assessed mammals in a Central American forest using occupancy modelling applied to camera trap data, and demonstrated changes in the populations over time which were hypothesised to reflect the impact of increased human hunting in the area. This provided an additional motivation for developing these statistics for the Berbak Carbon Initiative (BCI) site, on the basis that their development could be used in the future as baselines against which to compare future population statistics as part of an impact assessment. This topic is discussed in the next section.

2.1 Policy impact assessment

Policy interventions need to be properly assessed to ensure resources are spent efficiently (Andam et al., 2010; Ferraro and Pattanayak, 2006; Ferraro, 2009; Miteva et al., 2012; Andam et al., 2008; Angrist and Pischke, 2009; Nelson and Chomitz, 2011; Sanchez-Azofeifa et al., 2007; Baker, 2000). Assessments must properly account for biases. This is particularly the case for the selection of protected forest areas' locations. Joppa and Pfaff (2009) showed that protected areas are more likely to be found in remote places far from the drivers of deforestation. However, determining the impact of a policy is fraught with difficulty. This is due to a series of issues arising from the use of observational data. Observational studies differ in a number of ways from experimental data (Angrist and Pischke, 2009). In the latter, such as in a stylised laboratory experiment, subjects which are as similar as possible are identified, such as mice from the same brood. The subjects are then randomly assigned into control and treatment groups. The control groups and treatment groups are then kept in identical conditionals, except for exposure in the treatment group to the treatment (e.g. mice to a chemical suspected of being carcinogenic). The comparison of the mean of outcomes (e.g. the presence of tumours) in the treatment and control groups (a between-groups estimator) is then interpreted as the treatment effect. This is justifiable since the randomisation of the subjects across groups ensures that there is no systematic difference between the groups prior to the treatment. However these conditions cannot be replicated in the case of observational data. This presents considerable problems for causal inference. Forest conservation interventions present a good example of such observational data and the problems arising, which leads to discussion of the present study of tropical forest management under REDD+.

Consider a further hypothetical example: a coffee firm aims to improve sustainability in the agroforestry farms which provide them with coffee beans. This is because unsustainable production involving increased deforestation on farms presents a risk to the brand's reputation. To mitigate the risk, the firm develops an incentive scheme for farmers to retain more trees on their plots, with the intention of improving forest cover and providing habitat for an endangered forest bird. The rate of deforestation is measured before the incentive scheme (the treatment) is implemented. The deforestation rate is measured again three years after the implementation of the scheme. The rate of deforestation is found to have decreased, and therefore the company deems the project a success. However this naïve pre-post within-subject estimation is flawed, since it does not take into account the changes in deforestation that would have occurred in the treated farms in the absence of the treatment. Deforestation may have decreased in the treated farms anyway, due to a fall in the price of gas canisters which provides a substitute for timber as a fuel source. In order to be able to detect the impact of the project, the analyst must therefore control for time-varying factors in the economy which affect project outcomes but which are not themselves influenced by the project, such as changes in agricultural conditions (Ferraro, 2009; Angrist and Pischke, 2009).

An apparent solution is to establish comparison sites where the farms are not themselves treated. These are expected to experience the trend in deforestation that would be experienced also in the treated site, in the counter-factual situation where there is no treatment. Under this set up, the between-subjects difference in deforestation between the treated and the comparison sites before and after the incentive scheme would be interpreted as the treatment effect. Yet, this set up could still be vulnerable to confounding effects: Naïve comparisons between the treated and comparison sites which fail to adjust for any systematic differences between the two could provide flawed estimates of the treatment effect. Both farms and protected forests tend to be non-randomly distributed (Joppa and Pfaff, 2009). For instance, the farms in the comparison site may have had a higher prior deforestation risk anyway due to their proximity to a local town with a large market for farm output. As such, deforestation may have been higher in the control than the treated site. In practice this issue has presented a problem in the analysis of success of national parks established to protected forest. Apparent success attributed to parks in reducing deforestation has been shown in some cases to simply reflect the choice of poor comparators, and the fact that protected areas are often located in remote areas and are therefore simply further from the drivers of deforestation (Nelson and Chomitz, 2011). Such biases likely occur because of development trade-offs: land with high private opportunity costs in production (e.g. for high oil palm profits) is expensive not to exploit, and moreover prices do not include the negative externalities of deforestation. On the other hand protected areas provide public goods and are allocated without the positive externalities being priced in, and so are more likely to be located on marginal land than agriculture with high private profits (Pfaff and Robalino, 2012).

A solution to this problem is to use quasi-experimentation methods. One approach is the use of exact matching methods (Angrist and Pischke, 2009). These are used to pair treated subjects with untreated but near-identical subjects. In the hypothetical case described here, the treated farms would be matched in terms of deforestation predictor variables to untreated farms (Nelson and Chomitz, 2011; Ferraro et al., 2011). The difference between the matched control site and the treated site would then be interpreted as the treatment effect. Nonetheless, exact comparators can be extremely difficult to find in practice. If this is true, then other quasi-experimentation techniques can be used. Quasi-control sites can established by selecting untreated areas which match as far as possible the attributes of the treated area (Angrist and Pischke, 2009). Because the treated and quasi-control sites are not exactly matched in their attributes, then systematic differences between must be dealt with. In the case of deforestation, this can be done by controlling for the drivers of deforestation in each site (Nelson and Chomitz, 2011) (see chapter 3 for a full discuss on the determinants of deforestation). Further, because the treatment and quasi-control sites are not identically matched, then it would still not be justifiable to make a direct comparison in the outcomes between the two. However a solution arises when data are available over time. This is because it is reasonable to assume that controlling for the drivers of deforestation, the *trends* of deforestation in each site are the same over time. Further it is reasonable to assume that in the absence of an intervention, and controlling for the drivers of deforestation, that the difference between the trends in the treatment and control site would remain the same over time. This difference between the treatment and control groups can therefore be interpreted as a fixed effect. If this assumption is reasonable, then any observed *differences in the differences* between the treated and control site following the treatment can be interpreted as the treatment effect. Under this set-up, the null hypothesis is that the difference in the deforestation rate between the two sites is constant over time following the treatment.

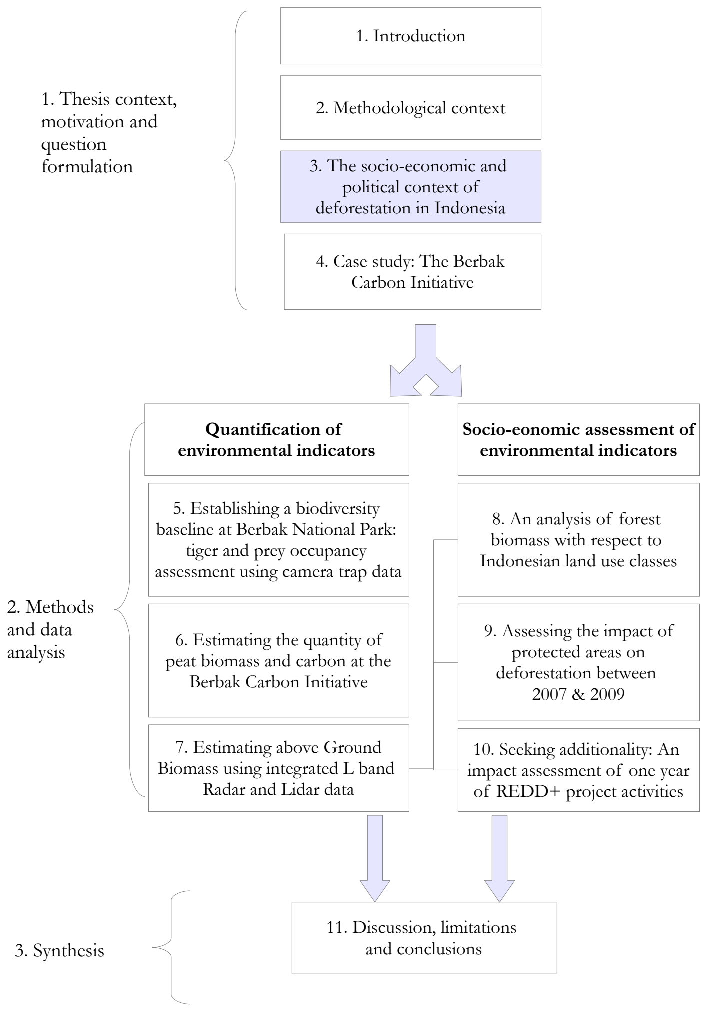
Whilst this seems convoluted, these issues are absolutely fundamental to robust impact assessment and policy evaluation, particularly in development economics (Baker, 2000). Here evaluation is used to determine what works and what doesn't, and in the latter case to cancel programmes (Essama-Nssah, 2006). It was the realisation that biodiversity conservationists were not using robust inference techniques that caused Ferraro and Pattanayak (2006) to write a paper called 'Money for nothing' calling for empirical testing of the performance of biodiversity conservation investments. This applies equally to the present context of the tropical forest sector.

This has long been the subject of management interventions, through the creation of national parks; supplier certification (e.g. Forest Stewardship Council certification); or projects which seek to intervene in the management of a pre-existing national park, such as the World Bank's Integrated Conservation and Development Projects (ICDPs). REDD+ comes on the heels of these various initiatives. However the stakes for correct causal inference under REDD+ are arguably higher, due to the incentive structure proposed under this system. That is, REDD+ payments are proposed to be structured upon measured performance in reducing deforestation. As such, incorrectly estimating the treatment effects of a REDD+ implementation would lead to the wrong amount of carbon credits being attributed, and ultimately to an inefficient policy that did not contribute optimally to climate change mitigation. One quite recent paper by Nagendra (2008) for instance concluded that parks globally had been successful in reducing land cover change, albeit with regional variations such as losses in Asia. However, this assessment was problematic methodologically because it simply compared change rates inside and outside the park, and then pre-post creation of the national park, without controlling for the predictors of deforestation. By contrast, in a more robust assessment Joppa and Pfaff (2009) demonstrated that in fact there is a considerable bias in the location of protected areas which tend to be biased towards higher altitude areas that tend to be distant from the drivers of deforestation. This means that the average conservation impact of these interventions is likely to be low (Pfaff and Robalino, 2012). In an assessment of protected area impact in Costa Rica, Pfaff et al. (2009) find that avoided deforestation impacts are greatest when the areas are under greatest threat, although by contrast Sims (2010) found that protected areas near cities had less of an effect in Thailand.

Yet there are more nuances still to the effects of location upon policy impacts. As set out above, policy impacts can vary by location because of the baseline conditions in each location: baseline deforestation is low in an area which is distant from the drivers of deforestation for instance. However Pfaff and Robalino (2012) explain how in addition, different mixes of political-economic pressures drive the location of different policies, and that policies can cause spillover effects which differ by location. In theory, transport costs imply that *ceteris paribus* profits from agricultural products for sale in a city will fall the further a parcel of land is from the city (Pfaff and Robalino, 2012). In Indonesia, one of the most relevant studies to this review was undertaken by Gaveau et al. (2009a) who used matching techniques to test the effectiveness of protected areas in reducing deforestation on Sumatra. They found that between 1990 and 2000, despite continued deforestation inside protected areas, they were nonetheless effective in reducing deforestation against matched pixels outside the protected areas. The call for robust assessment of conservation policy, and the availability of the data set created in chapter 9 provides for a re-assessment of this finding, whether deforestation seven years after the end of the study period defined by Gaveau et al. (2009a) still conformed to the same patterns, and whether deforestation was still reduced regulated by protected areas. An additional remote sensing data set for 2010 overlapped the first stage of implementation of a REDD+ pilot project. This provided the opportunity for what may be the first assessment ever undertaken on the impact of REDD+ in practice.

Chapter 3

The socio-economic and political context of deforestation in Indonesia



3.0.1 Introduction and chapter objectives

Deforestation is a multi-faceted phenomenon driven by formal and informal institutions, incentives and organisations across scales (Angelsen and Kaimowitz, 1999; Brown and Pearce, 1994; Kaimowitz and Angelsen, 1998; Jepson et al., 2001; Smith et al., 2003). It involves different agents in multiple contexts, from forest clearance by multi-national corporations for the establishment of industrial plantations at one extreme, to small-scale clearance for subsistence agriculture at the other (Geist and Lambin, 2002; Lambin et al., 2003). Understanding the drivers of deforestation and the various contexts in which they operate is fundamental to the implementation of an environmental policy which seeks to influence the level of that deforestation, such as REDD+. The underlying drivers of deforestation may in turn influence policy-makers, whose decisions are influenced by socio-political institutions and historical context (Lindayati, 2002). Moreover, socio-political institutions regulate policy makers preferences (*ibid*).As such it would be difficult indeed to understand either how REDD+ fits into Indonesian forest policy or its potential to mitigate CO_2 emissions in practice, without considering the socio-economic history of forestry, the drivers of deforestation, and the choices of policy makers in that country. A study of REDD+ in Indonesia would therefore be incomplete without a background description of the drivers of deforestation and the specific socio-economic and institutional conditions that have resulted in contemporary patterns of deforestation and land use, and the policy developments which have both influenced and been influenced by them. These factors in turn provide the background to how Indonesia interacts with the international community and efforts to mitigate and adapt to climate change. This chapter therefore seeks to provide both that socio-economic background, and the recent developments in Indonesian policy on climate change and the environment.

First, the chapter takes a wider perspective and describes research on the determinants of deforestation from studies across the tropics. It then focuses in on the study country of Indonesia to discuss the specific contexts of deforestation and land use here. The geographical; political; socio-economic and institutional aspects of forest management are addressed. This is done from the Dutch colonial period, through to independence and the control of Suharto's military autocracy; and then through *reformasi* to contemporary multi-party democracy. Finally, this history is used as a backdrop to describe Indonesia's engagement with the international climate change policy regime and REDD+. The issues are considered at a national scale, but there is also focus on Jambi province in Sumatra. This is because Jambi is where the case study of the Zoological Society of London's REDD+ project, the Berbak Carbon Initiative (BCI), is located. This project is the subject of a dedicated case study in chapter 4.

3.1 Characterising deforestation

Under the United Nations Marrakesh Accords, forests are defined as *”a minimum area of land of 0.05-1.0 hectares with tree crown cover (or equivalent stocking level) of more than 10-30 per cent with trees with the potential to reach a minimum height of 2-5 metres at maturity* in situ. *A forest may consist either of closed forest formations where trees of various storeys and undergrowth cover a high proportion of the ground or open forest. Young natural stands and all plantations which have yet to reach a crown density of 10-30 per cent or tree height of 2-5 metres are included under forest, as are areas normally forming part of the forest area which are temporarily unstocked as a result of human intervention such as harvesting or natural causes but which are expected to revert to forest”* p.58 Annex A.1.a (UNFCCC, 2001). This definition of forest essentially refers to land with trees on it, and ignores biological processes such as succession, which underlies the concern that the definition fails to acknowledge the complexity of forest ecosystems and their biodiversity (Sasaki and Putz, 2009). Similarly, as Angelsen (1995) points out, there is no single definition of deforestation; and defining it as a simple binary process whereby trees are removed from the land over the long term risks oversimplifying a complex process: forest clearance for palm oil production by a multi-national agri-commodity business is very different from deforestation caused by traditional shifting *swidden* agriculture. Nonetheless, this chapter is not intended as a discussion on the appropriate definitions of forest and deforestation, and as such the definitions from the Marrakesh Accords are followed here.

At the broadest level, in characterising researchers' attempts to understand deforestation, Lambin et al. (2003) describe how two 'camps' have emerged: one cites single factor causation, whilst the second emphasises the 'irreducible complexity' of the phenomenon. Yet the authors argue that such a distinction is not really necessary, and that in fact there are factors which do emerge from studies across scales which show consistency in their contribution to deforestation.

These common factors are used to estimate deforestation models. These do make some simplifying assumptions about nature of the processes involved. However, this is true of any modelling exercise, and moreover the use of models provides a logical and conceptual framework to analyse and more rigorously consider deforestation (Angelsen and Kaimowitz, 1999). When considered sufficiently robust, models also provide means to assess the potential impacts of policy interventions on deforestation rates, which is of course fundamental to the design of policies and activities to reduce deforestation under REDD+.

Forest clearance is driven by factors relating to the physical environment, politics, and the economy; and involves different types of actors, incentives and institutional conditions (Kaimowitz and Angelsen, 1998; Ikenberry, 1988; Angelsen and Kaimowitz, 1999, 2001; Barbier et al., 1995; Lambin et al., 2003; North, 1990).

Angelsen and Kaimowitz (1999) characterise the variables affecting deforestation as a) the underlying causes of deforestation, such as macroeconomic variables and policy instruments; b) the immediate causes of deforestation, which are the parameters that directly affect deforestation including institutions, infrastructure, markets, physical conditions, and technology; and c) the sources of deforestation, which constitute the agents of deforestation themselves, such as firms and households. On the other hand Lambin et al. (2003) characterise the drivers of deforestation as either proximate causes (constituting agricultural expansion, wood extraction and expansion of infrastructure), or underlying causes (constituting demographic, economic technological, policy/institutional, and cultural or socio-political factors). They add to these causes the biophysical 'pre-disposing events and drivers', such as the quality of the soils underlying the forest. However they assert that such biophysical properties only ever moderate the level of deforestation rather than fundamentally altering the deforestation process.

It is particularly important to note that these various drivers do not act in isolation. Multiple factors and processes interact with one another, meaning that a combination of the physical and socio-economic properties of a landscape will determine how much deforestation occurs and for what reasons (Brown and Pearce, 1994). This means that both the physical and economic landscapes need to be understood together in order to begin to understand deforestation. Specific drivers and their inter-relationships are therefore now discussed.

3.1.1 The determinants of deforestation

In the physical realm, there are several factors which affect the ease with which agents can clear forest, and the value of the land underneath. Whilst Lambin et al. (2003) state that these merely moderate the rate of deforestation rather than drive it, these factors are nonetheless worthy of attention for a study concerning REDD+, which has as its ultimate goal the moderation of deforestation rate against a baseline. These physical factors include the steepness of the terrain; the quality of the soils; whether soils are waterlogged; the navigability of rivers and their direction of flow; and the distance of a patch of forest to the nearest forest edge. On average, forest on steep terrain is more difficult to clear than flat lowland forests, which raises costs to agents of deforestation. This means that all other factors held constant, forests on hilly and mountainous terrain are less likely to be cleared than forests on flat ground (Chomitz and Gray, 1999; Newton, 2007). Nonetheless, on Sumatra, some of the last remaining forest is found in the mountains, and so by definition a lot of deforestation is currently occurring here (Gaveau et al., 2009b). The fertility of the soils underlying the cleared forest has been shown to be generally important in moderating deforestation since this determines the revenues from alternative land uses: Holding other factors constant, soils with higher fertility are associated with increased deforestation rates (Newton, 2007).

The amount of drainage also affects deforestation rates, since well-drained soils are more likely subsequently to be of higher value for agriculture than boggy environments, such as peat swamps (see chapter 6). Such ecosystems require extensive drainage via the construction of canals before they can be used for agriculture. This increases costs to the agents of deforestation (Joppa and Pfaff, 2009). The costs of deforestation are also raised by the distance of any patch of forest to the forest edge, and to the markets where timber and agricultural products from newly-cleared fields can be traded. This edge effect, whereby deforestation itself reduces the costs to access the remaining forests, means that there is a degree of endogeneity in deforestation: where deforestation occurs, there is likely to be deforestation. This is due to the reduction of transport costs, which all else being equal, will increase profits from agricultural outputs and lead to increased deforestation (Pfaff and Robalino, 2012). This partly explains the expansion of agriculture along an 'arc of deforestation' in Amazonia (Coe et al., 2013). Here, the pattern of deforestation also often follows navigable rivers. Where these flow in the direction of towns and markets, rivers can be used for transportation of sawn wood and forest products: The proximity of a forest patch to a navigable river has been shown to be positively related to the probability of deforestation (Newton, 2007).

The same is also true of roads which reduce costs to economic agents and so forests nearer to them tend to experience higher rates of deforestation (Angelsen and Kaimowitz, 1999; Lambin et al., 2003; Newton, 2007). Such locations with better access are often chosen for conversion to plantations of high value crops such as palm oil, which in turn involves building a larger and better network of roads. Road building and surface improvements act in synergy with other factors, further reducing the costs of accessing the newly-revealed forest frontier and improving access to markets, creating a further endogenous process (Gaveau et al., 2009c; Venter et al., 2009a). A synergistic process of road building and improved market access has been shown to strongly affect the probability of commercial forest exploitation in Belize (Chomitz and Gray, 1999) and more generally (Marcoux, 2000). This process of the building of roads which then allows new agricultural development is an example of what Lambin et al. (2003) would call 'chain-logics' causation, whereby one socio-economic development process interacts with and enhances another.

However such interactions and feedbacks can also occur between natural and socio-economic systems. For instance selectively logged moist forests experience an increased incidence of fire compared to unlogged forests (Soares-Filho et al., 2012), which in turn further accelerates the rates of land use change. Fire is a particularly noteworthy driver: it has recently been the most important proximate drivers of deforestation in Indonesia. In the Amazon, there appear to be feedbacks between deforestation and local environmental changes. There is evidence for large scale changes in fire and drought regimes across the region, which have occurred even in the presence protected forests, which suggests that localised forest protection is insufficient to achieve forest conservation without addressing changes at the landscape level (Coe et al., 2013).

In Indonesia, studies estimate that fire caused as much as 89 % of all Indonesian deforestation between 1989 and 2008 (Dennis et al., 2005; Carlson et al., 2012). In recognition of this, following the extensive forest fires of 1997/8, the Association of Southeast Asian Nations (ASEAN) Regional Haze Technical Task Force (HTTF) developed a Regional Haze Action Plan (RHAP) in partnership with the US Forest Service. However, 15 years later fires are still the scourge of Indonesian forests: At the time of writing in 2013, Indonesian forest fires dominate the news headlines, with huge palls of smoke billowing across the Malacca straights, causing levels of particulate concentrations that are hazardous for human health, and even grounding international flights in Singapore. Embarrassingly for the Indonesian government, many of these fires were recorded by remote sensing in forests protected by the REDD+ moratorium which has nonetheless bee met with strenuous denials by the plantation companies alleged to be using fire to clear land illegally (Bloomberg, 2013).

Intuitively, logging would seem a source of deforestation, and in the 1980s at least was the bane of the environmental movement. However there is some evidence that suggests that timber production *per se* is not actually a major cause of deforestation, at least in the case of Indonesia (Barbier et al., 1995). This is because selective logging only involves the removal of target tree species and not the complete removal of the vegetation and the destruction of the seed bank. However, deforestation can result where forests are subject to clear-cutting and are prevented from regenerating. In addition, the finding of Barbier et al. (1995) ignores the way in which logging can reduce costs to other agents of deforestation, such as palm oil producers in Indonesia (Palmer and Engel, 2009). This demonstrates the problem of considering each driver of deforestation in isolation. Logging plays a key enabling role (Marcoux, 2000) by creating roads, which as described above reduce access and transport costs to agents seeking land, for example when logged forest is subsequently cleared and burned for agriculture (Marcoux, 2000).

This suggests that the impact of each driver of deforestation in isolation is highly variable. The context-specific nature of the impact of logging is highlighted by the experience of one of Indonesia's neighbours, the Philippines, whose forests were largely cleared through widespread logging (Casson and Obidzinski, 2002). In such cases, farmers move in to the forest following logging, creating a two-step process whereby the loggers create the initial clearings, and farmers clear the remaining vegetation which prevents forest regrowth. Lambin et al. (2003) call this the 'logging-agriculture tandem', and an instance of 'concomitant occurrence', but what might more simply be called a synergy.

Nonetheless the historical perception of logging as driving excessive deforestation led to the development of policies to control it, but which may have ultimately had a perverse impact: In the 1990s there were a series of bans on the import of Indonesian timber by concerned consumer nations, in addition to new domestic taxation on the export of sawn wood (Barbier et al., 1995). The authors claim that in practice, the net effect of these policies may have in fact been to reduce incentives to maintain timber production forests by raising the costs of producing timber relative to other land uses. If this interpretation is correct, then when considered in combination with the increasing returns from other land uses such as 'fast-wood' *Acacia* plantations, policies designed to protect forests may have led to increases in the substitution of natural production forests with other land uses. There is evidence from other countries for the importance of changes in relative prices and costs in driving land-use change, having been shown to be important in the expansion of agriculture in countries as different as Sudan (Elnagheeb and Bromley, 1994) and Thailand (Panayotou, 1993). Underlying these changes in relative prices, and indeed many of the other above mentioned processes, is the ultimate driver of increased demand for food and raw materials from a growing human population which is increasing consumption levels.

Human population density generally has been shown in Latin America to be positively related with deforestation (Newton, 2007). Yet caution is needed with the generalisation of such localised studies, since the relationship between population and deforestation is actually quite complicated. It manifests itself in different ways and is moderated by multiple other processes (Lambin et al., 2003). As Marcoux (2000) points out there is a fundamental difference between the static and dynamic aspects of human population density. That is, high human population at a point in time should be expected on average to be inversely related to the level of forest cover, simply because larger numbers of people tend need to clear more land to build settlements and develop agriculture. However the role of population dynamics is much less clear, due to what Marcoux (2000) calls the 'diversity of population-forest linkages'. These are context dependent, depending upon initial conditions, such as whether the population is growing in an area which already has low forest cover. The linkages themselves are also moderated by economic and institutional factors, such as relative wealth of the population, type of agricultural development and the efficacy and enforcement of land-use regulations and policies. This complex relationship has been partially illustrated in a study across countries containing biodiversity 'hot spots'. Jha and Bawa (2006) found that the impact of human population growth on deforestation is significantly moderated by the Human Development Index, providing further evidence for the hypothesis that the level of human development is an important dimension of deforestation. For instance Alix-Garcia et al. (2012) found that the impact of PES schemes in Mexico depended on the relative wealth of participants. The poorer groups increased deforestation, possibly due to release of a credit constraint, whereas wealthier groups appeared to reduce deforestation.

Finally, the dynamics of the political economy have also been shown to affect deforestation rates. In Indonesia the electoral cycle has been linked to increases in forest clearance, because incumbent politicians seeking re-election need to raise campaign funds, and they often do this by leasing new logging concessions to increase licensing revenue (Burgess et al., 2012).

Notwithstanding the evidence presented here which suggest an understanding of deforestation processes, there are still gaps in knowledge. For instance Angelsen and Kaimowitz (1999) state that there is still uncertainty over how input prices, land tenure and technological advances affect deforestation. But according to a later paper by the same authors (Angelsen and Kaimowitz, 2001), what evidence that does exist suggests that improvements in agricultural technology and intensification of production increases deforestation. Nonetheless, this assertion is contested, with Harrison (1992) stating that improvements in agricultural technology can reduce and offset the increases in deforestation pressures caused by rising human population. Between these apparently polarised views, Lambin et al. (2003) present a much more varied picture, where agricultural intensification is balanced by extensification, which means increasing areas of lands coming under agricultural production. This can occur where technological advance is non-uniform and where technological involution' (a regression in technological capacity) occurs and agriculture expands with low technological inputs.

Despite these apparent uncertainties and gaps in knowledge, researchers have nonetheless attempted to attribute degrees of significance to the individual drivers of deforestation. Angelsen and Kaimowitz (1999) suggest that one of the most important variables in both theoretical, empirical and simulation models is the level of off-farm employment. This is thought to be the case because in theory this reduces the pool of labour available to the agricultural sector: Assuming a fixed supply of labour, and the absence of large changes in the development and application of technology, increased off-farm employment therefore raises costs in the agricultural sector and reduces the returns to forest clearance and agricultural expansion. Yet the way that agents respond to these incentives of increased wages in non-farm sectors is moderated by institutions and attitudes (Lambin et al., 2003). For instance, labour market flexibility is likely to be lower for a highly regulated societies. As an example, a correspondent from rural Jambi province told the author that a *Surat Jalan* (a travel permit) from the local government was still required in 2004 by Indonesians to move even between regency (*kabupaten*, one of Indonesia's smallest political divisions) borders. So even if wages were higher in a neighbouring province or regency, workers movements may be restricted. Inter-province migration is still regulated according to forestry officials in Jambi, who further state that illegal deforestation is being driven by illegal migrants. This is discussed in the next chapter, number 4. In practice however, technology can offset increased labour costs: mechanisation can also reduces the demand for unskilled labour in agriculture, as classically occurred in the agricultural development of western European countries. However this interaction does not appear to have been quantified in the context of tropical deforestation, likely because the tropics are still going through this intensification process.

Against this general background on the drivers of deforestation, the next stage is to turn specifically to Indonesia and examine the history of forestry and land use; the local determinants of deforestation and the socio-economic conditions which have driven the process in this country.

3.2 Indonesia's forests and their management

Indonesia is a vast archipelago, comprising some 17,000 islands spanning the sea between the Malay peninsular and Australia. It is the world's 4th most populous country, with at least 230 million people (World Bank, 2011). The following section contains a summary of the modern political history of the country from the Dutch colonial period through to the modern day, and how the political-economic and institutional context influenced contemporary forest management regimes. This is followed by a discussion of how Indonesia is now fitting into the international climate change management regime through its participation in REDD+, and how new regulations, laws and policies designed to implement it are being challenged by actors and organisations whose interests are not aligned with forest conservation.

3.2.1 A summary of the modern political history of Indonesia

In contemporary Indonesia, the central government is based in Jakarta and headed by the President of the Republic. The Republic is divided into 34 provinces, each headed by a governor. Each province is itself sub-divided into areas called *Kabupaten*, each of which are headed by a regent called a *Bupati*. However, the islands that today comprise Indonesia have historically been administered under a range of different systems. Rule by religious kingdoms and regional chiefs gave way to European domination in the 17th century. The colonial period was followed by independence and the development of a military dictatorship which constituted a kleptocracy, and which lasted up until 1998. This was followed by a period of social and economic chaos and the 'reformation' (*reformasi*), which precipitated the relatively peaceful multi-party democracy which continues to the present day. Each of these periods is discussed below.

3.2.2 The colonial period

Indonesia was governed by the Dutch as an extractive colony by the Dutch East India company from the 17th century through to 1947, with only a brief interlude of British rule at the beginning of the 19th century. After 1830 when the Dutch regained control they implemented a quasi-feudal cultivation system under the administration of village officials (Szcezepanski, 2002). In the outer lying islands, Indonesians carried on farming in their traditional manner, which involved communities making land use decisions based on customary law called the *adat*. Although varying across the archipealgo, this was essentially a communal system of sustainable forest management. This created a dual legal system: one for the colonial Dutch and employees, and one for Indonesians as yet largely outside Dutch influence. However a new 1870 law called the *Agrarische Wet* heralded a shift in the way in which all land was managed in Indonesia. This law introduced European land titling and registration across all Indonesia's islands. Any land which could not be proven to be owned with formal western-style titular documents became the property of the state to be rented out. The Indonesian peasantry and indigenous groups operating under Adat were unfamiliar with such western-style legal documents and could not prove ownership (Szcezepanski, 2002). Because of this the *Agrarische Wet* served as a legal means to expropriate land from huge numbers of Indonesians, and centralise control and rents for a colonial kleptocracy operating under a western legal institutional framework. It represented a direct conflict between the communal land systems of the Indonesians and the individual land ownership regimes operating under the institutional norms of a western European colonialist state.

3.2.3 Independence and the New Order period

Indonesia secured independence from Holland in 1949 following the second world war and the brief period of Japanese occupation. Indonesia's constitution was drafted during this period. It is based on Dutch law, and is still in place today, re-iterated by Law 10/2004. Iskandar (2004) sets out the heirarchy of Indonesian laws as follows, with the Constitution taking primacy, and regional regulations having the lowest significance.

- 1945 Constitution *(Undang undang dasar 1945)*
- MPR Resolution
- Law *(Undang undang)*
- Government Regulation Substituting a Law *(Peraturan Pemerintah Pengganti Undang undang)*
- Government Regulation *(Peraturan Pemerintah)*

- Presidential Decree *(Keputusan Presiden)*
- Regional Regulation *(Peraturan Daerah)*

Early independence saw the development of a domestic Communist movement, which was brutally crushed, with as many as 700,000 suspected communists murdered across the country. Following this crack down, Indonesia fell under the control of the military strongman General Suharto in 1966. Suharto was the head of the New Order regime (*Orde Baru*) which was called as such to contrast it with the old order of Sukarno, who was Indonesia's first post-independence President. General Suharto ruled for 32 years until 1998 with a powerful centralised and militarised bureaucracy, running on a system of crony capitalism dominated by client-patron relationships amongst the inseparable political and business elite (Smith et al., 2003). This elite undermined the independence of the judiciary (Lindayati, 2002) and set about influencing law-making and policy directly for private gain, finally creating a highly centralised kleptocracy focussing on natural resources (Palmer, 2005; Ross, 2003; Jepson et al., 2001). Dunggio, an Indonesian researcher, described this context as one of 'Collusion, Corruption and Nepotism' (KKN: *Kongkalikong, Korupsi dan Nepotisme* (Collins et al., 2011a). This period is extremely important for the history of forestry since Suharto's regime continued the process of centralisation of the control of forest management and natural resource rents which had begun in the colonial period, and now progressively excluded communities operating small scale logging and natural resource extraction operations.

The legal basis of New Order resource management was Article 33(3) of the 1945 constitution which states that "Land and water and the natural riches therein shall be controlled by the State and shall be exploited for the greatest welfare of the people" (Szcezepanski, 2002). However up until 1960 the dual legal system (based on civil law and *Agrarische Wet* for the Dutch colonialists, and adat for Indonesians) persisted, with 95% of the archipelago still operating under the various regional forms of adat (Szcezepanski, 2002). This predominance of adat was eroded by the passing of the Basic Forestry Law UU5/1967 which supported central state sovereignty over resources rather than community ownership (Szcezepanski, 2002). Sovereignty was declared over 'unowned land' which in practice was actually often under traditional adat community management. Adat is a form of common property management. Under these new laws this land could then be legally seized and rights management transferred to bureaucrats in Jakarta. These extraction rights were then redistributed in the form of 20 year *Hak Pengusaha Hutan* licences to multinational logging firms via links with the Suharto family and to the army. The connection with military force (*Tentara Nasional Angkatan Darat*; TNI-AD) was used to ensure that nobody else logged the forest (Casson and Obidzinski, 2002). Indeed as part of a process of paying off the powerful players in Suharto's kelptocratic game, logging firms were in many cases actually even operated by the military and police (Lindayati, 2002), via *Yayasan*, foundations set up to channel income from the 'private interests' of the military and police.

The 1960 Basic Agrarian Law, supplemented by the Basic Forestry Laws of 1967 and 1999, and the 1992 Spatial Planning Law, were intended to unify all land law into a single system. The 1967 Basic Forestry Law brought 70% of all Indonesia's land under the control of the Ministry of Forestry and Estate Crops; and allowed for concessions run by state and private conglomerates (Casson and Obidzinski, 2002; Szcezepanski, 2002). This was done in a way which again, as per the *Agrarische Wet*, focussed on individual land title and did not genuinely accommodate the communal system of adat. Whilst it gave some formal recognition to adat it did so in a way which made it difficult to be seen as legitimate. Specifically, adat was restricted to instances where it did not conflict with religious laws; agrarian laws; was not contrary to Indonesian socialism, or run against the interests of the state: but since these concepts were not defined, these guidelines were meaningless (Szcezepanski, 2002). Communities therefore continued to engage with the large logging firms in order to be able to secure some income from the forests which in many cases they once had the rights to themselves (Casson and Obidzinski, 2002). To some extent this represents a parallel with the employment of peasant farmers under the Agrarische Wet: resource ownership was lost to rural Indonesians who then needed some way to regain a livelihood.

Accordingly, and conforming to the pattern of the centralisation of power and resources by an elite, logging became an increasingly oligopolistic affair. By 1995 only five multi-national and national timber conglomerates controlled almost one third (30%) of the Indonesia's timber concession holdings (Casson and Obidzinski, 2002). This prioritisation of the large companies meant further marginalisation still of the small firms and people with fewer political connections actually living near the forests. Moreover the disenfranchisement of the rural poor and the centralised pooling of resource rents to develop crony networks became Indonesia's natural resource management strategy. Indonesians across the archipelago finally became trespassers on their own land: in 1967 between 40 and 60 million people lived in areas which then fell under the Basic Forest Law that prohibited communal and individual ownership (Szcezepanski, 2002), whilst a handful of logging companies had now secured the legal rights exploit the land and forests under the protection of the military and police that in some cases were even running their own logging operations.

The Production, Protection and Conservation forest classes seen on contemporary maps of Indonesia are therefore the final outcome of centuries of centralisation of resource control which ultimately led to the expropriation of land. However a new version of the Basic Forest Law was created in 1999 after the resignation of Suharto, in the democratic reform period, and so it is to this era which this chapter turns now.

3.2.4 Post-Suharto: reformasi and regional autonomy

Suharto's three decades in power came to an end in 1998 when the Asian financial crisis hit. This external shock created widespread economic chaos. The Indonesian currency, the *Rupiah*, went into freefall, creating unemployment and ultimately undermining any remaining support for Suharto as President. The pressure release of his resignation combined with the financial crisis led to a period of intense social, political and economic upheaval called 'The Chaos' (Kingsbury and Aveling, 2003). This period was followed by the development of a movement for reform and change in Indonesia called the reformation (*reformasi*).

One aspect of change demanded was increased local control over natural capital in the outlying islands: the representatives of these resource-rich provinces had now realised they were no longer in thrall to the military strongman in Jakarta *(ibid.)* In the most extreme case this served as an opportunity for provinces and islands to seek independence. Ultimately only East Timor achieved this, albeit at great human cost. To resolve these demands for increased access to rents and political power and quell the desires for independence, a system of regional autonomy was developed. Both Papua and Aceh at the extreme west and east of the archipelago achieved special autonomy status,called *Otonomi Daerah Istimewa.* Under regional autonomy, administrative powers were devolved to the *kabupaten* level under Law No.22/1999. The roll-back of centralised power led to a 'blossoming' (*pemakeran*) of regional government, and the number of *kabupaten* grew by 65% from 298 to 483 (Burgess et al., 2012). Whilst regional autonomy provided a means for resource-rich regions to take a larger share of revenues, the decentralising laws themselves nonetheless stated that conservation and exploitation of natural resources were to remain a national concern, meaning that Jakarta still retained ultimate control of all land classes in principle.

3.2.4.1 Indonesian land classes under regional autonomy

Indonesia's land classes are today are separated into non-forest, protection forests and production forests, but with sub-categories of each. Forests designated for extractive industry fall under the umbrella term of Production Forest (*Hutan produksi*). Production forest in turn constitutes Limited Production Forest *(Hutan Produksi Terbatas)*; Conversion Production Forest (*Hutan Produksi Konversi*); or Permanent Production Forests, (*Hutan Produksi).* Limited production forests is a class for low-intensity logging, often on sloping land where the forest is used to prevent erosion. Conversion forest is designated for clearance and conversion into other uses such as agriculture. Permanent production forest is designated to remain a permanent part of the forest estate and not converted to other land uses. Protection Forest (*Hutan Lindung*) is a class of protected forest. It does not enjoy the same level of legal protection as national parks, and does not have dedicated protected area offices like national parks. Protection forests are often used to protect particular ecosystems and ecosystem services such as watersheds. Natural Protected Forest which include national parks *Taman Nasional*, are typically larger than Protection Forests, and are located in places that protect unique landscape values including the mountainous habitat of Sumatra's Kerinci Seblat and Gunung Leuser which hold some of the last populations of Sumatran tigers and rhinos. A final category is non-forest land called *Areal Pengunaan Lain* (lit.'land for other uses'). Whilst all forests are owned ultimately by the state and, different forest classes at different scales fall under different management organisations under the system of regional autonomy.

The majority of forest classes are administered by the Ministry of Forestry (MoF) in Jakarta, but protection forest, and all production forest, are administered by regency (kabupaten) forestry departments (DINAS Kehutanan Kabupaten). However in the case that either of these classes overlaps the boundary of two or more districts, the provincial government gains management authority under the provincial forestry service (*DINAS Kehutanan Propinsi*) (Collins et al., 2011).

Nonethless, the decentralisation laws were vague about the extent of regional autonomy for resource planning and control. The report of a World Bank official working on a Sumatran forest conservation project during the period summarises the effect of decentralisation and regional autonomy on forestry: 'Law enforcement with respect to park protection was poor even before reformation *[reformasi]* and decentralization. After decentralization, the break-down in law and order, illegal logging and encroachment have proceeded unchecked and are uncheckable. Illegal logging is a major national problem. Conservation cannot work in a situation where there is no effective governance' (WorldBank, 2003) p.18.

This reference provides an interpretation of the events of this time from a quite narrow perspective. That is, it does not consider where the laws that created the protected areas originated in the first instance; and whether these were a fair and just approach to land management. In practice, what *reformasi* meant for forests and land management was that the local communities and entrepreneurs which had long been excluded from forest resources under first the colonialist Agrarische Wet, followed by Suharto's *Hak Pengusaha Hutan* and protected area system, suddenly realised that finally there were now few repercussions from entering prohibited forest areas. This was especially the case following President Habibie's efforts to reduce the influence of the Indonesian military after he was elected as Indonesia's third post-Independence President, albeit briefly (Casson and Obidzinski, 2002). This realisation of reduced restrictions is what forest protection officers operating in Indonesia today call being *berani*, meaning brave, when describing people's behaviour following *reformasi* (author's conversation with Pak Ragil, a forestry officer in Air Hitam Dalam, on the border of protected forest and Berbak National Park): the climate of fear, reprisals and punishment which had kept people out of forests had now evaporated. Whereas in the previous three decades only those people with the closest connections to Suharto and the military were allowed into protected areas to access resources, people and officials in the regions suddenly now saw and took the opportunity to take a larger share of resource revenues locally. Under new autonomy regulations, local officials at the kabupaten level were now legally entitled to licence concessions of 100ha (Casson and Obidzinski, 2002). This included the issuance of logging licences by Bupatis (the heads of Kabupaten government) in land set aside by Jakarta for conservation (Jepson et al., 2001), or otherwise simply to a profusion of logging concession licences at the local level under fixing agreements (Palmer, 2005) with collusion between local officials and loggers (Smith et al., 2003).

However, because of the sudden novelty of regional autonomy and the new powers at the kabupaten level, the distinction between what was 'legal' and 'illegal' became blurred. For the World Bank official cited above in their report on the Kerinci Seblat ICDP, illegal logging was simply the result of a collapse in law and order following the drastic changes of central government. Yet these events represented a reversal of a long history of local dispossession, and moreover 'illegal' action under national law was actually now being legalised by the permissions granted at the local kabupaten level.

The headline-capturing explosion in illegal logging was therefore more nuanced than a one-dimensional collapse in governance. And as a nuanced process, it would also not be true to say that what happened in forestry during this period was simply a romantic tale of dispossessed Indonesians regaining title to ancestral lands and rents historically seized first by colonialists and then a military kleptocracy.

The history has multiple threads, and there does also persist an institutionalised culture of corruption which was established during Shuarto's tenure and which emanated from the very top of Indonesian society (Palmer, 2005). This has meant that many problems such as the 'illegal' logging and timber smuggling have persisted after *reformasi* and into the democratic period (Smith et al., 2003; Indrarto and Murharjanti, 2012). These problems continued even after the re-elevation of many decision making powers to the to the provincial level under Law 32/2004. For instance, Palmer (2005) describes 'wet positions' in the Indonesian bureaucracy, (so-called since they provide access to a 'pool' of rents), giving the example of a border crossing between Indonesia and Malaysia where there are even bidding wars for official positions. At the national level the reforestation fund created in 1989 to support reforestation and rehabilitation, and ensure long-term wealth creation for Indonesia was subject to very high levels of corruption (Barr, 2006). This persistence of corruption in norms of behaviour despite the seismic shifts of *reformasi* and regional autonomy is consistent with the path-dependency which North (1990) explains is characteristic of institutional change.

Despite the costs to logging firms of having to pay bribes to rent-seeking local officials in these wet positions, there are still large incentives to enter the forestry sector because of super-normal profits. This has undermined demand side regulation such as through certification schemes, where illegally cut Indonesian timber has simply been re-constituted through smuggling networks (Obidzinski et al., 2006) as legal timber in Malaysia (Palmer, 2005). However, despite the fact that illegal logging in Indonesia continues at a rate of approximately 40 million m^3 per year (with associated loss of $US600m tax revenue yr^{-1}) it has nonetheless declined since the *reformasi* period. According to Obidzinski et al. (2006) it is much less of a problem *per se* than the abuse of licences by the road building and plantation industries which now have huge interests across the country. It is to this industry that the chapter now turns.

3.2.4.2 The substitution of forests for oil palm

One of the largest changes to have occurred during the *reformasi* period was that land managed for timber production has become relatively less lucrative following the increased global demand for crude palm oil derived from the African oil palm *(Elaeis guineensis)*. The fruit of this species is energy rich and has a wide range of uses from cooking oil through to biofuel. Indonesia is already the world's largest producer and was able to meet 57% of the increase in global demand in the decade 2000-2009 (Rianto, 2010). To achieve this, between 2000 and 2009, the area of mature palm oil was expanded at an average annual rate of 10%, leading to an increase in production of 17.4% annually (*ibid*). On Sumatra this has amounted to 600,000 hectares being planted in that period, a growth rate of 6% (Shean, 2009). Overall in the decade 1999 to 2009 the area of palm oil plantations in Indonesia grew 87%, from 3.9 to 7.3m ha with 65% of these on Sumatra (Rianto, 2010). This includes 748,118ha (10% total) in South Sumatra, and 484,671 ha (7% total) in Jambi province in 2009 (ibid). Aside from the decentralisation of land use management, this palm oil expansion was possible due to the government's provision of subsidised credit through discounted loans and even cash grants, funded by Indonesia's reforestation fund *Dana Reboisasi* (Barr, 2006). This helped to foster an environment conducive to investment from international firms with the capital to increase production (Shean, 2009). Furthermore the export market was encouraged by establishing progressive export duties (Rianto, 2010). As with the periods of control under Dutch colonialists and General Suharto, the expansion of the palm oil industry has been linked with allegations of corruption and land grabbing and wealth transfer from local land users to more politically powerful and capital-rich multinational corporations. As with the 'illegal' logging discussion however, this may provide an incomplete picture. Rianto (2010) claims that small land holders make up as much as 47% of plantation areas, whilst Fadil Hasan, the director of the Indonesian Oil Palm Association is cited as claiming that more than a third of Indonesia's oil palm comes from smallholders (McClanahan, 2013).

Regardless, creation of these plantations is driving land use change across Indonesia. Huge CO_2 emissions are created in the process, particularly where the development occurs on peat. Approximately 80% of Indonesia's Greenhouse Gas (GHG) emissions are from Land Use Land Use Change and Forestry (LULUCF) which now makes Indonesia infamous as the third largest emitter of carbon after China and the USA (Sari et al., 2007). It is these emissions that have brought the country into the international spotlight in the drive to mitigate climate change, particulaly through REDD+.

3.3 Deforestation, climate change and REDD+

Indonesia's third place in global emissions rankings is due largely to deforestation and degradation and the burning of peat (Sari et al., 2007). Approximately 50% of the world's peatland, or 22 million ha, are in Indonesia, in coastal and sub-coastal regions on Sumatra, Borneo and West Papua (Page et al., 2007). With such high levels of emissions from land use change, the potential for REDD+ emissions reductions is huge. So in response to these rising emissions, Indonesia is taking action at the national level and cooperating with international donors.

Indonesia is already a party to the UNFCCC and the Kyoto Protocol, ratified through Act No. 6/1994 and Act No. 17/2004. Indonesia has signalled the intention to take a central role in climate change mitigation, and in particular REDD+ under the incumbent President Susilo Bambang Yudhoyono (SBY). At the G-20 Summit in Pittsburgh in September 2009, SBY pledged to voluntarily reduce Indonesia's emissions by 26% by 2020 in relation to the business as usual scenario. This reduction would be increased further to 41% with international support. In addition to international commitment and pledges, Indonesia has opened pathways to implement domestic activities including the launch of the National Action Plan - Addressing Climate Change when it hosted COP13 in Bali in 2007. The presidential decree on the National Action Plan to Reduce Greenhouse Emissions (RAN-GRK) signed in 2011 under PerPres 61.2011, is intended as a framework document to plan Nationally Appropriate Management Activities (NAMAs). This is a national guideline document designed for guiding emissions reduction. The broad cross-sectoral plan addresses agriculture, forestry, industry, energy, and infrastructure as well as instruments like taxation, investment policies, and awareness raising. It covers 70 programmes, to be conducted by government and local and regional levels in conjunction with the private sector and civil society. The Plan was officially incorporated into the country's national development strategy under the coordination of the Ministry of Planning in 2008.

In 2008 SBY also established a National Council on Climate Change (*Dewan Nasional Perubuhan Iklim*; DNPI). The Council, formed by 17 Ministers and chaired by the President, is in charge of coordinating Indonesia's climate change policies.

Land Use, Land Use Change and Forestry is thought to be one of the cheapest ways of mitigating climate change if one uses the McKinsey abatement cost curve, which indeed heavily influences the DNPI's own abatement cost estimations (DNPI, 2010). The DNPI claims that Indonesia could reduce emissions by 2.1 Gt by 2030, which if achieved would mean that emissions would be 67% lower in two decades time than they were in 2005, representing an enormous 7% of the total global emissions reductions thought to be required by the IPCC to mitigate the worst effects of climate change by 2030. Significantly for this thesis, since LULUCF is the largest contributor to Indonesian emissions reductions, the DNPI aims to achieve 87% of emissions reductions through reductions in deforestation and peatland conversion. In an attempt to start this process, Indonesia's REDD+ demonstration activities regulations were published in 2008 (Permenhut no.68 Menhut II/2008). Additionally, P. 30/Menhut-II/2009; PP6 and PP. 30/Menhut-II/2009 outline the areas in which REDD+ activities may be developed, and procedures required to implement activities (Collins et al., 2011a).

Nonetheless there are problems with this approach. The actual implementation of REDD+ is a huge challenge in a dynamic economy where it is also government policy to increase the production of agricultural commodities which are largely being developed on deforested land. In particular the government seeks to double the production of palm oil by 2020 from 2009 levels: this would mean Indonesia producing 40m tonnes of crude palm oil in 2020 and becoming the world's largest producer (Austin et al., 2012). There therefore appears to be a direct contradiction between the DNPI carbon emissions reduction commitments, and the government objectives on expansion of industrial palm oil expansion. However, the two goals do not necessarily need to be opposed to one another. There are already large areas of degraded land in Indonesia that could be planted on. These are already cleared of forest, but are not being used for agriculture and therefore have low biodiversity, carbon and productive values e.g. Alang-alang grasslands *Imperata cylindrica).* This could potentially supply the demand for land for increased palm oil production, and in recognition, the World Resources Institute has created an online degraded land mapping system, which has already identified 14m ha of this land on Kalimantan (Stolle et al., ated), which these authors are quoted as estimating is sufficient for 20 years of production (McClanahan, 2013). Nonetheless, a fundamental problem with this strategy surround the base assumption that all of these areas are unused by local people and have little or no agricultural value. Adjusting the blanket 'abundant degraded land hypothesis', a cautionary note is that some 'degraded lands' may in fact already be used by local small holder farmers or be otherwise culturally or socially important, and as such palm-oil development in these areas could lead to social conflicts and increased poverty (Gingold et al., 2012).

There are other potential problems of focussing solely on land use conversion to reduce emissions: it assumes that past trends will predict the future, yet as GDP per capita rises, an increasingly wealthy Indonesian populace is likely to increase consumption. Indonesia now constitutes the largest car market in Asia pacific for instance, with 940,000 vehicles purchased in 2012 (Wibisono, 2012). Suzuki Indonesia is also reported as planning a two year $800m investment in Indonesia, and General motors is investing $150m to reopen a factory on Java (ibid.). Thus the investment of two car companies alone will match in two years the total amount of Norway's REDD+ funding for 7 years from 2014. In addition the aviation sector has undergone enormous growth: it has doubled in size from 37.4m passengers in 2008 to 72.5m in 2013 (CAPA, 2013). As Indonesia's economy grows, these structural changes will continue, along with different sectors' relative contribution to the country's GHG emissions. Nonetheless, current strategies focus on land use change which for the moment do remain the main source of emissions. The main driver of action currently is an agreement between the Governments of Indonesia and Norway.

3.3.1 A Letter of Intent with the government of Norway and a forestry moratorium: first steps in implementing REDD+

In 2010 the governments of Indonesia and Norway signed a Letter of Intent (LOI) under a climate change partnership. The purpose of the LoI is to achieve emissions reductions from deforestation, forest degradation and peatland conversion through a) the development of a policy dialogue on climate change policy and REDD+; and b) to collaborate in the development and implementation of Indonesia's REDD+ strategy. This partnership will mean the Indonesian Government receives $1bn over seven years from 2014, based on 'contributions-for-delivery', which means the payments are to be conditional upon results (Solheim and Natalegawa, 2010).

The partnership is broken down into three phases, which are 1. Preparation; 2. Transformation; and 3. Contributions for verified emissions reductions (Solheim and Natalegawa, 2010). The preparation stage involves the creation of domestic organisations and institutions, specifically a REDD+ strategy; the creation of a REDD+ agency; and the development of an independent organisation for the monitoring, reporting and verification of the emissions from LULUCF. A REDD+ agency was created under Decree 62/2013 with the mandate of developing a national REDD+ strategy; forming REDD+ safeguards and coordinating law enforcement with regards REDD+ activities. The agency will also develop the standards and methodologies for measuring GHG emissions. The final element of the preparation stage of the partnership is the selection of a national REDD+ pilot province, which was chosen as Central Kalimantan.

The second phase of the partnership scheduled for January 2011 is called 'transformation', with the aim of preparing Indonesia to receive results-based funding, whereas the third and final phase is planned to start in 2014 and is focussed on

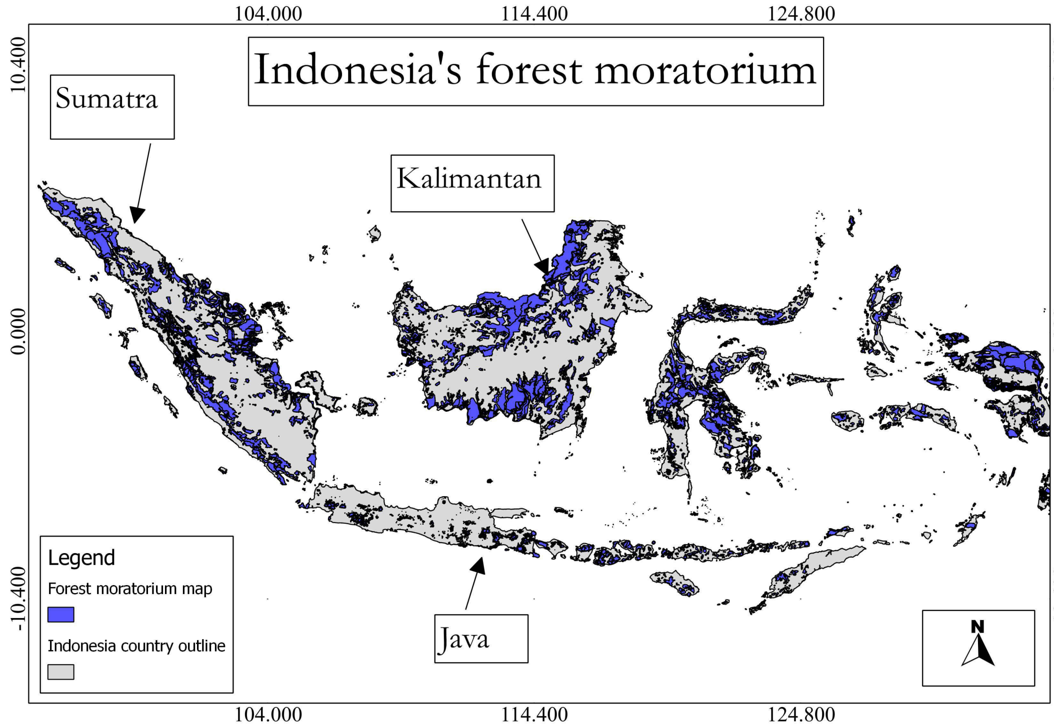


Figure 3.1: A map of Indonesia showing the indicative forest moratorium map

providing the financial contributions for verified emissions reductions from 2013. The focus in the transformation stage is on national level capacity building, policy development; and legal reform and law enforcement. One of the requirements was that Indonesia implement a two-year suspension on all new concessions for conversion of peat and natural forest. One of the first actions of President Yudhoyono after the LoI was signed was the development of a moratorium on the issue of new extractive concession licences in Indonesian forests and on peatlands for two years from summer 2011 under Presidential Instruction 10/2011 on *'The postponement of issuance of new licences and improving governance of primary natural forest and peat land'*. The moratorium covered the issuance of new licenses across 65m hectares of forest, but excluded existing licences. It was extended for another two years in 2013 under Presidential Instruction Inpres 6/2013. As with the first moratorium, the second iteration prohibits new licenses for the conversion of what is defined as Primary Natural Forests and peatlands. This includes primary natural forests within protected areas and in production forests. But it excludes secondary forests, and also activities deemed to be of 'strategic interest' including such as geothermal energy and gas exploration. This is significant since 80% of geothermal sources are found in conservation forests (Townshend et al., 2013; Indah, 2011). These exceptions account for some 3.5m ha of land which are otherwise inside the moratorium map boundaries (Austin et al., 2012).

That the moratorium has faced stiff resistance from the oil palm industry in particular reflects both the incentives to enter the palm oil and timber industries but more generally the Indonesian economy's (over) reliance on natural resources (Harvard Kennedy School, 2010). Representatives of the sector cite the moratorium as a barrier to Indonesia remaining the world's largest palm oil producer. Further, representatives of the Indonesian Oil Palm Association (GAKPI) have highlighted the restriction on economic growth more generally, against the employment benefits from expanding palm oil production: GAKPI states the industry employs 6.7m people and contributes $600m per year to Indonesian GDP (Lubis, 2013b). This reasoning is probably behind the decision to exclude projects of national importance such as geothermal energy from the moratorium (Murdiyarso et al., 2011a)

Whilst it has been opposed by the oil palm industry, the moratorium has also not been without controversy for organisations concerned with forest conservation. Many of the forests covered by the moratorium were already protected under the 1999 Basic Forestry Law anyway. The moratorium covers protected areas thereby providing what Agus Purnomo (SBY's special aide on climate change and the secretary-general of the DNPI) calls the 'double protection' of Indonesian law (JakartaPost, 2011). From one perspective, if existing laws enacted to protect forest cannot be successfully implemented, it seems rather disingenuous to simply produce more laws rather than operationalise existing legislation. This could be interpreted as a reflection of the sense of imperiousness that continues to pervade the bureaucracy post *reformasi* (Harvard Kennedy School, 2010). However, as described above, the story over law, legality and forest classification is not straightforward, especially following regional autonomy. Even if the moratorium achieves Purnomo's 'double protection', forests could still be cleared for projects of national importance: as will be explained in the next section, REDD+ legislation appears to have incentivised competing land use legislation to circumvent the new restrictions on forest clearance. REDD+ is clearly introducing further layers of legal complexity in system which is already byzantine.

3.3.2 Legislation to convert the status of protected forest

There appear to be struggles in Indonesia between the organisations which have historically controlled forest resources and the new organisations created to manage and implement REDD+, in particular the REDD+ Task Force (which became the REDD+ agency in late 2013 under Presidential Decree 62/2013). The REDD+ programme threatens to reduce access of the Ministry of Forestry to the forestry licensing fees which have historically been the source of its power (Barr, 2006). It is worth re-iterating that the 1967 Basic Forest Law brought 70% of Indonsia's land under control of this single ministry. The REDD+ programme further threatens to reduce the access of the palm oil and timber industry to new concessions and profits. Indicative of this struggle are new regulations which appear to run counter to the goals of the moratorium: new decrees provide new legal means for forests' status to be changed and even exempted from the moratorium. In particular Law No.10 of 2010 is designed to change the status of conservation forest and protected areas; whilst the Minister of Forestry Decree No. SK.292/Menhut-II/2011 was specifically designed to change the status and functions of designated forestland in East Kalimantan. Indeed eleven days after the first moratorium was declared in 2011, SK.292 was used to convert 1.67 m ha of 'conservation area forestland' to 'non-forestland'; 34,497 ha of conservation area into convertible production forest (*hutan produksi konversi*); 9,048 ha of conservation area into permanent production forest (*hutan produksi*); 4,867 hectares of 'conservation area' into limited production forest (*hutan produksi terbatas*); and 33,078 hectares of 'protection forest' (*hutan lindung*) to limited production forest. In summary SK292 is thought to have converted on paper a total of 1.67 million hectares of forestland to non-forestland, in addition to changing the functions of 690,000 ha of forests (Greenomics, 2011). A less cynical interpretation than this representing the in-fighting between the REDD+ Taskforce and the Ministry of Forests is that the forest areas in question had actually been degraded anyway, and were no longer in reality primary forests requiring moratorium protection. As such the SK292 was simply making an adjust on paper to update a land use classification which also existed mainly on paper and was not followed in the first place. Nonetheless a further 240,000 ha of forest in east Kalimantan may be re-designated in this way as a part of a complete re-design of the spatial plan *(Tata ruang)* for the province, involving further conversion of protection into production forest *(ibid)*. As of the time of writing, the decision to authorise these changes to provincial spatial plans are still with the House of Representatives (Dewan Perwakilan Rakyat; DPR), not only for the East Kalimantan, but for all Indonesian provinces.

Both SK292 and Law No.10 could partially undermine REDD+ goals by facilitating the clearance of forest which is currently legally protected. However in addition to this, further clearance of forested land can now be facilitated by another new MoF regulation called Permenhut No.18/2011. This provides for the expansion of development activities in both production and protected forests for the following development (*pertambangan*) activities, which are broad and varied: plantations; mining; forest industry; transportation; energy exploration; telecommunications; infrastructure; climatology stations; defence and security; temporary disaster evacuation; construction of places of religious worship (Dr Iswan Dunggio, Email, 4/3/2013). Of particular interest to REDD+ is where these laws have been used in practice for the conversion of protected forest. Two cases involve east Kalimantan as mentioned above, but also the Sumatran province of Aceh, which was involved in some of the first REDD+ developments in Indonesia.

3.3.3 The application of the new land use change laws in Aceh and east Kalimantan, and implications

Aceh is the most heavily forested province of Sumatra, and is the site of the ambitious Ulu Masen project developed by Carbon Conservation Ltd. and supported by the American investment bank Merrill Lynch. This was supposed to have been one of the world's first and largest REDD+ projects under the voluntary carbon market. This was strongly supported by the then-governor Irwandi Yusuf, a former Acehenese separatist fighter who came to power amongst other things on the back of 'green' credentials aiming to protect Aceh's forests. The end of his governorship was marred by allegations of granting concession rights to an oil palm company in the Tripa swamps, one of the last remaining blocks of forest on Sumatra supporting orang utans. However this pales in its impact compared to events under the incumbent, Zaini Abdullah.

As of April 2013, the Ministry of Forestry was reported as being close to accepting a new spatial plan (*Tata ruang*) which would see 1.2m ha of protection forest re-zoned into production forest. If approved the new spatial plan would grant an additional one-million hectares of land for mining, 416,086 ha for logging, and 256,250 ha for palm oil. This includes the development of Miwah, a 6000ha open-cut gold mining pit in the heart of protected forest by a company called East Asia Minerals. As primary natural forest, this should not be permitted under the REDD+ Moratorium. However Law No. 10 and Permenhut No.18 2011 are being deftly used to circumvent it. If this interpretation of the law is true, then this finding has important implications for Indonesia's deforestation baseline, since it suggests that far more forest could be cleared in the future than is currently anticipated. Particularly concerning for the development of Indonesian trust in REDD+ as a genuine and legitimate new form of income, East Asia Minerals has been able to access the Miwah area after having bought into the ownership of Carbon Conservation Ltd., the very company which had developed the Ulu Masen REDD+ project purporting to be the saviour of Aceh's forests. At worst this has led to suspicions in the Ministry of Forestry that Carbon Conservation had simply been speculating and taking the opportunity to arbitrage land rights when the mining company made an attractive offer to the Carbon Conservation's owners (Bachelard 2012).

3.3.3.1 Land use classification on Kalimantan

In the case of East Kalimantan, the MoF's justification was that the changes in forest had already happened on the ground anyway, such that the designated forest areas no longer had primary forest cover which warranted protection under the moratorium. As such their argument was that land status needed to be changed, and the moratorium maps updated. However an alternative response was available to the MoF. It could have instead recognised the failure to properly manage forest resources on the ground in accordance with the original land status, and implemented a plan to restore these forests rather than allow them to continue to be degraded and converted to other uses. But instead it simply allocated the land to other uses. The implication is that MoF passively accepts unauthorised changes of land use, and tacitly grants immunity for transgressors. Furthermore, the MoF will actually officially re-designate the land *post-hoc* to the new use to which it has been illegally converted. If this analysis is correct, then it is difficult to see how these laws do not present an incentive for further illegal deforestation. However, this process may be occurring because the central Ministry of Forestry has lost much of its power under decentralisation and regional autonomy, and the regents (*Bupatis*) have already made decisions about land use locally that differ from the on paper classifications of central government. So if this interpretation is correct, then many of the changes on the ground which appear to represent illegal deforestation were actually authorised for instance under the small scale logging permits system.

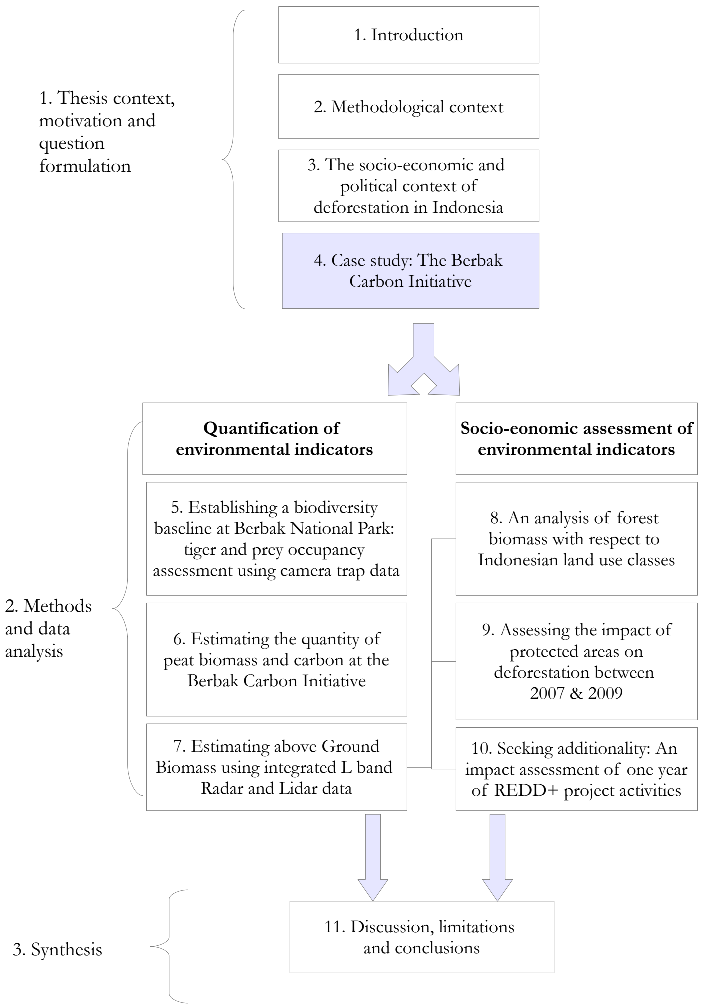
Nonetheless, in light of additional laws that facilitate extractive industries and infrastructure development including within protected forests, Agus Purnomo's 'double protection' for forests seems an increasingly logical approach. Indeed it highlights the challenges of managing the government's stated goal of economic growth through expansion of infrastructure, extractive industry and agriculture on the one hand, and the reduction in forest conversion for mitigation of climate change on the other. Indeed, as a recent review of the World Bank's Forest Carbon Partnership Facility states: *"REDD+ is a more expensive, complex, and protracted undertaking than was anticipated at the time of the FCPF's launch"* p. XIX (World Bank Independent Evaluation Group). Many of these complexities are due to multiple drivers of deforestation; complications of forest management on the ground; lack of existing capacity and entrenched illegal behaviour from both corporations and government.

This perspective reflects the findings of a Collins et al. (2011a), who suggested that fundamental institutional problems presented huge problems to the narrative of a simple transaction to stop countries cutting trees. With a long history of unconditional donor development money flowing into tropical countries, there is a possibility that the notion of conditionality and payments for performance has not been fully appreciated in Indonesia. Certainly, if deforestation continues at a fast rate, there is a possibility that Indonesia will not receive much of the money which has been offered by the Norwegian Government. On the other hand, as mentioned previously even relative to the investments of car companies the amounts being offered are relatively small and must be discounted since the income is to be received over 7 years based on performance, whereas other land use options like expansion of palm oil offer short term benefits.

In order to provide a window onto the realities of these issues in practice, they are now explored in detail in the context of Jambi province and the case study site at the Berbak Carbon Initiative.

Chapter 4

Case study: the Berbak Carbon Initiative



4.1 Introduction

Chapter 3 provided an overview on the drivers of deforestation and the history of forest management in Indonesia. This chapter provides a detailed summary of the conditions at the case study site, the Berbak Carbon Initiative in Jambi province, Sumatra. It discusses the local drivers of deforestation and degradation and the responses of the provincial offices of the Ministry of Forestry. These were informed by a field trip to Indonesia. This trip provided insight into the conditions at the site, particularly through in-depth conversations and informal interviews with Pak Nuksman (Head of Berbak National Park); Pak Wahyu Widodo (head of the Minstry of Forestry's Jambi office *Dinas kehutanan Provinsi*); Pak Mulya Shakti (Jambi Project Manager, ZSL); Pak Ragil (Forest Ranger at Air Hitam Laut); two additional forest rangers (names withheld); and an employee from a local NGO whose name was withheld due to the sensitivity of the allegations he made. A problem with a small sample size and unstructured informal interviews is a potential bias in the opinions of the respondents and the ultimate impression given. However, these were not intended to be formal data collection procedures, rather to help in building a picture of the conditions in the region and provide specific examples of the issues generalised in the previous chapter.

4.1.1 Berbak Carbon Initiative Site description

The Berbak Carbon Initiative (BCI; 104 20'E 1 27'S; figure 4.1) is a pilot REDD+ project in Jambi province, Sumatra established by the Zoological Society of London (ZSL) in 2009 and funded by the UK Darwin Initiative.

The project area comprises 238,608 ha of forest in four different land use classes. These are Berbak National Park, which is under the control of central government in Jakarta; a Forest Park *Taman Hutan Raya; TAHURA* and a Protection Forest *Hutan Lindung* which are both under the control of the Jambi provincial government; and two limited production forests concessions *Hutan Produksi Terbatas* which are administered by the provincial government and licensed to concessionaires. The area of each forest class is summarised in table 4.1.

The BCI area is covered largely by late successional forest on a combination of ombrogenous (rain-fed) tropical peat swamp and mineral soils. Large areas of forest in the centre of the park were burned in the fires of the 1996/7 'el nino' event, and these areas now harbour low-lying scrubby swamp vegetation. The main river flowing through the park is the Air Hitam ('black water') river which is highly acidic, and typical of peat swamp forests at pH 4.5.(A full description of the nature of the development of the peat at the site, and the quantification of its volume are set out in chapter 6).The Berbak ecosystem is one of the largest remaining freshwater swamps in SE Asia, providing important habitat for the critically endangered Sumatran tiger *(Panthera tigris sumatrae)* and the endangered false gharial (*Tomis-*

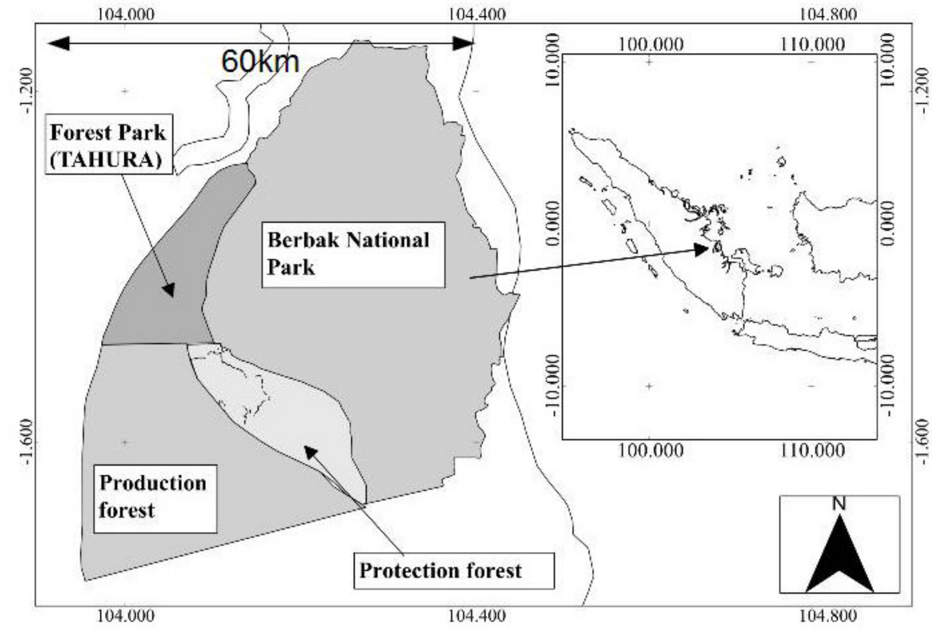


Figure 4.1: A map of the Berbak Carbon Initiative, a pilot REDD+ project which includes Berbak national park and the adjacent hutan linding protection forest; protected TAHURA forest park; and production forest concessions

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toma schlegelii) (IUCN, 2013). Twenty three species of palms have been found here, making the site the most palm-rich peatland swamp known in SE Asia. It is also a site of particular importance for highly specialised air-breathing peat swamp fish (stenotopic acidophilic icthyofauna), particularly of the family *Osphronemidae* and the genus *Betta*, one species of which *Betta splendens* is popularly kept as a pet under the name 'Siamese Fighting Fish'. (A description of the biodiversity systematically recorded at the site is provided in chapter 5). The rich biodiversity of the site led to Berbak being declared a RAMSAR site and Wetland of International Importance in 1992 (Ramsar, 2013), when it was upgraded from a Wildlife Refuge *(Suaka Margasatwa* to a national park by the Minister of Forestry under SK No.285/Kpts-II/1992.

On the north and east of BCI (principally along the Batang Hari river, and along the coast) are 32 villages. There are no indigenous people living in the area, although one woman in the coastal village of *Cemara* was claimed by a community member to be the last surviving member of an ethnic group that once did. However this could not be substantiated.

The landscape surrounding the BCI is a matrix of coconut palm plantations along the coast to the east, and logging concessions, remnants patches of forest, and palm oil plantations to the west and south west. The land continues to be drained and cleared for access to timber and land for legal and illegal agricultural expansion. To the North, the BCI is bounded by the Batang Hari river. To the

Site	Zoning	Area, ha
Berbak National Park	National Park TN	140,204
Hutan Lindung	Protected Forest Area HL	18,700
Taman Hutan Raya	Forest Reserve TAHURA	17,593
Total Production Forest Zone	Limited Production Forest HPT	62,102
PT. Putraduta Indah Wood	Production Forest TPTI/THPB	34,730
PT. Pesona Belantara Persada	Production Forest TPTI	20,826
Total		238,601

Table 4.1: The components of the Berbak Carbon Initiative

south, and contiguous with Berbak is the Sembilang National Park, a mangrove forest.

This matrix of different land use is a microcosm of Jambi province. Pak Wahyu Widodo, the head of the Ministry of Forestry's regional forestry office (*Dinas kehutanan Propinsi*), said that according to his figures, 42.1% of the land in Jambi is classified as forest land, with 57% being set aside for other use which includes agriculture and urban areas (Areal Pengunahan Lain; APL). However he was aware that what was classified forest land on his maps did not necessarily reflect the biological conditions on the ground because of the pace of formal and informal land use change. Multiple processes are causing extensive deforestation and forest degradation across the province.

4.1.2 Proximate drivers of deforestation and biodiversity loss in the project area

Local drivers of deforestation in the BCI area comprise a combination of illegal and legal activities. On the north, south and west of the park there is evidence of anthropogenic disturbance through illegal canal creation to drain the land in order to expand agriculture. There are no roads in the park, however there are railway tracks leading into the production forest, which were used to extract timber from a previous cutting cycle in the concession.

Pak Wahyu Widido asserted that immigration was a fundamental problem for forest degradation in Jambi. He said that immigration was largely informal, whereas officially migration permits were required to be issued by the local government. Yet due to poor enforcement, he claimed immigration was now out of control with entire families moving (instead of single economic migrants), and largely from neighbouring Riau province. He claimed the migrants were occupying and clearing Jambi's forests, and further protesting for land rights in his province. Pak Wahyu emphasised that this was illegal and that moreover many migrants were not really the landless poor, but rather land speculators that would want to sell land that they claimed rights to. Unfortunately he was not able to provide any statistics on the actual numbers of people moving into Jambi province, nor the area of land they had cleared. By contrast, the evidence from the literature suggests there is no single clear impact of immigration on deforestation (Lambin et al., 2003), and moreover a common theme throughout modern history has been to blame outsiders or immigrants for socio-economic problems (Ferguson, 2006), a process which may be being replicated here given the lack of evidence. In conclusion, without data it is not possible to verify the assertion that immigration was one of the main drivers of land use conversion in Jambi, nor indeed the levels of migration.

Logging and agricultural expansion One of the main drivers of forest degradation in the BCI project area is logging. The two concessions on the western side of the project both have had permits to undertake selective logging only. Howevever neither concession is active as of 2013 due to financial problems in one firm, and the lack of proper management plan being written by the other. No formal agreements have yet been made between the concessionaires and ZSL over the inclusion of the concessions into the BCI area. So without a change in land use class, for instance to become a protected area, these forests will be logged again in the future. With REDD+ funding, they could be logged less intensively, generating carbon credits as an Improved Forest Management component to the project. Further, canals have been built into the nominally protected *hutan lindung* and TAHURA forest to the north and west of Berbak as a precursor to agricultural development, and possibly to facilitate timber removal, since sporadic cases of illegal logging do continue to occur inside the park (see figure 4.2 and 4.6). According to Citra N. (a field coordinator for ZSL Indonesia), in the most severe cases this had led to officers from *Dinas Kehutanan*n being attacked by machete-wielding loggers. Yet in terms of relative importance, even these dramatic cases are insignificant compared to fire which has already destroyed a large part of Berbak's forests.

Fire is one of the major drivers of deforestation in Indonesia (Dennis et al., 2005). It is used by land owners to clear the land of vegetation, but these are normally poorly managed and can spread out of control and create enormous forest destruction. In addition, where peatland forests are burned, the dried and oxidised and hence highly flammable organic matter also ignites. These fires can release huge amounts of carbon, since peatland store up to one 1000Mg C ha^{-1} (see chapter 6 for a full discussion of the importance of peat). At Berbak, between 2001 and 2012, the MODIS satellite detected 3213 fire 'hotspots' within the BCI borders (data from NASA/FIRMS: https://earthdata.nasa.gov/data/near-real-time-data/firms). The distribution of fires is shown in figure 4.3. The fires are highly concentrated in the areas of forest which have already been burned down, particularly in the western part of the project area. The 127km^2 'hole' in the middle of the national park is the result of a huge fire in the 1997/8 season. There was speculation amongst the ZSL Jambi team that the fishermen who had moved into the national park were responsible for starting the fires which ultimately caused the huge destruction in 1997/8. There is no evidence that this is the case however. Nonetheless the

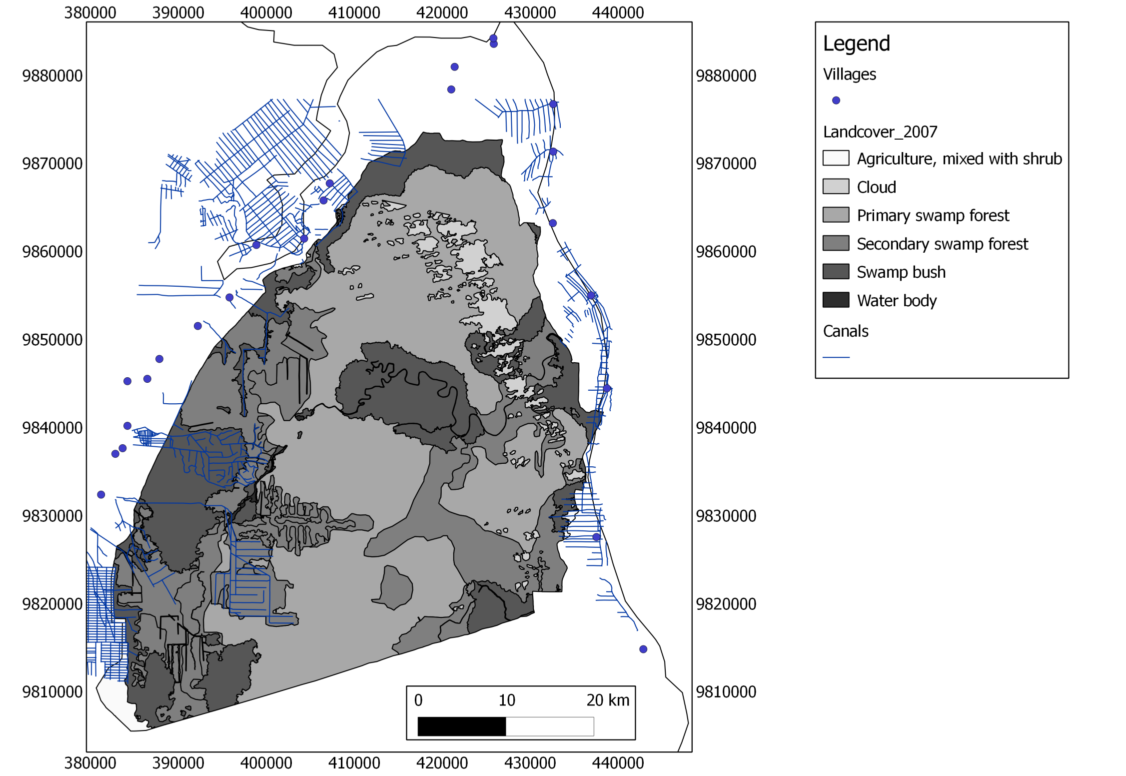


Figure 4.2: The forest classes of the BCI, showing villages and canals

fishermen have the most visible profile at the site, which is having an unquantified effect on the aquatic biodiversity of the site.

Fishing and the communities neighbouring BCI Fisherman have a well-established presence inside Berbak national park, and have established riverside buildings well inside the park borders which are used as staging posts to launch fishing expeditions, and as processing centres for the fish. The principal wild target species appears to be the 'snakeheads' from the family *Channidae* (author's observation). In addition, fish breeding ponds have been established on the north western border of the park near Air Hitam Dalam in the canals dug to drain the peat swamp. These ponds were still being used in 2011 to meet the demand for catfish of the genus *Clarius* which is used to make the Indonesian street food called *Pecel lele*. This was clearly therefore not just occasional subsistence level fishing. In Figure 4.4 snakehead fish are being dried in the sun in an artisanal fish processing centre inside the park.

Presently there does not appear to be any attempt to regulate fishing by the park authorities. On the contrary, field observation suggest the opposite is true. The author was obliged to pay a forest policeman (POLHUT) to accompany his expedition into the forest, ostensibly to enforce park regulations and laws. However, the officer actively participated in fish extraction from the park. Specifically, the officer a) confronted the author over the release of fish caught during a biodiversity survey, since he wanted to eat them; b) ate cooked fish from a fisherman working well

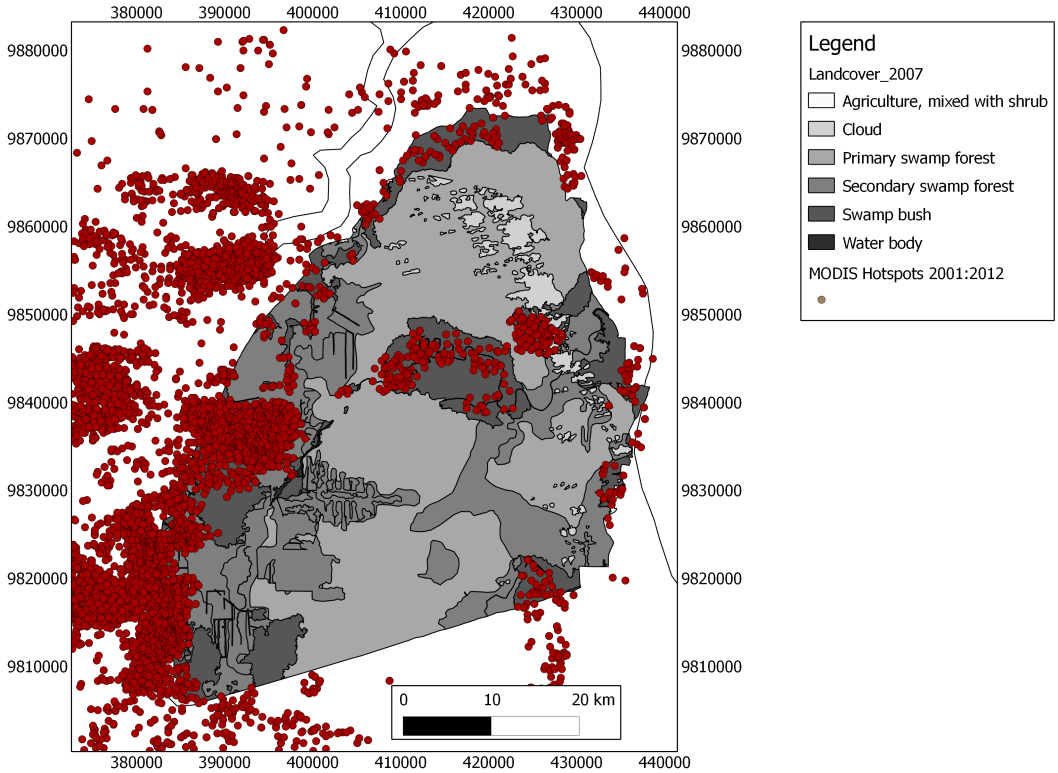


Figure 4.3: Fire hotspots at the BCI between 2001 and 2012 as recorded by MODIS.

inside the park boundaries, and c) insisted that the expedition help a fisherman tow his unmotorised boat and catch from a small tributary to the main river channel. The ranger received a small bucket of fish in return for the transport. See figure 4.5 for image of the forest police officer eating fish from national park. This put the author in the perverse position of using ZSL and research council funding to directly subsidise biodiversity loss from the park under the pretence of law enforcement.

Pak Nuksman, the head of the park said that fishing in the park was widely known about but was accepted by the authorities since the fishing was 'sustainable'. However, he was unable to provide any evidence for this apart from a 'feeling' or 'sense' (*rasa*) that it was quite low level. By contrast, the author's conversations with fishermen in Air Hitam Dalam suggest that in fact big fish were now becoming rarer, and they were having to travel further into the park to catch fish. If this anecdote is true, this suggests a significant biodiversity conservation problem for the site, not just for the fish populations but also the dependent species such as the False Gharial *Tomistoma schlegelii*. The problem is not currently being addressed but will need to be under CCBA requirements for REDD+ project development (see chapter 5). It would also provide interesting and novel questions for future research.

Citra Novalina, tiger survey co-ordinator for ZSL in Berbak, said that she was frustrated by this attitude of disregarding fish extraction, since to her fish were an important part of the ecosystem too, and should not be ignored. Pak Nuksman was unable to explain why fish were treated differently qualitatively from the other components of biodiversity at the site: This is probably a case of the prioritisation of 'cute and furry' species which people prioritise for conservation (see Kontoleon and Swanson (2003) for further references on this topic). It would be inconceivable that commercial hunting of large mammals or birds from the park would be officially tolerated in such a way, if only the off take were sustainable. The very fact that people are travelling into the centre of the park of to find fish may suggest that fishing elsewhere is not sustainable; and the existence of large fish stocks at the site is probably due to the fact that Berbak is a protected area and the forest ecosystem has not been damaged or completely removed as it has elsewhere in the region.

Yet there is ongoing hunting in the park, primarily through the use of snares which are placed along animal trails. This is a major conservation problem which is a main focus of conservation effort. Nonetheless it was in one of these snares in which the carcass of a large male tiger named 'King Arthur' was found rotting in June 2012 by a joint ZSL-POLHUT patrol.

It may be that the fishing is accepted not only to keep peace with the local communities for whom fishing represents a profitable activity, but also because the forest rangers can also top-up their salaries by participating in fishing in this way. Pak Nuksman confirmed that national parks used visiting researchers to supplement salaries, which illustrates the entrepreneurial nature of people in government positions, who supplement their wages with side businesses. The author has observed this elsewhere in Indonesia, including Wildlife Protection Officers (KSDA) in Sulawesi taking 'day jobs' instead of being at their posts (Collins et al., 2011a). Pak Nuksman (who received a net monthly income of Rp3,617,675/ US$360 as of a pay slip dated July 2011) stated that his salary was insufficient to live well on, and that he and his wife owned a travel business on the side in order to supplement his wages. This suggests that not only is there insufficient budget available to send officers into the field very often, but that the salaries paid are insufficient to demand the full attention of employees, leading in some cases to moonlighting (Collins et al., 2011a). Where employment opportunities are limited such as in coastal areas of Jambi, one obvious additional source of income is to work with the local communities to take a proportion of the natural resources being extracted as a payment to ignore illegal behaviour. This practice is called asking for *uani piro* in the Javanese language: a payment to 'look the other way'. Nonetheless the only evidence of something like this being true at the site is the present example of opportunistically working with fishermen. However this is more like active assistance than simply looking the other way.

4.1.3 Contested land tenure

4.1.3.1 Local communities adjacent to Berbak national park

Land tenure arrangements are fundamental to understanding land use change. Without understanding what processes are occurring at both the landscape scale and the local level, it will be difficult to develop project activities that bring a solution to the forest degradation at the site, and achieve the goals of the project. As shown in figure 4.2, there are numerous villages surrounding the project area. Many of the fishermen described above are from these villages, and it is with these communities that ZSL is expected to work under the Climate, Community and Biodiversity Alliance (CCBA) standards (Niles et al., 2005) in order to demonstrate net social benefits. (See chapter 5 for biodiversity aspects of CCBA certification). However, thus far there is relatively little information available about the socio-economic status of the people in these villages. So as part of the project's community engagement programme, ZSL hired a consultant to performed surveys of the people living in the 32 villages directly adjacent to the park itself. Unfortunately there were problems with implementing the survey, and as such it is not possible to provide much summary information about these communities. However, it was possible to derive some anecdotal information from the consultant whilst he was still working with the project. One case which has potentially large implications is the case of a community living near a village called *Sungai Rambut*. The inhabitants claimed that when the park was gazetted in 1992, it included 2000ha of their land. As such, the consultant claimed that the community is now seeking to excise this land from the park and convert it for agriculture. Whilst this would provide benefits to the community from increased agricultural productivity, it would also contradict the goals of the project of reducing deforestation. It could also set a precedent for re-zoning the protected area, which concerned Pak Nuksman. He referred to ongoing work to document what he called 'enclaves' (in English) inside the park boundaries that were created when Berbak was designated a Wildlife Refuge *(Suarka Margasatwa)* before becoming a national park. He felt that his office did not have the right to eject people from the land in these areas since they they were already occupied when the national park was created. Yet he felt the presence of enclaves were a potential problem in that it seemed from the outside to set a precedent for people to live inside the protected area. As discussed in the previous chapter, the post-Suharto era has been characterised by increasing local control of forest resources, and people becoming more 'brave' in their transgression of Suharto era land use classifications, whilst the authorities have been increasingly unwilling to enforce these laws by ejecting small farmers from national parks e.g. coffee farmers from Bukit Barisan Selatan (Gaveau et al., 2009b)

A correspondent from a local NGO who wished to remain anonymous said that in his opinion local people would only accept a REDD+ project at Berbak if it recognised their commitment to protecting and using the forests, and that it was difficult to explain to them the concept of additionality or the necessity of national parks: the local people believed they were best placed to protect the forest. He also felt that REDD+ incentives were incorrect since they rewarded destructive companies rather than local people who acted as forest stewards. (However in the literature, the effect of local land tenure on deforestation is uncertain (Angelsen and Kaimowitz, 1999)). When asked about the Berbak enclave and the Sungai Rambut situation he suggested that one solution may be to bring the enclave and villages surrounding the park into the broader REDD+ project by involving them in a Community Based Forest Management (CBFM) system under regulation P6/2007. The options to do this would be to create either 'village forests' (*Hutan desa*), 'social forest' (*Hutan kemasyarakatan*) or 'community plantation' (*Hutan tanaman rakyat*). An important precedent was that first ever *hutan desa* licence issued in Indonesia was in Jambi province, in nearby kabupaten *Bungo*.

However he immediately provided several caveats to this strategy. The bureaucracy involved in developing these land classes is challenging, particularly obtaining the permissions letters required to change the land class. The letter which had been issued in Jambi and which set the important precedent took six months to obtain, but this does not complete the process: the final stage is the receipt of a verification letter providing use rights *(hak mengelola)*, which must be then signed by the minister of forestry. According to the anonymous correspondent, due to these time delays there were only 82,000ha of hutan desa in all Indonesia in 2011. In Jambi there were at least 17 villages in Jambi province that were currently waiting for a hutan desa licence and who had been waiting for over one year to hear about their applications. This underscores the uncertainty of land tenure for Indonesians generally, but also of the difficulties of using different land classes to participate in REDD+, and of doing so at Berbak.

This demonstrates that not only are there unresolved land tenure issues in the project area, but also that there are different options for their resolution which offer quite different futures for the management of the park. On the one hand, a flat refusal to allow the development of enclaves in the park could in principle retain more forest for the project and achieve greater reduced deforestation. However if the local community can demonstrate uncompensated expropriation of land for the creation of the park, the REDD+ project could be interpreted as reinforcing and repeating the inequities of land tenure arrangements as described in the socio-economic background chapter. This could possibly be a barrier to achieving the CCBA certification under social benefits criteria. The CBFM option may provide a solution, and co-management solutions have been developed in other places in Indonesia, particularly where the 'fences and fines' model of protected area management fails anyway because the park is ineffective (Engel et al., 2010; Kaimowitz, 2003).

4.1.3.2 Land use management decision making

An additional complication of obtaining the land use tenure is that great uncertainty also surrounds the taxation of these land classes. The NGO correspondent explained how if these new land classes create REDD+ income then the central government would tax this income, but that there was uncertainty about taxation in the case in which it generated no carbon revenues. This latter case seems a likely outcome since the community forest schemes in Jambi that the correspondent referred to were extremely small-scale, between 2 and 5ha, which would not be viable as REDD+ projects in their own right and would therefore require some form of pooling to create a larger project that would reduce transaction costs.

The correspondent claimed that the potential government revenue was the most important factor in making land use decisions rather than the benefits to local people, and that if there was no income due from community forest schemes, then this makes them less attractive to government than high-revenue agro-forestry plantations. To illustrate this, the correspondent provided more detail on the situation for the 17 Jambi villages waiting for their community forest licences. He said that they were facing competition from a single large agro-forestry company who had already obtained a licence to operate in the same area of forest to develop oil palm, which crop has been a central feature in the conversion of natural forests in Indonesia over the past decade (see socio-economic background chapter 3) At the time of the interview, the decision had not been made on whether the land would be granted to the local community or to the agro-forestry company. According to the correspondent, in practice this decision centred around power; the returns to government; and the agro-forestry company's interactions with officials.

The correspondent compared the incentives to the local government and the Minister from the 17 communities seeking *hutan desa* licences on the one hand and the agro-forestry company on the other. He described how the the agro-forestry company would be obliged to pay a US$5 per hectare stumpage fee *retribusi* for the Ministry of Forestry's reforestation and regeneration fund. This has been subject to large levels of mismanagement and corruption in the past and allegedly still provides extra income for some forestry officials (Barr, 2010). In addition, he alleged that a US$1 per hectare would be paid to the head of the local government *(Bupati)* if the agroforestry company got the right decision, as a form of *upeti*, which is the Indonesian word for tribute, harking back to the client-patron relationships of the Suharto era.

The respondent said that where the forest in question overlapped two *kabupaten* that a further unofficial fee of \$2 ha^{-1} was paid to the provincial governor. To further encourage a decision in favour of the agro-forestry company, the correspondent alleged the company had an 'entertainment' budget of some Rp 450,000,000 (US$500,000) available to provide local officials with lifestyle gifts such as expensive hotels and travel, which he called *'uang jalan-jalan'*.(Incentives are summarised in table 4.2. On the other hand, the only revenue that could be generated by creating the new *hutan desa* and other CBFM forest classes was the possibility of earning carbon credits, at some point in the future, which therefore provided little incentive.

He set this lack of potential income against the regents' (*Bupati*) requirements for *'fresh money'* to spend on election campaigns, which was the destination of the the unofficial fees. The correspondent said that the case demonstrated how the local government could be bought *('bisa dibeli')*. Because of this, and that the scale of the *upeti* and entertainment budget was so impressive, exposure of the findings needed to be well-managed for maximum impact and to ensure personal safety of the investigators involved, hence the masking of this correspondent's name and organisation.

Yet these claims of unofficial payments remain unproven allegations and the story cannot be verified, and should therefore be read cautiously. Yet the description is supported by Indonesia-wide studies that demonstrate the close link between elections and logging, and the increase in logging associated with the *pemakeran* era expansion in local government (Burgess et al., 2012). In addition illegal payments being made for local logging permits have been well-documented in other parts of Indonesia (Smith et al., 2003).

	Incentive from agro-forestry company	**17 villages in Jambi seeking *hutan desa* licences**
Area ha	83,000	49,000
Reforestation fees	US 5 per ha, Total US$415,000	Total US$0 plus any REDD+ returns
Unofficial (alleged)	Rp10,000 per ha (US$ 1) to Bupati. Plus (US$ 2) to the governor if the forest class is spread over two regencies	Total US$0

Table 4.2: Competing incentives to local government for alternative land uses

4.2 Responses to deforestation and biodiversity loss

Forest law enforcement in Jambi

There are clearly multiple drivers of land use change in Jambi and in the Berbak area, which the Ministry of Forestry is trying to tackle. However, one of the main barriers to achieving this is sufficient management capacity in Jambi, as Pak Widodo explained. Across Jambi's 2.1m ha of forest, he commanded 200 forest police in regency-level forestry offices (*POLHUT* in *Dinas Kehutanan Kabupaten*). Of these he estimated that 40 individuals were ineffective or too old to work in the field. Of the remainder, he explained that only half the team could be deployed to the field at any point, meaning there were only 5 rangers at any time in the field in each of Jambi's 16 *kabupaten*.

However, these are supplemented by 40 POLHUT in the provincial forestry offices (*Dinas Kehutanan Propinsi*) and further 200 special police (*SPORS*; *POLHUT Khusus*). In summary he said that there were some 400 active forest police in Jambi, which on average means they are managing 5,000 hectares each. This area of land per ranger has also been reported in 2013 as the Ministry of Forestry's planned management strategy (Lubis, 2013a), and at Nantu Forest in Gorontalo province during the author's previous research there (see Collins et al. (2011a) for details). Crucially though, Pak Widodo said that budget was only available for paying wages rather than the operating costs to send people into the field for enforcement activities *(penegakam hukum)*. This meant that people were employed as forest rangers would come to the office, but rarely achieved their purpose of actually enforcing the law in the field. This leads to questions about the efficacy of the Indonesia civil services, since if indeed 20% of the forest police were incapable of fulfilling their job requirements properly, the budget currently spent on their wages would be better spent on actually sending the capable officers into the field. This is party of a broader problem of bureaucratic reform in Indonesia. President Yudhono is keen to institute reform, yet to do this, the government has established a new Ministry, called the Ministry for Bureaucratic Reform: PAN Kemeng.

Figure 4.4: Forest police officer (POLHUT) eating the national park's wildlife.

4.2.1 Addressing the underlying causes of deforestation: Sustainable development in Jambi province

Pak Wahyu Widodo described how Jambi was taking a proactive stance on sustainable forestry and land use practices, irrespective of the development of REDD+ and the Letter of Intent with Norway (see chapter 3. In particular there were plans to undertake reforestation in two regencies: Sarolangun and Merangin. Of central interest was a new forest land class called village forest *(Hutan desa)* which had been mentioned by the anonymous correspondent. However Pak Widodo was able to provide more detail. Principally these forest classes were intended to be in areas where forests protected the watershed, and where hydroelectric power could be generated. He said that in addition to the management of water and forests, his team was attempting to develop areas *(lubuk larangan)* and seasons where fishing was disallowed, in order to let stocks recover. The local people enforce the rules, and if people take fish out of season, they had to pay a fine (Pak Wahyu referred specifically to killing a goat or other livestock). He also highlighted the Wanatani community programme where people ran agroforestry activities on the margins of officially protected forest. In return for deriving the benefits of using this border forest, the farmers acted as guardians which prevented people from cutting wood inside the forest. This approaches appeared to integrate ecosystem service provision, and incorporate local informal institutions into management, which is similar to the *adat* form of forest management (see chapter 3). Pak Wahyu said that Jambi was the only province in Indonesia running this system, and the spatial plan *(tata ruang)* for a more ambitious expansion of the system across Jambi was in review in Jakarta as of 2011.

Furthermore he described a Jambi-wide programme of agricultural intensification rather than extensification. This focussed on a four year programme of rubber plantation development and an eight year programme of plantation development using Jelutung, a native timber species *Dyera costulata*. He explained how this would be supplemented with aloe-wood for export to the Middle East (*Gaharu* of which there 16 species in Jambi).

Finally he described Community Reforestation Gardens (*KBR; Kebun bibit rakyat*) which were being developed to reforest land critical for the economy *(lahan kritis)*. He said the forest department was planning 200 KBR, with 50 million seedlings each, meaning up to a billion seedlings planted on critical lands.

Figure 4.5: The park ranger assists with the transport of fish caught inside the park. Fish stored in white bucket.

He emphasised this was a 'bottom-up' programme, with the species chosen by the local communities, reflecting a move towards community-led land management. Overall, Pak Wahyu said that the hope was that these programmes would provide a better living environment for local communities than palm oil plantations. He saw a future for Indonesia in wood plantations, and that it was better for Indonesia if native species were chosen.

Moreover he emphasised that these programmes existed outside of REDD+, though he thought that REDD+ funding could support the activities already established and planned, and further could support macro-economic change that reduced direct dependency (*jasa*, literally 'service') on the land and agriculture. In this context he said that the Governor of Jambi sought to invest heavily in human resources in Jambi, and get 60 people into PhD (S3) programmes, and 200 people on master's degree programmes (S2) as a part of SBY's basics of growth: Progrowth, Pro-poor, Pro-employment, Pro-environment. However in the opinion of Pak Wahyu this should also include Pro-justice. By this he meant that historically only big companies could get access to the forest whereas now the poor were gaining access too via the Hutan desa licence. However, as explained above, obtaining the *hutan desa* licences seems to actually be quite difficult in practice. If the case described by the anonymous respondent is true, aspirant small land holders face stiff competition by well-financed and allegedly unscrupulous agro-forestry firms, a history in which Indonesia is steeped (Smith et al., 2003).

Furthermore, whilst these forestry plans seem to offer a more sustainable path than oil palm, they are mostly still plans. To be implemented, the plan requires public funding via the Ministry of Forestry, which appears to already be struggling to meet current budget commitments. Meanwhile, despite the plans for expansion of sustainable plantations with native species, the palm oil sector continues to grow (see chapter 3). As an example, in an image from June 2013 taken by the new earth-observing satellite called LANDSAT 8, a huge new clearcut of 54.9km^2 has been made up to the border of the BCI (see figure 4.6. Clearcutting is not permitted in production forests indicating this is clearance for a new plantation).

So whilst at Berbak, some form of community management could prove a productive avenue to explore, actually implementing this more generally across the province and creating a more sustainable future for Jambi's forests means addressing the long-standing patterns of land use management, and corrupted decision making processes.

4.2.2 Law enforcement in Berbak National Park

The BCI faces increasing pressures including, the reformasi-era social de-legitimisation of protected areas (see chapter 3 and the reluctance to enforce land use laws against the rural poor (Gaveau et al., 2009b); huge areas of swamp forest with difficult access; restricted budgets and poor staff incentives, which are now discussed.

The easiest way to access Berbak's core forest is to enter the Air Hitam river by the sea yet the park does not own a functioning boat. Due to the the large scale of the park and the inaccessibility of its swamps, the park owns a light aircraft, however it does not have the funds to maintain it, or pay for fuel or a pilot. This immediately

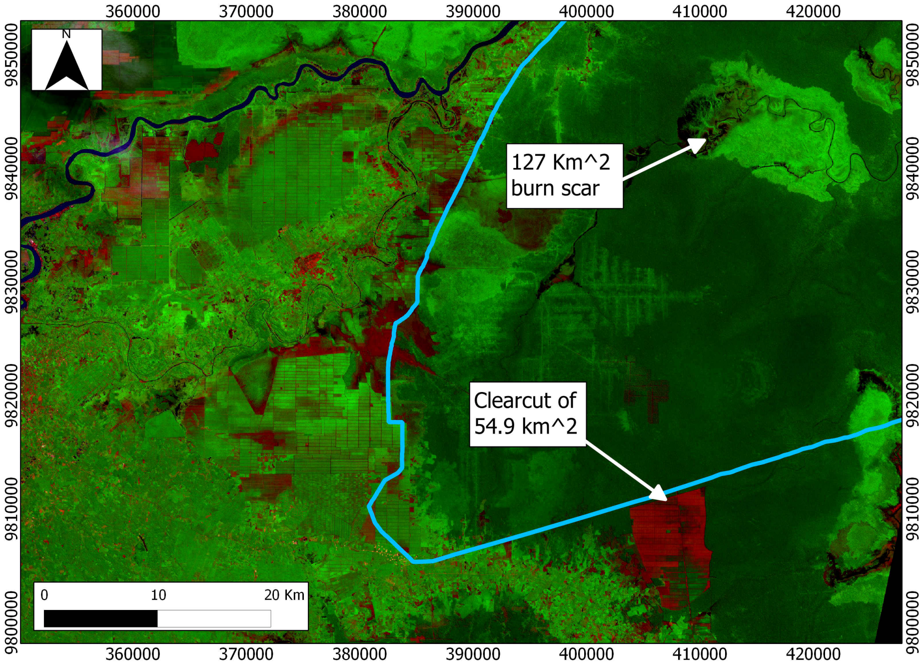


Figure 4.6: A false colour Landsat 8 image (composite bands 753) of eastern Jambi from June 2013, showing the BCI project area. A new clearcut has been created just south of the BCI. The BCI is outlined in red

places constraints on the forest police POLHUT, who have to use public transport to access guard posts.

Communications are a basic requirement for field operations. However the field radio has a limited range, and mobile telephone signals are not available. As such field patrols have to return to base if they needed to make a report, or call for backup if they needed to arrest people. By comparison, Pak Nuksman gave the case of the Alas Purwo park in eastern Java, where the Resort Based Management (RBM) system was developed (a 'resort' is a local field base in a sub-division of a park). At Alas Purwo, phone signal was available through much of the park, along with internet access, which allowed the reporting of illegal activities directly to base and for teams to take immediate action. He claimed Alas Purwo was more successful at combating illegal activities because of the ease of communication. However this problem could also be interpreted as a management issue, combined with a lack of field team autonomy with hierarcy and bureaucracy taking precedence over actually taking action in the field. This seems to be an instance of 'empowerment failure', which is an interruption of work that occurs due to waiting for approval from a manager.

Berbak's National Park's swamps are vast (140,000ha) and difficult to navigate. Yet as of July 2011, only three rangers patrol the park for only four days per month. A ZSL wildlife biologist visiting the site observed that: "*...currently [park staff are] struggling to [manage the park]. They have only received a third of the operating budget they requested for 2009-10 and received...$30 from tourism revenue in 2007.*

They have...15 forest police to patrol an area of 1600 sq. km. and the operating budget only allows one patrol per section of the park per month, for...six months of the year. On ZSL's last visit to the park the National Park's only boat was broken meaning access to the park was only possible by...hiring boats." (Maddox, 2008). Pak Naksman thought this current management capacity was about '40% effective', although this assessment was not based on formal analysis. To rectify the situation he aspired to implement RBM to create a larger number of more manageable units of forest. The park would be divided up into 11 areas (resorts), of approximately 15,000ha allocated per resort. However the precise size of each resort depends on field conditions such as levels of human disturbance and conflict.

Yet again, the budget was the major constraint on this change, since Pak Nuksman had only Rp 1,800,000 (\$180) per resort per month. He stated that with this current resource it was simply 'not possible' to protect the national park. To him, looking after the park was like looking after a house: 'if you don't secure the house, you'll get robbed'. He concluded from his previous experience working at Tesso Nilo park in neighboring Riau that the most important factor in protecting and controlling a park was consistency and regularly being in the field. To gain control of Berbak he wanted to put rangers in the field for 12 days per month, requiring a tripling of his budget. This would mean an additional Rp475,200,000 (US\$47,500)yr^{-1} for protection of the entire park.

However, this resource-constraint reasoning was rejected by Pak Beebach, a project manager for the Wildlife Conservation Society (WCS). He stated that the results achieved in the Bukit Barisan Selatan (BBS) National Park in south-western Sumatra demonstrated this. He claimed that the Indonesian Rhino Foundation (*Yayasan Badak Indonesia*) had achieved great success in reducing poaching and deforestation by implementing new systems of training, leadership, project management and incentives rather than increasing park funding. He considered that it wasn't low wages, but the structuring of salaries and incentives in the forest service that were crucial. He said that current forestry department promotion structures based on the accumulation of credit points *(Angka kredit)* was a problem that led only to ever more bureaucratic systems. An officer needs 20 credit points to increase his pay grade. He highlighted how each report is worth 0.041 credit points, and that this was more credit than for actually going into the field to patrol. Officers were incentivised to reduce patrolling work, and instead generate reports, often based on dubious information. According to Pak Beebach, this leads to under-reporting of illegal activity. Thus senior management would believe that there were in fact fewer problems in the park than was really the case. Pak Beebach's solution revolved around implementation of a new management system called MIST, a spatially explicitly management system that records when and where teams actually patrol using GPS logs. He had observed that in the past, office-based training had simply been followed by participants seeking certificates to prove their participation so that they could gain more *angka kredit*, rather than actually implementing their training in the field.

In addition, Pak Beebach emphasised the problem of officers willing to receive payment to ignore illegal behaviour or release suspects (*wani piro*), which needed to be stamped out. The randomisation of patrols under the MIST system meant that even the police officers on the patrol did not know their patrol route until the last minute, reducing the possibility for corrupt individuals to forewarn hunters or loggers of the impending patrol.

These accounts present quite different interpretations of the true nature of the problems facing Berbak. The first suggests that the park is underfunded and that the only way to secure it is provide large sums of additional finance. The alternative suggests the core problem is the structure of existing incentives. The truth is probably a combination of these two. The huge areas of swamp are often inaccessible on foot, requiring access by boat, yet the park officers have to rely on public transport. At least one case of *wani piro* was observed on a field trip, which was facilitated by being at a location without any communication with the park office. So with the ongoing threats of fire; illegal land conversion and hunting for fish and setting of snares for ungulate meat and tigers; there is a need for both an increase in budgets and improved management. This provided the basis for ZSL's project intervention.

4.3 ZSL's intervention

Berbak is one of the few large remaining blocks of forest on Sumatra. Yet as this chapter has described, the park has limited funding from the Ministry of Forestry to undertake even basic management tasks to counter the increasing deforestation and degradation pressure, in addition to the direct threats to biodiversity from snares and commercial fishing in the park itself. T.Maddox, a tiger biologist who was working for ZSL beween 2008 and 2010, decided to intervene by developing the Berbak Carbon Initiative. The goal was to reverse the trends of deforestation and degradation in the Berbak ecosystem, and save the tigers. According to the application to the Darwin Committee, park officials *'initiated (the BCI) project in early 2008 by requesting help from ZSL in finding a way to conserve the park and its species'* (Maddox, 2008), p.3).

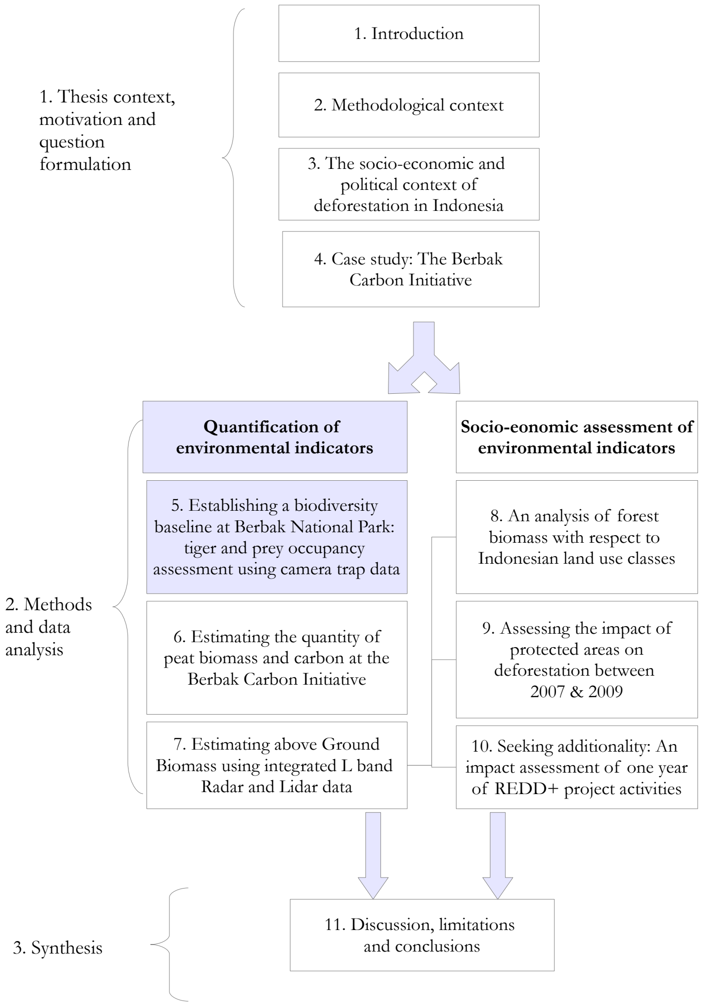
At this time there was a great deal of excitement about how REDD+ could generate billions of dollars for forest conservation (Baker et al., 2010b) and even internalise the costs of biodiversity conservation (Collins et al., 2011b). So, because of the large amounts of carbon in the peat swamp forests of Berbak, ZSL's Darwin proposal to support Berbak national park was based upon potential revenue generation from REDD+ activities. Yet the fact that the park should already be protected under Indonesian law and the UN Convention on Biological Diversity meant that in principle there was no marginal carbon emission mitigation benefit in setting up a project (called 'additionality' in REDD+ jargon). This is why the logging concessions to the west of the park needed to be included in the BCI area, to provide a credibly high baseline of deforestation against which to generate carbon credits.

The development of an ambitious forest carbon project comprising a national park and other land use classes requires significant investment in order to model the projected deforestation; establish a management body; pay for activities and market the credits. In order to raise these funds, ZSL applied to the UK Darwin Initiative. This fund, managed at the UK's Department for Environment, Food and Rural Affairs (DEFRA) seeks to meet the UK's commitments to the United Nations Convention on Biodiversity (CBD), to support conservation in biodiversity-rich but financially- poor countries, and has distributed 88.5m to 781 projects in 155 countries since 1992 (http://darwin.defra.gov.uk/dec/). ZSL's application was accepted and awarded £298,068 for three years from 1 April 2009 to 31 March 2012 under grant number 17-029 entitled 'Berbak to the Future: Harnessing carbon to conserve biodiversity', with the stated purpose: 'To create a financial incentive to landscape stakeholders in eastern Sumatra to conserve peat swamp habitat and thus the biodiversity, carbon potential and other services it contains' (Maddox, 2008) p.3.

The BCI has now been established officially as a pilot REDD+ project, and in Jakarta in 2011 signed a Memorandum of Understanding with the Ministry of Forestry to co-manage the national park. However, there are not yet agreements in place with the other land managers involved in the BCI project area. Crucially this includes the concessionaires to the west of the park, from where the project's REDD+ additionality derives. As such there are still fundamental challenges to overcome before the project is ready to market credits. This thesis makes several applied contributions to overcome some of these hurdles, including addressing aspects of the CCBA requirements for ensuring biodiversity benefits in REDD+ projects, which is covered in the next chapter.

Chapter 5

Establishing a biodiversity baseline: tiger and prey occupancy analysis using camera trap data



5.1 Abstract

Forest carbon projects are certified to assure buyers their emissions reductions are genuine. Parallel certification schemes such as the the Climate, Community and Biodiversity Alliance standard (CCBA) exist to assure buyers that projects provide biodiversity benefits. A core requirement of these certification schemes is that the project provides net positive biodiversity benefits. This requires a biodiversity baseline at the outset of the project against which to measure future benefits. This chapter uses existing modelling techniques to develop estimates of the probability of occupancy Ψ for tigers and their potential prey species (e.g. Macaques, wild boar) to be used as such baseline. These species were chosen due to the focus of the project on harnessing carbon payments to ensure tiger conservation. To make the occupancy estimates, a camera trap was survey run in Berbak National Park in 2009, with cameras to detect large mammals for a total of 1627 camera days at 36 sites. Models were selected using a combination of Aikake's Information Criterion to assess relative model quality, and parametric bootstrapping to estimate model fit.

Forest biomass was the only clear covariate of occupancy for potential tiger prey species occupancy. Using this variable produced an estimate of $\hat{\Psi}$=0.71 (95% CI= 0.52:0.84). For tigers, a total of 21 photographs were recorded in 5 of 36 sites during the survey, producing a naïve occupancy of 0.14. The final model used to estimate tiger occupancy used forest biomass to estimate both occupancy and detectability sub-models. The fitted occupancy when using the minimum level of biomass was $\hat{\Psi}$=0.27, 95% CI=0.14:0.45. Continued data collection and occupancy modelling over time may be used to measure project performance in biodiversity conservation and potentially as a means to measure the impact of ZSL's project for CCBA audit. More generally, such longitudinal occupancy studies using camera trapping may also provide a framework for assessing other certification schemes that incorporate biodiversity.

5.2 Introduction

Carbon credit buyers on the voluntary carbon market choose forest carbon credits *inter alia* because they perceive that they will also be conserving biodiversity (Diaz et al., 2011). To ensure that forest carbon projects do provide this benefit, there is an organisation called the Climate, Community and Biodiversity Alliance which produces procedural standards (Niles et al., 2005) designed to ensure projects also provide positive biodiversity externalities; 'co-benefits', in the REDD+ jargon. Carbon credit buyers often demand this certification (Diaz et al., 2011). In this case there is a need to develop robust measures of these benefits, particularly for species of conservation concern which attract greater public attention and may be somehow linked to carbon market value e.g. Dinerstein et al. (2013). These methods need to be both sufficiently robust to detect change over time and also be be effective with respect to logistical and financial constraints that conservation projects operate under. That is, there is also a need to recognise that these high profile species are often rare, cryptic and live in environments which are very difficult to access and work in (like peat swamp forests), which makes the required population assessments extremely challenging.

The criteria of the CCBA that are used to ensure performance in biodiversity conservation are comprehensive, and it would neither be academically interesting nor feasible to address all of these in a single PhD chapter. As such this chapter focuses on a single criterion: B1 *Net positive biodiversity impacts*. This criterion states that *'The project must generate net positive impacts on biodiversity within the project zone and within the project lifetime, measured against baseline conditions'*. To demonstrate this, the project developer should *"use appropriate methodologies...to estimate change in biodiversity as a result of the project. This estimate must be based on clearly defined and defensible assumptions. The scenario with the project should then be compared with the baseline without project biodiversity scenario...The difference...must be positive"*. The objective of this chapter is therefore to establish a biodiversity baseline for the project site. This should be able to be used by the project in the future in order to demonstrate a positive biodiversity impact.

Camera trapping offers considerable opportunities to monitor rare and cryptic forest mammal populations (Sunarto et al., 2013; Wibisono et al., 2011; Ahumada et al., 2013; O'Brien et al., 2010; O'Connell et al., 2011; Rowcliffe and Carbone, 2008; Linkie and Ridout, 2011; Jenks et al., 2011; Sharma et al., 2010). Methodologically, occupancy modelling is a popular option to assess tiger populations. This is because it uses robust statistics that account not only for the observations of the presence of a species, but also heterogeneous detection prob-

Figure 5.1: A Sumatran tiger photographed at Berbak National Park. Image supplied by ZSL Indonesia.

ability across sites. This is explained formally below. On Sumatra this occupancy analysis has recently been used to make an assessment of the tiger's conservation status in Riau province (Sunarto et al., 2013); and across the entire island (Wibisono et al., 2011). More recently, a multi-year camera trapping project in Costa Rica has been used to show changes in mammal occupancy over time (Ahumada et al., 2013). These authors demonstrated that even over a relatively short period of five years, occupancy declined for some species in the study site, hypothesising this to be due to the impact of increased human hunting. This kind of wildlife population information could be used to satisfy monitoring for CCBA criterion B1 for the Berbak project, because it can show changes over time using a standardised methodology. If the causal mechanism were clear (such as reducing the number of snares in the park) changes in tiger occupancy $\hat{\Psi}$ over time may in principle be attributed to the project activities. To do this requires baseline occupancy against which to compare future occupancy. This chapter sets out to establish this baseline for tigers and their prey using six months of camera trapping data.

5.3 Methods

5.3.1 Camera trapping

Camera traps were operated at Berbak national park from May until October 2009, with a total of 1627 trap days. The cameras were placed in a grid of 36 2.5 x 2.5km cells in the core forest area (see figure 5.2). Sampling areas of this size have been used in Malaysia to estimate tiger populations (Kawanishi and Sunquist, 2004). The grid covered a matrix of swamp bush, and primary and secondary forest. However due to limited number of cameras available to the project, the grid cells were sampled progressively rather than simultaneously. That is, after being left running in the field for several weeks, the field team returned to the camera sites, changed the digital memory cards and the batteries and then moved them to the next unsampled grid cell and set running again. The camera trap operational history is set out in figure 5.4. Within each grid cell, the specific camera site was chosen after having surveyed the area for animal trails. At each location the cameras were attached to trees at a height to maximise the chance of capturing tigers and their prey (O'Connell et al., 2011). The camera units themselves were a combination of DLC and Cuddeback models, which were placed in steel cages to protect against animal damage and theft.

5.3.2 Analysis: Occupancy modelling

Whilst no novel aspects of occupancy modelling are developed here, in order to aid the comprehension of the chapter, the formal basis of occupancy modelling is now

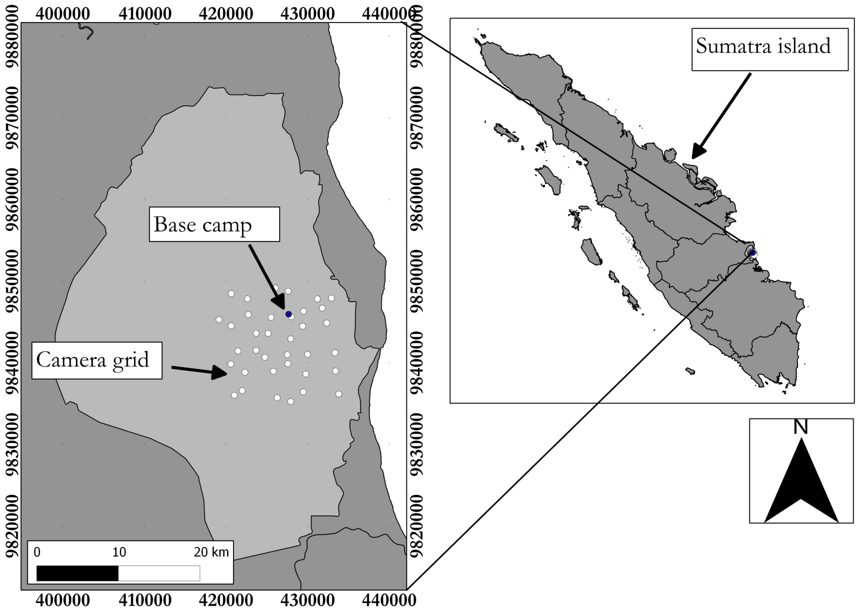


Figure 5.2: The location of the camera trapping grid placed in 2009. Berbak national park is outlined in light grey

set out. Occupancy is the probability of a species or set of species being present in a given year at a site, corrected by estimated detection probability $\hat{p}$ (Ahumada et al., 2013). A site may be occupied with a probability $\hat{\Psi}$ or unoccupied with a probability 1-$\hat{\Psi}$. If a site is occupied, there is a probability p of detecting a target species, and a chance of not detecting it (1-p). The ultimate probability of the presence of a species being detected is the product of the probability that the site is occupied and the probability that the cameras can detect the species given that it's present. Hence if there is a species detection history of 1,0,0,0,1, then the probability of the capture history is calculated as:

$$\Psi * p_1 * (1 - p_2) * (1 - p_3) * (1 - p_4) * p_5. \tag{5.1}$$

where the p_i is the probability of detection in period i. Maximum likelihood estimation is used to estimate the values of the parameters which best explain the observed data. MacKenzie et al. (2002) set the model out as follows:

$$Likelihood(\Psi, p \mid h_j, h_j, ...h_j) = \prod_{i=1}^{S} Pr(h_i) \tag{5.2}$$

where h$_i$ are vectors of the detection histories at the ith site. This equation therefore describes the product of all the possible outcomes of the camera trapping, accounting for where the species is present, absent, present but not detected, and absent. This aggregates to:

$$= \left[\Psi^{S_D} \prod_{j=1}^{K} p_i^{S_j} (1 - p_j)^{S_D - S_j} \right] \left[\Psi \prod_{j=1}^{K} (1 - p_j) + (1 - \Psi) \right]^{S - S_D} \tag{5.3}$$

In equation 5.3, the first term in square brackets calculates the likelihood for the sites where it is known that the study species is present. This means that it is possible to say that Ψ is 1, and that the occupancy estimate is therefore moderated by the product of the detection probabilities where the species was ($p_i^{S_j}$), and was not $(1-p_j)^{S_D-S_j}$ found. The term in the second set of square brackets is the likelihood for the sites for which it is unknown whether the species is present or absent. In this case, the lack of detection could be due to either a) the species not actually being present at the site; or b) the species being present but never detected. Because of this, the likelihood calculation uses the sum of the probability of both conditions. In the case of five surveys, the detection history is [0,0,0,0,0]. If the species is present but not detected, then the site occupancy probability history is $\Psi(1-p_1)(1-p_2)(1-p_3)(1-p_4)(1-p_5)$. The additional superscript $S-S_D$ is the total number of sites minus the sites where the species was detected. In the case that the species is in fact absent from the site, the probability is simply (1-$\hat{\Psi}$).

The most simple approach to occupancy modelling is to use a single-species, single-season occupancy model with survey-specific detection probabilities $\hat{p}$ (MacKenzie et al., 2002). These models can be calculated using the code library called 'unmarked' and its 'occu' function, written in R language (Fiske and Chandler, 2011). The detection probability and occupancy are modelled using logistic regression sub-models, which means that the occupancy model has a double right-hand side. These can incorporate observation and environmental detection co-variates. The results are then estimated in a Maximum Likelihood framework, which maximises the probability of the model given the data.

5.3.2.1 Treatment of the data

Since trapping rates were low in this study, this caused the estimates of $\hat{p}$ to be low, which can affect the subsequent modelling (Ahumada et al., 2013). As such the camera data were aggregated into periods of 10 days. This manipulation only affects $\hat{p}$ and not the final occupancy estimates, and is an established approach to deal with low detection probabilities (Ahumada et al., 2013; Sunarto et al., 2013). Additionally, the overall number of detections was low for each species identified in the study. Having few data points causes poor model performance and large uncertainties in the estimation of occupancy. This is a distinct problem for tigers which are the focal species of the project. However, since the concern in the current exercise is the conservation status of the tiger, those species which make up its prey base can be aggregated in order to develop more robust occupancy models and estimates. The precedent in the literature for doing this is Ahumada et al. (2013) who grouped sparse photographs of different species of cats into one group in order to make a 'cat occupancy' estimate. Species considered as tiger prey in this study were the medium-sized ungulates Bearded Pig (*Sus barbatus*, wild pig (*Sus Scrofa*), Greater Mouse Deer (*Tragulus napu*) the ground-dwelling primates pig and short tailed macaques (*Macaca fascicularis and nemestrina*), and one *Perissodactyla*, the Malayan tapir (*Tapirus indicus*).

5.3.3 Independent variables

Detection was modelled against variates which were hypothesised *a priori* to affect the probability of a photograph being taken. These were the distance to rivers, which has an influence on the type of vegetation; and the quantity of biomass which, as demonstrated in chapter 7 is directly related to the condition of the forest. Higher biomass forest is more mature, with a more well-developed canopy. A more intact canopy absorbs more of the light incident upon the forest, and hence reduces the amount available to the vegetation of the under-storey. This more open environment was hypothesised to increase the detection probability. Occupancy $\hat{\Psi}$ was similarly modelled against a combination of environmental covariates. These were the estimates of distances to: rivers (which determines the suitability of habitat for terrestrial mammals); and the forest edge (hypothesised to have an impact due to 'edge effects' e.g. Sunarto et al. (2013)). The estimate of biomass in 2007 was also added, with higher biomass forest hypothesised to be less disturbed and better quality habitat for forest mammals.

The mean biomass at the sites where cameras were located was 151 Mg ha^{-1}; the mean distance to rivers was 1.6km, and the mean distance to forest edge was 1.4km. The summary statistics for the independent variables extracted for the sites at which the cameras were located are set out in table 5.1.

Distance to rivers m	Distance to forest edge m	Biomass Mg ha^{-1}
Min. : 6711	Min. : 107.8	Min. : 0.37
1st Qu.: 364.5	1st Qu.: 138.4	1st Qu.:112.09
Median : 885.9	Median : 923.5	Median :180.44
Mean :1653.9	Mean :1473.3	Mean :151.36
3rd Qu.:2734.9	3rd Qu.:2355.6	3rd Qu.:215.58
Max. :7603.4	Max. :5212.0	Max. :235.90

Table 5.1: Summary statistics for the independent variables for camera trapping

5.3.4 Model specification and selection

All modelling was then performed using the unmarked package (Fiske and Chandler, 2011). In order to select the final models to make the occupancy assessment for both tigers and their prey, saturated models were first fitted for both the detection and occupancy sub-models. The saturated models included the main effects (distance from rivers, forest edge and the estimated 2007 forest biomass), and also two-way interaction terms between the distance to rivers, forest edge and biomass.

The candidate models are listed in table 5.2. Of these candidate models, the relative values of Aikake's Information Criterion (Burnham and Anderson, 2002) were explored using the modSel function in unmarked (Fiske and Chandler, 2011) which summarises model values. The AIC value provides an estimate of the relative quality of the different models in terms of the goodness of fit of the model to the data and the complexity of that model.

Then, in order to test the absolute fit of individual models to the observed data a parametric bootstrapping procedure was used. Sampling with replacement was simulated 10,000 times for each model. Specifically, this was done using the parboot function which is included in the unmarked package. This bootstrapping function simulates datasets based on the predicted values from the fitted model and then evaluates a fit-statistic for each of the simulations. The fit statistic used was χ^2, which is used to investigate whether distributions of categorical variables differ from one another. The R code for the χ^2 function was provided by Stolen (2012). In this case it was used to test the null hypothesis that there is a significant difference between the distributions of the observed data and the data from the fitted model. In this case p values smaller than the critical value of p=0.05 implied that there was a significant difference between the distributions and hence that the model did not fit.

0.	p(.) psi(Riv + (Riv2)+Bio+Edge+($Edge^2$))
1.	p(.) psi(Riv+(riv^2)+Edge+($Edge^2$)+ Bio + (Riv*Edge))
2.	p(.) psi(Riv+(riv^2)+Edge+($Edge^2$)+ Bio + (Riv*Bio))
3.	p(.) psi(Riv+Edge+Bio+(Riv*Bio))
4.	p(.) psi(Riv+Bio+(Riv*Bio))
5.	p(.) psi(Riv+Edge+Bio)
6.	p(.) psi(Edge+($Edge^2$)+Bio)
7.	p(.) psi(Riv+(riv^2))
8.	p(.) psi(Bio)
9.	p(.) psi(Edge)
10.	p(Bio) psi(Riv+(Riv^2))
11.	p(Bio) psi(Riv+(Riv^2)+ Edge+($Edge^2$)+Bio+(Riv*Edge))
12.	p(Bio) psi(Riv+(Riv^2)+ Edge+($Edge^2$)+Bio+Riv*Bio))
13.	p(Bio) psi(Riv+ Edge+ Bio + (Riv*Bio))
14.	p(Bio) psi(Riv+ Bio + (Riv*Bio))
15.	p(Bio) psi(Riv+Edge+Bio)
16.	p(Bio) psi(Edge+($Edge^2$)+Bio)
17.	p(Bio) psi(Bio)
18.	p(Bio) psi(Edge)
Constant	p(.) psi(.)

Table 5.2: The candidate models used for tiger and prey occupancy. Riv=distance from rivers. Bio=biomass estimated in 2007. Edge=distance from forest edge

5.4 Results

5.4.1 Camera trap history

In the data frame for the final tiger prey analysis there were a total of 138 periods (of 10 days) with no recorded capture. There were 76 periods which recorded at least one capture, and 326 periods with NAs which are caused when the cameras are not operating concurrently. This explanation is more readily understood by examining the visual operational history of the cameras as shown in figures 5.3 and 5.4. The 1s indicate where a camera was placed and recorded the target species, the 0s where cameras were operational but did not record the study species and the gaps where no camera was running.

Thirteen mammal species were recorded during the survey. The highest numbers of photographs of any tiger prey species were taken of the Greater Mouse Deer, Wild Pig and the ground-dwelling Pig-tailed Macaque. These data are summarised in table 5.3. The maximum number of prey observations per site was 15; mean=3.7; and number of sites with at least one detection=22. The naıve occupancy estimate was therefore 0.61 (detections in n sites / total n sites surveyed). For tigers, a total of 21 photographs were recorded in 5 of 36 sites, producing a naïve occupancy of 0.14. In the next sub-sections, the rationale for the selection of the tiger prey detection and occupancy sub-models is set out.

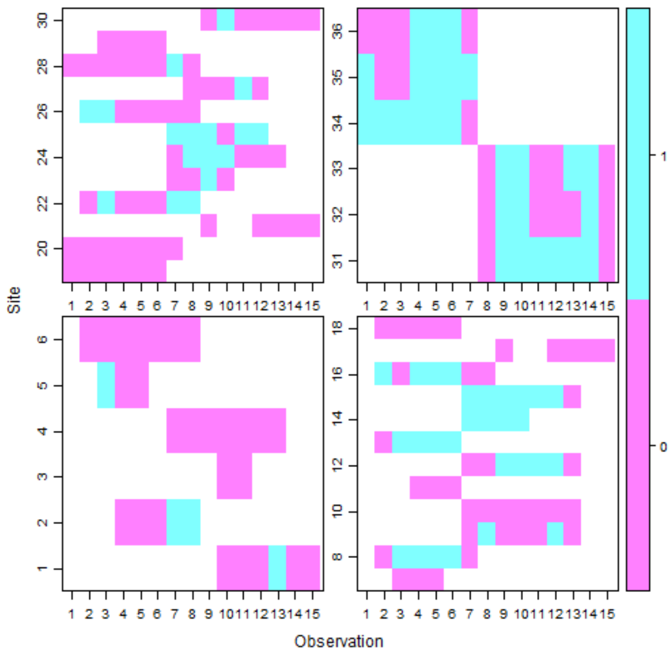


Figure 5.3: The operational history, and the detection/non-detection history of tiger prey. This is an automated graphical output from the unmarked package. The 1 (blue) signifies a detection, whereas the 0 (pink) signifies non-detection. Where the space is blank, no camera was in operation. The observations on the X axis are the number of trapping periods. The graphic is split into four panels in order to accommodate the detection histories from the 36 camera sites.

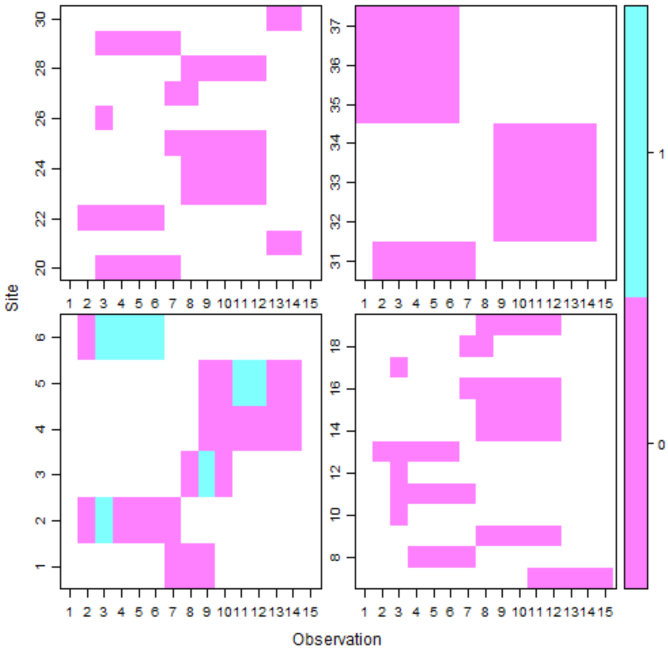


Figure 5.4: The operational history, and the detection/non-detection history of tiger prey. This is an automated graphical output from the unmarked package. The 1 (blue) signifies a detection, whereas the 0 (pink) signifies non-detection. Where the space is blank, no camera was in operation. The observations on the X axis are the number of trapping periods. The graphic is split into four panels in order to accommodate the detection histories from the 36 camera sites.

English name	**Latin name**	**Total events N**
Binturong	*Arctictis binturong*	1
Bearded Pig	*Sus barbatus*	5
Greater Mouse Deer	*Tragulus napu*	72
Leopard Cat	*Prionailurus bengalensis*	1
Long-tailed Macaque	*Macaca fascicularis*	4
Long-tailed Porcupine	*Trichys fasciculata*	1
Mongoose-Short-tailed	*Herpestes brachyura*	2
Pig-tailed Macaque	*Macaca nemestrina*	87
Porcupine	*Hystrix bracyura*	1
Sun Bear	*Helarctos malayanus*	3
Malayan tapir	*Tapirus indicus*	19
Sumatran Tiger	*Panthera tigris sumatrae*	21
Wild Pig	*Sus scrofa*	89

Table 5.3: A list of mammals photographed in Berbak National Park during the two camera trapping grids

Tiger prey						
Model	K	AIC	ΔAIC	AICwt	C.Wt	χ^2
Constant p(.)ψ(.)	2	259.06	0.00	0.43075	0.43	0.055
8. p(.)ψ(B)	3	260.01	0.95	0.26770	0.70	0.13
17. p(B)ψ(B)	4	261.57	2.51	0.12253	0.82	0.154
9. p(.)ψ(E)	3	262.84	3.79	0.06490	0.89	0.048
18. p(B)ψ(E)	4	264.52	5.46	0.02812	0.91	0.04
7. p(.)ψ(E)	4	264.58	5.53	0.02718	0.94	0.057
10. p(B)ψ(R+R^2)	5	266.58	7.53	0.010	0.95	0.06
4. p(.)ψ(R+E+B)	5	266.99	7.93	0.00817	0.98	.08
5. p(.)ψ(E+E^2+B)	5	268.01	8.95	0.00490	0.98	1.7
6. p(.)ψ(R+E+B+(R*B)) + R+ E+ B	6	268.63	9.57	0.00360	0.99	0.014
3. p(B)ψ(R+B+(R*B))	6	268.69	9.63	0.00350	0.99	0.068
14. p(B)ψ(R+E+B)	6	268.80	9.74	0.00331	0.99	0.76
15. p(B)ψ(E+E^2+B)	6	270.01	10.95	0.00180	1.00	0.12
16. p(.)ψ(R+R^2+E+B)	7	270.44	11.38	0.00146	1.00	0.32
0. p(B)ψ(R+E+B+(R*B))	7	270.63	11.57	0.00132	1.00	0.038
13. p(.)ψ(R+R^2+E+E^2+B+(B*R))	8	272.44	13.39	0.00053	1.00	0.07
2. p(.)ψ(R+R^2+B+E+E^2)	8	273.13	14.07	0.00038	1.00	0.033
1. p(B)ψ(R+R^2+E+E^2+B+R*B)	9	274.44	15.39	0.00020	1.00	0.039
12. p(B)ψ(R+R^2+E+E^2+B+(R*E))	9	275.13	16.07	0.00014	1.00	0.05
11. p(B)ψ(R+R^2+E+E)	9	275.13	16.07	0.00014	1.00	0.05

Table 5.4: Candidate models for tiger prey occupancy sub-models ranked by AIC, and reporting χ^2 for model fit. K =number of parameters; C.Wt = cumulative weight. B=forest biomass 2007. R=distance from nearest river. E=distance from forest edge.

Tigers						
Model	K	AIC	ΔAIC	AICwt	C.Wt	χ^2
15. p(B)psi(E+E^2+B)	6	48.30	0.00	7.3e-01	0.73	0.07
17. p(B)ψ(B)	4	51.87	3.58	1.2e-01	0.85	0.29
18. p(B)ψ(E)	4	53.41	5.12	5.7e-02	0.91	0.4
5. p(.)ψ(E+E^2+B)	5	54.45	6.16	3.4e-02	0.94	0.24
Constant p(.)ψ(.)	2	54.60	6.31	3.1e-02	0.98	0.41
8. p(.)ψ(B)	3	56.27	7.97	1.4e-02	0.99	0.05
9. p(.)ψ(E)	3	56.69	8.39	1.1e-02	1.00	0.6
7. p(.)ψ(E)	4	80.52	32.23	7.3e-08	1.00	0.99
4. p(.)ψ(R+E+B)	5	82.52	34.23	2.7e-08	1.00	0.99
6. p(.)ψ(R+E+B+(R*B))	5	82.52	34.23	2.7e-08	1.00	0.99
10. p(B)ψ(R+R^2)	5	82.52	34.23	2.7e-08	1.00	0.99
3. p(B)ψ(R+B+(R*B))	6	84.52	36.23	9.9e-09	1.00	0.99
14. p(B)ψ(R+E+B)	6	84.52	36.23	9.9e-09	1.00	0.99
16. p(.)ψ(R+R^2+E+B)	6	84.52	36.23	9.9e-09	1.00	0.99
13. p(.)ψ(R+R^2+E+E^2+B+(B*R))	7	86.52	38.23	3.7e-09	1.00	0.99
0. p(B)ψ(R+E+B+(R*B))	7	86.52	38.23	3.7e-09	1.00	0.99
1. p(B)ψ(R+R^2+E+E^2+B+R*B)	8	88.52	40.23	1.3e-09	1.00	0.99
2. p(.)ψ(R+R^2+B+E+E^2)	8	88.52	40.23	1.3e-09	1.00	0.99
11. p(B)ψ(R+R^2+E+E)	9	90.52	42.23	5.0e-10	1.00	0.99
12. p(B)ψ(R+R^2+E+E^2+B+(R*E))	9	90.52	42.23	5.0e-10	1.00	0.99

Table 5.5: Candidate tiger detection sub-models ranked by AIC, and reporting χ^2 for model fit. K =number of parameters; C.Wt = cumulative weight. B=forest biomass 2007. R=distance from nearest river. E=distance from forest edge.

5.4.2 Occupancy modelling for tigers and their prey

The results of the model selection process are shown in the tables 5.4 and 5.5. The results are ordered by the results of the AIC ranking. The final model selected for predicting occupancy for tiger prey was constant detection p(.) and occupancy dependent upon the forest biomass. The top AIC-based model was the constant model p(.)ψ(.). However, this was rejected based upon the results of the χ^2 test, which at 0.55 suggested that the modelled results and the original data were from different distributions. On the other hand, the χ^2 for the fitted values of the next best model, p(.)ψ(B), was 0.13. This suggested that the null hypothesis that the fitted values were from the same distributions should not be rejected, and thus that the model fitted the data. In order to obtain predicted values for occupancy probability, the mean of the biomass was used. The final estimate for prey occupancy probability was $\hat{\Psi}$=0.71, 95% CI=0.52:0.85. The final selected model for tigers was p(biomass)ψ(B). The first model suggested by the AIC value alone was p(.)ψ(.), but as with the tiger prey, this final model was selected based upon both the AIC value, and also the χ^2 value. The p(.)ψ(.) model χ^2 value was 0.07 suggesting that the model's predictions and the observed data were from different distributions. Both the tiger prey and tiger occupancy models were fitted using the site-specific biomass values. The predicted values were then derived by using the mean values of the biomass. The χ^2 for the simulated dataset from this model was 0.29. The fitted occupancy value when using the minimum level of biomass was $\hat{\Psi}$=0.27, 95% CI=0.14:0.45.

5.5 Discussion

Implications for project impact assessment and causal inference.

These results provide the project's first quantified biodiversity baseline, which could be used for an assessment of project performance. To do this, ideally the same camera sites would need to be resampled following ZSL's intervention to standardise the environmental covariate fixed effects; and the analysis would need to use the same definition of a time period for each camera (10 days) in order to standardise the estimates of $\hat{p}$. Wibisono et al. (2011) suggest a period of five years between repeat occupancy surveys, although there is no data presented as to why this period should be chosen. On the contrary, there is evidence that annual estimates of change can be made (Ahumada et al., 2013). If there is an increase in occupancy, if analysed robustly, this could be attributed to the actions of the project. To be robust in this assessment, a future analysis would need to control for variations in the population due to unobservable factors, for instance site specific differences in food supply. Ideally to do this the results would be considered alongside the trend in a control site without a policy intervention. In practice, the probability of being able to do this will increase as the costs of cameras falls. New cameras can be left running for months at a time, which further reduces the costs of data collection. Nonetheless, this assumes that suitable control sites can be found easily. As is shown in chapter 10, a fundamental barrier to estimating change in the site is finding suitable comparators for the site receiving the additional policy. Because of the extensive habitat loss across Sumatra, there are now only a few tigers left in pockets of forest surrounded by a sea of humanity - see chapter 9 for images of extensive deforestation. This means that it is unlikely that there will be a good match for Berbak: the forest here is one of the last remaining blocks of habitat in this part of the island. Furthermore, whilst monitoring the tigers is important for attempting to measure the project impact, at some point there is a tradeoff between refining methods of causal inference for project impact on tiger populations which can only ever be indirectly regulated, versus the measurement of other correlates of tiger statues, principally the evidence of human efforts to kill them (Sommerville et al., 2011), and which can be directly regulated through enforcement activities.

Model performance and future impact assessment.

Significant changes of the tiger and prey occupancy would need to be greater than the confidence intervals of the original and post-project estimates. Continuing data collection and model development will therefore be a crucial part of project activities, in order to demonstrate to potential credit buyers and to a CCBA auditor that the project can provide biodiversity benefits. Nonetheless, mathematicians have begun to question whether occupancy modelling is *necessarily* the gold standard to measure population attributes in wildlife ecology (Welsh et al., 2013). These authors highlight how when abundance varies across space and when detection is dependent upon abundance, occupancy models can suffer bias which is as bad as if detection probability was ignored in the first instance. In their simulations, even in ideal conditions, occupancy estimates are variable, because of multiple solutions arising to equations under maximum likelihood estimation. This may present a challenge to the approach of Ahumada et al. (2013) measuring occupancy change over time. Moreover, because individual tigers can be recognisable in photographs, given sufficient data, other methods to determine population attributes are available. Specifically, capture-mark-recapture exercises can allow abundance and density estimates (Karanth et al., 2006; Sharma et al., 2010), which option should be explored if more data becomes available.

Research and development yields tools that provide valuable information in an applied setting that help inform decision making processes. However the methods used will continue to be refined over time. Having credible windows onto attributes of tigers at a site should provide more than sufficiently convincing for an auditor and credit buyers, which is one main objective of the work. Nonetheless, some authors have questioned the idea *per se* of trying to measure the status of rare animals (Sommerville et al., 2011). They instead propose that changes in the rates of anthropogenic drivers of species loss be used as more powerful indicators of conservation project impacts than the species population statistics themselves. At Berbak, repeat detection/non-detection surveys for tiger snares could be used for instance. This could provide an interesting direction for future applied research, and the results considered with data from other sources.

Triangulation with other data sources.

From a broader perspective, tiger and prey occupancy probability estimates could be also triangulated with other research in order to develop a more holistic picture of biodiversity and tiger conservation at Berbak. This perspective is based on the notion that evidence from multiple sources is more likely to provide a true picture of the nature of a system than choosing one piece of evidence such as habitat loss alone. First, from the camera trap data, it is possible to say that tigers are present and breeding at the site: video footage from cameras in 2013 revealed a parent with two cubs. Second, it is possible currently to estimate tiger prey occupancy probability. This is important because there is a direct relationship between tiger population status and prey status (Karanth et al., 2004), and more generally between prey biomass and carnivore density (Carbone and Gittleman, 2002). Third, there is direct relationship between anthropogenic pressures and species status (Sommerville et al., 2011); in this case hunting and the number of tigers. Incidental encounters with tiger snares are being recorded by the project, but a more systematised approach coordinated with park rangers could allow for quantification of occupancy probability of snares for instance. This statistic would be directly correlated with hunting effort, and allow measurement of change against a baseline, and therefore provide another piece of information for project impact assessment. Fifth, there is a relationship between habitat quality, extent, and loss, and tiger density/occupancy in Sumatra (Sunarto et al., 2013; Wibisono et al., 2011; Sunarto et al., 2012). Chapter 7, of this thesis shows how it is possible to use the most recent technologies to quantify forest attributes including change even in cloud-covered regions. By considering these five distinct pieces of information together, even in the absence of an occupancy statistic for tigers with narrower confidence intervals, it is possible to quantify changes in the correlates of tiger occupancy.

Baseline conditions.

Once the baseline occupancy for tigers is considered robust for Berbak, the next stage will be to consider the change in that occupancy (Ahumada et al., 2013). This raises questions over whether change can necessarily be negative or positive. This is because if tigers are already at the current maximum carrying capacity for the park, it would be unlikely for occupancy to increase. On the other hand it is certainly possible for future change to be negative: (the tigers could go locally extinct). Yet, it is not known whether present occupancy reflects carrying capacity. This is a crucial point for impact detection. To re-iterate, if the Berbak fauna is currently in-tact, then it would not be likely to see occupancy increase following the project intervention. Rather, occupancy may be expected to remain constant or decline at a less steep rate than the surrounding landscape. This would represent 'biodiversity additionality', analogous to REDD+ additionality. To continue the analogy, the area of forest cannot greatly increase at Berbak, because most of the park is still forest, but it could be deforested at a slower rate than the surrounding landscape. Once again, this serves to highlight the importance of selecting credible counter-factuals.

Uncertainty in ranging responses to density changes

Additional uncertainty derives from unquantified relationships between the ranging behaviour of carnivores when the population is reduced independently of prey depletion. So, whilst it is known for instance that carnivore density is constrained by the amount of energy available in the prey biomass (Carbone and Gittleman, 2002), carnivore density also co-varies with exogenously imposed constraints on abundance such as human hunting. Yet it is unknown currently whether tiger ranges covary with abundance, controlling for prey availability. Following removal of tigers from a population the remaining individuals could a) retain the smaller ranges from the previous equilibrium, therefore leaving unoccupied 'gaps' without tigers in the landscape, or b) expand their territories to include those of the now-removed individuals. The implication for monitoring is that if people were hunting tigers from a site, then in situation a) we would expect to see reductions in occupancy in the cells where tigers had been killed, but no change in occupancy of other cells. However, in situation b) we might expect to continue to see similar occupancy rates across the landscape as the remaining individuals expand their range, but a reduction in detection probability. Given this uncertainty, any significant changes in detection probability at a site over time larger than the confidence intervals of both estimates should perhaps be of equal importance for assessing the population status of tigers as the changes in the level of occupancy. Clearly if both occupancy and detection probability decrease, it is unlikely that the status of the tiger population is improving. However if occupancy remains high but detection falls significantly there is the possibility of a population reduction. This provides interesting questions for future research, and whilst it remains unanswered, the problem needs at least to be acknowledged here.

A further potential problem with the camera trapping analysis presented here concerns the tiger prey species. Multiple species were aggregated in order to provide an estimate of the occupancy of tiger prey overall. This was because the species of principal concern to the project and probably for carbon credit investors, is the sumatran tiger rather than any of the prey species individually. However a problem may arise if there are changes of the composition of the prey group over time, for instance if there is increased human hunting pressure on deer and the population falls, but the number of wild pig increases. If the changes in the status of these species were approximately equal but with different signs, then the occupancy model would not record and changes in the prey status. For an assessment of biodiversity more generally then, individual occupancy models could be created for each of the prey species individually if sufficient data is available.

Project certification and credit pricing.

It is likely that the Berbak project will require CCBA certification in order to gain market access for its credits, since so many buyers demand this quality control (Diaz et al., 2011). This means that the Berbak project needs to measure its performance not only reducing emissions but in conserving its most charismatic species. This chapter has tested an approach to do this, and provided a baseline against which future changes can be measured. Moreover this chapter has demonstrated that the approach can work in a peat swamp environment which is very difficult to work in. The efficiency of this approach can also be expected to increase as camera technology improves, meaning that the camera units can be left for longer in the field and the price per camera unit falls. This should reduce the costs to the project of monitoring biodiversity: if more cameras can be left operating in the field for longer, the costs of hiring teams to run expeditions into the forest to change camera batteries and cards can be reduced.

Whilst monitoring costs could fall, there are some reasons for anticipating a higher carbon price for credits which are associated with tiger conservation. In experiments to estimate the value of different species, respondents regularly state preferences for large, powerful and dangerous mammals with binocular vision e.g. Kontoleon and Swanson (2003). Tigers are a prime example of a powerful species that are used as a 'flagship' to raise conservation funds and attention internationally. ZSL hopes that by simultaneously conserving tigers and reducing carbon emissions, they will attract a higher price for carbon credits generated from Berbak. Unfortunately to date there is no evidence in the voluntary market of a biodiversity premium price being paid (Diaz et al., 2011). Nonetheless, the voluntary market on which that report is based is very small, and moreover the report emphasises that voluntary trades are made over-the-counter between willing buyer and willing seller, rather than in a liquid dynamic market place with spot prices that might reveal a price premium. This suggests that tiger conservation may be able to generate higher carbon credit prices if the right credit buyer can be found who values tiger conservation.

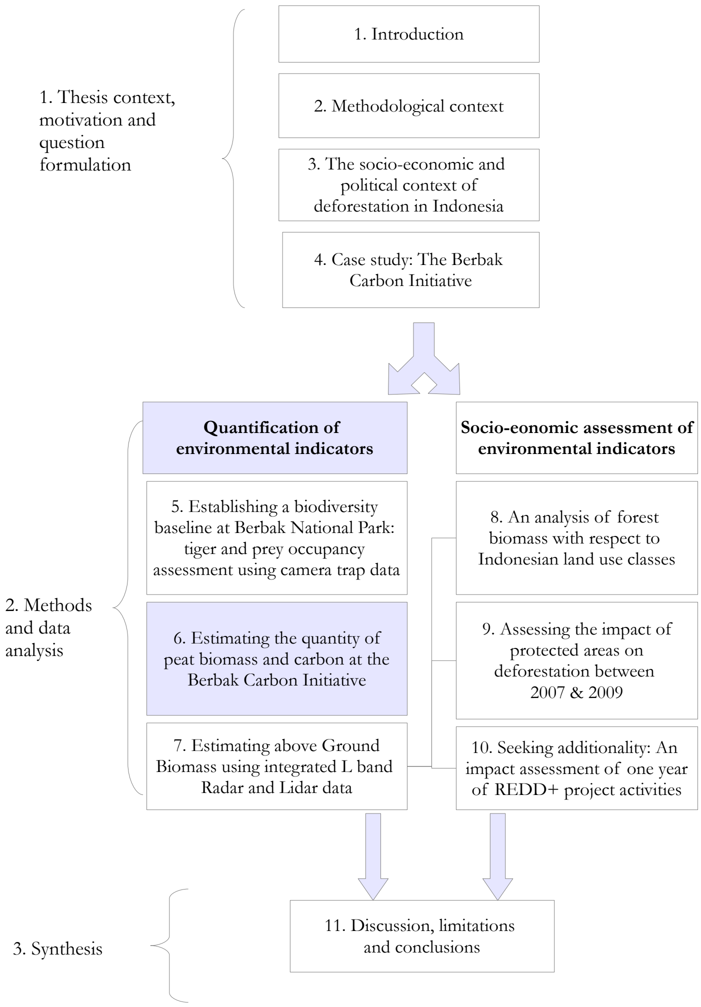
However, some of the problems described here surrounding causal inference and uncertainties in occupancy analysis are, with respect to the CCBA criteria, literally academic. This is because even producing a single photograph of a tiger at Berbak qualifies the project for 'Gold Standard' certification meaning that the project provides 'Exceptional Biodiversity Benefits' (CCB criterion GL3). This means it is not even strictly necessary to monitor changes in tiger population status to receive CCBA certification. Nonetheless, the risk of not doing so is that a decline in the population of the species the project was established to protect may go undetected. Detecting such declines early is probably the only hope for being able to act and prevent extinction, and hence loss of the Gold Standard. In addition, Berbak constitutes a key part of the landscape for conservation of the Sumatran tiger, and so ZSL and Berbak national park have responsibilities to maintain the tiger population under national law and Indonesia's national tiger recovery programme (Ministry of Forestry, 2010). Because of the importance of the tiger to Indonesia's biodiversity conservation goals, and their potential value to the project to raise at least the marketability if not the price of the credits, the rationale for focussing monitoring efforts on this species is clear.

Finally, as a REDD+ project the core activities still need to focus on the reduction of carbon emissions from the site resulting from deforestation and forest degradation, and from the draining and drying of peat. So it is to the quantification of carbon stocks that the thesis now turns: first to the quantification of peat carbon in the next chapter, and then to the quantification of forest carbon stocks in chapter

7.

Chapter 6

Estimating the quantity of peat biomass and carbon at the Berbak Carbon Initiative



6.1 Abstract

Peat swamp soils contain huge amounts of carbon. Drainage of peat swamp to access land leads to huge carbon dioxide emissions. Climate change mitigation strategies such as REDD+ are set to address emissions from this source in places like Indonesia which holds the largest stock of tropical peat soils. However the extent and volume of peat are still uncertain, which makes their management all the more difficult. REDD+ projects such as at Berbak need to quantify their peat carbon stocks and potential emissions in order to generate carbon credits. A consultancy company was tasked with developing a model to quantify peat stocks across the entire Indonesian archipelago. Yet did not perform well in the Berbak landscape. This left a large information gap for Indonesia and the Berbak project. To fill this gap, two options were explored, both based on 3D modelling. The approach was based on a classical model in which peat forms a dome shape on the landscape, which is deepest where its elevation is highest. So a relationships between 289 measured peat depth samples from Berbak and three different models of the surface of the earth were estimated to test for such a classical relationship at Berbak. However no distinct peat domes were apparent in the models of the earth's surface. Further, the relationships between the peat depth and the three earth surface models were poor (R^2 = 0.03,0.17,0.21). This directly contrasting findings in the literature. Because these relationships were weak, the geostatistical technique kriging was used instead to create a 3D model of the peat. This model was cross-validated with leave-one-out comparisons, estimating 6,554 x 10^6 m^3 peat within the border of the Berbak Carbon Initiative site, holding 380 x 10^6 Mg C.

6.2 Introduction

Tropical peatlands are a major store and sink of carbon (Sorensen, 1993; Page et al., 2002; Page, 2009; Page et al., 2007, 2011) They can store up to an order of magnitude more carbon than forest on mineral soils (Jaenicke et al., 2008). Indonesia has the largest area of tropical peatland within the borders of any country (Hooijer et al., 2012). However, these areas are now being exploited to provide access to timber and land for agricultural development (Miettinen et al., 2011). When they are drained and cleared, huge amounts of carbon are released to the atmosphere (Hooijer et al., 2012; Page et al., 2002). Peatland drainage, oxidation and fires now account for up to 3% of all anthropogenic carbon emissions(van der Werf et al., 2009). Accordingly peatlands have taken centre stage in Indonesia's climate mitigation plans through REDD+ (Austin et al., 2012; Paoli et al., 2010). For REDD+ and sustainable land management plans more generally, information on peatland extent and depth is essential. However there is a great deal of uncertainty in both of these metrics, since peat cannot be directly measured through remote sensing. The areas where the peat is found are also vast, remote and difficult to work in. The most recent method to estimate peatland extent and depth across Indonesia used regression models based on the position of rivers and other geomorphological landscape features to predict peat presence and depth across the landscape, in a programme called the Quick Assessment and Nationwide Screening; (QANS).

QANS involved the collaboration of NGOs working across Indonesia, contributing data to a Dutch environmental consultancy called Deltares, which built the final model for peatland extent and volume estimation. However, the approach was not successful in eastern Jambi and the area where the Berbak carbon initiative is located. This leaves a gap in Indonesia's inventory of peatland. This also presents a problem for the development of ZSL's pilot REDD+ project at the site: reductions in emissions from the peat at the site could generate large amounts of carbon credits. But without a credible baseline of peat carbon stocks, this will not be possible. This chapter addresses this information gap. The objectives are therefore to: 1. to estimate the quantity of total amount peat and carbon in the landscape surround the Berbak project; and 2. to calculate a potential emissions estimate that accounts for the fact that only that peat above the physical drainage limit is likely to be oxidised.

6.3 Methods

In order to calculate the volume at the Berbak site, the depth of the peat needs to be modelled across the landscape using the fragmentary data from point sampling of the peat soils. There are three different approaches to model the peat depth:

1. With the use of co-variates, develop a regression model and apply this across the landscape. This is the essence of the QANS approach: using landscape features such as distance to rivers and topography to predict peat depth.

2. By estimating of a relationship between the height of the surface of the earth (Digital Elevation Model;DEM) and measured peat depth e.g. (Jaenicke et al., 2008)). The depth can then be extrapolated across the landscape from the DEM to produce a 3D model. This requires the production of DEMs which control for the height of the forest vegetation over the surface of the earth.

3. Finally, by exploiting spatial autocorrelation in the depth data in order to make predictions by either a) kriging or b) inverse distance weighting (IDW), and thereby similarly producing a 3D model.

As set out in the introduction, the principal motivation for this chapter was that the QANS estimation for the depth and extent of peatland was not successful for the landscape surrounding. The remaining options are therefore 2 and 3 above, which are the focus of this chapter and addressed in order. Option 2 uses models of the earth's surface (Digital Elevation Models; DEMs) to determine the upper surface of the peat. If a robust correlation can be established between the peat depth and the DEM, then the remaining unobserved depth values can be predicted from the DEM. However, in the absence of a strong relationship between depth and the DEM, the remaining option 3) is to use Geostatistics such as kriging or Inverse Distance Weighting to model the unsampled peat depth.

Multiple steps were required in order to decide which option to take, and to achieve finally the chapter's two objectives. For clarity, the entire process is enumerated below, and set out in the flowchart 6.1.

1. Collect peat depth cores from the Berbak field site
2. Estimate the margins of the peatland using a combination of remotely sensed optical imagery and field data, where the peat depth was measured as 0m.

Create a digital elevation model (DEM) for the Berbak site using three different methods:

3. The raw SRTM data;
4. Spatial interpolation of the patches of bare earth revealed where the forest was burned (the bare earth krig DEM); and
5. A novel method developed for this thesis which involves estimating the vegetation height and subtracting it from raw Shuttle Radar Topography Mission (SRTM) data (a 'virtual deforestation' DEM).

Then estimate the volume of the peat at the site using:

6. The relationship between the DEM and peat depth if the relationship is robust (following (Jaenicke et al., 2008)), or
7. spatial interpolation (kriging) of the peat depth readings.

Then quantify the total amount of carbon stored in the peat by:

8. multiplying the volume estimate by the peat bulk density and the proportion of carbon in the peat.

Each of the numbered steps and are now discussed in detail.

6.3.1 Peat depth sampling

Peat depth samples were collected by ZSL at 211 separate sites across the Berbak landscape. To do this a 10m long soil core sampler was drilled into ground and through the peat soil layer until the mineral soil pan or bedrock was reached. The sampling locations were chosen by the Berbak project manager, and were intended

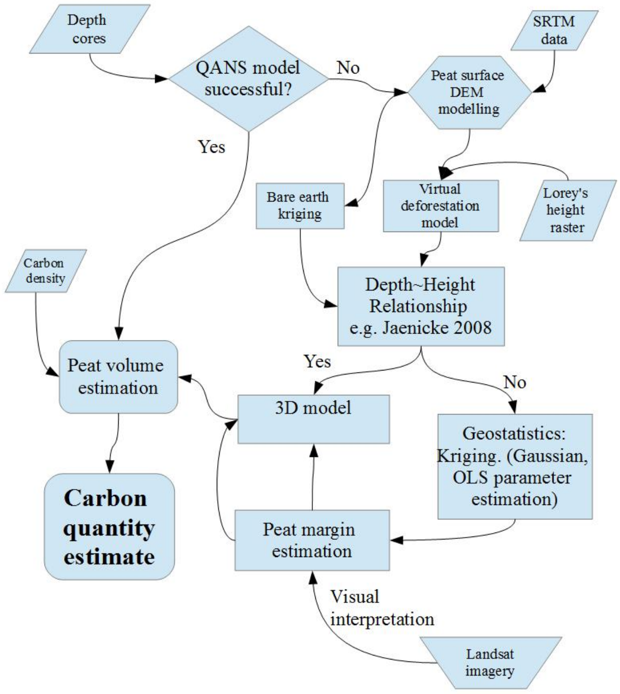


Figure 6.1: Peatland estimation processing chain

to provide a representative sample of the landscape. These ZSL data were supplemented with a further 78 depth samples provided by an environmental research company called Deltares Consultants, giving a total of 289 peat core readings.

6.3.1.1 Processing the optical remote sensing data

In order to identify the extent of the peatland, optical remote sensing data was used. These are essentially photographs of the surface of the earth from space. These data are freely available from NASA's LANDSAT programme. Data from the LANDSAT 7 was used by Jaenicke et al. (2008) to identify the peatland extent in their 3D modelling exercise. However, the imagery from this satellite is now degraded following the failure of a component called the Scan Line Corrector, which results in black data-less bands across the downloaded images. These gaps can be filled with other cloud-free imagery from a different time period. However such cloud free imagery is very rare because Berbak experiences high cloud cover in the wet season, and is shrouded by smoke from forest burning in the dry season. As such, even after attempting gap filling, the image quality was too low for peatland identification. Because it was not possible to fill the Landsat 7 gaps, data from a older satellite (Landsat 5) was used instead. Landsat 5 does not have any such problems with missing data.

The Berbak site is at the intersection of two paths of the Landssat satellite over the surface of the earth (Landsat paths 124 061 and 125 061). This means that two cloud-free images needed to be sourced and stitched together to create a mosaic of the entire study area. The only relatively smoke and cloud-free images were from 31 May 2009 for scene 125 061 (the western half of the mosaic) and from 20 August 2006 for scene 124 061 (the eastern side of the mosiac). These raw images were downloaded from the USGS website (http://glovis.usgs.gov/), and processed in PANCROMA software (http://www.pancroma.com/). Subsets of image bands 5,4 and 3 were created for both scenes at the area overlapping Berbak. Since the two images were taken by the satellite at different dates, there are differences in the spectral properties of each of them. Because of this it was necessary to normalise the data in the two images against one another to ensure that the final mosaic was consistent and so that peatland features could be identified. This relative normalisation was performed manually by extracting a selection of pixels from both scenes where the images overlapped. A relationship was then established between these extracted values using Reduced Major Axis regression, since which minimises the errors on both axes (as opposed to those on the Y axis as in ordinary least square regression), which is appropriate given that neither variables are controlled experimentally (Sokal and Rohlf, 1995; Legendre, 2013; R Core Team, 2013). The resulting relationships were then applied to the target scene (124 061) to normalise it.

6.3.2 Identifying the peat margins

At the border between peatland and mineral soils, called the 'frontier of accumulation', the peat is not expected to accumulate to levels above the mineral soils (Moore and Bellamy, 1947). This means that it was necessary to use multiple independent data sources to identify the peat margin, because height alone cannot provide information on the border. The hydrological characteristics (river networks) of the study region were an important indicator, since the basic model of peat formation requires shallow basins near rivers. Away from the zone of accumulation, elevation data from the DEM should indicate raised areas of peat accumulation in otherwise flat lowland plains, which is characteristic of the classic peat dome. In addition, the presence of mineral levees was also used as an indicator of peat margins. These are mineral deposits formed near the banks of rivers through repeated flooding of the river. Finally, blackwater rivers and lakes were searched for by eye in the imagery in the optical imagery (Jaenicke et al., 2008, 2010). However this approach was undermined in the present study by the fact that Berbak has already experienced significant human disturbance over a long period. As such many of these natural features have already been modified. Given this, anthropogenic features were also assessed as proxies for the presence of peat. For instance, canals are used to drain waterlogged peat and can be identified from the optical imagery as straight line features extending from fields into the main river channels. Nonetheless, this was still an arbitrary approach and ultimately it was more parsimonious to simply draw a minimum convex polygon using QGIS (QGIS Development Team, 2009) around peat depth measurements which were either a) at the point where depth readings changed from 0m to >0m, or b) were the outermost recording of any peat depth >0m.

6.3.3 Creating a digital elevation model (DEM) of the project area

Radar data from NASA's Shuttle Radar Topography Mission(SRTM) provided the initial digital elevation model (DEM). However the radar used by SRTM does not fully penetrate the forest canopy. As such it would be more accurate to say the SRTM data actually estimates a vegetation elevation model (VEM). Using this VEM to estimate peatland volume would introduce errors as peat elevation would be biased upwards. This presents a further problem for peat volume analyses, as well as to other remote sensing applications which require the use of a DEM derived from SRTM data. This problem can be resolved by using kriging on the areas of earth exposed by forest clearance and fires, or by subtracting independent estimates of forest height from the SRTM data in order to 'virtually deforest' the landscape. Both of these options are tested here, in addition to the use of the raw SRTM data unadjusted for vegetation height. i.e.:

1. using the raw SRTM data;
2. perform kriging on areas of the bare earth where forest has been burned or otherwise cleared (bare earth kriging DEM);
3. estimate forest height across the site and subtract this from the VEM (creating a virtual deforestation model).

6.3.3.1 Estimating a DEM by kriging the bare earth patches in SRTM data

To create the bare earth kriging DEM, a fishnet of points at 1000m intervals was created in QGIS across those areas which appeared as burned in the Landsat imagery. The SRTM values at each of these points was extracted using R. These height samples were then interpolated using kriging in the GeoR package (Ribeiro and Diggle, 2001) with a OLS model fitted to determine semivariogram parameters of sill and range.

6.3.3.2 Estimating an vegetation height layer to substract from the SRTM data

A raster of estimated forest height was produced across the landscape by using a novel integration of ALOS-PALSAR L-band radar data, Lidar transects from the GLAS ICESat mission. The full production process of the vegetation model is the focus of chapter 7 of this thesis as a component of the above forest biomass estimation. This vegetation model, which predicted forest heights of between 0 and 25m was directly substrated from the raw SRTM data to poduce the 'virtual deforestation' model.

6.3.3.3 Normalisation of the vegetation model and the SRTM data

Since the SRTM data and the vegetation model were produced using different technologies (C and L band radar respectively, which have different wavelengths) there was variation in the estimation of vegetation height for the same pixels between the two data sets. In order to be able to subtract the estimated vegetation layer from the VEM (thereby virtually deforesting the site), the vegetation layer needed to be relatively normalised to the VEM such that the estimated forest heights in each raster approximated one another. Both the PALSAR radar and SRTM data had already been warped in chapter 7 to ensure that the pixels directly overlapped one antother. Then, 1000 pixel values were randomly extracted from each raster using the sampleRandom command in R(Hijmans, 2013; R Core Team, 2013). This function takes a random sample from the pixel values of a Raster object without replacement. A linear regression was then performed on these data producing the equation Lorey = 2.79+ (0.4*SRTM). This equation was then applied to the Lorey's height estimate raster such that SRTM-12.79/0.40=Lorey to normalise the two layers. In order to test the normalisation procedure, a further 1000 pixel values were extracted from the normalised Lorey's height raster, and a futher a regression model was then run on these values to confirm the linear dependence upon the SRTM data. Finally, this normalised vegetation layer was from the DEM to provide the 'virtual deforestation' model.

6.3.4 Testing the three DEMs for dome-shaped structures

In order to assess the extent to which there was the classic dome-shaped surface at the site, the raw SRTM DEM; the bare earth kriged DEM; and the virtual deforestation DEM were sampled by creating 'virtual transects' across the rasters. In practice this involved drawing polylines in QGIS (QGIS Development Team, 2009) and extracting pixel values. These values were then plotted against distance along the transect and the scatter fitted with a smooth line in ggplot2 in R (Wickham, 2009; R Core Team, 2013) in order to test for the shape of an idealised domed surface.

6.3.5 The relationship between the three DEMs and the peat depth

For the next stage of this analysis data was extracted from the raw SRTM data; the bare earth DEM; and the virtual deforestation model at the 289 sites where peat-depth data had been taken. As a first stage of data analysis, the two DEMs were explored for dome-like features in the landscape which might indicate the presence of a classic peat dome. To do this, virtual transects were run across the surface of the two DEMs. In practice, this meant creating a vectors in QGIS along which points were made every 100m. Data was then extracted at these points from the two DEMs. These were then explored visually for the presence of a distinct dome shape. The next step was to attempt to establish a relationship between the height estimates from the DEMs and the point samples of the peat depth. To do this, values from both DEMs were extracted at the 289 locations where the peat had been sampled. To do this regressions using ordinary least square were performed to test the relationship between elevation from the three DEMs and the 289 measured peat depths.

6.3.6 Kriging the peat depth readings to create a 3D depth model

The final step was to using kriging to develop a 3D model of the peat depth, which would be independent of the surface modelling described above. This was done by using the GeoR package in R (Ribeiro and Diggle, 2001). This has pre-coded functions to make semivariograms and to produce predictive models based upon these. First, the peat depth readings were loaded into R, and a semivariogram was created from of the data using the variog function in GeoR. These were produced with a maximum distance of 20km, since this was on the order of magnitude of a peat dome (Jaenicke et al., 2008). The variograms allowed the estimation by eye of the values for range, sill, nugget and partial sill (see the background and literature review chapter for further details on these values). These were used for the initial values for an empirical variogram created using a function called 'variofit' in GeoR, programmed to determine a function using Ordinary Least Squares. This model provided the final empirical parameter values which were then used to fit the final spatial model and to predict values across the landscape, making a 3D model. Visual representations of the model were created using the rgdal package (Bivand et al., 2013).

6.3.6.1 Model diagnostics

Model diagnostics were performed by using a pre-built cross-validation procedure from GeoR package called xvalid (Ribeiro and Diggle, 2001). This function validates the model by comparing observed values with those predicted from kriging. The leave-one-out option was chosen, whereby each of the 289 data locations is removed in turn, and the depth at that location is predicted using the remaining 297 data points. The validation reports the errors between the estimated and observed values.

6.3.7 Calculating the volume of peat

For this final stage the total quantity of peat and carbon contained therein were calculated. First, the extent of the final 3D model was clipped to the extent of the minimum convex polygon created around the depth readings. The volume of this clipped model was then estimated by taking the sum of the depths per metre^2 across the model. The volume of carbon was calculated by multiplying the depth of the peat under the interpolated depth surface by dry bulk density:

$$\zeta = \gamma * \beta * \varphi \tag{6.1}$$

where ζ is the total quantity of carbon, γ is the volume of peat, β is the bulk density and φ is the proportion of carbon in the soil.

The literature widely uses a generic carbon content of 0.58, along with a dry bulk density of (0.1g cm $^{-3}$, which equates to 58kg m^{-3} e.g.(D et al., date). However site-specific data for Berbak suggests a carbon density of 73.8 Kg Cm^{-3} (data collected by Jenny Farmer/CIFOR), so this value was used for the carbon stock estimation.

6.4 Results

The 289 peat core samples were approximately normally distributed (see figure 6.2 with probability density curves plotted). The deepest peat recorded was 12m in the south west of the site, and the minimum was 0 in the mineral soils outside the peat formation zone. The mean depth was 5.5m.

6.4.1 The peat margins

Both the optical and topographical imagery derived from the remote sensing data were used to determine the estimate of the peat extent. Figure 6.3 provides Landsat 5 imagery showing the lattice of access roads and drainage canals used to drain water-logged soils in the region to the west of Berbak whilst 6.4 shows the broader landscape and the position of the peat core samples. The cores in the south west of this scene were amongst the deepest in the entire data set at depths up to 12m. However on the east and northern borders of Berbak the maximum extent of mineral soils in the core samples was located i.e. peat depths of 0m. Because the final analysis estimates the peatland border where the peat is still deep (because that is the last recorded data point), it is likely that the analysis underestimates the actual extent of the peatland.

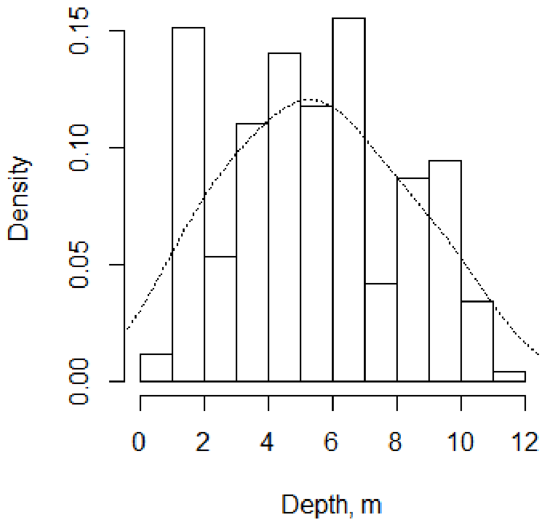


Figure 6.2: Histogram of the peat core data

6.4.2 Creation of a DEM for the project area

The bare earth kriging DEM produced a smooth surface estimate for the surface of the earth. These data were loaded into the R environment as the first DEM. The next approach for estimating the DEM was to create a virtual deforestation model. This required the normalisation of the SRTM and vegetation height models via regression upon extracted values from both datasets. The normalisation equation is summarised in table 6.1. The verification regression is provided in 6.2, which shows that following normalisation, the coefficient for the SRTM data regressed against the vegetation height was 1 ($p<0.001$).

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2.7898	0.7755	3.60	0.0003
SRTM2	0.4071	0.0295	13.82	0.0000

Table 6.1: Results of the Normalisation of the vegetation height model and SRTM data

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0240	1.9055	0.01	0.9899
SRTM2	1.0003	0.0724	13.82	0.0000

Table 6.2: Verification of the normalisation of the SRTM and Lorey's height estimate

As such, this virtual deforestation model was loaded into R as the second DEM. It produced a more noisy image than the smooth surface of the kriging (see figure 6.6),

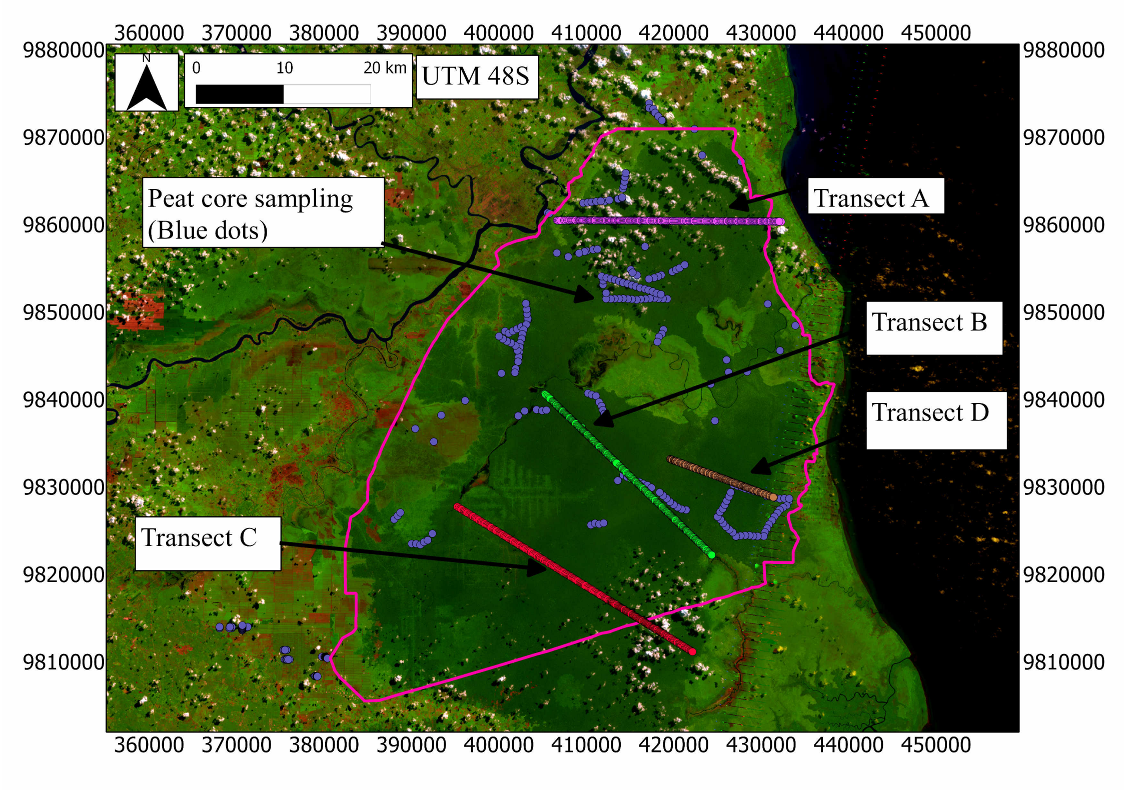


Figure 6.3: Outline of the Berbak project drawn in pink and peat core sample as blue points

because the kriging depends upon functional relationships between values of points in space, whereas the vegetation height model has independent per-pixel estimates of forest height. In addition, the SRTM data was collected in 2000, whereas the ALOS PALSAR data which was used to create the vegetation height model was collected in 2007. As such there may have also been real changes in the forest cover in the interceding time between the collection of the two datasets. A 3D representation of the results of the virtual deforestation process are shown in figure 6.5. The flat area in the centre of the model is the result of fire damage from the fires from the 'El Nino' seasons of 1996/7.

6.4.3 The peat surfaces and their relationships with peat depth

Following the creation of the DEMs, the next stage was to explore whether a dome-like shape was present, using the virtual transects across the surface of the DEMs shown in figure 6.6. Overall it was difficult to identify by eye any particularly distinct dome shapes in either raw SRTM data; the kriged surface DEM, or the the virtual deforestation DEM. The next stage of the analysis involved assessing a statistical relationship between the three DEMs and the peat depth readings (Jaenicke et al., 2008, 2010). There was little evidence of a relationship between peat depth readings and the raw SRTM DEM; the bare earth krig DEM; nor the virtual deforestation

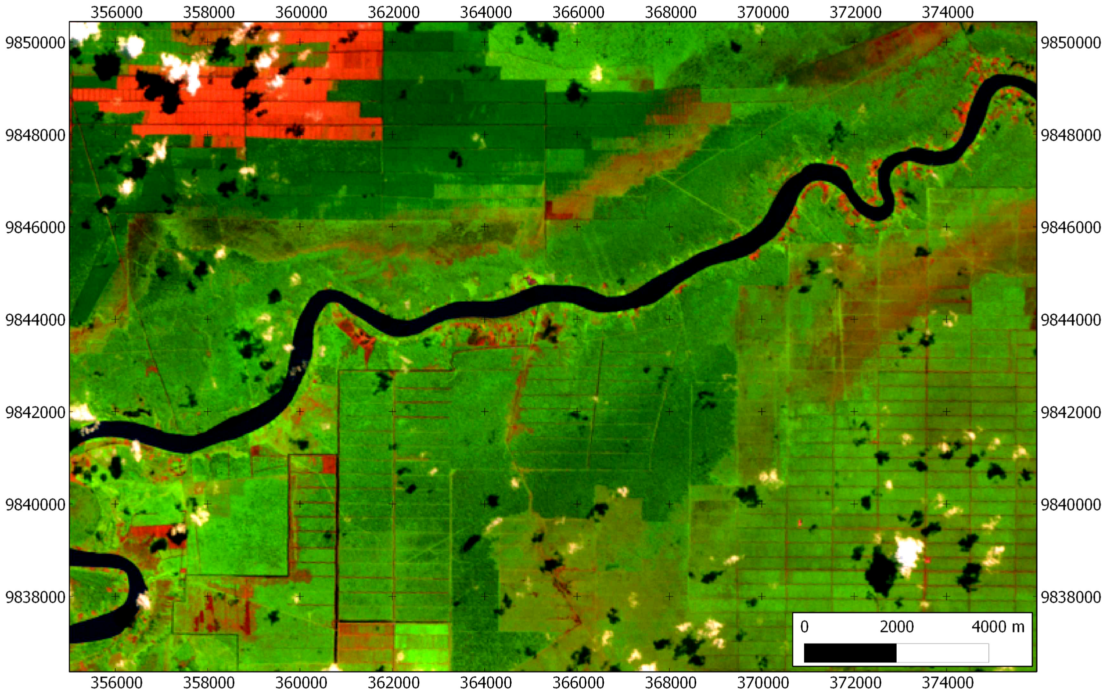


Figure 6.4: Lattice of canals draining the peatland

DEM. The R^2 values were 0.03, 0.17 and 0.21 respectively for the OLS regressions on peat depth. In the absence of a strong relationships it was not possible to emulate the methodology from Jaenicke et al. (2008, 2010) for the estimation of a 3D volume of peat for the Berbak area. Instead it was necessary to rely upon kriging of depth readings to make an estimation of the volume of peat.

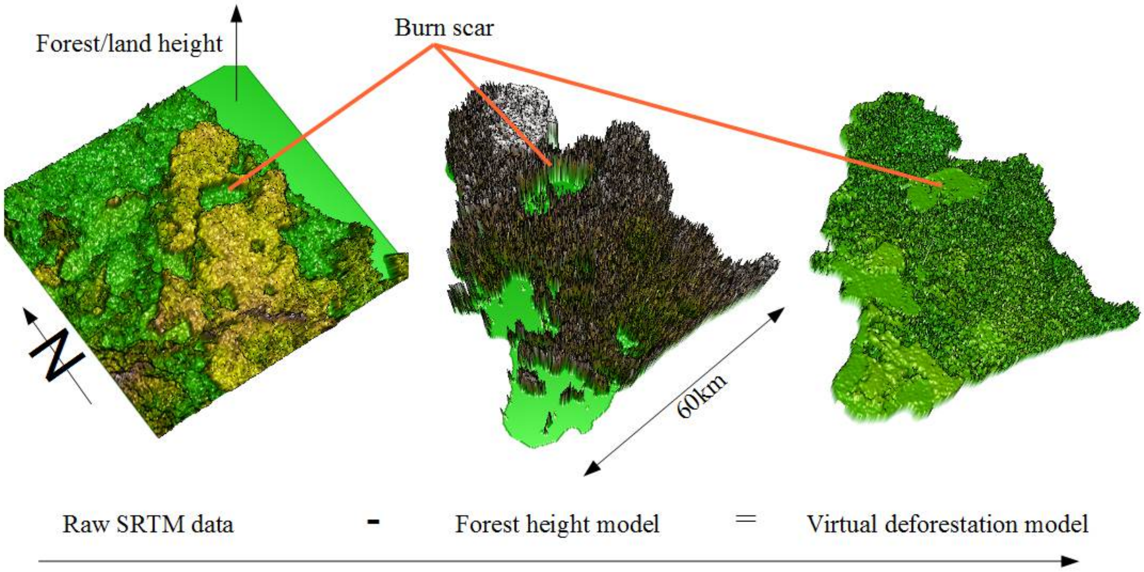
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	7.1572	0.6839	10.46	0.0000
Peat depth	-0.0678	0.0264	-2.57	0.0107
$R^2 = 0.03$. N=297.				

Table 6.3: Results of the regression between peat depth and the digital elevation model created directly with the SRTM data.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.6651	0.5487	3.03	0.0027
Peat depth	0.2908	0.0404	7.21	0.0000
$R^2 = 0.17$. N=297.				

Table 6.4: Results of the regression between peat depth and the surface model made by kriging the patches of bare earth in the SRTM data.

Figure 6.5: The 'virtual deforestation' model, with vegetation height subtracted from the srtm data



	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	5.5211	0.1527	36.16	0.0000
Peat depth	0.0684	0.0082	8.35	0.0000
$R^2 = 0.21$. N=297.				

Table 6.5: Results of the regression between peat depth and the surface model made by 'virtually deforesting' the project site.

6.4.4 Results of the Geo-statistics to estimate the peat volume

The empirical semivariogram estimated σ^2 (the partial sill) as 9.4 and ϕ (the range) as 8385.3. As shown in the diagnostics plot 6.8, the errors appear to be normally distributed, with the predicted values clustered around the predicted values.

Figure 6.6: From top to bottom: Transects A,B,C,D

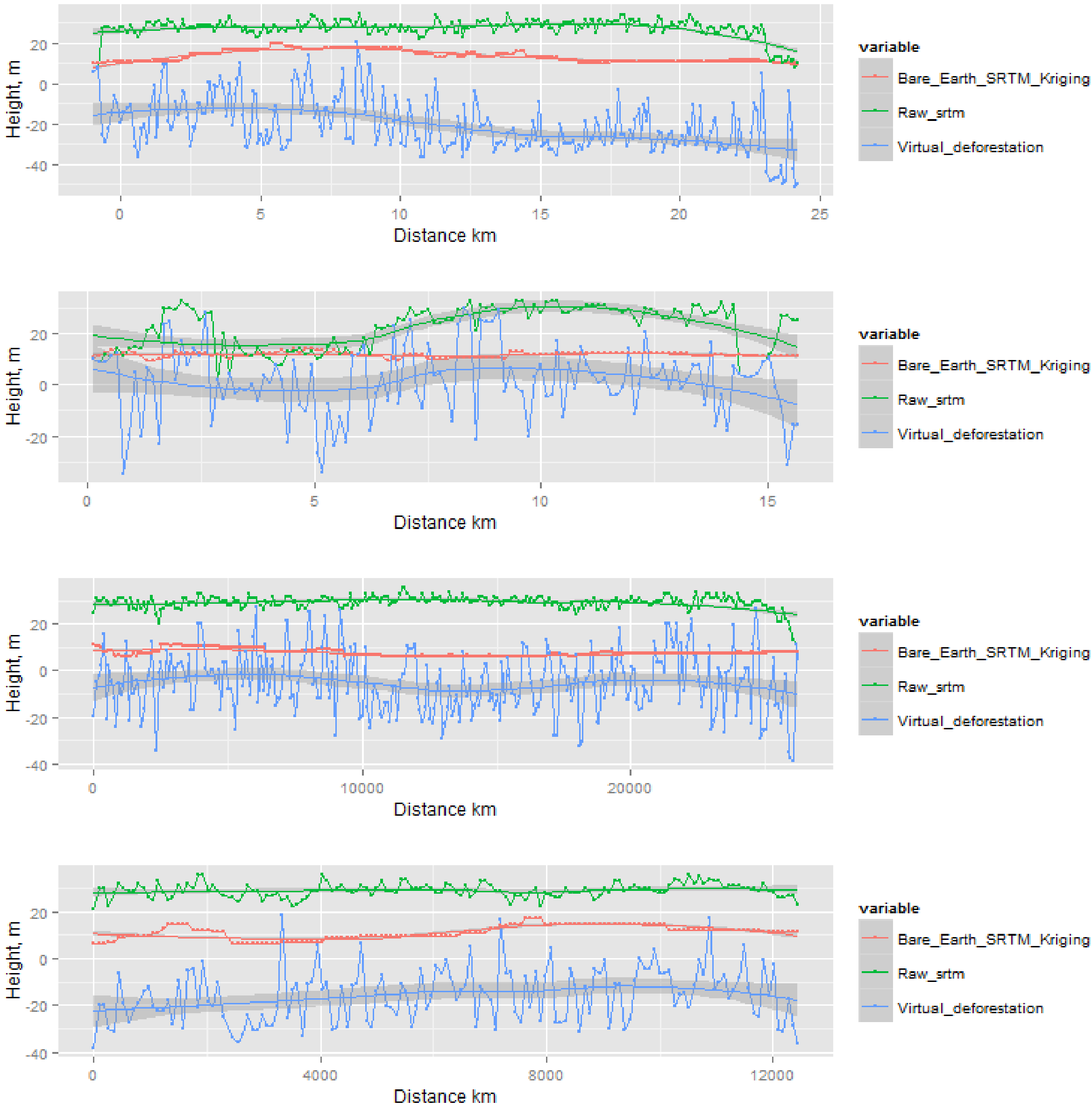


Figure 6.7: Semivariogram for the peat depth data

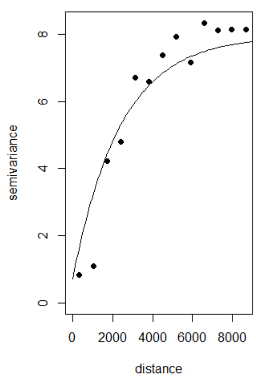
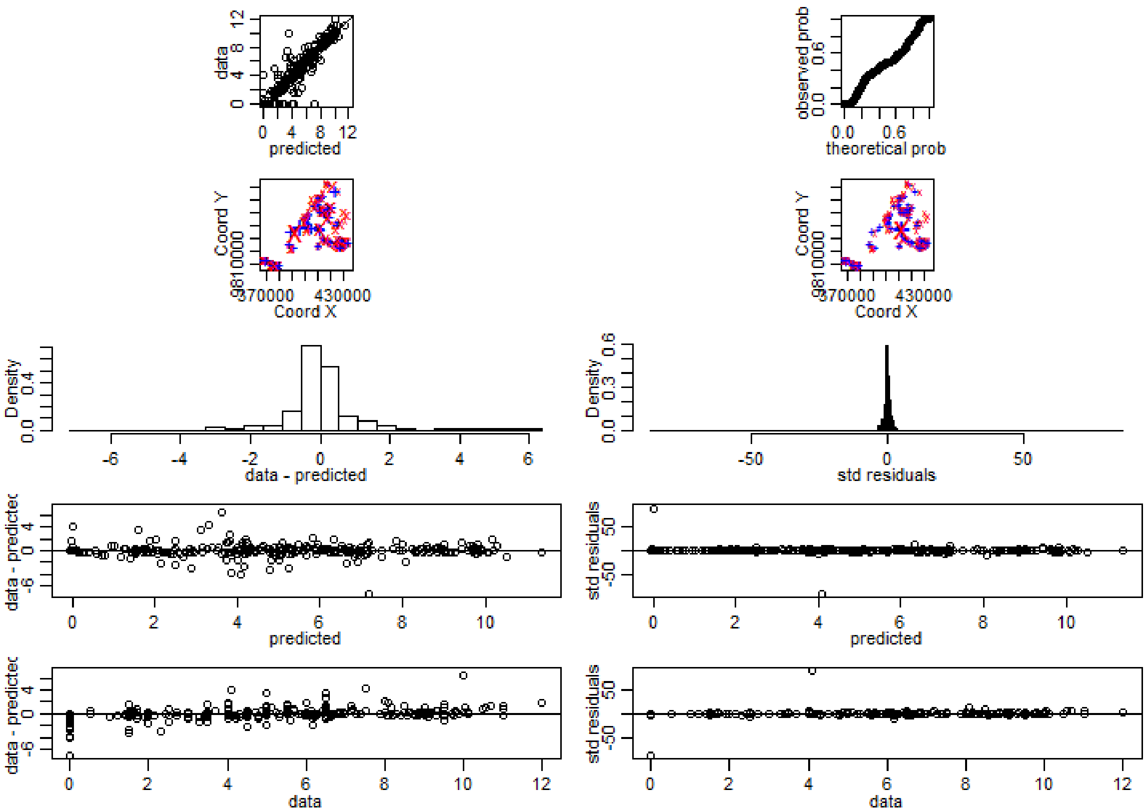
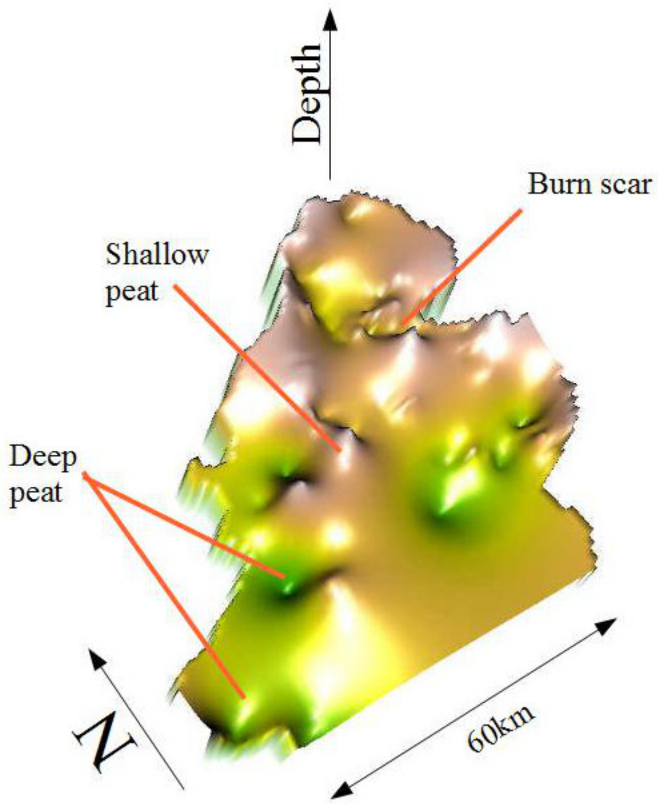


Figure 6.8: Model validation for the kriging of the peat depth data



The 3D model in figure 6.9 shows an undulating surface with particularly deep peat (marked in darker shades of green) in the south west of the image, and shallower (pink) peat towards the north. In order to compare the image with the other maps and diagrams in this thesis, the location of the burn scar is also highlighted.

Figure 6.9: 3D model of the peat at Berbak



The final total volume estimated using the 3D model developed by kriging was 6,554 x 10^6 m^3 peat. Using the peat carbon content estimate of J.Farmer (CIFOR/University of Aberdeen/unpublished data), this total volume of peat within the borders of the Berbak Carbon Initiative stores 380 x 10^6 Mg C.

6.5 Discussion

The estimation of the height of the peat surface led to the development of a new technique to 'virtually deforest' the study site. This may be useful in other contexts, and in other case study sites in the future. However, it is moreover a demonstration of the potential of technique, since future applications this will also depend upon future data availability, since the SRTM, ALOS PALSAR and Lidar data used to do this are not currently being collected. In the present applied context, it was not possible to establish a strong relationship with the the measured peat depth and the virtual deforestation model (nor for the bare earth kriged estimate or raw SRTM data). This directly contrasts with the work of Jaenicke et al. (2008, 2010) who found a strong relationship between the surface layer height and the peat depth, with correlations >r=0.8, r^2=0.64. In this case, with a weaker relationship, to extrapolate the relationship across the peat surface to establish peat depth. The weak relationships between the peat depth and peat surface height, and the poor performance of the QANS model in the Berbak area raises questions about the nature of the peat at the site, since it does not appear to be distributed in a similar way to other peatlands. In the virtual transects that were set across the surface of the three DEMs, no distinct dome shapes were apparent. This may be part of the explanation. In addition, there may have been issues with the peat depth data collected from the Berbak site. In particular with biased selection of the soil depth sites. Because of the logistical problems associated with field work in a tropical peat swamp forests, the field team collected depth readings near to rivers, but according to theory Moore and Bellamy (1947), the deep peat forms in the centre of accumulation zones which are furthest from rivers. This means that the depth readings may consistently underestimate the depth of the peat across the study site. This would be expected to reduce the volume of the peat estimated in the kriging exercise, compared to measurements in the middle of the accumulation zone. More data from the centre of the accumulation zone may address this problem, however in practice this is difficult given extremely limited access to the core forest zones at Berbak.

Kriging does not account for the theory behind the formation of peat, such as the distance to rivers, which are included as co-variates in the QANS model. However, given this approach did not work for the site, kriging does present a means to use an established geo-statistical technique to estimate a model. Moreover, the estimation of the volume of the peat also depends on the determination of the extent of the peat across the landscape, which introduces further errors into the process.

6.5.1 Errors

6.5.1.1 Peat margin estimation

Multiple sources of information were used to demarcate the peatland extent, including anthropogenic evidence (drainage canals), and observed peat depths of 0m. It was not possible to easily identify blackwater rivers and lakes from landsat imagery, as suggested by Jaenicke et al. (2008, 2010). This may have been due to the fact that those authors used Landsat 7 imagery instead of Landsat 5 as in the present study, or physical differences between the study areas. A minimum convex polygon was therefore the most parsimonious means to determine the peatland extent. However, some of the points used to make the polygon had recorded large depths, but were used since they were the outermost available data points to make the polygon. This is likely have resulted in an underestimate of the extent of the peatland in the Berbak area. Yet in the absence of additional data points it is not justifiable to expand the estimate of peat extent.

6.5.2 Implications for REDD+

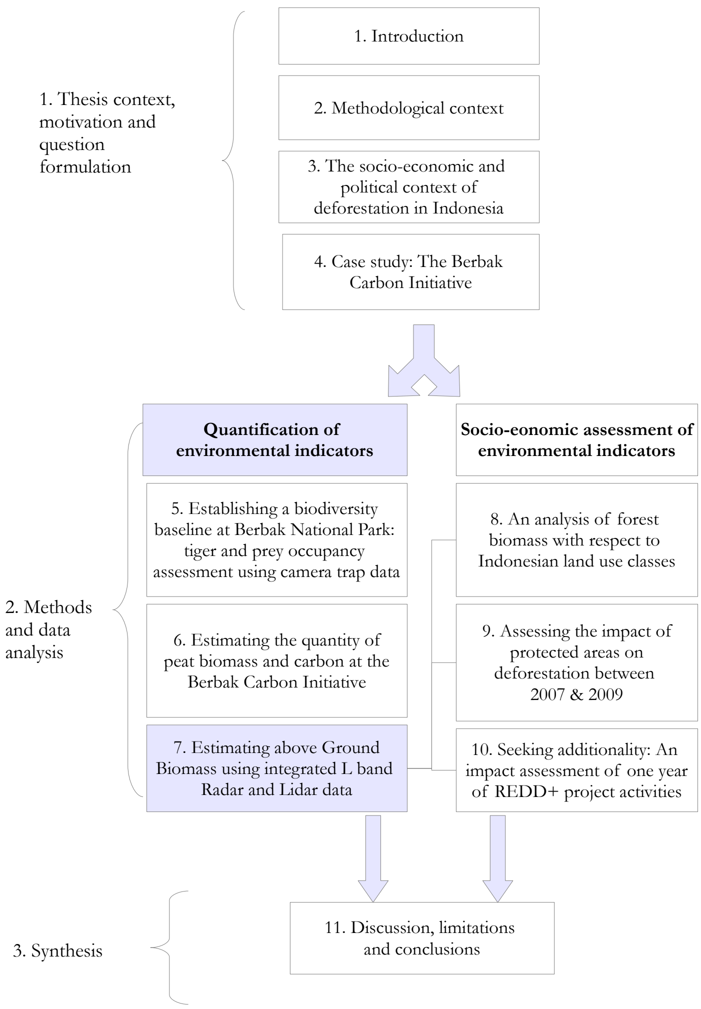
The quantity of carbon estimated here represents a significant store of carbon. In the absence of an intervention in the area, continued deforestation and forest degradation (see chapter 7) will cause the peat's carbon to oxidise and be transferred to the atmosphere. This serves to highlight the importance of developing land use management strategies that correctly price the emissions associated with land use change. However, despite the Indonesian government's first efforts at implementing REDD+ under the Norway agreement, the drainage and conversion of peatland continues apparently unabated. LANDSAT 8 imagery from 28 June 2013 (shown in chapter 4) shows that a huge new clear cut of 55km^2 has been created on Berbak's southern border. This is likely to have significant impacts on the hydrology of the area, and of course Berbak itself. In addition it will increase the ease of access for the area, presenting further challenges to achieving REDD+.

6.5.2.1 Future research

Were more data collection possible these could be used to refine the kriging models, and also to re-running the QANS models for the area. To achieve a better understanding of regional stocks, future research could aim to collect depth samples from the mangrove swamps of Sembilang National Park which is contiguous to the south of Berbak. Mangrove forests also form store large amounts of carbon, which is 'comprised of rootlets and soft (*parenchymatous*) parts of larger roots'...collect[ing] allochtonous peat-like sediments' (Joosten, 2009). been shown to store larger amounts of carbon than soils on mineral soils, at up to 1000 t C ha^{-1} (Donato et al., 2011).

Chapter 7

Estimating Above Ground Biomass using integrated L band Radar and Lidar data



7.1 Abstract

This chapter integrates Radar and Lidar data from earth-observing satellites to create an estimate of forest biomass in 2007. A total of 503±105 x 10^6 Mg are estimated in above ground biomass across a 7.2 Mha study area, which encompasses Jambi and South Sumatra provinces. By using a time series of radar data, it was possible to estimate annual changes in this biomass. A total of 229,760 ha of the study area were estimated to have been deforested between 2007 and 2009, a deforestation rate of 1.6% yr^{-1}. In the first year between 2007 and 2008, 18.5 ±3.9 x 10^6 Mg of biomass were cleared (3.6 % of the 2007 total), leading to estimated emissions of 34 ±7.1 x 10^6 Mg CO_2e. In the second year between 2008 and 2009, 13.1 ±2.7 x 10^6 Mg of biomass were cleared (2.6% of the 2007 total), leading to emissions of 24 ±5.0 x 10^6 Mg CO_2e. The results demonstrate the suitability of time-series of medium wavelength (L-band) radar data for forest change detection. It provides a contribution to research and development for remote sensing of forests in a region that is both undergoing rapid forest loss. Crucially, radar is able to penetrate smoke and cloud which normally obscure both forest and land cover change. This approach is a promising development for the monitoring of Indonesia's forests, including under REDD+.

7.2 Introduction

This chapter has two aims. The first is to establish a baseline estimate of above ground biomass of the study area using integrated analysis of radar backscatter and Lidar data. The second objective is to determine whether this technology can be used effectively for annual change detection in tropical forests, and could contribute to monitoring REDD+ activities. Measuring above ground biomass (AGB) loss is central to assessing REDD+ performance, and ideally analysts would have high resolution maps made for each year to detect annual change in AGB. Yet no satellite sensor directly measures biomass (Woodhouse et al., 2012), and relationships between remote sensing data and biomass tend to break down at medium to high biomass levels. Because of this, there there is a loss of sensitivity to high biomass forest (Mitchard et al., 2009a). This is a major issue when the objective of the monitoring exercise is to monitor high biomass tropical forest.

When optical data is used, cloud cover is a significant problem, because it obscures the target (the forest) from view. This means that researchers resort to making composite images from multiple years. However, in areas where land cover change is occurring rapidly, mature natural forest may be lost and rapidly replaced with secondary regrowth or a plantation, which ultimately looks similar to the natural forest. Where this happens, forest loss is masked (Hansen et al., 2009; Margono et al., 2012).

This is the central challenge of the chapter: to quantify forest biomass and short term change obscured by cloud. Lidar data can be used to produced biomass maps (Lefsky, 2010; Asner et al., 2010) but these are expensive to obtain. However Lidar samples are available from the (ICESat) Geoscience Laser Altimeter System (GLAS) sensor, which can be used in conjunction with secondary data sets that do span the landscape (Shugart et al., 2010).

Radar data has already been used to measure biomass in Kalimantan, Indonesia (Morel et al., 2011), but by using direct regression between backscatter and field biomass measurements without incorporating LiDAR. The novel approach presented here for Indonesia is to integrate three years of L-band Synthetic Aperture Radar (Phased Array L-band Synthetic Aperture Radar, PALSAR, wavelength 23cm; on board the Advanced Land Observing Satellite, ALOS) with four years of data from the space-borne LiDAR sensor (ICEsat GLAS; 10,944 footprints from 2003-2007), in order to greatly supplement a small biomass field dataset of 56 field plots. Using these data measure the quantity, extent and change in biomass over two years (2007 & 9) in eastern Sumatra, Indonesia.

7.3 Methods

7.3.1 Field plot data

A carbon stock assessment was performed during the initial phase of the ZSL project, which included AGB estimation using field plots. Plot locations were chosen through stratified random sampling, based upon a habitat classification map using 2008 SPOT V imagery analysed by ZSL Indonesia. In the field, plot locations were verified with a Garmin 60CsX handheld GPS unit. A total of 56 plots were sampled, with 36 in primary swamp forest, 14 in swamp bush and 6 in secondary peat swamp forest. In each plot, trees were sampled in a series of five nested sub-plots for different stem size classes. Specifically these were: a 10 x 10m subplot recording every tree between 15 and 30cm circumference; nested in a 20 x 20m subplot recording every stem between 30 and 105cm circumference; nested in a 20 x 125m plot recording every stem of 105cm circumference and above. The AGB for each tree in each sub-plot was then calculated using an allometric equation for wet tropical forests, where:

$$AGB = exp(-2.557 + 0.940 * \ln(\rho\delta^2\eta)) \tag{7.1}$$

Where ρ= oven-dry wood over green volume (wood density), δ=diameter at breast height (1.3 m), η= tree height (Chave et al., 2005). Wood densities were collected from the literature for Indonesia peat swamp trees (Murdiyarso et al., 2011b). Where trees are not individually identifiable in the field plots, the Food and Agriculture Organisation recommends an arithmetic mean for tree wood density. This is 0.57g cm^{-3} for Asia (Reyes et al., 1992), or a generic 0.58 g cm^{-3} (Chave et al., 2004)

This was done for a total of 1.3% stems in the 10 x 10m sub plots, 0.87% stems in the 20 x 20m, and 44% of stems in the 20 x 125m plots.

7.3.1.1 Calculating tree height

Tree height data was not recorded from the forest plots by the field team. Equations published by Morel et al. (2011) were therefore used to relate tree height to DBH for S.E. Asian trees, whereby height η:

For stems where $\delta < 20cm$:

$$\eta = 8.61 * ln(\delta) + (-8.85) \tag{7.2}$$

$$(r^2 = 0.16; p < 0.01)$$

and where $\delta > 20cm$:

$$\eta = 16.41 * \ln(\delta) + (-33.22) \tag{7.3}$$

$$(r^2 = 0.62; p = 0.001)$$

where δ is diameter at breast height. The estimated height for each stem was then used to calculate Lorey's height for each of the plots. Lorey's height weighs the contribution of trees to the stand height by their basal area. It is calculated by multiplying tree height η by its basal-area α, and dividing the sum of this by the total stand basal area.

$$Lorey'sheight = \frac{\sum(\eta \times \alpha)}{\sum(\alpha)} \tag{7.4}$$

7.3.1.2 Estimating the relationship between the measured biomass and height

The next step was to calibrate the relationship between plot-level AGB estimates and Lorey's height (L) estimated in the steps above. This involved following the approach of (Mitchard et al., 2012) and Saatchi et al. (2011), which is to estimate a non-linear least-squares regression: $y = a * (x^b)$. This was estimated using the NLS function in R (R Core Team, 2013).

7.3.2 Radar and LiDAR data

The Radar data are ALOS-PALSAR mosaics from 2007, 2008 and 2009 downloaded from the Japanese Aerospace Exploration Agency (JAXA) Kyoto and Carbon website. The Polarimetric L-band Synthetic Aperture Radar (PALSAR) data is collected in two polarisations: Horizontal-send Horizontal-receive (HH) and Horizontal-send Vertical-receive (HV), and is provided at a 50m resolution. Lidar data is taken from the ICESat GLAS sensor. These data were collected between 2003-2007, and provide waveforms for transects across the earth's surface. The final data used here were the estimates of Lorey's height from each waveform derived from coincident tropical ground data, as processed by Sassan Saatchi (Saatchi et al., 2011). The data already has some cloud filtering applied, but on examining the data visually there were clearly many points over areas that were known to be covered in forest (from field observations) but that were influenced by smoke and cloud cover because they had low lorey's height values. To deal with this the Lidar footprints were filtered for any false negatives. To do this an independent land cover data set from the European Space Agency (ESA) called GLOBCover was used (Bicheron et al., 2009). This provides estimated land cover type across the study area, and at 300m resolution it is the highest resolution land cover data available. Lidar footprints were removed from the dataset which had Lorey's height values of 0m but which were over forest in the GLOBECover data. By this process 11,031 Lidar footprints were removed that had a Lorey's height value of 0m and yet were over forest in the ESA dataset. This left 10,944 points remaining for calibrating the radar data.

The PALSAR DN data in both HH and HV polarisations at each of the Lidar points were extracted using IDL-ENVI 4.7 (EXCELIS). Since the Lidar footprints are 70m in diameter and therefore overlapped the 50m PALSAR pixels, the mean values of the four 50m pixels in the radar HV and HH data was extracted.

7.3.3 Calibration of the biomass, Lidar and radar data

7.3.3.1 Calibration of radar and Lidar data

For 2007 the cloud-filtered Lidar dataset was calibrated with the value of backscatter of the pixels in which the footprints fell. In practice, since the Lidar footprints are 70m in diameter and therefore overlap the 50m radar pixels, a mean the four coincident radar pixels was taken. The digital number (DN) PALSAR data values were converted into decibels (dB) using:

$$dB = 10 \times \log(DN^2) - 83 \tag{7.5}$$

In order to estimate the functional relationship between the Lorey's height readings from the Lidar data, and the PALSAR backscatter data, Reduced Major Axis (RMA) regression was used. This method minimizes the error on both the X and Y axes, which is pertinent to this case where errors exist on both axes and since neither variable is controlled experimentally (Sokal and Rohlf, 1995; Ryan et al., 2012).

The data was then 'binned', whereby the mean backscatter was calculated at each height using the 'aggregate' function in R (R Core Team, 2013; Hijmans, 2013). This was necessary because for an ideal regression a similar number of Lorey's height estimates are necessary at all radar backscatter levels. However Lidar data over this type of mixed and degraded forest landscape typically contains far more data points at lower values of Lorey's height, with very few readings greater than 30m. The relationships using the HV backscatter were superior to those developed using the HH backscatter, and the experiment was continued using this polarisation.

A physical limitation of the L-band radar data is that it does not fully penetrate the forest canopy, and the signal saturates at higher biomass levels. This is demonstrated by a collapse in the functional relationship between the Lorey's height measurement from Lidar and the backscatter, which occurs at approximately 25m Lorey's height in this instance, corresponding to 190.6 Mg ha^{-1}, and as shown in figure 7.3. To account for the collapse of the functional relationship at this point, the modelled biomass was limited to 190.6 Mg ha^{-1}. For any pixel with a predicted value greater than this limit, a mean biomass value was attributed. This value was taken from the Berbak field plots which had values of over 25m Lorey's height, which was 236Mg ha^{-1} (n=9; s.d.=75 Mg ha^{-1}). This is more conservative than the generic 350Mg ha^{-1} for Asian forests as suggested by the IPCC (Eggleston et al., 2006; Penman et al., 2003).

The functional relationships between backscatter and Lorey's height was then applied to the 2007 HV backscatter raster 7.2. This created a raster which estimated Lorey's height per pixel.

7.3.4 Radiometric normalisation of the HV backscatter rasters and additional processing

Annual variations in measurement conditions, such as moisture on the ground and in vegetation introduces variance in backscatter between years which does not constitute changes in forest cover that may be attributed to anthropogenic disturbance. In the wet tropics these changes can be large. For change analysis this represents a problem because any differencing between data sets over time to detect change could lead to errors whereby backscatter change actually reflects differences in measurement rather than actual changes in the properties of the attribute being measured, such as the forest in the present case. In order to correct for this, remote sensing data needs to be radiometrically normalised such that the measured properties of a pixel in year x approximate the properties of the pixel in year y where no land use change has occurred. In order to do this with the radar data, 500,000 pixels were sampled from each year of HV backscatter data. These data were used them to develop a linear relationship between each pixel over time, using Ranged Major Regression in R (Legendre, 2013), and assuming that the pixels which were deforested during the study period would constitute errors in the regression. The resulting relationship was then applied to the 2009 data such that the pixels in 2009 and 2008 approximated those in 2007.

7.3.4.1 Local terrain slope calculation

PALSAR backscatter is affected by topography. Because the sensor is sideways-looking, any slope facing the sensor will reflect more energy than slopes facing away from the sensor. This introduces errors into the data, since a deforested sensor-facing slope could reflect more energy than a forest-covered slope facing away from the sensor. The Kyoto & Carbon PALSAR mosaics have undergone some correction for geo-location errors caused by slopes, but are not radiometrically corrected for slopes, that is to say the brightness difference between slopes facing towards and away from the sensor still exist.

In order to remove areas of the radar scene which would have been affected by topography, a Local Terrain Slope (LTS) raster was created. The LTS is created as a function of the slope and aspect of the earth's surface. Slope and aspect were derived from a gap-filed Shuttle Ranging and Topography Mission (SRTM) data set processed and gap-filled by CGIAR (90m resolution; (Jarvis et al., 2008). Specifically, LTS is calculated for east-looking radar as:

$$LTS = \tan^{-1}(\tan\phi) \times \cos(\omega - 90) \tag{7.6}$$

where ϕ is slope and ω is aspect. Using this LTS layer any pixels for which the LTS was greater than 5 degrees were excluded from analysis, since this is when radar data is heavily affected by terrain and radar 'shadows'.

7.3.5 Creating the 2007 biomass layer

In order to create the final biomass map for 2007, the functional relationship between Lorey's height and HV backscatter (reported in table 7.2) was applied to the HV backscatter raster. This produced a raster of estimated Lorey's height. Then the relationship between Lorey's height and biomass (eqn. 7.8) was applied to the Lorey's height raster. The resulting biomass estimation rasters were processed at UTM projection (48S) at 100m resolution in order to allow stocks to be readily calculated per hectare.

Since this analysis concerns with the loss of natural forest, only pixels which had at least 53Mg biomass ha^{-1} in 2007 were considered in the change analysis. This is because in a study of forest classes in neighbouring Borneo using ALOS PALSAR data, Morel et al. (2011), found that this was the mean biomass of plantations, whereas values above this on average were remaining natural forests. This was also deemed to be in keeping with the definition of 'forest' under the Marrakesh Accords, as set out in chapter 3. This process excluded the creation of zero-probability zeroes when the differences in backscatter were calculated between years. In order to reduce any noise in the estimation of what constituted natural forest, a bespoke majority value moving window was programmed in R and applied to the natural forest estimate raster.

Next, flooded forest pixels were excluded. This was done by excluding any natural forest pixel, which had a ratio of HV / HH backscatter of less than 0.5. This is because in the HH polarisation, there is a double bounce of the radar signal between the water surface and the structure of the forest which increases the HH backscatter value relative to HV. By definition, pixels which were estimated in 2007 as having low levels of biomass cannot subsequently lose a great deal of biomass. Naïve differences in backscatter between years which include pixels with low biomass will therefore produce estimates of pixels that have experienced no change, but crucially which had a low or zero probability of losing biomass.

7.3.5.1 Exclusion of flooded areas

Seasonal flooding can cause changes in radar backscatter that could subsequently be misinterpreted as deforestation. Flooded forest has high backscatter values in the Horizontal send, Horizontal receive (HH) polarisation relative to the Horizontal send Vertical Receive (HV) polarisation. So flooded forest can be detected by looking at changes across space in the ratio of these two polarisations.A separate raster file was therefore calculated for HH/HV ratio. Any areas which were deemed to be natural forest (as calculated in the section above; >53 Mg ha^{-1} but which had an HH/HV ratio of <0.5 were excluded from the analysis. These areas are shown in figure 7.1.

In order to reduce noise in the flooded forest and non-forest/forest layers, a bespoke 5*5 pixel majority-value moving window was programmed in R based on the focal function from the raster package (R Core Team, 2013; Hijmans, 2013) and passed over each raster. This removed individual outlying pixels speckling the data.

7.3.6 Change detection: the determination of deforestation

Whilst there is small-scale degradation in addition to deforestation at the study site, we are concerned here with land use change as a binary, exclusive event. The threshold used to define change between years represents a tradeoff between sensitivity and uncertainty. The lower the threshold for change detection, the more sensitive the process is. Equally, the more sensitive the process is, then the greater the chances that errors in the normalisation process are detected as false positives. A level of 1.5dB was chosen since a change of this magnitude in what was assessed to be both natural and non-flooded forest (as defined above) would necessarily constitute a reduction in backscatter per pixel from a high value associated with high lorey's height and high biomass (relatively in-tact forest) to a low value associated with low lorey's height and biomass (deforested). This explanation is more readily understood with reference to figure 7.2.In order to detect change, each of the normalised scenes were subtracted from the preceding year. This provided change maps between 2007 and 8; between 2008 and 9 (and also between 2009 and 10 in chapter 10).

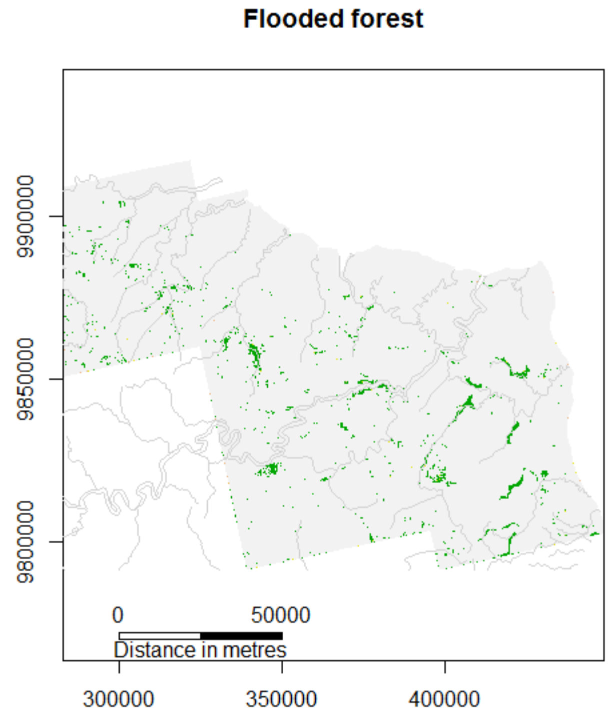


Figure 7.1: This map shows a close-up of the study area around Berbak national park. The light grey lines are rivers running through the area. The green pixels are those estimated to be natural flooded forest. These are pixels with an estimated biomass of > 53 Mg ha^{-1} but with HH/HV ratio of less than 0.5. This provides visual verification of the accuracy of the process, because the flooded pixels are clustered around the rivers

.

In summary, a pixel was only classified as having lost forest if it originally had a value of greater than 53 Mg ha^{-1} in 2007 and was not flooded (did not have a HH/HV value of greater than 0.5) and whose backscatter value was reduced by greater >1.5dB in the subsequent year.

7.3.7 Calculating errors and uncertainties

In a study estimating biomass there are a combination of random and systematic errors propagating throughout the calculations. Mitchard et al. (2011) characterises the errors as those concerning a) accuracy and b) precision. Accuracy concerns the distance of the mean from the true value and hence systematic biases, whereas precision concerns the distance of a measurement from the mean of multiple measurements of the same attribute and is this due to random errors. In a comprehensive review of errors in biomass estimations, Chave et al. (2004) highlight how in practice

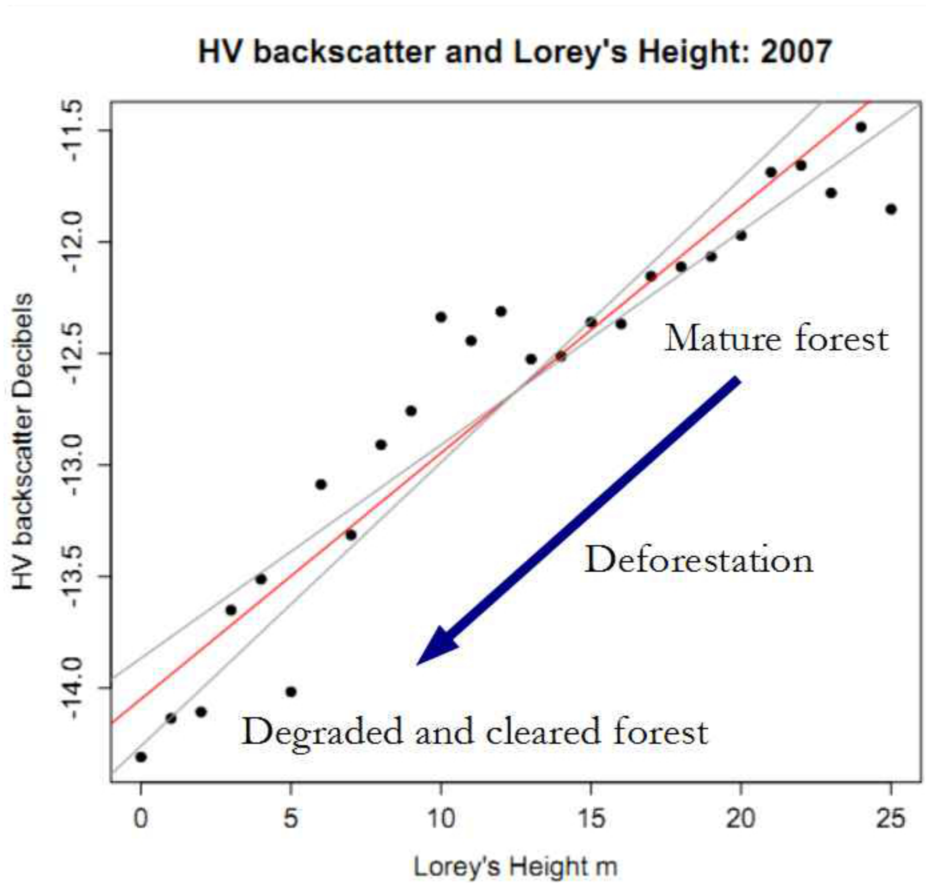


Figure 7.2: Linear relationship between backscatter and Lorey's height. This diagram demonstrates the logic behind the selection of the 1.5dB threshold for the definition of deforestation.

these errors can occur when for instance taking the measurements of the individual trees themselves; random errors in the identification of tree species; spatial errors relating to geo-location.

Each of the potential sources of error were considered in turn, namely those deriving from the binary forest map from the ESA; the tree species identification, and height and AGB estimations; errors in the Lidar data and Lorey's height estimates; and the relationships estimated between Lidar and radar backscatter. In order to combine these multiple errors, which are assumed to be uncorrelated, the following formula was used:

$$U_{total} = \sqrt{U_1^2 + ... + U_n^2} \tag{7.7}$$

7.4 Results

7.4.1 The relationships between Lorey's height and biomass; and HV Backscatter with Lorey's height

The non-linear regression on the Lorey's height and forest plot biomass estimate resulted in the power relationship in equation 7.8. The model results are summarised

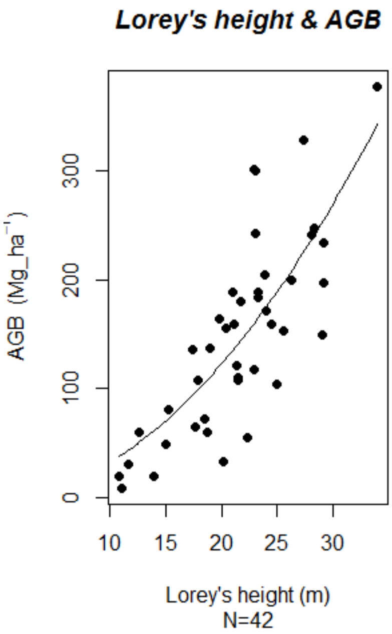


Figure 7.3: Non-linear relationship between Lorey's height and biomass

in 7.1, and a chart of the relationship shown in table 7.3. The modelled relationship between HV backscatter and Lorey's height is summarised in table 7.2. A plot of this relationship is provided in figure 7.4.

$$AGB = 0.37L^{1.94} \tag{7.8}$$

AGB and Lorey's height

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.3660	0.3357	1.090	0.28
Lorey exponent	1.9416	0.2840	6.838	p<0.001
Residual standard error: 55.76 on 40 degrees of freedom				
Number of iterations to convergence: 3				
Achieved convergence tolerance: 4.079e-06				

Table 7.1: Results of the non-linear regression between Lorey's height and the above ground biomass in the forest plots.

Data set	RMA Regression: PALSAR dB HV to Loreys height	RMSE	R^2
2007 HV dB	-12.7 + 0.068	2.6	0.94

Table 7.2: Regression equations for relationship between HV backscatter and Lorey's height

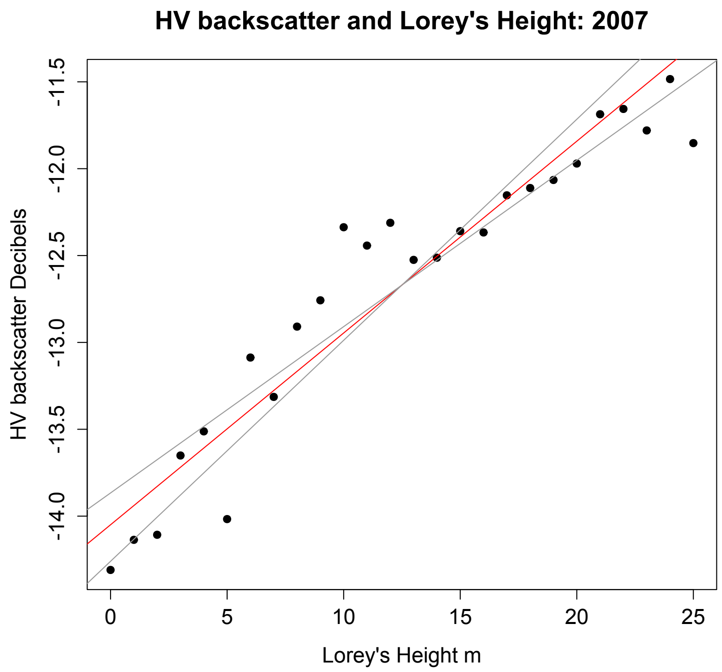


Figure 7.4: Linear relationship between backscatter and Lorey's height

7.4.2 Biomass stocks

In summary, integrating the field plot data, the Lorey's height data and the HV backscatter data; and excluding pixels with a terrain slope of greater than 5^o, and summing the stocks across all the 100m x 100m pixels produces an estimate of a total of 503±105 x 10^6 Mg of above ground biomass across the 7.2M ha study area for 2007.

7.4.3 Change detection

The data indicate rapid changes in biomass associated with large scale forest clearances over a two year period. A total of 229,760 pixels of 1ha were estimated to have been deforested over this period 2007-8; 2008-9.

- 2007:8 change is 18.5 ±3.9 x 10^6 Mg biomass and emissions of 34 ±7.1 x 10^6 Mg CO_2e.
- 2008:9 change is 13.1 x ±2.7 x 10^6 Mg biomass and emissions of 24 x ±5.0 x 10^6 Mg CO_2e.

For both the total biomass estimation and for the change in this, there are uncertainties. Their estimation is discussed below.

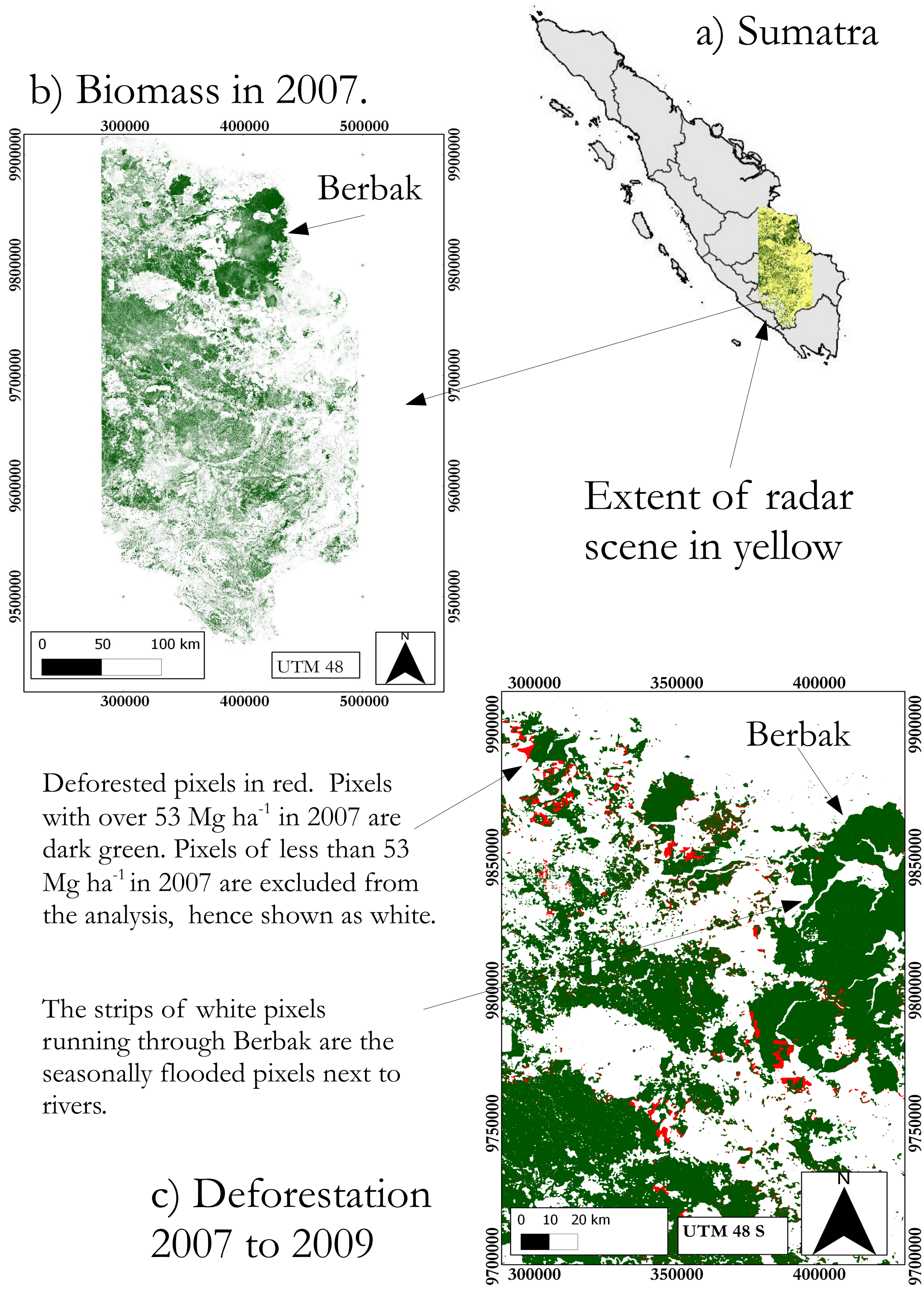


Figure 7.5: This diagram sets out: a) The location of the study area in Sumatra for this chapter as defined by the radar data. b) A map of the estimation of above ground biomass in 2007. The dark green pixels have the highest biomass, up to the maximum detectable limit using this technology of 236 Mg ha^{-1}. The relatively in-tact nature of Berbak national park is obvious since as a block of dark green in the image, except for the large white patch in the centre which is the area which burned down in the 1996/7 fires. c) The estimate of deforestation between 2007 and 2009. The red pixels show the areas which are estimated to have been deforested, which in this image are largely at the edge of the remaining high biomass forest, which is shown in dark green.

7.4.4 Errors and Uncertainties

7.4.4.1 Binary forest map from ESA

A binary forest/non-forest map from the 2005 ESA Globcover (MERIS) which was used to remove Lidar points which suffered cloud and smoke interference. This causes three potential problems: 1. this land cover classification contains errors, which are introduced into Lidar-backscatter relationships for non-forest vegetation. Indeed the classification's creators describe forest area overestimation where data is poor (Bicheron et al., 2009); 2. The Lidar data was collected between 2003 and 2007, and so overlap the MERIS dataset. Nonetheless, given the rate of change observed in this study, land cover change could have occurred between the collection of the two datasets; 3. The GLOBCOVER data has a relatively coarse resolution of 300m, meaning some non-forest areas will have been classified incorrectly as forest and vice versa. Artefacts relating to these errors will increase noise in the relationship shown in figure 7.4, but should not change the absolute relationship which is dominated by the signal in the data.

7.4.4.2 Tree species identification, height estimations and AGB estimations on forest plots

There were problems identifying tree species in some plots, which is a problem working in Indonesian peat swamp forests where tree identification is an ongoing scientific endeavour. This meant that it was not possible to specify wood densities for 1.3% stems in the 10 x 10m sub plots, 0.87% stems in the 20 x 20m, and 44% of stems in the 20 x 125m plots. Moreover the plot data did not contain tree height measurements, requiring using a published height to DBH relationship for S.E. Asia from Morel et al. (2011). Yet morphological differences between peat swamp trees and those measured by may introduce errors into our biomass estimations. In addition the model for stems where δ <20cm was poor with an R^2 value of only 0.16. This means that the predictions for the smaller stems are likely to have quite low accuracy, which is expected to have introduced further errors into the estimates of height. Another problem is that in order to calculate AGB, it was necessary to use pan-tropical rather than regional allometric equations. In order to account for these errors, a 20.3% error is ascribed to potential differences in regional estimates of biomass (Djomo et al., 2010).

7.4.4.3 Lidar and Lorey's height estimates

The relationship that was used to develop estimates of Lorey's height from Lidar returns is based upon field plots in the Amazon Lefsky (2010). To deal with the errors that this will create, a 5% error is ascribed to potential differences in regional estimates of Lorey's height from the waveforms as suggested by Mitchard et al. (2012).

7.4.4.4 Relationship between Lidar and radar backscatter

There are errors in the estimated relationship between the estimated Lorey's height and radar backscatter. The Root Mean Squared Error was used to quantify this, which is a measure of the difference between the values implied by an estimator in a statistical relationship and the true value of the parameter being estimated. For 2007 RMSE is 2.56Mg ha^{-1} (2.29 m).

7.4.4.5 Combining uncertainties

With 20.3% error for the biomass calculations for the trees and 5% Loreys height errors, this equates to 20.9% total uncertainty using the formula set out in equation 7.7.

7.4.4.6 Land cover change occurring in the time between the Lidar and radar data collection

Despite cleaning the Lidar data to account for interference from cloud and smoke, there were still anomalous results in variation in the backscatter plotted against Lorey's height measurements. This was particularly the case at higher measurements of Lorey's height. This may be due to the forest clearance occurring in the period between the beginning of the collection of the Lidar data (2003-2007) and the collection of the radar data (2007-2009). If an area of in tact forest had been measured by Lidar and subsequently cleared before measured by the radar, this would result in anomalous high Lorey's height values for low radar backscatter. Without contemporaneous Lidar data collection this will be the major limitation in studies using this approach.

7.4.5 Calibration over space

The radar data were calibrated using ground plots from Berbak. However, this limits the relationship to this ecosystem type, and so the analysis may be enhanced by having calibrations in different areas by partitioning the backscatter data and using sub-regional plots. However, in the absence of additional plot data sets this was not possible.

7.4.5.1 Detecting biomass in mangrove swamps

Not all ecosystems are equally well detected by Radar. An extensive mangrove forest south of Berbak (Sembilang Park) appeared to have low biomass in the biomass map. This is because Mangrove forest's low, open canopy and extensive root networks absorbs much of the L band radiation, causing weaker backscatter signals. The study therefore likely underestimated biomass in Sembilang. In order to correctly represent these systems a separate Radar backscatter to biomass regression equation would be required, based on field data that is currently unavailable. This would present useful avenues for future research.

7.4.5.2 Underestimation of biomass loss overall

The biomass loss and emissions estimates provided are conservative. First, the maximum biomass estimate of mature forest is limited, due to Radar backscatter saturation. Second, pixels on steeper terrain LTS were excluded ($> 5^o$). This necessarily excludes mountainous regions that are a last refuge for a lot on intact forest in Sumatra, because it is some of the hardest and costliest to clear and farm, and also because many such areas are protected (like Kerinci-Seblat and Bukit Barisan National Parks). Third, mangrove forest biomass is underestimated. Fourth, the large below ground biomass emissions associated with the clearance of forest on peat soils are not included (Page et al., 2002), and see chapter 6.

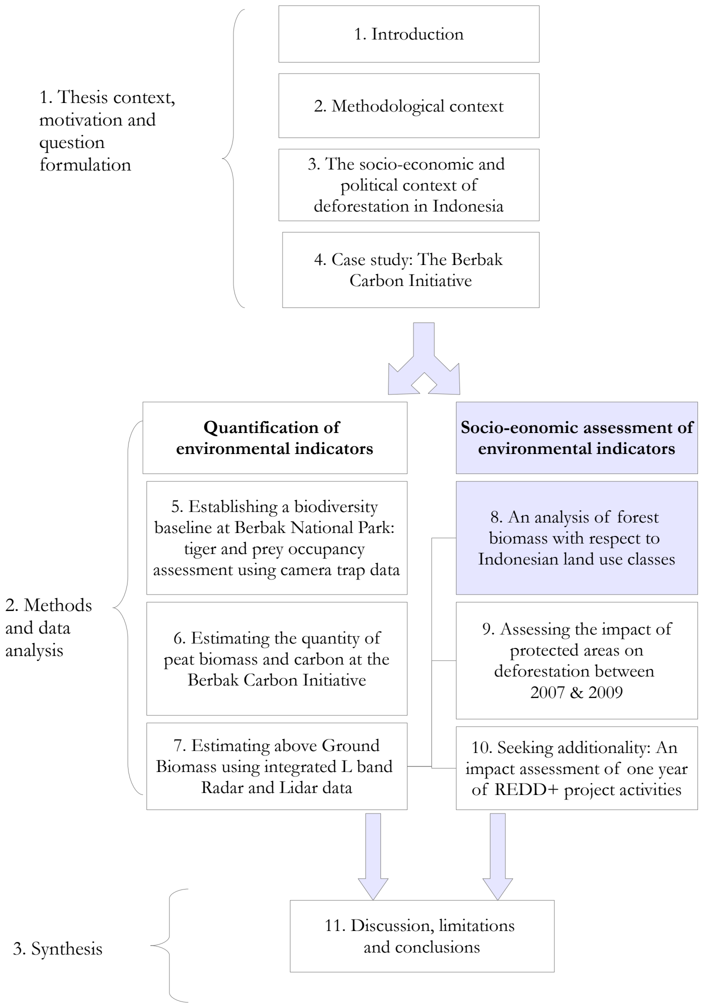
7.4.6 Discussion

Whilst the changes recorded in this study seem very high over such a short time period, the results confirm the results of other researchers. For instance in the month of June 2013 alone, 140,000ha were estimated to have been destroyed by fire in a 3.5M ha study area in Riau province (Gaveau, 2013). Indeed, even within the country with the some of the highest deforestation rates anywhere, the eastern lowlands of Sumatra have experienced have experienced the highest rates of change. By 2010, the eastern lowlands of Sumatra lost approximately half of their peat swamp forests existing a decade earlier, which is an extremely high loss rate of 5 % year^{-1}(Miettinen et al., 2011). The results of this study substantiate the concern that multi-year optical composites used to deal with cloud cover may mask the changes that the researcher intends to detect in the first place(Hansen et al., 2008, 2009). The change maps provide very high spatial and temporal resolution data for the direct estimates of biomass in each pixel, thereby contributing to the call for accurate forest monitoring data for Indonesia to contribute to REDD+ monitoring (Broich et al., 2011a). These maps are also valuable to a range of other stakeholders interested in forest carbon, tropical forest biodiversity and agricultural development. Being able to directly map biomass at 100m spatial resolution unencumbered by cloud or atmospheric particulates represents a significant advance in the ability to monitor Indonesia's forests. Further, the active sensing approach is able to estimate biomass directly per pixel rather than being based on forest classification, representing a methodological deviation from the work to map deforestation in Indonesia using optical data.

Nonetheless there are some technical barriers to continued efforts using the methodology set out here. Principally, since the failure of the ALOS-PALSAR senor, L band Radar data is not currently being collected, which will lead to large gaps in future data sets should these technologies be deployed again in the future. Finally, the estimation of per-pixel biomass requires contemporaneous Lidar samples, but the only freely available data set (ICESat) stopped collecting data in 2007. As such this study contributes to research and development in the use of Radar technology and the integration of additional datasets, which should prove useful to space agencies considering the development of new space based monitoring tools.

Chapter 8

An analysis of forest biomass with respect to Indonesian land use classes



8.1 Abstract

The objective of this chapter is to explore the results of the forest biomass quantification for 2007 with respect to land use classifications. This analysis is a first step in exploring forest management performance in the region. Contrary to expectations, areas classified as protected forest did not contain the highest quantities of forest biomass (98Mg ha^{-1}), which was instead found in the Limited Production Forest Class (104Mg ha^{-1}). The lowest forest biomass was found in community forest (39 Mg ha^{-1}), however this forest class covered less than 1% of the study area (1,987 ha). By comparison, the mean forest biomass of Berbak Carbon Initiative forest was 147 Mg ha^{-1}). This demonstrates the significance and potential of the Berbak Carbon Initiative project for forest carbon storage and conservation.

8.2 Introduction

Indonesian forests have undergone large changes over the past decades, with extensive logging and more recently with the development of plantations of 'fastwood' (*Acacia sp*) and Oil Palm (*Elais guineensis*) plantations (see socio-economic background chapter 3). These changes have had caused enormous carbon emissions (Sari et al., 2007; van der Werf et al., 2009), and unquantified impacts on biodiversity; ecosystem services and livelihoods. Chapter 4 sought to examine these issues in the specific case of the Sumatran province of Jambi and the Berbak Carbon Initiative, drawing upon qualitative information derived from informal interviews and a visit to the project site. By contrast, the objective of this chapter is to harness the results of forest biomass estimation (chapter 7), and develop a quantitative analysis of the results within the context of Indonesian land use classifications.

Across the 7.2 M ha study area it describes the proportion of the land area and biomass accounted for by each land use class, and provides the mean forest biomass per hectare. This is the amount of woody vegetation detected in the remote sensing analysis: high biomass is more in-tact forest, with low value representing cleared and degraded forest. Frequency distributions of the biomass in each class is then used to describe differences between each. These data are then examined within the context of Indonesia's natural resource management strategies and laws, and in particular REDD+ policy and the associated moratorium concessions in forest and peatland areas (see chapter 3. As such provides a detailed background of the conditions and context for REDD+ in Sumatra and in particular the development of ZSL's pilot REDD+ project at the Berbak Carbon Initiative (BCI).

The chapter aims to provide an assessment of the result of Indonesian land use classification and enforcement on forest. This allows the development of formal hypotheses about the biomass in each of forest classes. The core assumption of this chapter is that on average, the differences in the relationship between land use class and biomass density is correlated with institutional performance. This means that if the null hypotheses are rejected using data from across the entire study area, then this may indicate ineffective enforcement of land use and forest management regulations by the Ministry of Forestry. Finally, in addition the biomass statistics were extracted for both the BCI area and the area in the study scene covered by the REDD+ Moratorium Indicative Map. In terms of contribution to the overall thesis, these tests are intended to contribute to the discussion of REDD+ additionality and implementation for Jambi in general, and more specifically for the case of the BCI.

8.3 Methods

8.3.1 Hypotheses

A key determinant in the success of REDD+ implementation is the state's ability to implement and enforce land use laws and regulations. Since REDD+ has only been implemented thus far via the development of sub-national projects such as the BCI, and via a recent moratorium, the options for testing the ability of the state to implement REDD+ are limited. The impact of the BCI is tested in chapter 10. However the remote sensing radar data used in this study does not cover the time period when the moratorium was implemented. Whilst the caveat remains that past performance is no indication of future performance, this chapter first takes a static perspective to examine whether the historical designation of forest as protected has resulted in differences in the quality of the forest remaining in that class. The quality of forest is assumed to be correlated with the quantity of biomass estimated in chapter 7. If the Indonesian state had historically been an effective manager of forest resources, then it would be reasonable to expect to see that the forests which are classed as protected by the Ministry of Forestry had either:

- the same amount of forest biomass as production forest classes, in the case that the other forest classes had not been exploited or;
- more biomass than other forest classes, in the case that the other forest classes had been depleted at a higher rate on average than the protected areas.

This allows the statement of a formal hypothesis that: $H1_0$ Protected forests have equal or higher biomass on average than permanent production forests. Evidence that leads to rejection of this hypothesis is therefore evidence to suggest that the state has not been successful historically in ensuring the protection of forests which are officially designated as protected. The size of the difference is therefore a quantification of the relative success of the state, and is proposed an instrument for institutional quality.

8.3.2 Data processing and descriptive statistics

Forest biomass was estimated across a study area which comprised a section of Sumatra across Jambi and South Sumatra provinces. Full details on the process of the generation of this data are provided in chapter 7. Shape files (polygons) for Indonesian land use classes (*Tata ruang*) were provided by the ZSL Indonesia Programme, which had in turn obtained from the Indonesian governments planning agency, called BAPPENAS. Specifically, these land use categories are:

- Community Forest. Forest land designated specifically for the use of local communities, thus there is the expectation that timber and NTFPs will be removed from the forest on this land.
- Limited Production Forest. Forest land intended to be retained as forested over the long-term, with cycles of logging anticipated to cause forest degradation and regrowth.
- Production Conversion Forest. Forest land intended for logging and clearance before conversion to another use e.g. palm-oil plantations. Hence this land use class is expected to undergo forest degradation followed by complete deforestation.
- Permanent Production Forest. Forest land intended to be maintained as forest indefinitely, with cycles of logging. This land class is expected to experience intermittent forest degradation and regrowth.
- Non-forest. Land that is not designated for the retention of any forest, and may be used for development projects, agriculture, and infrastructure. This land class is expected to undergo complete deforestation.
- Protected forest: Forest land that is designated for permanent protection under either provincial or national jurisdiction. Under the former, this includes Hutan Lindung/watershed protection forests and Taman Hutan Raya (TAHURA)/forest parks. Under the latter this includes Taman Nasional National Parks (also see Collins et al. (2011a)). These forests are not intended for conversion nor exploitation and so should not be expected legally to be exploited. Therefore no forest degradation or deforestation is expected in this land class.

These shape files are shown overlaying the 2007 forest biomass estimate in figure 8.2 illustrating how the data was extracted per land class. In addition, the shape files for the Indicative Map for the REDD+ forest moratorium (see chapter 3 for details); and the BCI were also provided by ZSL Indonesia. The shape files for the land use classes and the pan-Indonesian moratorium were then clipped to the study area as defined by the extent of the biomass map as set out in chapter 7.

The estimates of biomass from 2007 were then extracted in each of these polygons, and summary statistics for each extracted dataset created using R and the

Raster package (R Core Team, 2013; Hijmans, 2013). Specifically, these statistics were: the total area for each forest class; the area proportion of the total study area; the mean biomass per hectare; total biomass in the land class; and the biomass per class as a proportion of the total biomass in the study scene.

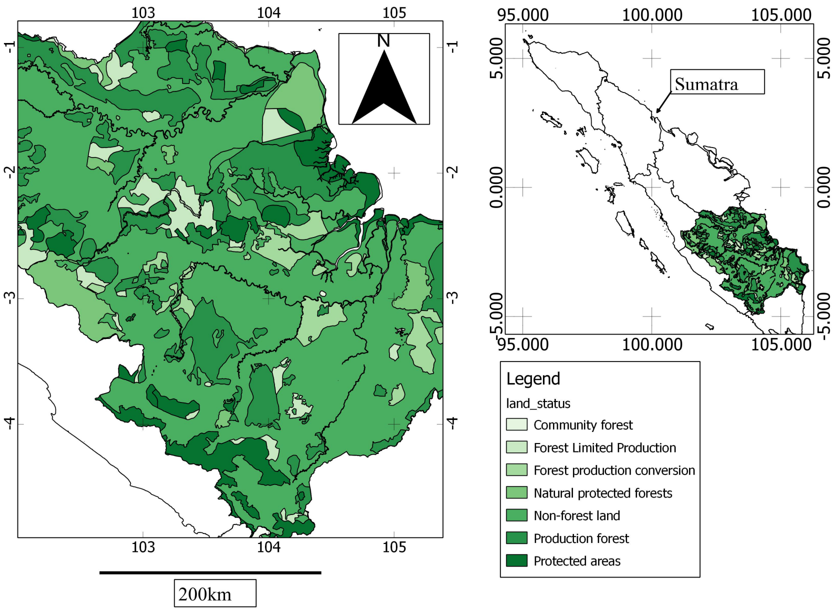


Figure 8.1: The different land classes in Jambi and South Sumatra provinces

However, whilst these summary statistics are useful to provide an overview of the carbon stocks of the forest in each class, it obscures variation within that class. In order to begin to explain the variation within each class, the data was tested for normality, in order to check the validity of using subsequent statistical tests. To do this, Shapiro-Wilks tests were performed on the biomass data from each forest class using the base package from R (R Core Team, 2013). Where there were too many data points for the function to operate on, 5000 individual points were then randomly sampled from that class of data using the *sampleRandom* function from the raster package (Hijmans, 2013). This function takes a random sample from the cell values of a raster file (in this case the forest biomass) without replacement, and of a size determined by the programmer. However, Shapiro-Wilks tests should not be taken to be absolutely correct, and the visual examination of data is also encouraged (Sokal and Rohlf, 1995). Accordingly, frequency distributions of the biomass in each forest class were plotted to allow a visual examination of the data. These were then supplemented with empirical cumulative distribution functions (eCDFs) for each of the land use classes and for the BCI and REDD+ Moratorium area.

In order to compare the data from the different forest classes and test the hypothesis, Kolmogorov-Smirnov equality of distribution tests were performed. This test explores differences in shape and location of the distributions (Sokal and Rohlf, 1995). It is a non-parametric test that compares the empirical cumulative probability functions to test for significant differences in distributions, in this case the

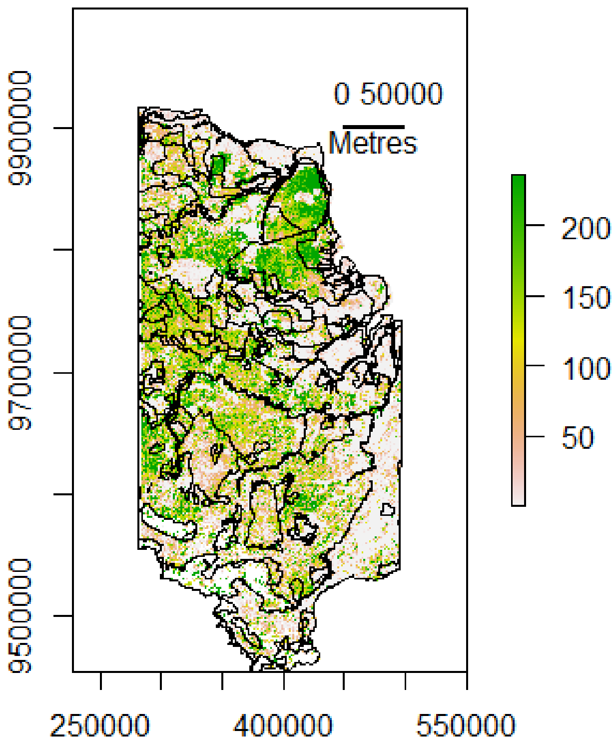


Figure 8.2: Extracting the data by land use class polygon in R

biomass data in each forest classes. It returns the maximum difference (D-statistic) between the eCDFs, and calculates a p value based on that and the sample sizes. The null hypothesis for this test is that the two samples are from the same distribution, and addresses the question: if the two samples are randomly sampled from identical populations, what is the probability that the two eCDFs would be as distant (in terms of median, variability or shape of the distribution) as observed? What is the probability that D statistic would be as large as produced by the test? Hence small P values indicate that the population distributions are different.

Kolmogorov-Smirnov tests for more deviations from the null than the Mann-Whitney test, having less power to detect a change in the median but with more statistical power to detect the changes in the distributions' shape (Lehmann and D'Abrera, 2006). However Sokal and Rohlf (1995) suggest that 'the Kolmogorov-Smirnov test is less powerful powerful than the Mann-Whitney U-test' with respect to differences in location (p.436). Statistics of location describe the position of a sample along a given dimension representing a sample, and yields a representative value of that sample, such as the arithmetic mean. This is in contrast to measures of dispersion such as standard deviation. As such Mann-Whitney U tests were also performed to compare distributions between selected classes. Similarly this is a non-parametric test. As such this is appropriate for the present data which are subsequently demonstrated to be non-normally distributed by the Shapiro-Wilks test and the frequency distribution graphs in the next section. It is the equivalent of a non-parametric t-test, wherein the null hypothesis for this test is that the true location shift is equal to 0.

Finally, having established whether or note there are significant differences between the distributions of biomass in each of the forest classes, the skewness of each distribution was tested using the skewness function implemented in R (Meyer et al., 2012). This quantifies how symmetrical the distribution is, such that a symmetrical distribution as a skewness of zero; an asymmetrical distribution with a long tail to the right in the higher values has a positive skew; and an asymmetrical distribution with a long tail to the left in the lower values has a negative skew.

8.4 Results: Descriptive statistics of biomass in each land use class

Community forests cover the smallest area in the study area at 1,987 ha, comprising one small forest unit. This forest class held an estimated 39 Mg biomass ha^{-1}, which is less than 0.1% of the estimated biomass across the entire study area. Limited production forests cover a much larger area of 295,284 hectares, 4% of the total, and with a mean biomass per pixel of 104 Mg ha^{-1}, with an estimated total biomass of 20 x 10^{6}Mg. Conversion production forests cover a slightly larger area of 342,157 hectares, but with a much lower mean density of 57 Mg ha^{-1}, holding a lower total biomass of 19 x 10^{6}Mg. Finally the Permanent Production Forest, covers 1.28 M ha at a mean biomass value per pixel of 78 Mg ha^{-1}, and a total of 100 x 10^{6}Mg of biomass. This accounts for 19% of the total biomass in the study area.

Protected forests cover 697,283 ha, or 10% of the total study area. These have a mean biomass per hectare of 98 Mg ha^{-1}, with a total of 69 x 10^{6}Mg of biomass and hence 14% of the total biomass. However, one notable exception was detected. This was a hutan lindung forest to the north-west of Berbak, which appeared in the to be entirely devoid of biomass, as shown in figure 8.7. The final category, non-forest, covers 4.3M ha, 62% of the total area, with a mean 62 Mg biomass ha^{-1}, which equates to a total of 4.5 x 10^{6}Mg biomass. This accounts for 54% of the total biomass in the study area (see table 8.3).

8.4.1 Descriptive statistics of the biomass in forests targeted for REDD+: the Moratorium area and Berbak Carbon Initiative

Following the signing of a deal between the governments of Indonesia and Norway to develop REDD+, the Indonesian government issued a moratorium on the exploita-

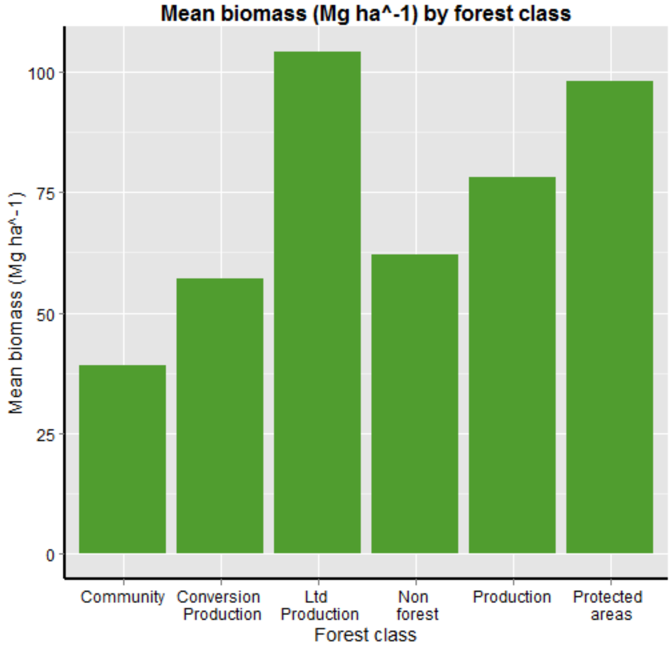


Figure 8.3: Mean Biomass per pixel by forest class

Forest class	**Mean biomass ha^{-1} by class**	**Area ha**	σ	**Proportion area %**	**Total biomass Mg**	**Proportion of total biomass in scene%**
Community forest	39	1,987	64	0	78 x 10^3	0
Limited Production Forest	104	312,334	73	4	32 x 10^6	6
Conversion Production Forest	57	352,157	72	4	20 x 10^6	5
Permanent Production Forest	78	1,286,958	76	18	100 x 10^6	18
Protected Forest	98	697,283	92	10	69 x 10^6	
Non-forest	62	4,468,162	78	62	278 x 10^6	55
BCI	147	236,674	83	2	35 x 10^6	5
Total		7,216,879			503 x 10^6	

Table 8.1: Summary statistics of biomass distribution in the study area by land class

tion of natural primary forests(see chapter 3). The moratorium map covers 1.3m ha over the study area, and holds mean forest biomass of 95 Mg ha^{-1}, and a total of 120 x 10^6 Mg biomass, which is 24% of the total in the study area.

The BCI, incorporating the National Park, TAHURA, Hutan Lindung and Hutan Produksi (see chapter 4 for a full description of the site) covers 236,674 ha, with a mean of 147 Mg ha^{-1}, and a total of 35 x 10^6 Mg biomass. Despite only covering 3% of the study area, the BCI accounts for 7% of the total biomass in the study area. Berbak national park itself covers only 2% of the study area but contains 5% of its total biomass, due to its much higher mean value of 166 Mg ha^{-1}.

8.4.1.1 Tests for normality: Shapiro Wilks

- Community Forest: W = 0.6672, $p<0.001$
- Limited Production Forest: W = 0.9361, $p<0.001$
- Conversion Production Forest: W = 0.7848, $p<0.001$
- Permanent Production Forest: W = 0.8697, $p<0.001$
- Protected Forest: W = 0.8389, $p<0.001$
- Non-Forest: W = 0.772, $p<0.001$
- BCI: W = 0.8729, $p<0.001$
- Moratorium: W = 0.8249, $p<0.001$

8.4.1.2 Summary descriptions of the empirical Cumulative Distribution Functions

The summary descriptions of the of the eCDfs all have identical minimum and maximum values, since these were imposed as a property of the modelling exercise in chapter 7. The variation is thus demonstrated in the remainder of the statistics.

8.4.2 Frequency distributions of the biomass per forest class

All forest classes exhibit a positive or right-skewed distribution (the distribution is asymmetrical and the tail is on the right hand side) except the limited production forest which is more normally distributed (see 8.4). Protected forest has large numbers of pixels with the highest biomass class of 230-240 Mg ha^{-1}. The substantive interpretation is that most of the forests in the study are already heavily disturbed, or indeed are already plantations, with only 0.007% of the study area retaining the highest biomass estimate, which is characteristic of late succession forests. This is defined here as having at least 236 Mg biomass ha^{-1}, and which is the highest level of sensitivity of the biomass mapping in chapter 7). The frequency distribution of the entire study scene (figure 8.6) reveals that the majority of pixels in the scene

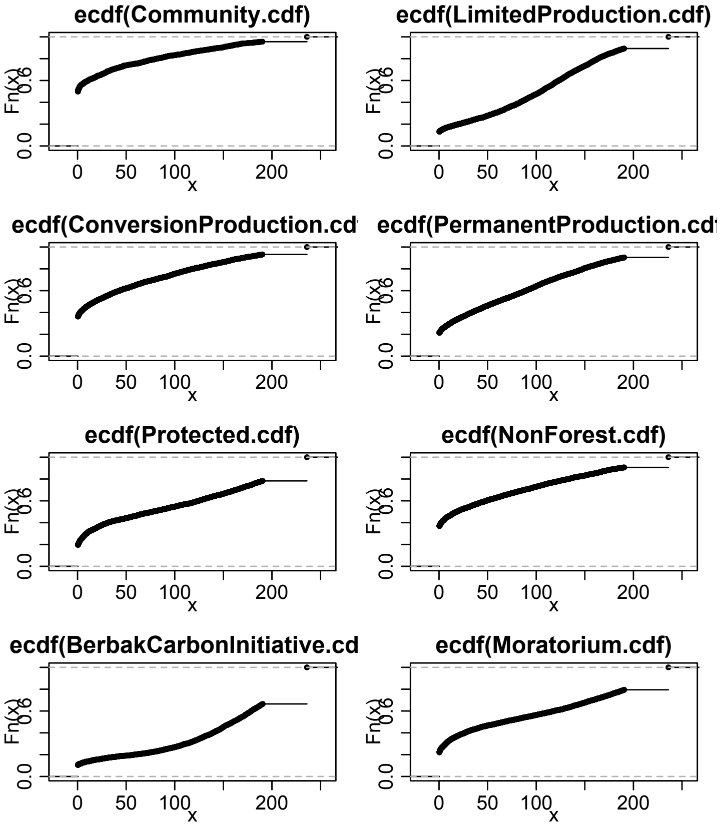


Figure 8.4: Cumulative Distribution Functions of each land use class,including Berbak and the Moratorium

have low biomass, which contrasts strongly with those for the moratorium area and Berbak national park. The former shows a greater number of higher biomass pixels, whilst Berbak national park shows a far fewer low than higher biomass pixels, reflecting the relatively in-tact nature of the park forest.

8.4.2.1 Kolmogov-Smirnov tests for differences between distributions

The tests of the distributions of the protected forest against all other forest classes suggested that the biomass in the protected forest was significantly different to all other classes using both the Kolmogorov-Smirnov and Mann-Whitney tests.

These tests indicate that the null hypotheses that the data are drawn from the same distribution should be rejected. The skewness of each distribution was then tested. The biomass in all forest classes was right skewed, with the most extremely skewed being the community forest, whilst the least positive skew was the limited production forest. By contrast the isolated case study site, the BCI had a negative skew of -0.49 which relfects the relatively in-tact nature of the forest here compared to the other forest in the scene. The results are summarised in table 8.2.

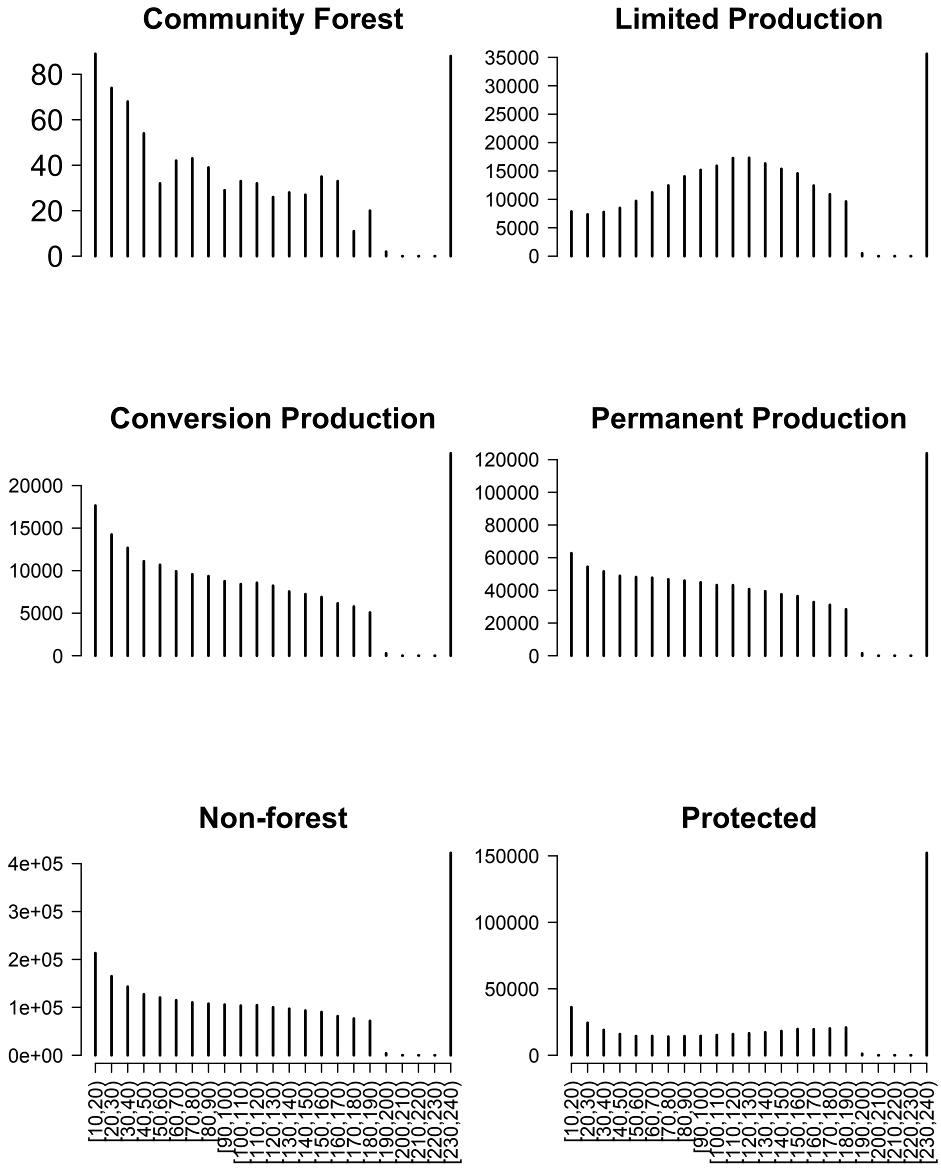


Figure 8.5: Frequency distributions of biomass. X axis is 2007 biomass Mg ha^{-1}

8.4.3 Errors associated with values per forest class

There are errors associated with each forest class due to the problems associated with non-uniform capacity to detect biomass across different ecosystem types, and due to lack of sensitivity to high biomass forests in the biomass mapping process. Of particular note is that the open canopy and web of roots which constitute mature mangrove forest are not well accounted for in the study, due to the lack of field calibration data. This means that the biomass in the Sembilang system to the south of BCI is underestimated which will in turn affect the descriptive statistics used here for the protected forest class. As described in chapter 7, the radar backscatter signal saturates at higher forest biomass values and had to be related to an additional independent data set (Lidar) in order to be able to estimate forest biomass up to 196Mg ha^{-1}, at which point the relationship between the lidar and radar data appeared to degrade. As such any forest with a estimated Lorey's height value

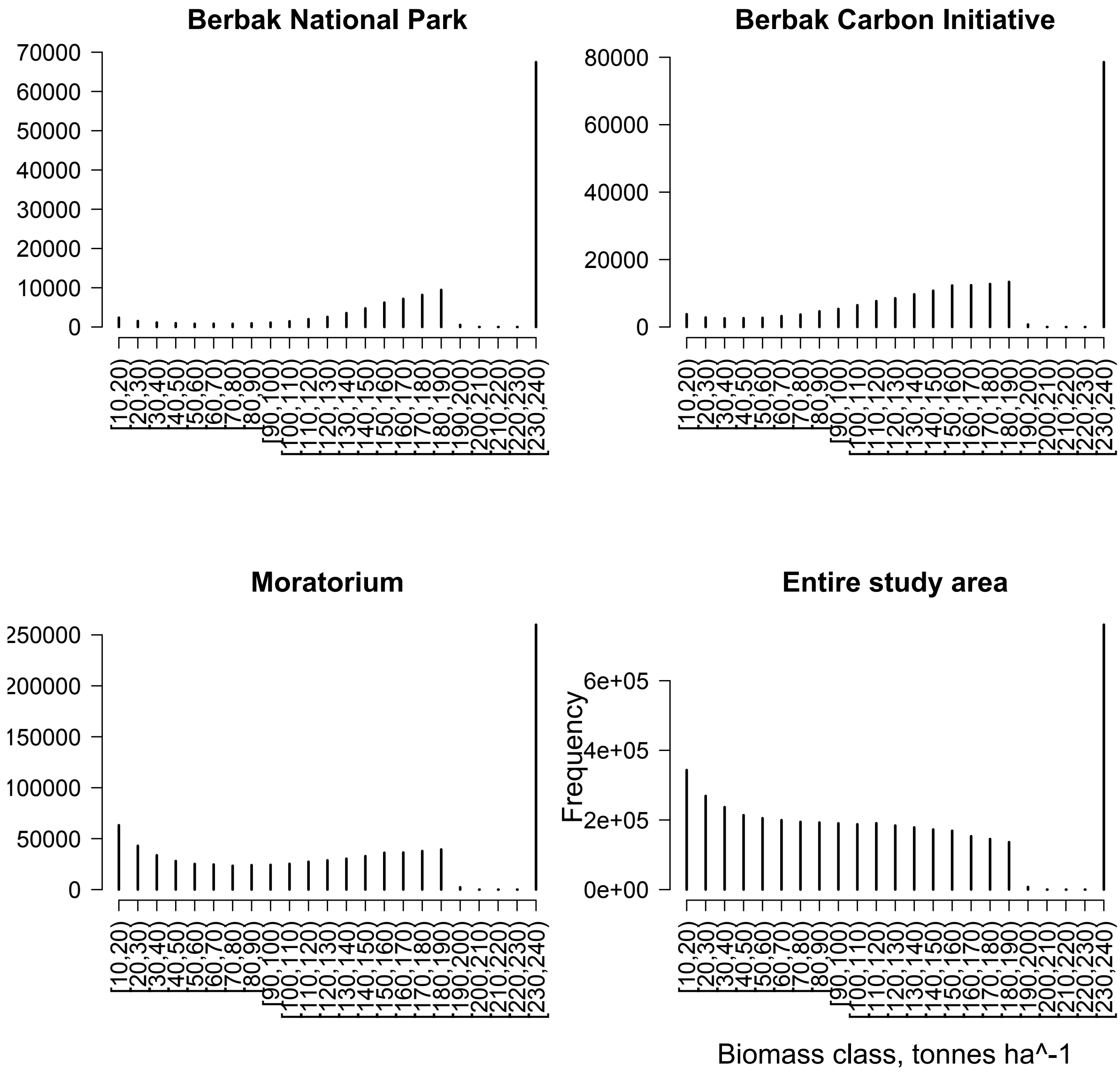


Figure 8.6: Frequency distributions of biomass per pixel in the entire study area, Berbak National Park, Berbak Carbon Initiative and the REDD+ Moratorium

greater than 25m was attributed a uniform value of 236Mg ha^{-1} (hence providing an upper bound to the data) which was taken from the mean value of the forest plots at BCI, but which is nonetheless lower than mean biomass values typically used for the region for mature forest (see chapter 7). This means that there is further underestimation of the biomass in the remaining mature forests, and hence lower per hectare values.

This degradation of the Lidar/Radar relationship and imposition of an upper bound provides an explanation for the apparent and abrupt drop-off in biomass distributions in the classes over 190 Mg ha^{-1}, and the spike in the largest class 230-240 Mg ha^{-1}. That is, we lose sensitivity in the accuracy of the forest biomass estimate somewhere above 190 Mg ha^{-1}, and whilst it is likely to be mature late succession forest, over-estimations are avoided by placing an upper bound of 236Mg

Compared with Protected forest	**Kolmogorov-Smirnov**	**Mann-Whitney**
Community Forest	D = 0.3149, p< 0.001	W = 7059365, p< 0.001
Limited Production Forest	D = 0.1814, p< 0.001	W = 11857618, p< 0.001
Conversion Production Forest	D= 0.2176, p< 0.001	W = 15849922, p< 0.001
Permanent Production Forest	D = 0.156, p < 0.001	W = 13795893, p< 0.001
Non-Forest	D = 0.195, p < 0.001	W = 15719543, p< 0.001

Land class	**Skewness**
Community Forest	1.733272
Limited Production	0.1752367
Conversion Production	1.155228
Protected Forest	0.3274264
Permanent Production	0.695537
Non Forest	1.095246
BCI	-0.49699
Moratorium	0.4428593

Table 8.2: Assessing the skewness of the biomass distribution

ha^{-1} .

8.5 Discussion

8.5.0.1 Differences in distribution of biomass per forest class

The comparisons between the different forest classes were striking: two different statistical tests indicated that distribution of biomass in the protected forest land use class was significantly different to the other classes. The small area of community forest had the lowest mean biomass, followed by the non-forest class, which itself constituted the majority of the study area. However, contrary to expectations, the protected forest did not have the highest mean biomass content, which was instead found to be in the limited production forest. This led to the null hypothesis set up for this chapter being rejected. The community; conversion production; permanent production; non-forest areas and protected forest classes all appeared to have tails to skewed to the right, rather than normally distributed. This may reflect (a) the way in which larger trees have been selectively removed from across these forests, meaning that across much of this region of Sumatra, only immature forest remains; and (b) the reduced sensitivity of the Radar data to the higher-biomass forests, which results in non-uniform detection across forest classes (and which is the reason

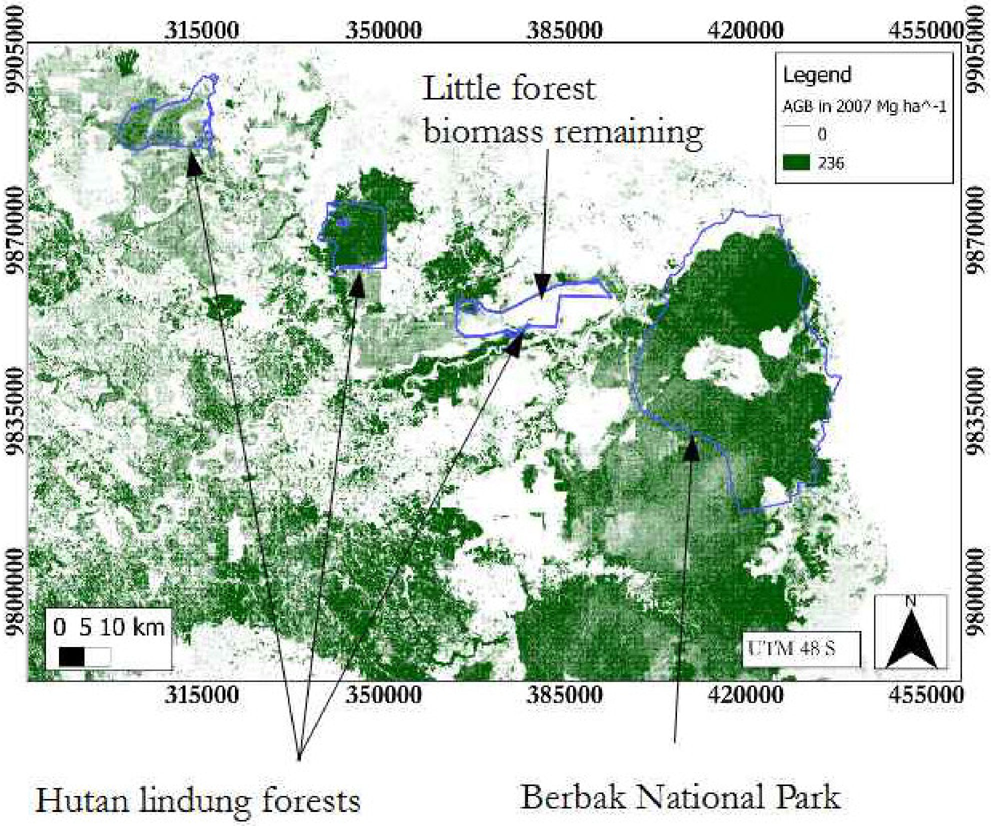


Figure 8.7: The above map shows three hutan lindung protected forests from west to east, with Berbak national park on the eastern-most extent of the map. The third hutan lindung from the left/west is appears to have very little above ground biomass remaining in 2007.

for the imposition of the upper bound of 236Mg ha^{-1} for maximum sensitivity as described above.

8.5.0.2 The importance of Berbak and production forests for carbon storage

By comparison, whilst it is not an Indonesian land class, the BCI had a higher left skew still. It also had the highest mean biomass per hectare of the any of the sampled areas. One possible explanation is that the on average, the Indonesian authorities have been less successful at managing protected areas than they have at managing the production forests in Jambi province. Another explanation is that the highest biomass forests has been earmarked for logging precisely because it has the most timber in it. That is the logging concessions and protected areas are not randomly distributed across the landscape. There are therefore major problems in using cross sectional data for anything more than a descriptive analysis. Attributing present forest condition to a policy requires longitudinal data, which sets the scene for the next chapter, where the impact of protected areas on deforestation is explored.

Despite this, the findings in this descriptive analysis are still significant. The generalities of the carbon stock distributions between different forest classes mask other interesting stories. One is that BCI retains much more forest biomass than the surrounding landscape, demonstrating the importance of the site for carbon stocks. It also suggests that Berbak national park may have been more successful than other protected areas in conserving forest, which allows the formulation of a hypothesis to be tested in the next chapter. A further interesting finding was the case of the hutan lindung peat forests to the north-west of the BCI. The contrast between three of these different management units is demonstrated in figure 8.7. As labelled in the figure, the westernmost protected area appears to be covered in high biomass forest. However the protected area to the east by contrast appears to be entirely cleared of biomass.

8.5.0.3 The case of the deforested hutan lindung and implications for REDD+

As described in chapter 3, the quality and efficacy of land use management in Indonesia is such that the land use in practice often does not match that designated by central bureaucracy. In the case of East Kalimantan described in that chapter, what had been *de jure* forest land but were *de facto* heavily degraded, were subsequently being reclassified to fit their new condition. The case presented here of the two adjacent hutan lindung areas suggests that similar processes of land (mis)management may have occurred here. The hutan lindung which appears to have been entirely deforested has production forest to both the east and west of it. This may have left it vulnerable to conversion by the managers of the adjoining concessions over-extending the spatial extent of their licenses, combined with insufficient field capacity of DINAS kehutanan to control this on the ground. However there is no evidence for this having happened currently and more local research would be required in order to develop a history and the reasons for deforestation at the site.

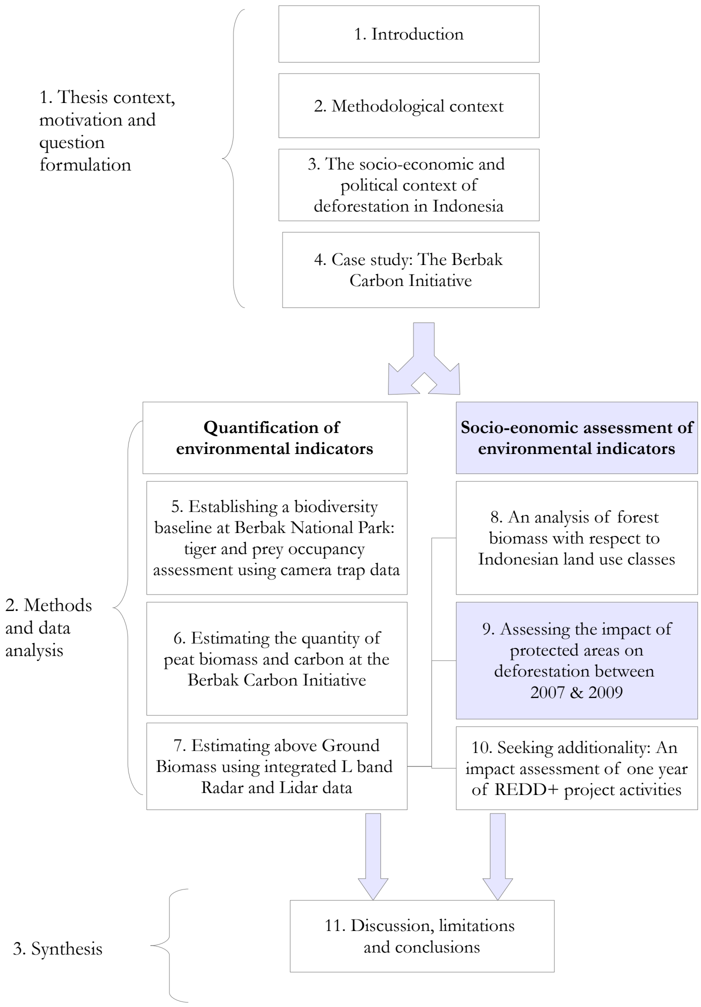
This would be an interesting avenue for research, not least due to the implications for REDD+. These implications are interesting because a) despite the lack of forest biomass in this site, it should still contain a large quantity of carbon in the peat (see chapter 6; and b) as an existing *de jure* protected area, it could potentially be reforested using existing mechanisms from the Ministry of Forestry, and would therefore not require any land use designation change for additional carbon removals to be achieved. It also suggests that REDD+ could be achieved simply by implementing existing laws.

With regards the peat carbon stock at of the hutan lindung, the physical stability of this stock will now depend upon the management in place at the site, such as the presence of drainage canals. However, were the area to be re-designated as a production forest following precedents in east Kalimantan, it is likely to be drained to make the land suitable for plantation development, thereby leading to peat oxidation and additional carbon emissions. Future research could determine the land use status and *de facto* management of this site, but should it remain officially hutan lindung, then it offers potential for REDD+ action, and additional carbon emissions through peatland restoration and reforestation. Yet it may be optimistic to expect reforestation here: domestic institutions existed well before REDD+ to enable forest restoration. A fund created to pay for reforestation and restoration *(Dana Reboisasi)* established in 1989 under Suharto generated $5.8bn over 20 years, financed by a timber volume-based levy on concessionaires. Yet the fund was undermined by corruption, making it unlikely that funds could have be secured to perform restoration: *weak financial management and inefficient administration of revenues by government institutions at all levels undermined effective use of the Reforestation Fund. Major public investments in ... rehabilitation of degraded forest lands have repeatedly fallen well short of their objectives...large sums... have been lost to fraud, diverted for other uses or wasted on poorly managed projects* (Barr, 2010).

Moreover, since these hutan lindung are managed by the regional governments, local priorities may differ from the goals of the national government. Whilst national initiatives such as the REDD+ moratorium satisfy the Government of Norway, local Indonesian governments at the regency level are mandated to foster economic development, create employment, and generate revenue. For deforested hutan lindung there are strong incentives for submissions to be made for the area to be reclassified for production forest rather than restored. Production forest generates known sums of *retribusi*, rather than uncertain (if any) finance to be received under REDD+ initiatives. Moreover if REDD+ is managed by the same organisations responsible for the Dana Reboisasi then without systemic reform and oversight there is a large risk that funds may be similarly be mismanaged, and at worst fraudulently spent.

Chapter 9

Assessing the impact of protected areas on deforestation between 2007 & 2009



9.1 Abstract

This chapter uses the changes in biomass estimated between 2007:2009 to address the question of the efficacy of protected areas (PAs) in reducing deforestation on Sumatra. By using matching methods, I was able to narrow the covariate distance between PAs and the unprotected areas (control for selection bias in the location PAs). Following this, a difference in means suggested a Sample Average Treatment Effect of deforestation being 1.8% (0.9% per year) lower in PAs than in similar areas under other use. Based on the assumption that the protected areas would have been designated as other land uses in the counterfactual scenario this suggests a) that PA designation works to protect forest in this part of Sumatra, but b) that deforestation nevertheless continues in those PAs at a lower rate. This supports previous findings on deforestation on Sumatra. The work also underscores the need for the development of robust causal impact methods for assessing the effectiveness of environmental policy, particularly in the context of development of REDD+. Finally it demonstrates the utility of analyses of time-series of Radar data to be able to provide data on changes in forest over a short time period.

9.2 Introduction

9.2.1 Summary of issues

The next two chapters concern policy impact assessment. This chapter addresses an assessment of the success of Protected Areas (PAs) in Sumatra in reducing deforestation, whilst the following chapter 10 addresses the marginal change in protection of a PA, following a REDD+ intervention.

There are several core issues to address in the introduction. **1**. The need for good questions, and the justification for undertaking policy impact assessment. This provides the research motivation. **2**. The background to the impact assessment literature which explores how the theory and techniques have developed in disciplines outside environmental economics. This should highlight the key differences between experiments designed using randomised controlled trials (RCTs) and observational studies exploring the impact of events which have already occurred, or for which randomisation is infeasible. Since this work is an observational study, I focus on this topic.

Before the researcher starts analysing data, it is useful **3.** to establish a conceptual model which sets out the key actors, resources, dynamics and interactions within the system and context of interest e.g ARDI (Etienne et al., 2011). The next stage **4.** is to choose whether to undertake either or both of i) a theoretical approach to impact assessment, which examines how a policy impact affects the theorised process in the system (a theory of change approach) or ii) a data-driven approach involving the use of an empirical model which allows a researcher to try to test how a change in the system affects the outcome variable of interest. At this stage the researcher should be aware of the assumptions and limitations of the identification strategies, which are the research approaches which used to address the well-chosen question. The chosen approach should ideally 'lend (itself) to a simple explanation of empirical methods and a straightforward presentation of results' (Angrist and Pischke, 2010). If the researcher chooses the empirical path, then the next stage is **5.** to address the methods which are ultimately used to estimate the parameter of interest. This stage will reveal the central issue of observational studies, which is **6.** bias, its sources, and the methods available for dealing with it. This stage includes assessing the basic empirical models that may be used, and the approaches to estimating the parameter of interest (e.g. covariate matching covariates and taking the difference in mean outcomes). When bias has been addressed, and an impact calculated, the results **7.** need to be interpreted in terms of internal, external and construct validity.

I discuss now these issues in turn, first considering the issues in the abstract sense, and then in the context of this thesis and the assessment of the impact of forest conservation policy.

9.2.2 Motivation

Understanding what works in public policy is a fundamental task since it may increase the future likelihood of achieving policy objectives, whilst projects which fail to meet their objectives may be cancelled (Essama-Nssah, 2006). Impact assessment findings can influence future policy such as the decision to continue to deploy training programmes for the unemployed (Ashenfelter, 1978). Within the context of forest management policy, governments aim to achieve targets such as the sustainable management of forests and their associated ecosystem services including the supply of biodiversity, non-timber forest products, soil fertility, fresh water and climatic regulation e.g. Pattanayak et al. (2010). Within the context of REDD+, outright conservation of forests under new PAs is an option e.g. Guyana has recently developed legislation to create a network of PAs influenced by its low carbon development strategy and financed with $250m from the Norwegian government (Nachmany et al., 2014). Since REDD+ involves conditional payments upon demonstrable reductions in deforestation, assessing what works in reducing deforestation is important for the government and agents seeking financial transfers under the mechanism (Pattanayak et al., 2010). Unsuccessful strategies will reduce potential REDD+ income and hence a) local welfare benefits in the recipient country and b) gains to global welfare in terms of the further loss of forests and their ecosystem services, particularly carbon storage and biodiversity.

9.2.3 Good Questions vs. Good Methods

Deaton (2010) is critical as to what he perceives as the increase in the development of empirical methodologies which focus on how to answer the question of whether a policy or project worked, increasingly at the expense of asking the correct, interesting and useful questions, including why a project succeeded or not. However Angrist and Pischke (2010) argue that the issue of methodology becoming the driving force of research is actually less of a problem than Deaton argues, and instead emphasise that with the 'con' taken out of econometrics, good interesting questions can be answered in increasingly robust ways. In the present context of forest management, the question of whether parks have provided forest protection can be supplemented with a why, which can refer back to the previous chapters on forest management in Indonesia and also to a conceptual model and broader economic theory. This means it is possible to retain the focus on a well-motivated question, but underpin it with robust techniques.

Ensuring the quality of research in this area is important since the development of PAs to conserve parts of the world's forest involves the investment of large sums of money and political capital, and can be controversial especially given they have sometimes been associated with forced evictions (Brockington and Igoe, 2006). Despite these large investments and risks, researchers have highlighted over the past decade both the absence of, and the need for, rigorous assessment of policy interventions to determine the extent to which they are actually achieving their objectives e.g. (Ferraro and Pattanayak, 2006; Miteva et al., 2012; Arriagada et al., 2012; Pattanayak et al., 2010), and the extent to which they cause externalities as moderating poverty (Andam et al., 2010). In Similarly, in a review assessments of Payments for Ecosystem services programmes, Pattanayak et al. (2010) do not find much work with what Angrist and Pischke (2010) call credible research designs. Identifying credible approaches therefore is clearly of paramount importance, and in order to clarify what determines work as such, I now discuss some of the core differences between research approaches.

9.2.4 Experimental data vs. Observational studies

In other branches of science where researchers are interested in treatment effects e.g. medicine and the effect of a new drug, it is standard practice for researchers to randomise treatment across subjects to create control and treatment groups, in order that any systematic differences between these groups and the outcome is minimised. As such the effect of the treatment can be isolated and calculated. More precisely, due to the random assignment, the treatment and control groups should be statistically identical on all dimensions except the exposure to the treatment (Greenstone and Gayer, 2009; Imbens, 2004). These are also called the 'confounders'; 'factors or events that also affect the measured outcomes and are correlated with the intervention' (Pattanayak et al., 2010) (p.8). Hence both the control and the groups or observations which receive the treatment can be manipulated. This is called a randomised controlled trial (RCT). Succinctly, the ultimate goal of experiment is to calculate an unbiased estimate of the true evaluation parameter or estimand, the Average Treatment Effect (ATE). The randomisation of the treatment across observations is assumed to eliminates any potential bias (which subject I discuss in more detail below). The fact that the treatment effect is the average across observations has and allows for the fact that there is variation in the treatment effect (Ho et al., 2011).

Since the RCT can remove bias, it is tempting to envisage this as the solution to estimating treatment effects in economics. Indeed Angrist and Pischke (2010) cite Zvi Grilriches' maxim that 'if the data were perfect, collected from well-designed randomised experiments, then there would hardly be room for a separate field of econometrics'. Further, Ashenfelter (1978) argued that in the absence of a robust specification that RCTs were the route of choice for calculating treatment effects. Frondel and Schmidt (2005) also argue that the RCT is the most desirable empirical strategy. Yet whilst Deaton (2010) counters that the evidence from RCTs is not automatically superior to evidence from other sources, having 'no special place in the hierarchy of evidence' (p.426), nor any greater ability to generate knowledge than other methods, Angrist and Pischke (2010) state that the increasing awareness of the need for improved study quality has meant that there has been an increase in the number of designed studies which have " 'prima facie' credibility" (p.3).

Yet unfortunately, in many cases, it is simply not possible to use RCTs to deal with bias. The issues include ethics (e.g. withhold medical funding from some villages in a poor country, but funding others), or simply that the question motivating the research concerns events which have already happened, and did not occur randomly, as it typically the case in economics. Due to non-random assignment, observational studies may suffer from a lack of reliability compared with those generating true experimental data (Greenstone and Gayer, 2009). In the case of this chapter, the research interest is in determining the impact of PAs on deforestation on Sumatra. The PAs were established decades before this research began. In such a case the treatment status (forest subject to PA or not) is determined by factors beyond the control of researchers (Greenstone and Gayer, 2009). This is the realm of observational study. Since the treatment (protected) and control groups (unprotected but potentially protected forests) are not randomised as in an RCT, this raises the possibility that the PAs have some attribute that increases the probability that they were protected (Pattanayak et al., 2010) (indeed this has been demonstrated by Joppa and Pfaff (2009), discussed below). Hence the major problem in observational studies becomes one of dealing dealing with bias. I now discuss this issue in more detail, before moving on to more details on various approaches in how to deal with it.

9.2.5 Bias

Bias is at the heart of the matter of impact assessment. It greatly complicates causal inference, or more strongly 'plagues the successful estimation of average causal effects' (Greenstone and Gayer, 2009). There are many ways in which bias can manifest itself. To take a hypothetical example, if a market research firm were to issue online surveys to discover more about customer satisfaction regarding a firm's products, the respondents are likely to be those with sufficient time. These people may be clustered in other attributes, such as age e.g. older retired people have more time to fill in surveys. This is a response bias, which means that the population has not been adequately sampled. Equally, people over 65 living in rural areas may be less likely to respond because of poor internet connections Such a non- probability sample does not therefore adequately represent the population, since retirees may be over-represented, whilst much older cohorts, and rural people may be excluded largely from the samples.

In environmental economics, there has been a blossoming of interest in impact evaluation for forestry policy and dealing with bias e.g. due to the need to assess Payments for Ecosystem Services (PES) schemes (Pattanayak et al., 2010), and more recently the development of forest carbon conservation projects and REDD+. Selection biases may occur in the allocation of treatment, or policy subjects. Research has shown that this is indeed for the case for PAs, which tend to be biased towards locations that are far from sources of anthropogenic disturbance and least productive. i.e. in those areas which are of least value for human use (Joppa and Pfaff, 2009; Pfaff and Robalino, 2012). Hence the distance to sources of disturbance (e.g. towns) and determinants of land productivity (e.g. elevation) are omitted variables that confound naïve assessments of PA success e.g. (Nagendra, 2008). In forest conservation direct payments schemes, people who are less likely to cause environmental damage anyway may be more likely than others to participate in a PES scheme (Arriagada et al., 2012). Land owners may be more likely to offer up land for conservation payments schemes that they were less likely to convert to other uses anyway, for other reasons than the payment (Pattanayak et al., 2010). Areas which are far from the drivers of environmental disturbance are less likely to be damaged. Yet if these sources of bias are not dealt with appropriately, then a researcher is likely to over-estimate the impact of the programme in question.

Dealing with non-experimental data and bias in practice With his criticisms of both the focus on methodology rather than good questions, and the focus on whether policies work whether than why they succeed or fail, Deaton (2010) argues for a more theoretical than empirical basis for impact assessment. This is a 'theory of change' approach. This is summarised by Carvalho and White (2004) who explore the case of social funds and provide a framework for analysis. The core of this approach is on theorising and conceptualising processes. Core issues include understanding the how and why of a series of cause and effects within a given socio-economic system. The identifying assumption of this approach is that theoretical processes operate correctly in practice to produce the outcomes intended. On the other hand Frondel and Schmidt (2005) argue that wherever possible one should consider empirical study over theoretical approaches. Yet this discrete-alternatives approach to impact assessment may be misleading, and the approaches may be integrated: Recent work in evaluation studies have shown investigators 'making both an institutional and data-driven case for causality' (Angrist and Pischke, 2010) (p3).

Nonetheless in their survey of PES assessment Pattanayak et al. (2010) found few cases of robust survey design in practice. This is probably what Greenstone and Gayer (2009) as the surfeit of 'associational evidence' in environmental policy making, which has meant that many environmental policies either fail or are inefficient. They therefore argue for quasi-experimental and experimental techniques that 'identify exogenous variation in the variable of interest' *ibid.* p22. Ultimately, what we would like to achieve from observational data in an impact evaluation study is to use ex-post information to determine the unbiased ATE, which is the 'true' evaluation parameter (Frondel and Schmidt, 2005; Imbens, 2004). The key finding is normally the difference in the mean values of the outcomes between the treated and control groups of observations following treatment (Angrist and Pischke, 2010, 2009).

To re-iterate the intuition, this means we would like to observe the outcome of the treated group, but in the counterfactual case that it was not treated. Of course we cannot do that since observations cannot be simultaneously treated and not so e.g. Angrist and Pischke (2009); Imbens (2004); Dawid (2000). As such we need to identify plausible observations which are as similar as possible to the treated observations, but which are not themselves treated (Frondel and Schmidt, 2005; Ferraro, 2009; Pattanayak et al., 2010). If counterfactuals can be identified, then the difference in the outcome between the treated and the control groups in principle can be interpreted as the causal effect (Imbens, 2004; Rubin, 1974).

9.2.6 Basic empirical models

There are different basic empirical models available to the researcher, and different estimators to calculate estimates in practice. The first basic empirical model is simply the differences between treated and control group means. This is called the Rubin causal model, wherein the causal effect is the difference between an observed outcome and its counterfactual (Rubin, 1974). Imbens (2004) argues that this is both the 'natural starting point for programme evaluation' and that 'almost any evaluation of a treatment involves comparisons of units who received the treatments with units who did not' (p.7). This is suitable for cases in which there is only time period.

Where there is more than one time period of data available, there arises the possibility of using the differences in differences (DD) as the basic empirical model. The key identifying assumption of DD is that the trends in outcome of the control and the treated group are parallel prior to the policy intervention, but that the absolute values may be different. e.g. deforestation is higher in one area than in another, but the trend in deforestation across both areas is constant over time. This is called the parallel trends assumption (Mora and Reggio, 2012). The principle can be demonstrated with a simple diagram as in figure 9.1.

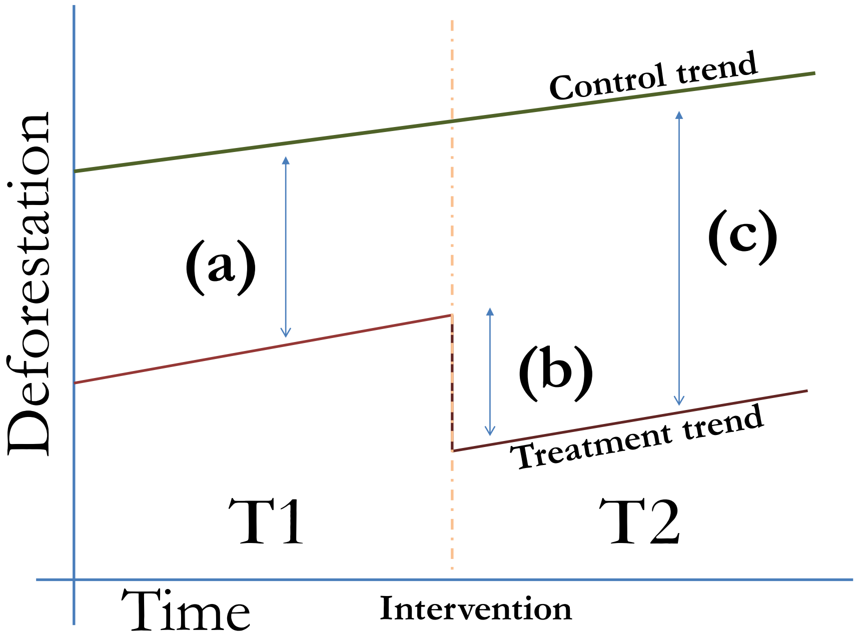


Figure 9.1: The chart provides a basic illustration of an idealised DD approach to causal inference. Deforestation is the outcome variable measured on the Y axis, with time on the X axis. There are two trends marked: the upper trend is for a control site, whilst the lower trend is for the forest which received the treatment. The treated and control groups have parallel paths, with differences in the absolute rates (a) of deforestation. At the point marked 'Intervention' on the X axis, a shock occurs, e.g. a team of rangers is employed to protect a park forest. This constitutes a treatment. The risk of being caught and fined reduces incentives to illegal loggers to cut wood in the forest, hence fewer people transgress the park rules and there is a concomitant reduction in deforestation. In T2, following the intervention the trends in deforestation in the treatment and control sites are still parallel, however the new difference between as measured by (c) them is greater than in T1. The difference in the differences, DD, measured by (b) is attributed to the effects of the intervention.

As with all models there are reasons for caution when using DD. Despite using appropriate techniques to identify controls that exhibit the trajectory of the treated group outcome in the absence of treatment, the results of the analysis may still be misleading if there are omitted variables. One of the canonical examples of the problems involved in estimating causal impacts even when a control group is available derives from labour economics. Ashenfelter (1978) examined the effect of training programmes in the USA upon workers' wages. Naïvely, the programmes appeared to increase wages for participants. However, the programme managers tended to enrol those workers with a recent history of trouble finding work. This means that for those individuals who were enrolled in the program had experienced downward bias on their earnings prior to enrolment. This means that some part of the increase in wages which occurred following the intervention were due to the earnings of those workers returning to the level which they were at prior to their employment troubles that led them to be enrolled in the training programme in the first instance. This phenomenon is known as 'Ashenfelter's dip' (Ashenfelter, 1978). In the context of forest policy, one can envisage how this effect may manifest itself in the opposite direction: if a forest policy was established in order to reduce deforestation in an area which was the result of a temporary spike in demand for wood, then the impact of protection could be over-estimated when the deforestation rate returned to its previous level. This was a major concern in the Indonesian province of Aceh following the destruction of coastal cities following the Indian-Ocean Tsunami (Ross, 2005).

9.2.7 Statistical techniques to control for bias

In order to control for bias in practice, we can use selection on observable characteristics to decide which observations of treated and untreated to compare. Imbens (2004) sets out the means with which this can be achieved, through: 1. regression. 2. Matching and 3. Propensity score methods (and also 4. Instrumental Variables).

Matching approaches have a strong theoretical basis (Ho et al., 2007). The theory is that the control group is identified using selection upon observables, which is assumed to remove the bias between it and the treated group. The causal impact, or treatment effect is calculated as the the differences in means in the outcome between groups (Ho et al., 2007), as is done in RCTs. More specifically, the aim of using matching is to maximise the similarity of the distributions of the observable characteristics, the covariates of the treated and the untreated groups (Frondel and Schmidt, 2005; Imbens, 2004). If this can be done well, it means that the treatment and control groups effectively become interchangeable because the differences in confounding covariates between treated and control sites tend towards zero. This allows the researcher to behave as if the treatment were in fact randomised, and for average treatment effects to be estimated by differencing the expected outcomes in the treatment and control groups (Ho et al., 2007; Angrist and Pischke, 2010).

One of the most appealing aspects of a properly-performed matching procedure is the reduction in the dependence of the final treatment effects on subsequent statistical model (mis)specification, in the case that a statistical model is employed post-matching to analyse the data instead of a simple difference in means. Combinations of approaches e.g. matching followed by regression to estimate the between-group differences is what Ho et al. (2011) call a 'doubly robust approach' (although Imbens (2004) (p.12) attributes this phrase to Robins and Ritov,1997). Further, these methods are increasingly more easy to implement because of the availability of code libraries in languages like R (Sekhon, 2011; Ho et al., 2011).

The assumptions of the matching approach are the in-principle un-testable assumption of unconfoundedness, and appropriate overlap of the variable space for the covariates of the control and treatment observations, called together the strong ignorability assumption (Imbens, 2004). In the case that there is not sufficient overlap, there is a clear challenge to validity, hence Imbens (2004) suggests limiting inference to that space where there is sufficient overlap. Further, where data is not representative of the population, we can claim only a Sample Average Treatment Effect (specific to the sample), but if the data represents a good population, then we would have a Population Average Treatment Effect (applicable to other samples drawn from the population).

Ho et al. (2007) are at pains to point out that matching in itself is a control strategy, not *strictly* an estimator as other authors state (e.g. Clements et al. (2010)) including the most influential and heavily-cited literature (Imbens, 2004)). They say it is not strictly a method of estimation since a further step is required after matching to estimate the treatment effect, which is most often the difference in mean outcome (Ho et al., 2007, 2011; Imbens, 2004).

Matching is increasingly being used in the literature. In a study to determine the impact of Costa Rica's renowned *Pagos por Servicios Ambientales* (PES) scheme, Arriagada et al. (2012) used pre-matching to identify as a counter-factual group those farms that were not subject to the policy intervention, but which were nonetheless eligible, and then selected farms based on geographical rules. Nonetheless, they found that there were still systematic differences between control and treated farms. They therefore subsequently used further matching methods to identify those pre-matched sites that were similar in other attributes such as slope, farm size, participation in previous farm schemes to create more precise matches. In a slightly different context, Clements et al. (2010) used matching methods to measure the impacts of conservation and development projects in Cambodia.

9.2.8 Matching: further technical details

With matching methods, treated observations are matched with untreated observations which are as near as possible to the treated with regards all other observable covariates. This contrasts with regression methods, where a linear model is created instead to control for the effects of the covariates. Yet whilst matching is a referred to as a single estimator (or control technique *vis* Ho et al. (2007)), there are multiple ways in which it can be implemented. One may either match on a matrix of covariates, or otherwise condense these into a vector of probabilities of receiving the treatment conditional upon those covariates. This is called the propensity score. The matching methods using either the matrix or the propensity score then include full; optimal; genetic; nearest neighbour; and coarsened exact matching (Ho et al., 2011). Within each of these there are different options, including whether to match with replacement, and then the tolerance of the distances between each of the matches (Ho et al., 2011; Imbens, 2004). In addition the researcher can use callipers to determine the acceptable difference between the treated and control samples (Sekhon, 2011). This can improve matching, but it also means that matches which do not meet the criterion are excluded, resulting in a reduced sample size (Ho et al., 2011). These options control the rigour of the matching processes, with a tradeoff between the sensitivity to distance between pairs of chosen treated and control observations, and the probability of obtaining suitable matches under tightening constraints.

With the evolutionary algorithms (EAs) used in Genetic Matching as implemented by Sekhon (2011), the options include the number of bootstraps used to evaluate balance (via Kolmogorov Smirnoff [KS] tests). The package author states that bootstrapping the results 'provides correct coverage (of the KS tests) even when there are point masses in the distributions being compared' (p.10). This means that by using bootstrapping a researcher can improve confidence in the ultimate tests of difference in covariate distributions to assess the success of the matching outcomes. With such EAs, one can pass a matrix of covariates to the main algorithm, or a propensity model (to limit the searches in the variable space to those combinations with higher propensities). Hence it can search the variable space to maximise covariate balance with or without input information from the user.

The intuition for the evolutionary approach is that at each iteration (or generation) of optimisation, the algorithm seeks to minimise the maximum observed difference between the matched and control variables (Sekhon, 2011) which generation is in turn selected upon to produce the best match, hence 'evolutionary'. Sekhon (2011) states that the theorems proving that EAs find good matches are asymptotic i.e. that we get closer to the final match as input n generations increases. This means there is a tradeoff based on asymptotic properties of EA solution and the computational power available to the user.

9.2.9 Validity

Following the estimation of the value of a parameter of interest it is essential to consider the extent to which that estimate is valid. Greenstone and Gayer (2009) and the widely-cited Meyer (1995) set out the challenges to validity of observational studies. Most broadly there are three types of validity: Internal validity, External validity; and Construct validity. 1. Internal validity concerns whether it is possible to draw the inference that any differences in the dependent variable is in fact due to the explanatory variable(s) of research interest, rather than other factors (Greenstone and Gayer, 2009). 2. External validity concerns how generalisable the result is. Since a value for an estimator is estimated by using a given set of data, its extrapolation to new cases relies upon speculation, because the data derives from a particular location at a time (Angrist and Pischke, 2010). In the present case, the parks may be shown to protect Sumatra's forest between 2007 and 2009, but this does not mean by extension that all of Indonesia's work effectively. 3. Construct validity concerns whether the investigator correctly understands the treatment itself (Greenstone and Gayer, 2009). As Meyer (1995) states, without being able to experimentally manipulate the treatment, then one must understand the source of the variation. Tests for bias include testing the balance of observable covariates against treatment and control groups (Greenstone and Gayer, 2009) and looking for group-specific trends that can invalidate the comparison between control and treatment groups of observations (Angrist and Pischke, 2010).

9.2.10 Assessing Sumatra's PA success in reducing deforestation

Deforestation in Sumatra continues apace, as quantified for a section of Sumatra in Chapter 7, driven by multiple underlying factors and immediate causes set out in chapter 3, including fires and the expansion of oil palm plantations (Palmer and Engel, 2009; Dennis et al., 2005; Carlson et al., 2012) Since Indonesia is a focus of international efforts to implement REDD+, it is important to establish what has worked and may work in the future to reduce deforestation. One approach historically has been the development of PAs, and which is a potential approach under REDD+. The motivating question for this chapter is therefore whether deforestation has been reduced in PAs relative to similar unprotected areas, and consideration of why.

First though, there are complexities surrounding the question of Indonesian parks' success to be addressed. As highlighted in the introductory chapters, the history of Indonesian forest management is riddled with intrigue, corruption, and periods of kleptocratic rule. This means that there are certainly normative issues concerning whether there *should* be national parks and PAs implemented in their current form in Indonesia, with local communities generally excluded from forest resources. However, these are different issues to the positive economic approach taken here which asks, given the parks are established in fact, what has their impact been on deforestation?

Once the argument for why to measure environmental policy impact has been made (we need to make better use of scarce resources; (Ferraro and Pattanayak, 2006)) and once the distinction between normative and positive economic thought has been clarified (the parks have been created-so what impact have they had?), the third and final issue is to address the not-inconsiderable issue of exactly *how* to measure the impact of park creation on Sumatra in practice. There are only limited examples of researchers having done this.

The most comprehensive study of the effects of PAs on deforestation on Sumatra was undertaken by Gaveau et al. (2009a). They used optical imagery from Landsat processed at $25km^2$ resolution for the ten years between 1990 to 2000. They used matching procedures to ensure that sites used to compare with the PAs were as similar as possible in their attributes to the control sites in 'unprotected' areas. They found that PAs had indeed reduced deforestation, even when compared with matched unprotected forests. Further analyses have been conducted on deforestation in Sumatra in the following decade (2000 onwards), such as Broich et al. (2011a,b). However, this work focus more on remote sensing and forest change detection rather than on analyses of the performance of PAs.

As such this chapter provides a novel contribution to the literature in that it assesses PA performance during a period of recent land cover change in Sumatra. Methodologically it is novel because it uses the remote sensing techniques developed in chapter 7. However this also means that the results from this chapter cannot provide a direct comparison with the main other assessment of PAs in Sumatra by Gaveau et al. (2009a). This is because the two studies are processed at different a) time periods (Gaveau 1990:2000 vs 2007:2009 this study) and b) covers a different extent (Gaveau all Sumatra vs. swathe of Jambi and South Sumatra this study); c) using a different technology (passive optical satellite imagery vs. active microwave radar imagery in this study). Nonetheless, overall substantive result of whether PAs reduced deforestation can be compared.

9.3 Methods

9.3.1 Basic conceptual model

An important first stage in the analytical process is to develop a conceptual model to characterise the system of interest (Etienne et al., 2011). This helps to frame how and why an intervention may have an effect (Dawid, 2000). In Indonesia, deforestation is being driven by a range of factors as discussed comprehensively in chapter 3. These include competition for land (e.g. the expansion of small-holder agriculture and an increasing human population; expansion of palm oil plantations, expansion of pulp and paper industry); and demand for the timber which constitutes the forest itself and may be extracted unsustainably. Hence some of the main ***Resources*** in demand are land and timber. However, forests provides many other goods such as non-timber forest products (NTFPs) and biodiversity; in addition to services such as carbon storage and sequestration. These goods and services are valued locally and globally e.g. people sell mushrooms from the forest; people buy forest carbon as offsets in the voluntary carbon market. The ***Actors*** are i) those who want to convert the forest land to other uses including large multi-national agri-businesses through to small-scale subsistence farmers ii) those who derive benefits from the forest and would in seek to ensure its conservation in the long term, including the national and local governments, and their agencies e.g. the regional forestry offices *DINAS Kehutanan*; and people who use the forest for NTFPs, and who otherwise derive benefits from forests including. The ***Dynamics*** are that increasing international and domestic demand for land and forest products, and products derived from non-forest land use like oil palm plantations, has driven deforestation across the island (Broich et al., 2011a,b; Gaveau et al., 2009b; Linkie et al., 2009). Because the costs to these activities are lower when land access is easier, this provides the conceptual basis for the choice of independent variables to use in the subsequent estimation strategy.

These represent some of the immediate or 'proximate' causes of deforestation (Angelsen and Kaimowitz, 1999; Lambin et al., 2003). Controlling for other factors, forests in mountainous areas are less likely to be deforested than forests on flat lands (Chomitz and Gray, 1999; Newton, 2007). Areas closer to markets reduce transport times and hence costs, the effect of which is to increase profitability of alternative land use and increase the risk of deforestation (Pfaff and Robalino, 2012). Where rivers flow in the direction of towns and markets, they can be used for transportation of sawn wood and forest products to markets. The same effect applies in that increases the profitability of the land and hence likelihood of deforestation: the proximity of a forest patch to a navigable river has been shown to be positively related to the probability of forest conversion by Newton (2007). The proximity of a road has a similar effect on the likelihood of deforestation (Angelsen and Kaimowitz, 1999; Lambin et al., 2003). These factors may all then interact to increase deforestation (Chomitz and Gray, 1999; Marcoux, 2000; Gaveau et al., 2009c; Venter et al., 2009a). Hence we would expect remaining forest land closest to roads, rivers and markets to be cleared more quickly than more remote areas, which by contrast are more likely to be designated as PAs *away* from the drivers of deforestation (Joppa and Pfaff, 2009). Hence by controlling for as far as is possible for these factors, it becomes more likely to identify the impact of policy interventions. The decisions of the actors in the non-protected areas are therefore assumed to surround short-term profit maximisation from all land uses options, whether that be applying for licences to undertake logging; plantation establishment.

Whilst such permissions continue to be given in order to foster economic growth, the Indonesian government also wishes to retain a certain proportion of forest in order to meet national goals and international targets e.g. under the United Nations Convention on Biological Diversity. (Note that understanding the process of the allocation of the treatment is important since it helps for the subsequent control of bias). The government has therefore established a series of PAs across the country, which cannot be exploited for uses other than the conservation of natural forests. Since the government is balancing short-term economic development objectives and conservation policy, it chooses areas for conservation of less economic value than others due to distance from markets etc., as described above and as argued by Joppa and Pfaff (2009). Hence in the subsequent estimation strategy we need to control for these selection biases. Crucially, I assume that in the counterfactual case that the PAs were not created, then those forest areas would be designated for the other uses that we observe today on Sumatra.

The essential ***Interactions*** of the system are that in the PAs, it becomes illegal to exploit the forest, and these laws are enforced in principle through the use of ranger patrols, and prosecutions for individuals and corporations transgressing these limits. The decisions at play here then for the actors are whether the disincentives associated with being caught are greater in than the the benefits of exploiting land and resources in *de jure* PAs. As set out in the background chapters, during *reformasi* there was contest over land rights and the issuance of small-scale permanence in PAs designated during central government. However by 2007, the assumption of the conceptual model is that this situation had stabilised following Indonesia's socio-political stabilisation and transformation into a relatively peaceful multi-party democracy. This is the conceptual basis for the PAs having a treatment effect on deforestation.

Findings published in the literature provide prior expectations about what we may observe in this basic model, which may in turn be used to develop hypothesis about the performance of PAs in the present study. Given the extensive land cover change has been observed in the region during the past two decades (Broich et al., 2011a,b; Gaveau et al., 2009b; Linkie et al., 2009), and given that (Gaveau et al., 2009a) found that PAs were having an impact between 1990 and 2000, it is reasonable to expect that deforestation is reduced in national parks as measured against comparable unprotected areas. The effect may have become more pronounced since 2000, especially since the forest outside the PAs has continued to be extensively cleared recently (Broich et al., 2011a,b). More generally, evidence from the literature suggests that secure land title and PAs are expected to reduce deforestation and forest degradation (Southgate et al., 1991; Krutilla et al., 1995; Ferraro et al., 2011; Nelson and Chomitz, 2011) in countries as diverse as Costa Rica and Thailand (Andam et al., 2010, 2008).

This leads to two hypotheses. Greenstone and Gayer (2009) state that a causal hypothesis should have a 'manipulable treatment that can be applied to a subject an outcome that may or may not respond to the treatment'....'that can be subject to a meaningful test' wherein 'all other determinants of the outcome can be held constant' (p.22). Whilst it is not possible to manipulate the treatment of protection on forests experimentally, as explained in the introduction it should be possible to emulate the randomisation to some degree through matching on covariates to remove selection bias. Further, it is possible to subject deforestation (outcome that could respond to protection treatment) across Sumatra to meaningful tests, that hold constant the factors which have been shown to influence deforestation.

- $H0_1$: Deforestation in the PAs is lower than in other land classes areas between 2007:9, controlling for the bias in the location of PAs.
- $H0_2$: The perceived protective effect will be reduced by contrasting the naïve comparison group with pixels matched on covariates.

The alternative hypotheses are that, due to increasing pressures on remaining forests, and the changes in land management and attitudes towards forestry following *reformasi* (see Chapter 3), even protected forests have been deforested. As such there will be no effect of comparing the PAs with matched unprotected pixels.

9.3.2 The dependent variable

In Chapter 7a threshold of 1.5dB change in backscatter between years was used to create binary deforestation/no-deforestation raster files with a 1 or 0 for each 100m X 100m pixel across the 7.2Mha study area. Pixels with a biomass value < 53Mg ha^{-1} in 2007 were excluded as either non-forest or plantation (Morel et al., 2011). This reduced the likelihood of inadvertently measuring the cropping cycles of plantations such as oil palm *Elaeis guineensis* in addition to clearance of natural forest. In addition, seasonally flooded forest was excluded using the process in chapter 7). This reduced the chances of false-positive deforestation detection caused by flooding. I then aggregated the dependent variable into landscape-scale grids of pixels such that each observation covered 5km x 5km. I took the sum of the 100m x 100m (1,0) change pixels and converted that into the percent deforestation in the two year period (sum deforested pixels/2500) x 100. For protected areas, only grids which were entirely within protected areas were considered, and hence only areas that were entirely outside of protected areas were considered 'unprotected'. This aggregation approach has with precedents in the literature from (Gaveau et al., 2009a; Laurance et al., 2002). The 5km x 5km resolution is the same as employed by Gaveau et al. (2009a) for Sumatra.

9.3.3 The control (confounding) variables processing and data extraction

Independent variables were created as confounders in accordance with the theory and evidence from the literature on the drivers of deforestation set out in the socio-economic background Chapter 3; and the basic conceptual model described above for the processes of deforestation. For instance the costs to exploit forests and land near roads is lower than the costs to do the same far from roads (Angelsen and Kaimowitz, 1999; Lambin et al., 2003; Newton, 2007). Along with the elevation, these variables also affect the probability of forest areas being treated as a PA (Joppa and Pfaff, 2009). So I created rasters of distance to roads, rivers, and towns.

To create these, shape files of roads, towns, and rivers were provided by the ZSL Indonesia office. These came originally from the Indonesian government land management department called *BIPHUT*. I rasterised these shapefiles using the vector to raster conversion tool in the open source GIS software called QGIS (QGIS Development Team, 2009). This was done using a raster template with 100 x 100m pixels set to UTM 48S. The next stage was to rasterize the shapefiles for all the PAs in the scene, with a 1 coded for pixels inside PAs and 0 for those pixels outside. Then, I used the raster analysis proximity tool in QGIS to create a proximity raster file. This proximity tool estimates the distance of any given pixel in the raster from the rasterised shape outline, for instance the shape of the roads. In this way the distance from the nearest road, river and town were estimated for each pixel in the study scene. An example of the production of the variables is shown in figure 9.2. Finally, I included the estimate of above ground biomass in 2007, in order to control for the initial level of forest at the beginning of the study period. This is because the largest changes in biomass are likely to occur where there is still enough forest to clear.

9.3.4 The basic empirical model

Overall I wish to determine the effect of the PA status on deforestation. For this experiment only one time step of deforestation is available, i.e. deforestation occurring between 2007 and 2009, as calculated in chapter 7. Hence time periods t=1, and we can only ever observe the post-treatment condition, and not the deforestation prior to the creation of the PAs, the pre-treatment condition indicated as T1 in the figure 9.1. I retain the identifying assumption of parallel paths remain for one time period. The basic model is therefore to calculate the differences between deforestation inside the PAs and compare these with similar areas based upon their covariates, but which are designated for other land uses, in the single time period. These areas which serve as the counterfactual scenario i.e. in the case where the treated observations are not treated (Greenstone and Gayer, 2009). This is based on the assumption that the bias in the location of PAs (Joppa and Pfaff, 2009) can be eliminated using the matching methods described below. More specifically, the identifying assumption here is that the sole source of omitted variables bias comes from a covariates which are correlated with the treatment. I assume that the PAs would be designated as other land uses in the absence of treatment.

In summary my basic formulation is to measure the difference in means between the post-treatment deforestation outcomes for treated (PA) pixels and untreated

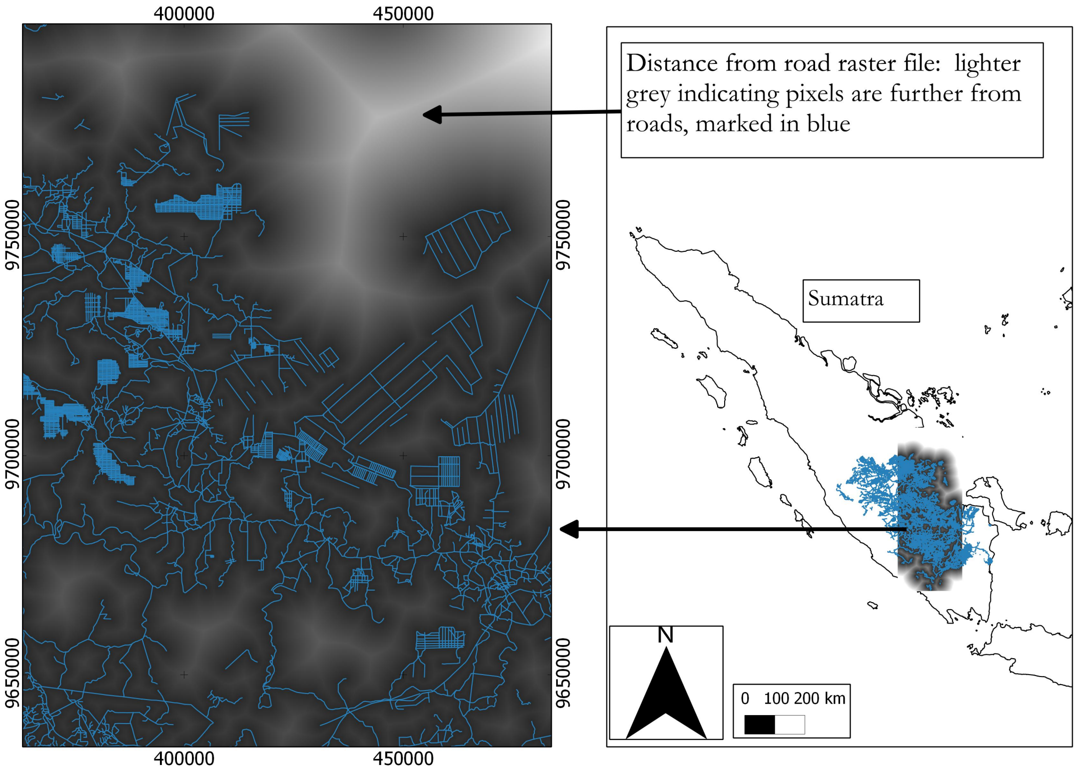


Figure 9.2: The creation of the distance from road as an independent variable. In the left hand panel the roads are highlighted in blue, and the distance from the road per pixel is shown by the shading in the underlying raster file. Lighter colours indicate the pixel is further from the road, and darker grey indicates the pixel is closer.

(unprotected) matched control pixels in one time period. The estimand is the Sample Average Treatment Effect (SATE) (Imbens, 2004; Rubin, 1974) calculated with difference between group means of deforestation rate in the treated and matched, but untreated groups:

$$\zeta = (\hat{Y}^{After}_{treat} - \hat{Y}^{After}_{control}) \tag{9.1}$$

where the outcome variable of interest $\hat{Y}$ is deforestation,and ζ is the SATE. This is based on the strong ignorability assumption that the matching procedure removes any conditional dependence of the treatment on the observed covariates which I identify in the basic conceptual model, and hence any selection bias.

9.3.5 Estimation in practice: matching on covariates, testing balance, and calculating the difference in mean outcome

Matching In order to control for the bias in location of PAs, I used Genetic matching (function GenMatch(...)) to balance observation covariates, implemented in the Matching package for R (Sekhon, 2011). This addressed the question of which observations should be compared (Imbens, 2004) to estimate the SATE. Genetic matching provided the best results compared against the other options of full matching, and optimal matching, using propensity score sub-models. The options I used were: ratio=1 (the number of control matches per treated observation); number of bootstraps=500 (determines the number of bootstraps used for the Kolmogorov-Smirnoff tests between distributions of the covariates in the matched data; the minimum for publication quality p-values is 500 (Sekhon, 2011)); and finally with population size = 500. This last argument controls the number of generations that the evolutionary algorithm (EA) uses find the matching solution. I retained the default setting of sampling with replacement.

Testing matching procedure success It is crucial to test the covariate balance in the matched treatment and control groups in order to test how well the matching procedure worked, prior to making the final estimation of SATE. This is because on the one hand the matching should reduce the covariate differences towards zero; on the other balance can actually worsen, resulting in inference that will be less accurate than if matching had been undertaken at all (Sekhon, 2011). I tested balance by using pre/post-matching quantile-quantile plots; and the outputs from the Matching package's summary() function. This provides distributional test statistics from Kolmogorov-Smirnoff (KS) tests. Whilst Gaveau et al. (2009a) used t tests to check for the differences between covariates, Ho et al. (2011) are explicit that one t-tests should never be used to test for balance. I followed the advice of the package author, focussing on distributional tests.

Estimating the estimand, the SATE In order to calculate the SATE, I again referred to the output from the summary() function. This calculates SATE, and assesses its significance with standard errors, a T-test, and associated p-value. The null hypothesis is that the outcomes of the matched and the counterfactual are from identical populations.

9.3.6 The experimental(observational) variable of interest: PAs

The PAs in the study scene included a range of formally PAs, including watershed protection forests (*hutan lindung*), wildlife reserves (*Suaka Margasatwa*), forest parks (*TAHURA*), and national parks (*Taman nasional*). The national parks included were Berbak national park and the south-eastern portion of Kerinci Seblat. There are a total of 984,010 1ha protected pixels in the 7.2Mh pixel study area. The distribution of these PAs across the landscape is shown in figure 9.3. In none of these PAs is any deforestation or forest degradation allowed by law. The *hutan lindung* areas are designated to protected ecosystem services like watersheds, national parks are designated to protected unique biodiversity features and ecosystems, as are the wildlife reserves.

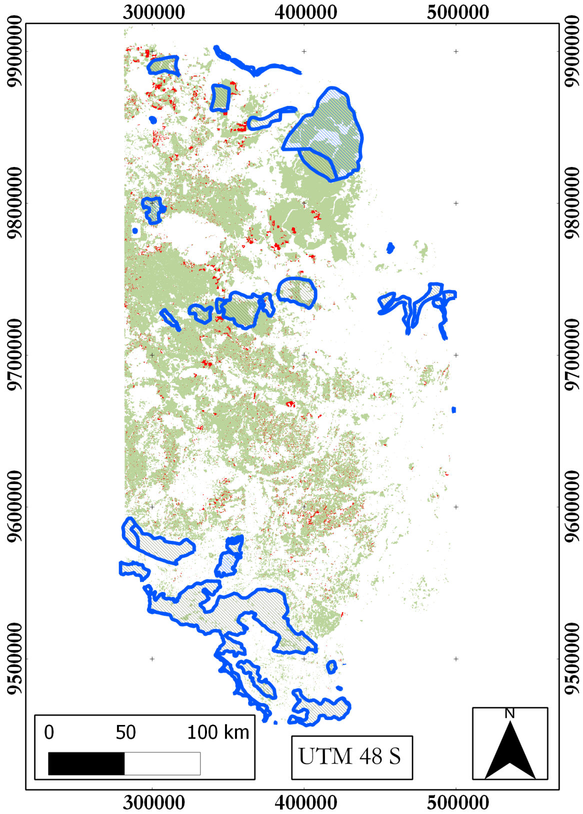


Figure 9.3: PAs (blue, diagonal lines) superimposed on in-tact forest (green) and deforestation that occurred between 2007 and 2009

9.3.7 Vegetation-dependent measurement bias

Whilst the use of radar has advantages over passive optical sensing, there are problems. As explained in chapter 7, the radar microwave energy is scattered differently by the open canopy and small tangled roots of mangrove forests than in swamp or mineral soil forests (e.g. forests dominated by trees of the family *Dipterocarpaceae*). This cannot be controlled for since no field data from mangrove forests was available for calibration. Sembilang national park (south of Berbak national park) was therefore excluded from this analysis, because it was not possible to accurately measure change here. In addition, PAs in the south-west of the scene included mountainous terrain. These were excluded from the analysis if the local terrain slope was greater than 5^o as per chapter 7. Figure 9.3 shows the location of the PAs (outline in blue) in the study scene overlaying the forest biomass estimate from 2007 (light green) and the change estimated for 2007 to 2009 (red).

9.4 Results

9.4.1 Covariate balancing

A summary of the covariate balance is provided in the table 9.1. The genetic matching algorithm succeeded in balancing the distributions in four of the five the variables, as measured by the KS statistics following matching. The quantile plots of the covariates in the control and treated areas are shown in figures 9.4. The fifth variable which was apparently difficult to match upon was the distance to rivers, which reflects a current absence of unprotected forest areas which are distant from rivers. Whilst the overall balancing of the elevation was successful, the qqplot shows that there remains some outlying high-elevation values in the treated PAs. Similarly this reflects the bias in the location of parks to the high altitude areas in Sumatra, and the relative absence of high altitude areas for other uses. Nevertheless these outlying treated observations did not prevent the selection of a set of control observations whose distribution was not significantly different from the treated observations at the 5% level (KS bootstrap p value=0.57).

	Elevation		Rivers	
	Before matching	After Matching	Before matching	After Matching
Mean treatment	223.74	223.74	4158.7	4158
Mean control	70.713	185.5	3025.8	3525.1
Std mean diff	32.953	8.23	33.474	18.72
Mean raw eQQ diff	157.34	40.81	1110.5	666.78
med raw eQQ diff	5	2	1019.9	449.38
max raw eQQ diff	1533	1353	4273.7	6221.3
mean eCDF diff	0.10	0.148	0.10319	0.055
med eCDF diff	0.11	0.011	0.11018	0.0454
max eCDF diff	0.16	0.06	0.15874	0.14
var ratio (Tr/Co)	12.38	1.81	1.7047	1.5756
T-test p-value	0.00	0.00	0.000	0.00
KS Bootstrap p-value	0.00	0.57	0.000	0.004
KS Naive p-value	0.00	0.64	0.00	0.0063
KS Statistic	0.16	0.06	0.158	0.14

	Roads		Towns	
	Before matching	After Matching	Before matching	After Matching
Mean treatment	7673.1	7673.1	21137	21137
Mean control	2175.8	7027.3	10614	20080
Std mean diff	87.076	10.23	68.09	6.8392
Mean raw eQQ diff	5465.4	651.75	10445	1438.4
med raw eQQ diff	5423.4	376.36	6043.4	930.77
max raw eQQ diff	12263	3970.5	28898	9191.4
mean eCDF diff	0.36502	0.025	0.2362	0.029667
med eCDF diff	0.40777	0.022	0.26215	0.022727
max eCDF diff	0.47294	0.068	0.33384	0.083333
var ratio (Tr/Co)	4.7068	1.194	4.326	1.1329
T-test p-value	0.00	0.00	0.00	0.00
KS Bootstrap p-value	0.00	0.53	0.00	0.295
KS Naive p-value	0.00	0.57	0.00	0.318
KS Statistic	0.47	0.068	0.333	0.083

	Biomass	
	Before matching	After Matching
Mean treatment	110.54	110.54
Mean control	72.395	108.35
Std mean diff	44.221	2.53
Mean raw eQQ diff	38.042	5.527
med raw eQQ diff	48.202	4.577
max raw eQQ diff	76.419	18.27
mean eCDF diff	0.15003	0.023146
med eCDF diff	0.15921	0.022727
max eCDF diff	0.19728	0.079545
var ratio (Tr/Co)	1.3783	1.0719
T-test p-value	0.00	0.26508
KS Bootstrap p-value	0.00	0.357
KS Naive p-value	0.00	0.37382
KS Statistic	0.197	0.079545

Table 9.1: Results of the covariate matching procedure using the Genetic Matching in the R Matching package. Note the size of the Kolmogorov-Smirnoff statistic before and after matching, and its associated p-value. This shows how the mean treatment and control values converged following matching, as represented in the convergence of their distributions in the qqplots.

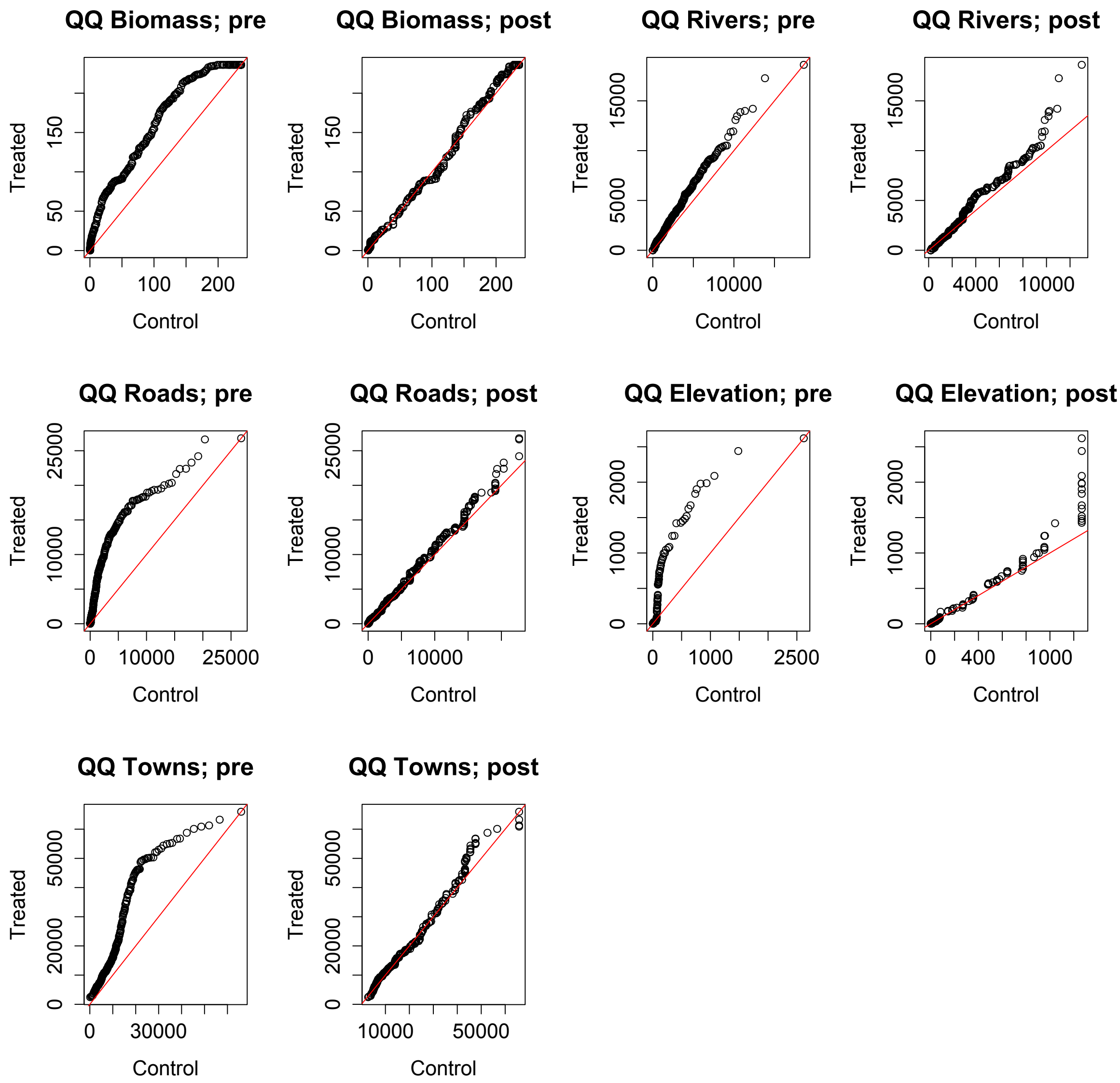


Figure 9.4: The quantile-quantile plots show the distribution of the treatment and control sites pre- and post-matching. In the naïve pre-matching comparison the control sites are any other observations than the treated. The post-matching control observations should be more similar in their distributions to the treated observations, than are the ‘any other’ observations in the naïve comparison.

9.4.2 Matching procedure estimate of SATE

Of a data set of 2638 observations of 5 x 5 km pixels, the 264 observations which covered the PAs were matched with 264 areas in other non-protected land classes. This provided an SATE of -1.74%, i.e. that PA status reduced deforestation by 1.74% compared to other land classes, controlling for biases in PA location. Note that this is the change of a two-year period (2007-9), hence an annualised average difference would be 1.74/2=-0.87%. The (Abadie & Imbens (Sekhon, 2011)) Standard Errors, were 0.61, with a T-statistic of -2.9, p=0.004, hence the difference was significant at the 5% level. The deforestation outcomes in the protected and unprotected areas before and after matching are shown in 9.5.

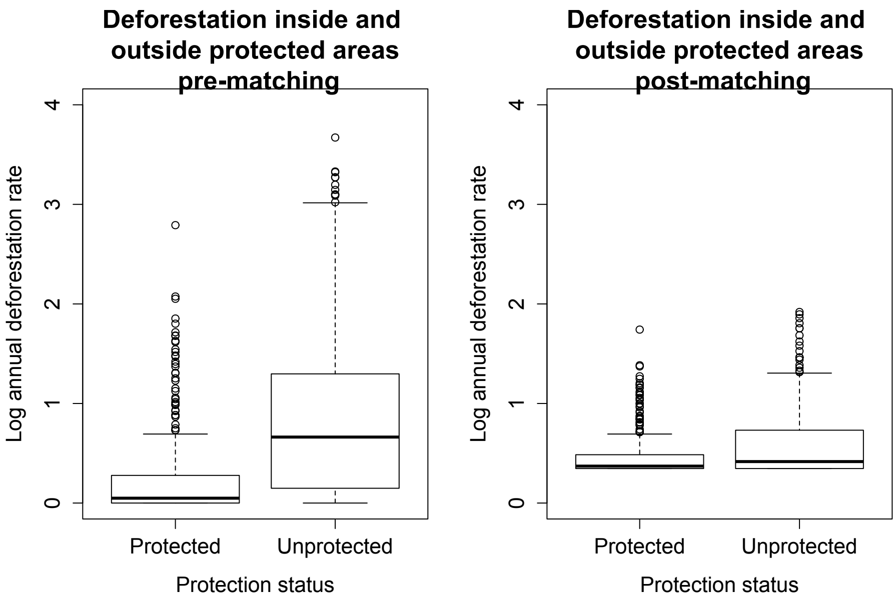


Figure 9.5: These boxplots show deforestation 2007-9 before and after the Genetic Matching procedure. The Y axis is % deforestation per year, log transformed. Following matching, the outliers in the control sites are reduced, and there is crucially a convergence of the observed outcomes due to selection of pairs of observations which are more similar in terms of the values which the literature suggests affects deforestation. This shows neatly how a naïve comparison between unprotected and protected areas would produce a biased result, and how improving covariate balance between comparisons addresses this.

9.5 Discussion

9.5.0.1 Controlling for biases: success of the genetic matching methods

. The matching procedure performed well in controlling for much of the bias in PAs location in this region of Sumatra. The success of the matching procedure was confirmed by the examination of the quantile-quantile plots, and the KS tests on the distributions of variables before and after the matching procedure. One variable was not well accounted for however - distance from rivers. This probably reflects the large number of PAs in the scene in the Bukit-Barisan mountain range, where there are fewer large rivers as recorded in the GIS files provided by ZSL Indonesia. This may also conforms to the finding of Joppa and Pfaff (2009) that PAs tend to be biased in elevation and distance from drivers of deforestation. Hence some bias remains since it is not possible to find perfectly matched pixels in river-distance variable space. This highlights the difficulty of robust causal inference in practice, and is expected to have introduced a small amount of bias into the final result.

9.5.0.2 The substantive finding

. During the two year study period it appears that the PAs have on average reduced the amount of deforestation relative to all other land uses by 1.8%. Hence, deforestation would be 1.8%/2 =0.9% per year higher in the PAs if they were designated as another land class. The magnitude of the protective effect is reduced by contrasting PAs with unprotected pixels that were matched based on their covariates. In terms of the direction of the finding, there is no evidence to cause the rejection of the second hypothesis. In addition this finding is consistent with other studies from elsewhere in the tropics that have found that the effect of PAs is reduced when used matched unprotected pixels (Andam et al., 2008). That the effect was not dramatic suggests that even Sumatra's more remote unprotected forests are now being cleared. Indeed the maps produced in Chapter 7 suggest that there is now relatively little high biomass forest outside Sumatra's PAs, and that only Berbak clearly stands out as a complete block of relatively in-tact forest. This is supported by the finding from Chapter 8 that the mean above ground biomass was higher in Berbak than any of the other forest classes. So as forest resources become increasing scarce, the last pockets of unprotected forests will also be cleared. This is supported by figure 4.6 in Chapter 4 which shows a very large new forest clearance on the borders of Berbak in 2013.

Overall, the results support the only other available estimation of the effect of Sumatra's PAs, (Gaveau et al., 2009a), and does not provide evidence to reject the first hypothesis.That the deforestation rate is lower in the PAs than elsewhere requires explanation. Referring back to the basic conceptual model, the government's policy in the creation of PAs was to retain certain areas of Indonesia as permanently forested to conserve biodiversity and other ecosystem services. Whilst on the one hand Indonesia has experienced severe problems with law enforcement in forestry (Collins et al., 2011a; Gaveau et al., 2009b), on the other hand policy implementation imperfection does not imply zero implementation. It remains illegal for people to degrade and clear protected forests and there are still sanctions for those caught breaking land use laws, including fines and imprisonment. These continue act as a disincentive to undertake activities that cause forest loss. Indeed the presence of law enforcement officials has been suggested to have an effect on the reduction of deforestation elsewhere in Indonesia (Macdonald et al., 2011). We may be observing this effect in aggregate, and were enforcement to be improved we could expect this effect to increase in size, such that deforestation approaches zero in the PAs.

In direct contrast with the protected areas, we expect to see a certain amount of deforestation in the non-protected areas. In conversion production forests for instance, we should expect there to be continued forest degradation and deforestation over time as logging takes place, followed by complete removal of the forest before new plantations are established. In the limited and permanent production forests, we should expect forest degradation to continue sporadically as the concessionaires undertake logging rotations, however in the absence of permission to change the land class to a conversion forest, we should expect there to be no deforestation. This means that we are observing the impact of creating PAs as measured against any other land class: it is not possible strictly to observe the effect of protection on forests, because there is no Indonesian forest class which is simply 'unprotected' and not under another designation.

9.5.0.3 Validity and limitations

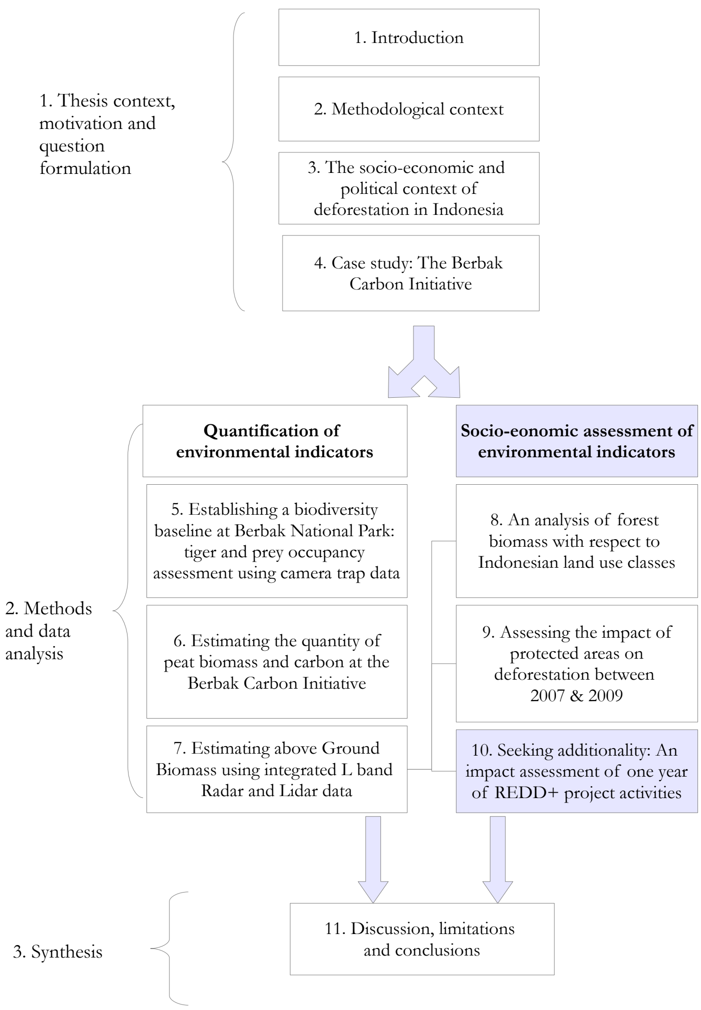
Whilst the results make intuitive sense, there are reasons for caution. First, the study area is limited to a swathe of South Sumatra and Jambi provinces only, as determined by the availability of Radar data (see chapter 7). This means that many PAs on Sumatra are excluded from the study. Hence the results must be interpreted within this study area, and as the Sample Average Treatment Effect, rather than the Population of PAs across Sumatra (external validity). With respect to the matching exercise, the restriction of the size of the study area may also mean reduced internal validity: This is because other more suitable matches may exist elsewhere on Sumatra, but which I do not observe, e.g. large areas of unprotected mountain forest. Nevertheless, the counter-argument for choosing more remote matches is that the further other matched sites are physically from the study area, the more likely it is that other unobservable region-specific factors are affecting deforestation, which are difficult to control for. These include governance levels; migration; cultural differences in land use; forest fires and rates of plantation expansion (Gaveau et al., 2009a).

A further limitation of the study which may limit internal validity is the time period examined. The study covers only two years of deforestation 2007:2009. There are two problems associated with this. The first is that this raises the chances of detecting a snapshot of random noise rather than longer-term differences in deforestation attributable to land use regulation. The second is that with only one time period the cross sectional approach has to assume that the trends in deforestation between the treated and the untreated areas were the same prior to the creation of the park: the trends cannot be tested empirically. As such the effects of forest protection may be both stronger in future studies that use the same technologies over longer time periods, and also more robust if the identifying assumption of parallel paths can be justified.

Finally, the demonstration here of the fact that deforestation can be detected over short periods is important because it will allow more direct feedback between REDD+ payment mechanisms and actual deforestation reduction results achieved. This high temporal resolution is exploited in the next chapter, to test the impact of ZSL's activities at Berbak national park.

Chapter 10

Seeking additionality: an impact assessment of one year of pilot REDD+ project activities



10.1 Abstract

This chapter is a project evaluation that assesses the marginal change in the performance of Berbak national park in reducing deforestation following one year of pilot REDD+ activities. Between 2009 and 2010 The Zoological Society of London (ZSL) built a new field base that was staffed permanently by forest police and ZSL staff. Prior to this there was no operational field base at the site. The raw deforestation data suggest that prior to the intervention in 2007:8, mean deforestation in Berbak was 0.037%; falling to 0.003% in 2008:9; and then in the year of the intervention rising to 0.049%. This suggests deforestation increased following the intervention. However, the variation may have been caused by factors unrelated to the project, hence I attempted an analysis within a robust causal inference framework. I preselected two protected (Hutan lindung) forests to use as control sites to estimate deforestation in the absence of deforestation. I ran a matching routine on the independent variables on pixels within those control sites in order to match control and treated observations with minimised covariate differences, yet the procedure did not improve balance. I therefore used unmatched data with a differences in differences (DD) model estimated with linear regression to calculate the impact of the project. This suggested that deforestation had increased by 0.05% following ZSL's intervention, however this was not significant statistically (p=0.37; heteroskedasticity robust standard errors). More problematically, the trends in the control sites and at Berbak did not meet the key identifying assumption of DD, that of parallel paths. The chapter highlights the difficulties of finding appropriate control sites with which to undertake robust causal inference in practice. Given these problems it is difficult to determine whether the apparent (naïve) increase in deforestation in Berbak is due to changes that would have happened in the site in the absence of the intervention, or to the effects of the intervention.

10.2 Introduction

The implementation of REDD+ faces multiple challenges. A central issue is how to actually create additional reductions in deforestation, and thus allow the payments-for-results envisaged under the mechanism. In order to be able to determine whether a given intervention implemented in the name of REDD+ has had any impact, the agents that would make payments for results require robust evidence that deforestation has actually been reduced against a counterfactual situation in which REDD+ was not being implemented. Activities failing to reduce deforestation may need to be discontinued(Essama-Nssah, 2006). This creates a strong motivation, and basis for a good research question (Deaton, 2010): do activities implemented in the name of REDD+ create additional conservation? This is a novel and topical question, requiring robust causal inference methods. A major distinction from the previous chapter is that a new policy under REDD+ could be in principle randomised, creating a controlled trial (RCT). However, since this is not the situation in present case, I once again return to the challenges of using observational data to make causal inferences (Angrist and Pischke, 2009; Imbens and Wooldridge, 2014).

As set out in the previous chapter, there is a range of options to consider when addressing such a question. These include the establishment of a basic conceptual model for the Actors, Resources, Dynamics and Interactions within a system (Etienne et al., 2011); deciding whether to draw more heavily upon a theory of change approach or the use of empirical data, or both (Carvalho and White, 2004; Deaton, 2010; Angrist and Pischke, 2010); establishing an appropriate empirical model for testing the putative impact; and deciding how to address the central issue of selection bias e.g. Miteva et al. (2012); Angrist and Pischke (2010, 2009). This involves understanding why the given REDD+ activity was implemented in the manner that it was, and where (analogous to the selection of certain areas as PAs (Joppa and Pfaff, 2009; Pfaff and Robalino, 2012)), which underpins the choice of controls that serve as plausible counterfactual scenarios (Angrist and Pischke, 2009; Ferraro, 2009) to reflect what would have happened in the absence of the REDD+ intervention. Finally there is then the consideration of appropriate statistical methods to estimate the empirical model.

On a broader level, environmental policy impact assessment is an important academic research issue, since externalities are at the heart of environmental economics (Greenstone and Gayer, 2009). So too are the development and implementation of appropriate methodologies to assess policy impact (Ho et al., 2007; Baker, 2000; Imbens, 2004; Frondel and Schmidt, 2005; Ferraro and Pattanayak, 2006; Angrist and Pischke, 2009; Pattanayak et al., 2010; Miteva et al., 2012; Steventon et al., 2011; Arriagada et al., 2012; Greenstone and Gayer, 2009; Sekhon, 2011). The development in research methods and also the appreciation of the issues involved in impact estimation is a process (Angrist and Pischke, 2010) which allows refinement and re-evaluation of previous findings e.g. in the labour market Ashenfelter (1978) and optimistically, better policy prescriptions. Within the past decade environmental economists have been looking over the shoulders of conservation scientists and managers with the growing realisation that a lot of conservation investment has occurred without either consideration of its actual impact and without use of the robust methods that have been developed in other fields (Ferraro and Pattanayak, 2006; Pattanayak et al., 2010). Where work has been undertaken to estimate the impact of policies to conserve forest, the analyses have often been overly-simplistic. Extreme examples include basic inside-outside comparisons of deforestation rates in an attempt to estimate the impact of protected areas (PAs) on deforestation rates e.g. Nagendra (2008). Such approaches do not take the crucial issue of selection bias into account, which has been identified as the central issue in observational studies in other fields for decades e.g. Ashenfelter (1978). I have described bias in more detail in the previous chapter, but since it is fundamental to the present question, I repeat aspects here.

To focus I turn to the concern of the present chapter. This aim is to understand whether a conservation intervention implemented under the name of REDD+ by ZSL in Berbak national park on Sumatra in Indonesia has had any effect on the deforestation rate outcomes at that site. Chapters 3 and 4 set out the detailed conditions at Berbak park and the basis for REDD+ intervention. However in summary the context is one of continuing deforestation in an area rich in terrestrial carbon stores, which is also in the Sundaland biodiversity hotspot (Myers et al., 2000) whose forests provide the last habitat for the some of the last populations of Indonesia's last sub-species of tiger. Reducing deforestation and forest degradation in this region should contribute to climate change mitigation and the conservation of one of the world's most charismatic species.

Deforestation is continuing rapidly in the face of *inter alia* new plantation and farmland development (see chapter 3), whilst forest degradation and clearance occurs even within conservation areas (Macdonald et al., 2011; Jepson et al., 2001; Gaveau et al., 2009b,a; Linkie et al., 2009); and as demonstrated in the previous chapter. This includes losses of forest at Berbak due to illegal logging, fires, and ecosystem damage arising from draining peat inside and outside the park border, increasing the risk of fires and carbon loss from peat soils (see chapter 6). With the prospect of funding becoming available via REDD+, ZSL saw the opportunity to try to both reduce deforestation, conserve the peat carbon stocks, and conserve Berbak's remaining tigers. ZSL sourced UK government funding to start a spatially-explicit REDD+ project here. The pilot phase involved building a field base, and running patrols into the forest to reduce the various threats to the forest, which is the treatment we would like to evaluate the effect of. The project thus in effect subsidised the Indonesian state in support of its management of Berbak national park, presumably based on the (unstated) assumption that this would not crowd out either present or future funding from the Indonesian government.

In this context there are multiple sources of bias, principally surrounding the selection bias in the allocation of treatments. Plural because, more specifically, Berbak is subject both to 1. treatment as a PA, and 2. a subsequent REDD+ treatment within that PA. In order to tease apart the implications of this, I first consider only the bias in PA designation, and then the bias surrounding REDD+ site selection.

10.2.0.4 The first treatment: the creation of Berbak national park

Protected areas tend to be non-randomly located in places which were unlikely to have been deforested anyway (Joppa and Pfaff, 2009; Pfaff and Robalino, 2012). Berbak is a peat swamp forest, which is of less value for conversion to other uses than dryland forests on mineral soils. Therefore this suggests that in the counterfactual situation that Berbak was not a PA it would have experienced nonetheless a lower likelihood of conversion to another use than easily neighbouring forests on dry mineral soil. Furthermore, the forests of Berbak are located on the eastern coast of Sumatra which has previously been difficult to access until the creation of new roads and plantations in the past two decades. Hence Berbak may also have been historically protected by having poor access which increased the costs to any potential agent of deforestation (Pfaff and Robalino, 2012). This also meant that there would have been fewer settlers in the region: communities in the region have historically been concentrated along the major *Batang Hari* river upon which Jambi city is founded, and along the coast. With lower population density than in the more readily accessible and valuable mineral soil forest areas, this would have similarly led to lower local demand for wood and Non-Timber Forest Products (NTFPs). These factors would have meant lower deforestation probability even in the absence of protection from PA status. This illustrates that PA status (treatment) is not independent of its attributes (a vector of covariates): This is selection bias. This is essential to appreciate, since a direct comparison between the deforestation rate in Berbak and neighbouring unprotected forests on easily-cleared mineral soils which suggested lower deforestation in the PA could be interpreted naïvely as PA success(Joppa and Pfaff, 2009; Pfaff and Robalino, 2012). In order to account for this spatial selection bias in Berbak's location, we therefore need to identify suitable controls which reflect as far as is possible the counterfactual situation whereby Berbak was not a PA, which in practice means finding other peat forest areas as similar as possible along a vector of covariates that determined its location, but which are not protected.

Finding suitable unprotected control sites to serve as counterfactuals for Berbak, and then estimating an empirical model to estimate the protective effect of the PA status e.g. via covariate matching would be appropriate if the objective were to estimate the effect of PA status, assuming that the counterfactual is that Berbak would have been otherwise allocated to any other land class than conservation. However, the assessment of PA impacts on deforestation was the goal of the previous chapter. There are two major differences in the present chapter. First, the aim is to examine the *marginal change in the effectiveness* of an *existing* PA following a REDD+ intervention. Second, there are three time periods of deforestation data available meaning that different economic models can be used to than those in the previous chapter. I now discuss these issues in turn.

10.2.0.5 The second treatment: the establishment of the Berbak Carbon Initiative REDD+ project

I described above the reasons that Berbak may have been designated as a PA originally. According to Imbens and Wooldridge (2014) the available literature on causal inference mostly focuses on such cases where there are binary treatments (treated or untreated). Yet in this case the treated (Berbak) has actually been treated twice: first as a PA, second as an existing PA plus ZSL's REDD+ project. Hence there is a two-stage selection process of PA(1,0), then if PA=1, REDD(1,0). This raises a series of issues in parallel with those relating to the selection of Berbak as a PA in the first instance, and hence another layer of complexity for causal inference. First there is the issue of why ZSL chose Berbak from a population of other protected and unprotected forests across Sumatra that could potentially have been the subject of a REDD+ project. In this case the location incentive (Pfaff and Robalino, 2012) for ZSL was the spatial correlation of large quantities of carbon in Berbak's peat soils and forest, which is at risk of release to the atmosphere; and a population of Sumatran tigers, the conservation of which species is one of ZSL's objective functions. In addition the selection of a pre-existing PA seems to have allowed ZSL to fit into an existing Indonesian organisational and institutional framework, hence reducing costs (but also crucially the potential additional conservation benefits, see Discussion).

A following question is why there are still tigers and relatively large areas of forest at Berbak compared to any other area. This is some combination of the protective effect of the properties of Berbak (peat swamp forest, difficulty of access etc) and the protective effect of PA status. Hence the choice of location of the REDD+ project provides another layer of selection bias: the intervention is focused on an area that was originally less likely to be deforested anyway due to its attributes, and was also more likely to receive PA status, which in turn meant it was more likely to be conserved. Following this, Berbak was then chosen amongst any other unprotected area or PA as the subject of a REDD+ project, driven largely by the presence of tigers. However the tigers are present because of the remoteness of the site and its protected area status: a series of compounded biases.

In order to deal with this, we need to be very careful in the selection of plausible counterfactuals observations. Since Berbak is already a PA, it is necessary to first 'pre-match' in order to generate a subset of data which includes only PAs. From this we could subsequently draw observations (Arriagada et al., 2012) using matching techniques to narrow the distance between a vector of covariates in the Berbak site and the pre-matched sites (Sekhon, 2011). In principle doing this should allow the creation of (a) counterfactual control group(s) which are virtually interchangeable with observations from Berbak along that vector of covariates which includes PA status=1.

10.2.1 The Differences in Differences model

Where there is more than one time period of data available, there arises the possibility of the use differences in differences (DD) as the basic empirical model. This model acknowledges that the absolute values of the outcomes of interest in control and treatment groups are not identical, but that the trends are the same over time. For instance a PA may be being deforested at a low rate, whilst the forest outside is being deforested at a higher rate, but it is assumed that these rates are constant over time. That the differences between the treated and control groups stay the same over time in the absence of an intervention, hence creating parallel paths, is the key identifying assumption of this model (Mora and Reggio, 2012). This is illustrated in figure 9.1 in the previous chapter, along with a more detailed description. The DD estimator is the final difference between differences between the treatment and control groups following the shock (Angrist and Pischke, 2009). Following the intervention, it is assumed that any difference in differences can be attributed to that intervention; which is the effect of the treatment on the treated.

In order to estimate this in practice, one can use matching to remove as far as is possible the differences in the confounding covariates. Another another approach is to use linear regression which controls for the differences in the covariates, and whereby the parameter of interest is the β on the interaction term between a dummy variable for the treated and the treatment time period.

Finally, estimation techniques may also be combined, such that a control data set is defined by matching, but instead of the simple difference in mean outcome being taken before and after the intervention, the DD can be estimated with the β on the interaction between treatment time period and treated observations in a linear regression, performed upon a dataset produced by a matching procedure. Indeed this approach has been suggested to be one of the most robust available (as being 'doubly robust'). This has been used in the present context of forest conservation by Arriagada et al. (2012) to estimate the impacts of deforestation on farms participating in Costa Rica's famous PES programme. This approach is suitable where there are not perfect matches for treatment and control groups.

10.3 Methods

Informing the basic conceptual model. Berbak is a national park bordered to the east by the sea (the Malacca straights) and a narrow strip of land with coastal villages. The local economy is based upon coastal marine and inland freshwater fishing within the national park and the surrounding canals and rivers; coconut plantations; and non-timber and timber extraction from Berbak itself (both of which are illegal, although the first is overlooked in practice). This is based upon my own visits to the site; having spent 8 months in Indonesia over the course of my PhD, and from surveys conducted by ZSL as a part of the project development.

The ***Actors*** in this case are the Indonesian central government which sees a low-cost way to participate in REDD+, and develop experience with the mechanism, and gain 'face' (Hofstede et al., 2010) with the international community for addressing climate change, deforestation and tiger conservation. This project involves no setting aside of any additional land for conservation or non-extractive use, minimising opportunity costs, and can potentially save money for the government if the income from ZSL crowds out the normal government funds for managing the park. ZSL is the project proponent, which instigated the REDD+ project after having observed the lack of facilities at the park offices, and noting the continued presence of a tiger population (see case study chapter for further details). The Berbak PA office in Jambi city stands to see improved funding, status, training and incomes from the REDD+ project. Officers supporting researchers receive *per-diem* payments in addition to their salaries. Additional training provides PA officers with points, the accumulation of which leads to higher salary. The local DINAS Kehutanan (regional forestry office) is responsible for the conservation of the watershed protection (Hutan Lindung) and the *TAHURA* that I considered as candidate pre-match control sites. Other actors are interested in exploiting forest resources largely irrespective of land status designated in Jakarta. People from the local communities regularly access the forest to catch and process fish for market (see photographs in case study chapter). Conversations with people who lived near the park also revealed that there was small scale illegal timber extraction from Berbak, whilst the ZSL office in Jambi confirmed larger-scale illegal logging operations in the south of the park that had led to a Forest Police (POLHUT) office being attached with a *parang* (Indonesian forest knife/machete). Thus in summary the actors are the government agencies, and an NGO on the one hand; and local communities and illegal logging gangs competing over the ***Resources*** of timber, carbon, biodiversity and land. The former group of actors is trying to 'protect' the resources from illegal use by the latter. Their impact upon the site will depend upon the ease of access the forest as regulated by the presence of roads and rivers, and these will also facilitate the removal of timber. Moreover those areas which have more timber are more likely to be targeted for logging, and this is reflected in the measurement of the biomass from 2007. Hence the ***Interactions*** are either direct conflict in the case of the illegal loggers, turning a blind eye in the case of fishing, and cooperation between the NGO and the Berbak office to improve conservation. The ***Dynamics*** of the system are that because of the imperfect enforcement of PA rules (e.g. ignoring people inside the park, and not being able to tackle the illegal logging), deforestation has continued, albeit at a lesser rate than comparable surrounding areas as described in the previous chapters. Hence ZSL has intervened to supply the resources to reduce the illegal activities in the park.

ZSL's first annual project report to the Darwin Committee explains how a joint

ZSL/Berbak National Park field base was built during the first year of the project in 2009, using a donation from KPMG, a consultancy company (see chapter 3 for the project background, and ZSL (2010)). The staff who built the base were all paid with the Darwin grant funding. According to this report, during 2009, the post was permanently staffed by ZSL and National Park rangers. In addition it hosted researchers from a forestry research organisation called CIFOR; and the Universities of Aberdeen, Brighton and IPB Indonesia (*ibid.*). The wooden building is built at *Simpang Malaka*, at the confluence of two rivers which drain the park, and which provides the major access into the core forest. It provides lodging facilities such as a electricity generator; kitchen, and rainwater collection (essential since the acidic peat swamp water is non-potable). Prior to this intervention there was no serviceable base at the site, and there was insufficient money to send rangers into the field often (ZSL, 2008). The increase frequency of patrolling in theory increases the probability of detection of illegal activities, and better support and training of rangers should enable them to deal with the subsequent law enforcement situation arising when illegal activities are encountered. Thus in theory the increased activity and patrolling instigated by the project is an intervention in the system (Dawid, 2000) that should reduce deforestation relative to the deforestation observed in the similar PAs which did not receive the additional funding for patrols.

10.3.0.1 Hypotheses for the treatment effect

The construction of the new based and additional park rangers constituted the experimental treatment or shock, with a new highly visible disincentive to undertake illegal activities in the park. The presence of additional researchers would also have raised the probability of detection of illegal activities. So the motivating question here is whether this had any effect on deforestation. The hypotheses is that:

- $H0_1$ The first year of pilot REDD+ activities at Berbak reduced deforestation compared to other similar PAs that did not receive the REDD+ intervention.

10.3.1 The basic empirical model

The basic empirical model is DD, with the expectation that this controls for time-invariant unobservable characteristics. The model used to estimate the average treatment effect (ATE) at Berbak following the intervention is as follows:

Let: $\bar{Y}_i^{before}$ be the outcome before the intervention for each 500m x 500m forest parcel i.

And: $\bar{Y}_i^{after}$ be the outcome before the intervention for each 500m x 500m forest parcel i.

The DD estimator is:

$$\beta^{DID} = (\bar{Y}^{treat,after} - \bar{Y}^{treat,before}) - (\bar{Y}^{control,after} - \bar{Y}^{control,before}) \tag{10.1}$$

$\beta^{DID} = \Delta\bar{Y}^{treat} - \Delta\bar{Y}^{Control}$

where $\bar{Y}$ is the population mean for deforestation.

10.3.2 Estimating the DD: data processing

10.3.2.1 Processing the dependent variable

The radar data used in chapters 7 and 9 cover a large swathe of southern Sumatra, encompassing the eastern half of Jambi province and the majority of South Sumatra province. However, instead of an entire mosaic which covered the whole area analysed in Chapters 7,8 and 9, JAXA provided five smaller scenes covering the area around Berbak national park only. The extent of this data is shown in figure 10.1, and reduces the geographical scope of this piece of work, including the selection of potential pre-matched controls sites.

These additional scenes were provided as raw data so needed to be processed to form a composite image. To do this, the raw data were processed first with the Alaska Satellite Facility's Map Ready Package(Alaska Satellite Facility, 2013), calibrated with Sigma geometry with output scaled to decibels, and at 30m resolution. Second, the five individual scenes were merged into a single raster using the merge function in the Raster package in R (R Core Team, 2013; Hijmans, 2013). Third, the 2007,8 & 9 backscatter data were clipped to the smaller extent of the 2010 data, also using the raster package. The 2010 data were then warped to the 2007 data using ENVI to ensure that all pixels overlapped to ensure maximum accuracy in the subsequent deforestation estimates. Pixels interpreted as non-forest areas or as forests that were flooded were excluded from the analysis following the procedures set out in Chapter 7. Only pixels with an estimated biomass of 53Mg ha^{-1} in 2007, and which were not determined to have experienced flooding were considered in the analysis.

Following the approach outlined in the last chapter, I aggregated the original 30m x 30m pixels 17 times to form 510m x 510m pixels, in which of each I calculated the proportion of the 289 pixels deforested (sum deforested pixels/289) x 100. I processed the data such that only grids which were entirely inside the Berbak protected area, or entirely within the hutan lindung areas were considered in the analysis, addressing any potential issues from overlapping land boundaries. Baccini et al. (2012) has produced global estimates of biomass using 500m resolution; Morton et al. (2006) analysed deforestation patterns and drivers in the Amazon using MODIS optical satellite data at 250m resolution (though mentions using products up to 1km resolution); Pfeifer et al. (2013) used MODIS at 500m resolution to analyse deforestation in east Africa; and the Global Forest Watch website (For, 2014) provides deforestation data at 500m resolution. Hence treating the dependent variable in this manner a) both creates an intuitive outcome for interpretation, b) at a resolution with multiple precedents in the literature.

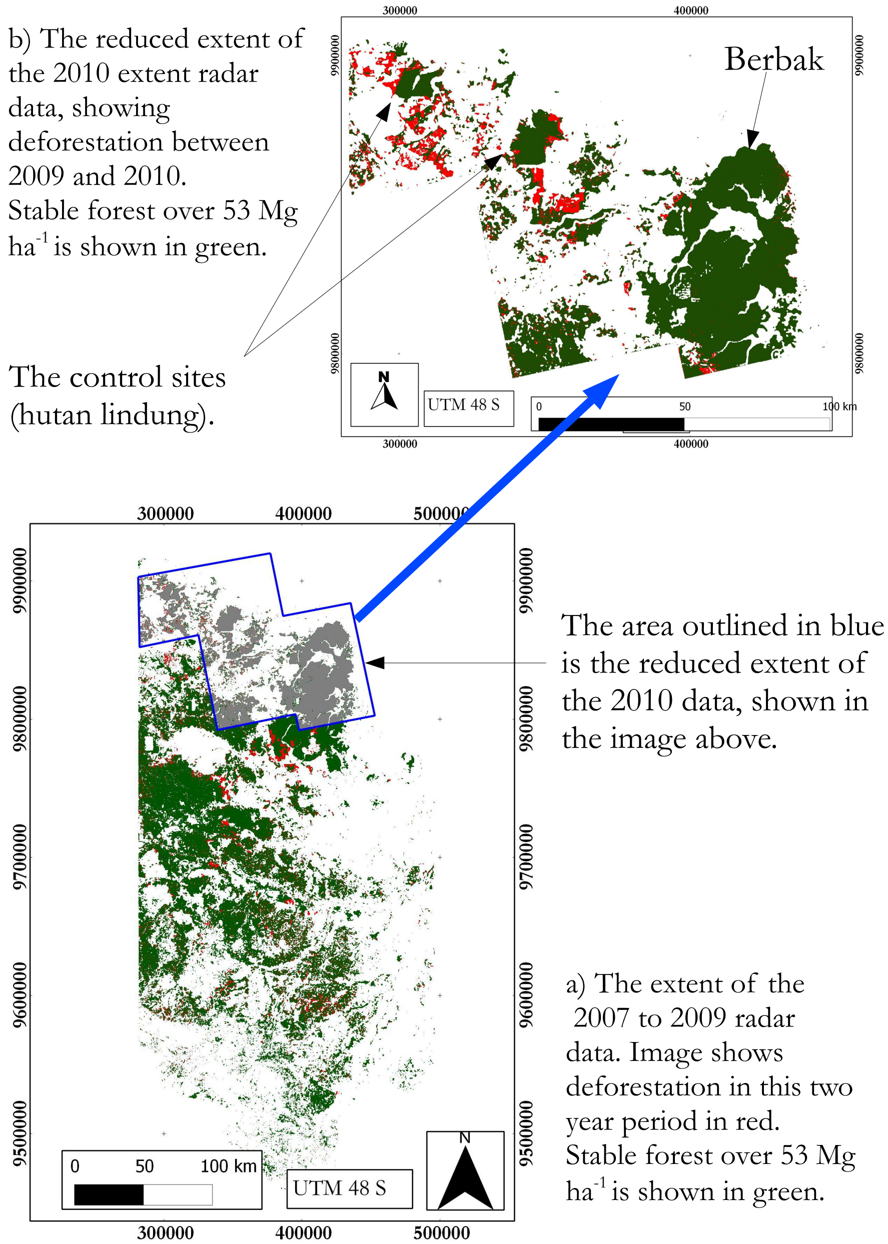


Figure 10.1: This diagram shows the reduced extent of the 2010 data and associated analysis. The bottom image (a) shows the extent of the radar data, and deforestation between 2007 and 2009. This is the extent of the data that was used in Chapters 7,8 and 9. The top image (b) shows the reduced extent of the 2010 data, and deforestation between 2009 and 2010. This is the extent of the data analysed in this chapter. Whilst on the one hand the additional data facilitated a novel analysis, it restricted the possibilities for the selection of potential counterfactual control sites.

10.3.2.2 Creating the independent variables

The independent variables were chosen based upon their significance in influencing the likelihood of deforestation (Kaimowitz and Angelsen, 1998; Ikenberry, 1988; Angelsen and Kaimowitz, 1999, 2001; Barbier et al., 1995; Lambin et al., 2003)). and as described above confounding the spatial selection of PAs (Joppa and Pfaff, 2009), introducing bias. The independent variables were created using the process described in the methods section of the previous chapter, including the distances to rivers, villages, roads and forest biomass in 2007. These variables were clipped down to the reduced size of the study area determined by the 2010 radar data. However some additional variables were created specifically for this analysis. Dummy variables were coded for pixels that were protected, matched (see below) and in Berbak National Park. In addition, a distance to village raster was created in which each pixel had an estimate of the geographical distance from the nearest village. This distance was measured using the proximity analysis tool in QGIS (QGIS Development Team, 2009). One important limitation to note is that a road map was available from 2005, two years before the start of the impact study. It is likely however that the road network expanded during the period 2005-10, as forest was cleared, and new plantations developed. This variation of a driver of deforestation over time and space cannot be captured in the present analysis therefore, which will introduce some small errors (the marginal changes in the road network 2005-2010 into the calculations of causal effects in this paper. This is because those areas which become in effect closer to the road (of course the contrary explains the actual dynamic) over those years will experience an increasing likelihood of deforestation over time which is not accounted for.

10.3.3 Estimating the DD: statistical methods

10.3.3.1 Summary

I now describe in summary the approaches I used to make the final estimation of the DD, before moving on to explaining each step in detail. I undertook several steps. First I re-visited the key identifying assumption of the DD model which is parallel paths: that the trend in the selected control sites and the treated sites are the same. To do this I examined the data graphically, plotting the trends in mean deforestation outcomes in Berbak, compared against those sites which had the potential to serve as counterfactual control sites within the geographical constraints of the available remote sensing data. Upon examining the results, I then used a Genetic matching algorithm to try to identify pairs of data which were as similar as possible upon a vector of covariates known to influence deforestation and confound the location of protected areas, hence to attempt to control for selection bias. In this chapter I do not include elevation, since we are now dealing with a subset of data which focuses on the eastern coast of eastern Sumatra only, and not the hills and mountains which rise up in the centre and west of the island. This also reduced the complexity of the matching procedures (the 'irreducible complexity' of matching on multiple variables referred to by Sekhon (2011)). In order to create the covariate data set, I created a series of rasterised images that calculated the distance from roads, rivers, villages and forest biomass in 2007, which are shown in the literature as those variables influencing deforestation and the site selection bias for PAs (Joppa and Pfaff, 2009). I then again examined the assumption of the DD model using these new matched data using graphical analysis. Based on the balance statistics the matching was ineffective, and the parallel trends assumption again could not be met following the matching. Nonetheless to provide an indicative result, I performed a least squares dummy variable regression on the unmatched data, to provide an imperfect estimate of the treatment effect. This was with the data from pre-matched controls merged together to produce a synthetic control, because the graphical analysis suggested that this synthetic control had the most constant deforestation rate over time.

There were two time periods that could have served as the contrast for the treatment time period: 2007 to 2008, and 2008 to 2009. I chose the former. This was because even though the field base was built in 2009, some preliminary scientific research activities in 2008, including the collection of the forest carbon data. Whilst the purposes of these surveys was scientific research, there is a possibility that this could have been confused with forest protection by local people. Because the objective of the study was to compare deforestation before and after the REDD+ activities started, it is therefore better to use deforestation from the earlier period, before any ZSL activities at all had started at the site.

10.3.3.2 Pre-matching the control sites

The aim is to assess the marginal change in the efficacy of Berbak following an intervention. As set out above, in effect this means that Berbak has been treated twice, first as a PA and then as the recipient of a REDD+ project. A plausible counterfactual would therefore be a site (or sites to create a synthetic control) which was also a PA that was as similar as possible to Berbak but which had not been the subject of a REDD+ project. Ideally, such sites would have included strict national parks i.e. of precisely the same institutional status as Berbak), experiencing the same pressures from the proximate drivers of deforestation due to having experienced the same spatial selection bias in their location. Further, these variables would correlate with unobservable factors such as local cultural differences in attitudes towards forest management, and regional economic development e.g. the same demand for timber from saw mills. If the perfectly matched sites experienced the same deforestation rates over time prior to the intervention then any differences in deforestation rates following the intervention might then be ascribed to that intervention. If the counterfactual sites had higher levels of deforestation, then the DD between the sites following the intervention might indicate the causal impact of the new REDD+ policy. However this was not the case in practice: the 2010 Radar data provided by JAXA which facilitated this analysis covered only a restricted area of eastern Sumatra. In turn this implied a major prior restriction on the possibilities for selecting PAs that could serve as the counterfactual controls.

As such I followed the approach of Arriagada et al. (2012) by pre-matching any sites that were PAs within the restricted dataset, and hence similarly potential REDD+ project sites. Unfortunately there were no other strict national parks available. There are five other protected areas than Berbak national park in the study area. I immediately discounted three. The first was the Hutan Lindung forest to the north of Berbak which I revealed in chapter 8 as being entirely devoid of forest: one could not compare Berbak with a site which had a zero-probability of any further deforestation. The next two sites are directly adjacent to Berbak national park, a forest park (Taman Hutan Raya; TAHURA) and another Hutan Lindung forest. I discounted both of these areas, because they technically fall into ZSL's area of interest (see case study chapter for details and map), and are hence subject to the treatment of increased patrols in the REDD+ pilot. The final two remaining PAs were two *hutan lindung* areas to the north west of Berbak as shown in figure 10.2 which I chose as the pre-matched control sites. However doing so already introduces an imperfection in the comparison: national parks are managed by the Ministry of Forestry in Jakarta and have dedicated local offices and a staff to manage them; whilst the *hutan lindung* areas are of lower conservation value, and managed under regional forestry offices *Dinas kehutanan* which manage a portfolio of forests (Collins et al., 2011a).

In the graphical analysis I plotted the mean deforestation rates over time in each of these two pre-matched sites; and then also merged the data from both sites to create a synthetic control, also plotting the mean deforestation over time from this data set

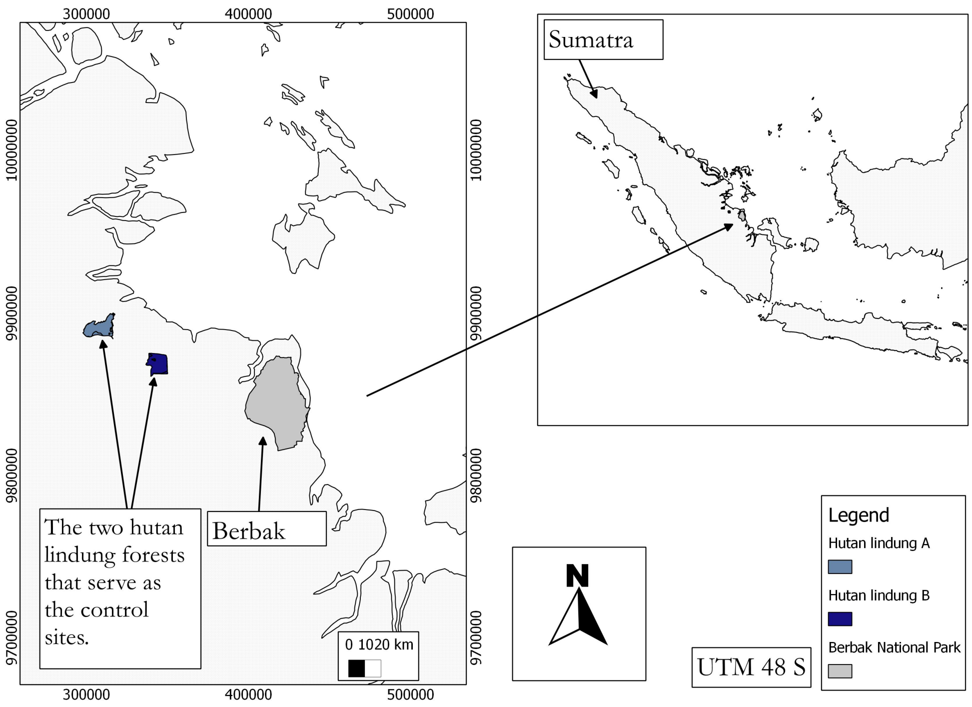


Figure 10.2: A map of the study area showing Berbak National Park and the two pre-matched hutan lindung control sites to the north-west

	Control HLa			
	Villages	Rivers	Biomass	Roads
Min.	6878	109	12.44	63
1st Qu.	13253	428	109	731
Median	15238	919	154	1641.5
Mean	14862	1039	137	1784
3rd Qu.	16839	1450	168	2712
Max. Qu.	19354	3541	192	5177
	Control HLb			
	Villages	Rivers	Biomass	Roads
Min.	8251	885	3	94.08
1st Qu.	11903	4870	140	678
Median	13450	7168	149	1509
Mean	13523	6905	142	1628
3rd Qu.	15362	8937	156	2432
Max. Qu.	17622	11342	188	4431
	Berbak			
	Villages	Rivers	Biomass	Roads
in.	668.6	89	1	117
1st Qu.	7779	1724	138	3827
Median	11317	3398	148	6337
Mean	12103	3775	140	6655
3rd Qu.	16022	5632	156	9249
Max. Qu.	26511	11159	191	16087

Table 10.1: The descriptive statistics for the for the two Hutan Lindung control sites and the treated Berbak national park.

10.3.4 Matching the pre-matched sites; testing covariate balance

Following the pre-matching procedure, I then used the Matching package in R (Sekhon, 2011) in order to find matched pairs of observations that balanced the covariates of the observations in the treated and untreated groups, producing summary statistics of the balance and graphical representations in the form of QQ plots. Specifically I used GenMatch, with nboots=500, and with a population size of 50, and with the default of sampling with replacement retained. I used the Balance-Match function to provide the final balance statistics.

10.3.5 Regression modelling to estimate the DD

In order to estimate the DD, I used linear regression modelling, where the DD is the β on the interaction between a time dummy and treated observation dummy. This approach does not compare the *levels* of outcomes between treated and control, just outcome and trends. In terms of the functional form, I assume that the effect of the treatment is linear and additive. The DD estimator is the ATE, deriving from the assumed exogenous variation imposed by the project intervention. Since DD deals with sample means it can be estimated equally well using panel data (repeated observations of the same individuals; pixels) or with repeated cross-sections (repeated samples from the same population).

The dependent variable was the deforestation (Def) rate in each 510m x 510m pixel. The control variables were the distance to villages (Vill), roads (Road), and rivers (Riv), and the amount of forest biomass in 2007 (Bio). The variables of interest are the dummy variable for the treatment time period (TreatT); the dummy variable for the treated observations at Berbak (Berb); and their interaction. The synthetic control of the combined HLa and HLb set as the reference category with respect to the Berbak treatment dummy; whereas the time period 2007:8 is set as the reference time period to the treatment time period of 2009:10.

$$Y_{it} = \alpha + \delta_0 X_i + \delta X_{it} + \delta_2 T_i + \beta X_i * T_i + \varepsilon_{it} \tag{10.2}$$

Since there are only two time periods in this study (2007:8 and 2009:10) and only two sites (Berbak and the synthetic control group of the merged Hutan Lindung areas), the dummy variables included in the model for the treatment time period and the treated observations at Berbak act to estimate fixed effects, specifically, least squares dummy variables estimation. The dummy variable for Berbak or the control site thereby represents all the unobserved factors that vary across Berbak and the control sites (such as cultural factors) but are constant over time. The dummy variable for the synthetic control site is the referent for the treated Berbak pixels. In practice the equation that I estimated in R was as follows:

$$Def_{it} = \delta Bio_{it} + \delta_2 Road_{it} + \delta_3 Riv_{it} + \delta_4 Vill_{it} + \delta_5 Berb_t + \delta_5 TreatT_i + \beta Berb * TreatT_i + \varepsilon_{it} \tag{10.3}$$

As diagnostic tools, I used the outlierTest function from the *car* library for R (Fox and Weisberg, 2011), and removed any outlying points with unusually high studentised residuals over 4 from the data set, before re-running the regression. I then plotted the relationship between the independent variables and residuals to check for evidence of omitted variables bias and changes to the mean model. I then plotted the fitted values against the model residuals to check for evidence of non-constant error variance, violating the central assumption of homoskedasticity. Following this I checked results for a log-transformed dependent variable and the error variance; before using heteroskedastic-robust standard errors to correct for heteroskedasticity. To do this I used code attributed to Dr. Ott Toomet (Goulding, 2011) implemented in R, which Goulding (2011) claims replicates the more commonly-known STATA 'Robust' command results.

10.4 Results

10.4.1 Testing DD model assumptions using data from the pre-matched sites

The trends in deforestation in Berbak were different to those in the pre-matched control sites. The location of the control sites is illustrated in 10.2, and the trends in deforestation shown in figure 10.3. Berbak exhibited a fairly flat mean trend at an absolutely low level of 0.1%, which fell below 0.1% in 2008:9, and then rose towards 0.1% again in the time step of the intervention 2009:10. Control site HLa showed a marked spike in deforestation in period 2008:9 at over two percent per year, before falling below one percent in the following time step 2009:10. Control site HLb showed quite a dramatic trend whereby deforestation rose from 0.2% in 2007:8, to 0.25% in 2008:9 before rising steeply to 1.1% in 2009:10. The synthetic control produced a value which ran between the two extremes, rising from 0.75% in 2007:8, to a hump of 1.25% in 2008:9; and then falling to just over 1.0% in 2009:10. As such none of the unmatched data satisfied the identifying assumptions of the DD model. Of the three, the synthetic control had the flattest trend. Yet since it was not parallel I then searched within the synthetic group for matches to a subset of Berbak pixels, in order to better be able to identify an untreated counter-factual group of observations. Descriptive statistics for the two pre-matched sites and the treated Berbak site are provided below.

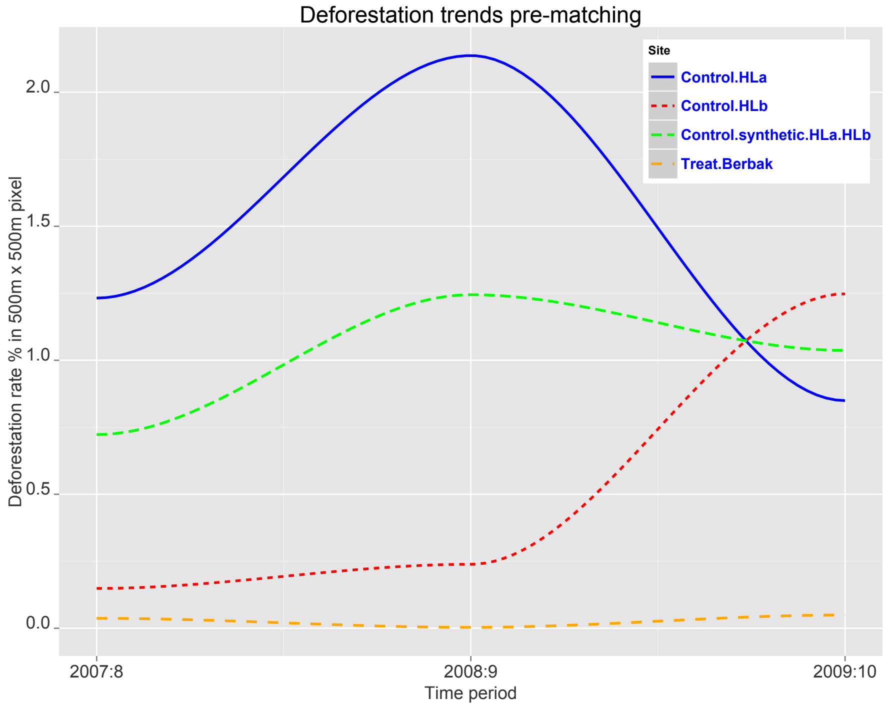


Figure 10.3: Trends in deforestation at Berbak and pre-matched control sites at Hutan Lindung a,b (HLa,b) and a synthesised group formed by combining data from both these sites, and thereby treating them as an individual control. The trend lines are formed from the mean deforestation rate in each site.

10.4.2 Genetic Matching results

The matching procedure performed poorly to identify observations in the synthetic control groups, as reflected in the Kolmogorov-Smirnoff test statistics, which suggested that the covariate distributions for all of the covariates were still significantly different following the matching procedure. The results are summarised in the table 10.2 below.

	Villages		Biomass	
	Before matching	After Matching	Before matching	After Matching
Mean treatment	14233	14233	139.3	139.3
Mean control	12082	13623	139.6	134.14
Std mean diff	87.3	24.7	-0.85	14.7
Mean raw eQQ diff	3427.9	2552.9	7.47	7.58
med raw eQQ diff	3670.4	1782.7	28.3	20.6
max raw eQQ diff	7157.9	5035.7	0.08	0.13
mean eCDF diff	0.19	0.16	0.16	0.32
med eCDF diff	0.174	0.176	0.11018	0.0454
max eCDF diff	0.38	0.27	0.15975	0.32
var ratio (Tr/Co)	0.19	0.28	1.42	1.41
T-test p-value	0.00	0.00	0.80	0.00
KS Bootstrap p-value	0.00	0.00	0.00	0.00
KS Naive p-value	0.00	0.00	0.00	0.00
KS Statistic	0.37	0.27	0.159	0.32
	Rivers		Roads	
	Before matching	After Matching	Before matching	After Matching
Mean treatment	3796.6	3796.6	1710.7	1710.7
Mean control	3781.1	3724.3	6629.3	2122.7
Std mean diff	0.44	2.09	-418.8	-35.1
Mean raw eQQ diff	963.08	188.5	4918.1	412
med raw eQQ diff	1002.8	140.9	4736.9	406.2
max raw eQQ diff	1914.6	1210	10910	846.49
mean eCDF diff	0.098	0.02	10910	846.49
med eCDF diff	0.1	0.016	0.414	0.10
max eCDF diff	0.19	0.07	0.44	0.06
var ratio (Tr/Co)	1.88	1.02	0.70	0.29
T-test p-value	0.88	0.00	0.11	1.26
KS Bootstrap p-value	0.00	0.02	0.00	0.0
KS Naive p-value	0.00	0.2	0.00	0.0
KS Statistic	0.19	0.07	0.70	0.29

Table 10.2: Results of the covariate matching procedure using the Genetic Matching in the R Matching package. Note the size of the Kolmogorov-Smirnoff statistic before and after matching, and its associated p-value. This shows how the mean treatment and control values following matching, which was not successful in that the algorithm could not find observations balanced the covariates in the treated and untreated groups such that the difference as measured by the Kolmogorov-Smirnoff statistic was no longer significant. This reflects the variable space of the data and the issues of finding suitable controls.

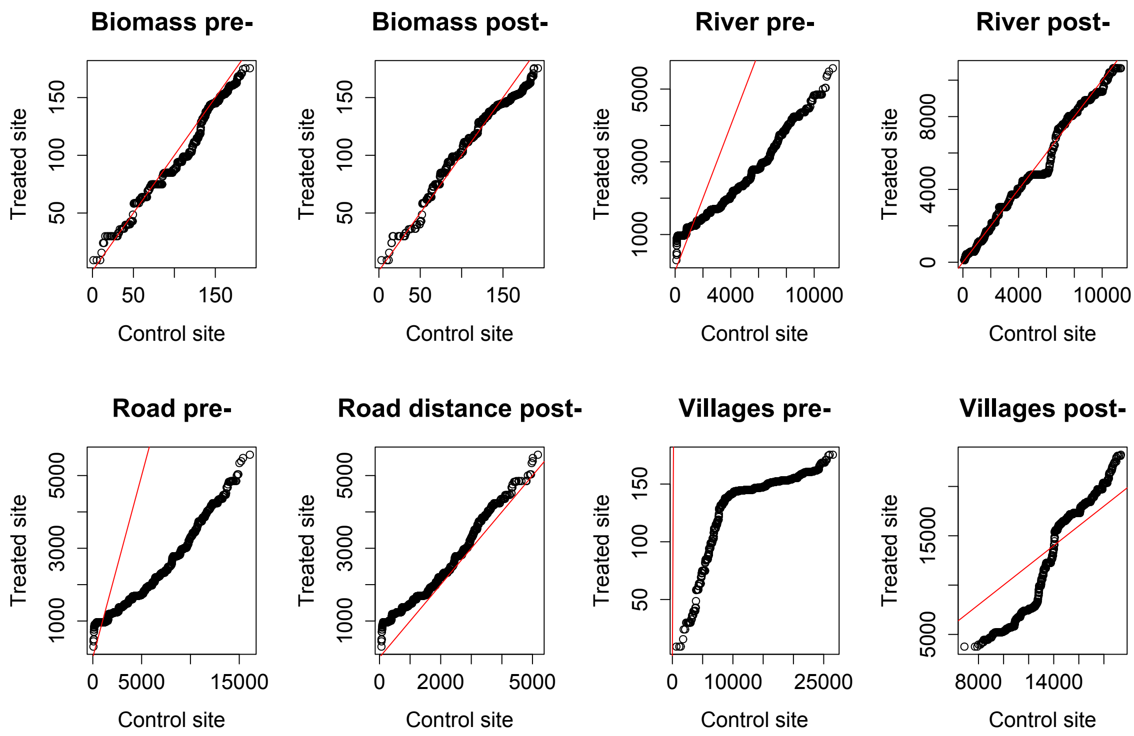


Figure 10.4: The quantile-quantile plots show the distribution of the treatment and control sites entitled pre- and post- the matching procedure. In the naïve pre-matching comparison the control sites are any observations in the two pre-matched control sites. The post-matching control observations should be more similar in their distributions to the treated observations, than are the ‘any other’ observations in the naïve comparison. However, the matching procedure was not as effective as in the previous chapter, as demonstrated in the balance statistics.

10.4.3 Testing DD model assumptions using the matched data

Following the matching of the co-variates the above procedure, I explored the trends in deforestation in the imperfectly matching data, illustrated in figure 10.5. The trends reflect the poverty of matching results presented above, because the trends appear almost as extreme as pre-matched site HLa in the pre-matching trend analysis, hence there does not appear to have been any benefit in matching either for achieving balance in the covariates or in satisfying the parallel trends assumption.

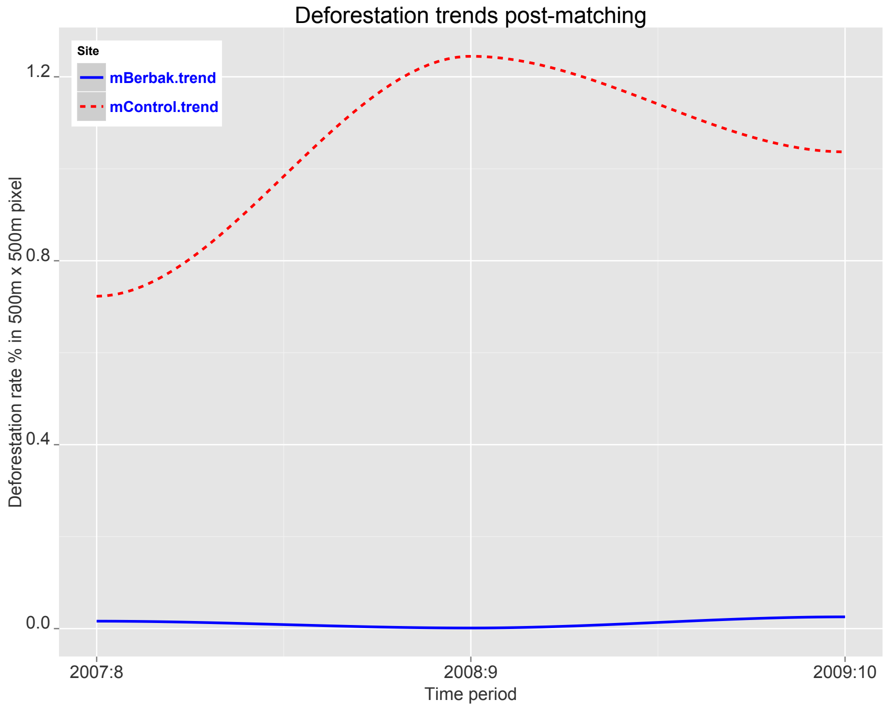


Figure 10.5: The trends in deforestation in Berbak and in the synthetic control group following the matching procedure. The matching procedure was unsuccessful with regards to moving systematic differences between the control and treated sites. Similarly it had no effect on the identification of pixels which were undergoing the same rate of deforestation as at Berbak. Hence the core identifying assumption of the DD method could not be satisfied.

10.4.4 Regression modelling

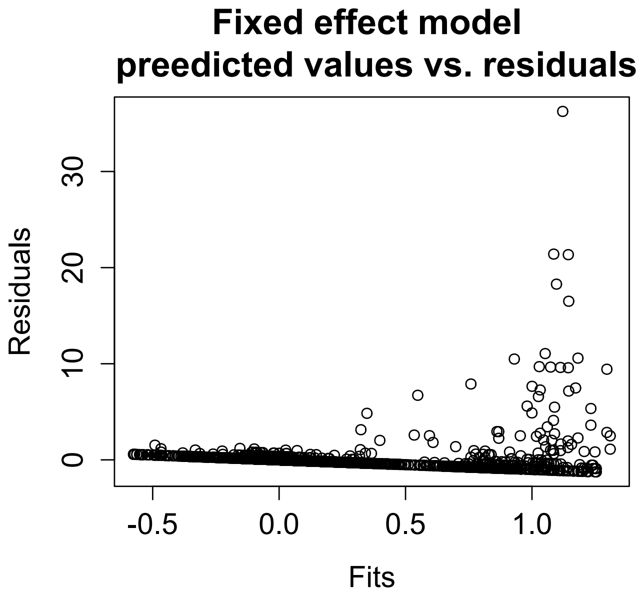
The regression model results are tabulated below in table 10.3. The reference category for the Berbak dummy was the synthetic control of the combined HLa and HLb datasets without the unsuccessful matching applied, and the time period 2007:8 as the reference time period compared to the intervention of 2009:10. Overall the model explains very little of the variation in the data, with an R^2 of <0.1. However, the concern here is not to create a predictive model, rather to understand the significance and effect size and sign for the variables for the β on the interaction between the treatment time period and the treated observations at Berbak. These analysis suggests that deforestation increased by 0.08% in Berbak following the inception of the project, holding other variables constant, assuming no omitted variables; yet this finding is not statistically significant (p=0.5).

Whilst there did not appear to be correlations between the independent variables and the residuals, the residual and fitted values suggested heteroskedasticity, with variance increasing in a 'funnel' with increasing fitted values. The log transformation of the dependent variable, deforestation, did not appear to correct for this. As such I used the results from heteroskedastic robust standard errors. In the table below I present both the results from the normal regression summary output, followed then by those from the robust standard errors. This latter correction reduced the apparent increase in deforestation following the intervention from 0.08 to 0.05%, and decreased the p value, yet not to a significant level, from 0.5 to 0.37.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.6419	0.1398	11.74	0.0000
biomass	-0.0021	0.0007	-2.85	0.0044
rivers	-0.0000	0.0000	-4.56	0.0000
roads	0.0000	0.0000	2.35	0.0187
factor(T910)1	-0.0604	0.1172	-0.51	0.6067
villages	-0.0000	0.0000	-4.57	0.0000
factor(class)Berbak	-1.0220	0.0877	-11.66	0.0000
factor(T910)1:factor(class)Berbak	0.0843	0.1289	0.65	0.5132

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.50	0.06	8.76	0.00
biomass	-0.00	0.00	-3.48	0.00
rivers	-0.00	0.00	-4.22	0.00
roads	0.00	0.00	3.59	0.00
factor(T910)1	-0.03	0.06	-0.62	0.53
villages	-0.00	0.00	-5.58	0.00
factor(class)Berbak	-0.32	0.04	-8.70	0.00
factor(T910)1:factor(class)Berbak	0.05	0.06	0.90	0.37

Table 10.3: Regression model results for Berbak national park, with the synthetic control of the combined HLa and HLb set as the reference category, and the time period 2007:8 as the reference time period. The upper table is the result with unadjusted errors, whilst the lower table is the result of using heteroskedasticity robust standard errors. Overall the model explains very little of the variation in the data, with an R^2 of <0.1. The interaction between the treatment time period and the treated pixels at Berbak suggests that deforestation increased by 0.05% following the inception of the project, using robust standard errors. However, this finding is not statistically significant, and furthermore the basis for the DD approach is undermined by the lack of a control site which exhibits the same trend in deforestation as the treated site.



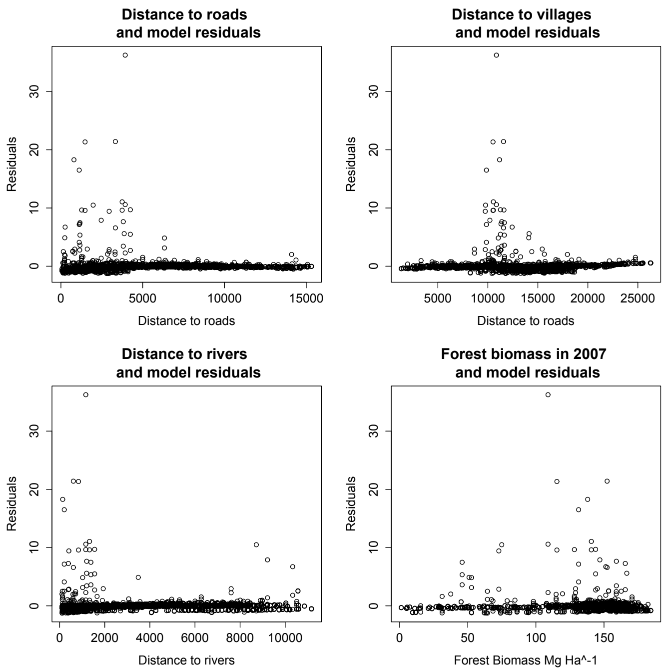


Figure 10.6: Model analysis to check for omitted variables. In the four charts above are the model residuals plotted against the explanatory variables used in the final model.

10.5 Discussion

10.5.1 Selection of counterfactual(s)

In the graphical analysis of the trends in deforestation in Berbak park itself, and the two pre-matched untreated sites, it was immediately clear that the sites were experiencing very different trends in deforestation over time. Two aspects of the data are striking. The first is that the deforestation in the untreated sites peaked very noticeably in the 2008:9 period, which was the run-up to the 2009 legislative elections in Indonesia. This is intriguing given that Burgess et al. (2012) suggested that deforestation in Indonesia followed election cycles, whereby local officials increased the number of logging permits in order to increase revenues to finance re-election campaigns. This may include areas designated for protection and yet managed at the provincial level such as hutan lindung forests. A related observation is that Berbak experienced no increase in deforestation during this time period. As such I hypothesise that the peak observed in the Hutan Lindung forests -which are managed at the provincial level-may reflect the political logging identified by Burgess et al. (2012).

The second substantive observation is that Berbak has a low absolute level of deforestation overall during the study period, at $< 0.1\%$. This suggests that there is little additional forest conservation benefit to be gained at Berbak currently, especially when compared with the hutan linung forests used as control sites. However, these data cover a very short time period of only three years, which is still in practice only a snapshot of what is happening to the forests in the region. For instance, the large 'hole' in the middle of Berbak was created by fires in the late 1990s. Hence if longer-term data were available over Berbak, then extremely large spikes in deforestation would be observable in the protected area, making a stronger case for an intervention in park management.

Most importantly the lack of suitable counterfactual sites against which to compare deforestation in Berbak presents a considerable challenge for causal inference. Of five potential candidate sites, three had to be discounted immediately since they were either devoid of forest biomass at the beginning of the study or were actually a component of the Berbak REDD+ project and so not independent. This meant that the two controls were the only available control sites rather than the best available. In an ideal setting there would have been an identical national park adjacent to Berbak with a simililar distribution of covariates to match upon, but the reality is less accommodating here.

The matching procedure was unable to improve this situation: it produced disappointing results, being unable to balance covariates amongst treated and untreated observations, and in direct contrast to the previous chapter. These results probably reflect the fact that the data used in this chapter deals with a much narrower geographical area and hence provides a smaller variable space within which to find suitable matches. This illustrates a broader point that whilst robust techniques are certainly required to measure policy impacts, it can be rather difficult to find the idealised counterfactuals in practice. This places increased emphasis on a discussion concerning more theoretical aspects of impact detection at the site.

10.5.2 Regression analysis

The key identifying assumption of the DD approach is parallel paths of treatment and control groups. However as described above, in neither the pre- or post-matching data was it possible to identify suitable counterfactual cases that exhibited exactly the same paths as Berbak. This illustrates one of the major problems of this model, which undermines the subsequent econometric analysis and estimation procedure. The estimate produced in the regression for the DD, i.e. the β on the interaction between the treatment observations and treated time period was 0.05 %, controlling for other variables, yet statistically insignificant at 0.37%, using heteroskedasticity robust standard errors. As such the estimation of the parameter in the regression should certainly not be treated as conclusive.

Finally, one potential source of error that should be acknowledged is that I assumed that there are only time-invariant independent variables in the system of interest, since we are examining such a short time period. However with a longer time period it is likely that some of the independent variables will be time-varying, principally the distance of a patch of forest from the road network, which will change as large amounts of deforestation occur, and as the road network expands. However, obtaining timely maps of road networks on the forest frontier in Indonesia is not easy. At the very least, the most up-to-date road maps should be used for a new analysis, to avoid inaccurate estimates of the effect of the distance to roads upon deforestation rates.

10.5.3 A more theoretical perspective

Due to the problems with the core assumptions of DD, and the insignificance of the effect estimated, it may be better to acknowledge other strategies to evaluation, including theoretical approaches. The absolute value of deforestation in Berbak overall is very low during the short study period. However, that the absolute amount of deforestation increased in Berbak is interesting. It is a protected area and so in theory should not be deforested at all. Referring back to the basic conceptual model set out in the methods, I hypothesise that the people surrounding the national park may have had their expectations about the use of the park and its resources altered by the project. Informal discussions with people living near Berbak revealed that the national park served as a source of timber, albeit illegal. When the project was initiated, the consultants sent out into the communities neighbouring the park and public information campaigns ('*socialisasi*') would have alerted illegal wood cutters to a future of more frequent and efficient park law enforcement. I hypothesise that this moderated the discount rate of loggers, who brought forward timber cutting today in anticipation of lost future benefits.

However in the intervention period, increased patrols should have also raised the risk of illegal loggers being captured and facing sanctions. Yet whilst the REDD+ project has initiated more patrols, these may be inefficient in the first period of implementation, and beset by inexperience in patrolling tropical peat swamp forest. One experience from the field supports this: Whilst undertaking a biodiversity survey, I joined a team of researchers who were accompanied by a team of local people acting as guides, and a ranger from the forest police armed with a machine gun. He fired a round upon debarking from the boat, apparently in an act of bravado. However, after having trekked through a kilometer of peat swamp forest, which involves at times sicking knee or waist-deep into black mud and water, the ranger became fatigued and handed his firearm to one of the local men to carry. Hence whilst the extrapolation of anecdote is not data, such experience of enforcement with armed rangers in practice may not provide the disincentive that one may imagine from a distance.

These hypotheses may serve as a basis for future research which could be undertaken alongside the implementation of the project itself, along with some randomisation of interventions to simultaneously address the problems of causal inference. In the meantime, a further note of caution is that whilst deforestation increases in 2009:10 following the REDD+ intervention, it is only a small absolute increase, and interpretation of the trends in deforestation should be done carefully, since the trend is only in fact three time points. Without longer time series and with low absolute amounts of deforestation, it is difficult to determine the extent to which changes in deforestation are simply random variations rather than observations of the effects of increased conservation upon the strategic decisions concerning resource use. For instance we know that historically very large areas of forest have been lost inside Berbak. Since this chapter has assessed only the first year of a pilot REDD+ project it is too soon to assess the overall impact of the intervention on deforestation at Berbak, which can only be assessed over the longer term. The analysis may soon be continued following the launch of the ALOS-2 mission which will provide continued L-band data collection, as used in this analysis.

10.5.4 Implications

In the previous chapter I demonstrated that forest loss is greater outside PAs than inside in this region of Sumatra. This suggests that there is greater potential for additional forest conservation benefits from acting to address deforestation outside PAs. Indeed, in the literature,Pfaff and Robalino (2012) find that marginal conservation benefits are highest in areas that are most at risk of ecosystem degradation. Hence there are probably decreasing marginal returns to conservation effort when the area of interest is already protected under law, and already subject to location selection bias as an area with a low risk of deforestation.

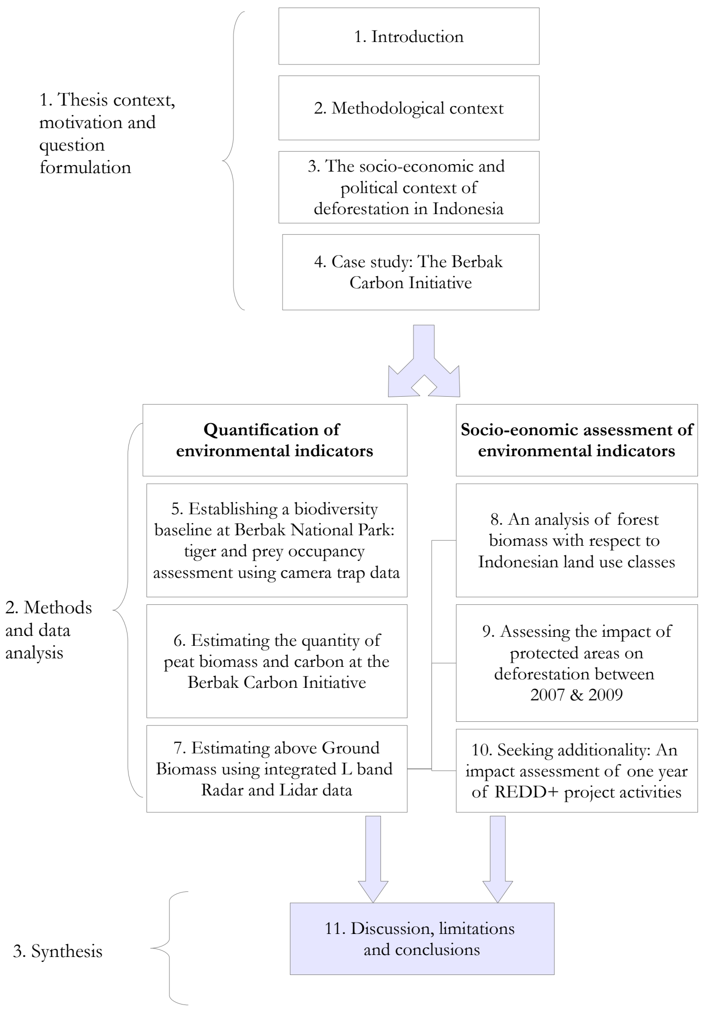
Nonetheless, in this instance, ZSL's interest in developing the project was really the conservation of tigers. This suggests that the location incentive to work with a remnant tiger population was greater than the additional forest conservation and carbon benefits that may have been accrued from acting elsewhere. As such perhaps it is indeed optimal for ZSL to develop a REDD+ project in Berbak, conserving the remaining tigers and still deriving some smaller marginal forest carbon conservation benefits from REDD+. In addition, it should be re-iterated that a component of the Berbak Carbon Initiative is actually addressing the deforestation and degradation occurring in the concessions adjoining the PA (falling into the Area of Interest; see the Case Study chapter for details). Hence the project does address this question of additionality in areas at greater risk of deforestation.

Yet in the spirit of the past two chapters, one should consider the counterfactual with regards to tigers as well. It may be the case that analogous principles of non-linear marginal returns to conservation effort are also at play in their conservation. Tigers are able to survive in a wide range of different environments, including those that are heavily degraded by humans, as long as there is sufficient cover, prey, and limited human persecution e.g. (Sunarto et al., 2012). In fact areas that are more heavily disturbed tend to have higher ungulate density than in in-tact forests, which means that one could envisage the creation of a new tiger conservation project area on degraded land near to an existing PA with tigers present, which could be restored to at least low scrub vegetation and pioneer tree species within a few years. In principle this could provide additional habitat for tigers to expand into, thus increasing the population. A question for future research then surrounds whether this might be a possibility for the Hutan Lindung area which I identified as being entirely devoid of forest biomass in 2007.

There is precedent for such a project: In 2004, the Ministry of Forestry passed a Decree on Forest Utilization Permits for Natural Forest in Production Forests which allowed the creation of ecosystem restoration concessions (IUPHHK-RE) (ERC) in Indonesia's Production Forest land use class, with the specific objective of allowing these forests to be managed for the restoration and provision of ecosystem services. This has allowed the creation of the 'Forests of Hope' *(Hutan Harapan)* in Sumatra by an NGO called 'Burung (Bird) Indonesia', the international arm of the Royal Society for the Prevention of Cruelty to Birds. Other ERCs are also being developed across Indonesia including in Gorontalo in Sulawesi (see Collins et al. (2011a) for background on the conservation in this area). With this in mind, ZSL could have chosen an area of forest outside an existing PA, and worked to form a new ERC. This could be one option for the forest concessions in the area of interest, and remain an option in the future for areas of remaining forest outside Berbak which are logged over. I now place these issues within the larger context of the thesis in the conclusion.

Chapter 11

Discussion



11.1 Summary

This chapter considers the main conclusions of the thesis within the broader context of REDD+ and discusses the implications both for policy and methodology. It also addresses the strengths and weaknesses of the thesis and considers avenues for future research. It tries then to synthesise the various findings and consider how these relate to the original research questions which motivated the research. These questions evolved from the continued destruction of forests in developing countries, and the importance of this process in contributing to both carbon dioxide emissions and hence climate change, and to the loss of other ecosystem services such as biodiversity provision. Together these present two of the most serious environmental challenges we face.

11.2 Achieving the objectives of the thesis

The challenge for this thesis was to address challenges whose resolution could help improve tropical forest management, and facilitate the implementation of REDD+. This required an understanding of the socio-economic background of Indonesia and its history of natural resource exploitation, provided in Chapter 3). The focus then shifted to indicators of the condition of the environment relevant to REDD+. Carbon credit buyers in the voluntary market state a preference for forest projects because they perceive that they support biodiversity. So the next objective was to ask how biodiversity could be quantified in the remote peat swamp forests of Berbak national park. The sumatran tiger is an international and national priority for conservation, and a highly charismatic and valued species, which formed a natural choice for this assessment in (chapter 5). However tiger conservation is a possible positive externality from REDD+. The objective of REDD+ is to reduce carbon dioxide emissions. So a significant challenge is estimating biomass and carbon stocks and change in these over time. Peat biomass was quantified in Chapter 6). Then forest carbon stocks and change were quantified in (Chapter 7 using a new methodology. The next objectives were to quantify how the forest carbon stocks in Indonesia were distributed with respect to land use classes (chapter 8). The next objective was to assess how changes in forest biomass were affected by the designation of protected area status, focussing on protected areas in Jambi and South Sumatra provinces between 2007 and 2009, which was achieved in (chapter 9). Finally the analysis then turned to the case study of the pilot REDD+ project at the Berbak Carbon Initiative. The performance of the project relative to best available control sites was assessed in (chapter 10).

11.3 Summary of key findings

The results of the thesis broadly fall into two categories. The first is the quantification of the environmental indicators, and the change in those indicators. The second is the assessed impact of policies designed to manage change in the forest use, specifically the impact of national parks on deforestation in the study area.

11.3.1 Quantification of environmental indicators

The thesis quantified the **forest biomass** of a swathe of the provinces of Jambi and South Sumatra using integrated space-based radar, lidar and field plot data. A total of 503±105 x 10^6 Mg biomass were estimated in forest biomass across a 7.2 Mha study area in 2007. Contrary to expectations, protected forest areas did not contain the highest amounts of forest biomass (98 Mg ha^{-1}). Rather the highest biomass stocks were found in the Limited Production Forest class (104Mg ha^{-1}). The lowest forest biomass was found in community forest (39 Mg ha^{-1}), however this covered less than 1% of the study area (1,987 ha). The mean forest biomass at the Berbak Carbon Initiative site was 147 Mg ha^{-1}. Whilst this is not a land use class *per se*, this finding did underscore the significance of Berbak for forest carbon conservation, and shows it to be the last remaining block of relatively in-tact forest in this part of Sumatra. The significance of the site is likely to become more pronounced over time as what little forest remaining outside protected forest is cleared at 1.6% yr^{-1}.

By using a time series of radar data, it was possible to estimate changes in this biomass stock over the periods 2007 to 2008 and 2008 to 2009. Using a change of 1.5dB per pixel between years as the threshold for deforestation, a total of 229 x 103 ha were estimated to have been deforested between 2007 and 2009. Because the medium wavelength L band radar can 'see' through clouds and smoke this is a significant advantage over optical methods, which have to use multi-year composite images that may mask annual changes occurring in this era of rapid deforestation. Between 2007 and 2008, 18.5 ±3.9 x 10^6 Mg of forest biomass were cleared, leading to estimated emissions of 34 ±7.1 x 10^6 t CO_2e. Between 2008 and 2009, 13.1 ±2.7 x 10^6 Mg of forest biomass were cleared, leading to emissions of 24 ±5.0 x 10^6 t CO_2e. However, a huge quantity of biomass and carbon is stored in the peat soils. Within the boundaries of the Berbak Carbon Initiative, there are an estimated 6,554 *10^6 m^3 of peat, holding 380 x 10^6 Mg C.

In addition to the carbon and biomass stored at the Berbak site, the ecosystem constitutes a crucial area for the Sumatran tiger and biodiversity generally. Indeed the presence of tigers at the site was the main reason for ZSL establishing the Berbak project. In a six month camera trapping study in 2009 in the centre of Berbak National Park, 13 mammal species were recorded. Occupancy modelling was used to estimate the tiger prey species and for tigers. For the prey species this produced an occupancy estimate of $\hat{\Psi}$=0.71 (95% CI= 0.52:0.84). For tigers, the naïve occupancy was 0.14. The final model used to estimate tiger occupancy used forest biomass to estimate both occupancy and detectability sub-models. The fitted occupancy was $\hat{\Psi}$=0.27, 95% CI=0.14:0.45.

11.3.2 Impacts of policy interventions

By using the time series of radar data, the impact of protected areas on deforestation in Jambi and South Sumatra was estimated using matching techniques. In the naïve comparison, Between 2007:9, the odds of deforestation inside protected areas were 70% ($p < 0.01$) lower than in unprotected areas. However, when contrasted with matched pixels that were selected using propensity score matching, the odds of deforestation were 68% lower. The same experiment was also carried out using the raw change in backscatter values rather than a threshold value for deforestation. Controlling for other predictors of deforestation these results also indicated that the protected areas were providing a protective effect as measured both against any other land use type, and also against the matched pixels, and when adjusting for spatial correlation in the mode disturbance term.

Obtaining an additional year of radar data for Berbak and the surrounding area allowed what is possibly the first ever impact assessment of a REDD+ pilot project. During this year, a new field base was created and permanently staffed by forest police and ZSL employees. This constituted the intervention. Protected Hutan lindung forest areas were used as contrasts for the assessment of deforestation in Berbak in a difference in difference model. The results were counter-intuitive: deforestation appears to have *increased* following the intervention.

11.4 Methodological contributions

11.4.1 Forest monitoring using radar data

The thesis underscores the power of radar data to be able to 'see through' cloud and other atmospheric particulates. It demonstrates that because of this, the data generated has great value for monitoring rapid land cover change in an area typically covered by smoke and cloud. This ability has important implications for land use management. In principle it allows governments to be able to measure the degree to which their land use designations are adhered to over the short term. By contrast, assessments using optical data from the Landsat and MODIS satellites typically require several years of data in this part of the world in order to be able to generate analyses because of the constant cloud cover. With land use change being so rapid here, this is a particularly important feature, especially with the growth in the development of REDD+ in Indonesia. An additional advantage of the approach developed in this thesis is that the radar data actively senses the environment:

optical data depends upon reflected light from the sun, whereas radar monitoring involves the emission of microwave energy and recording the backscatter of that microwave energy, the wavelength of which is the same order of magnitude as the tree limbs and trunks. As such the backscatter reading can be directly to another data set (lidar) which is directly related to the amount of biomass. Analyses using optical data rely on classification of different land cover types across the landscape which are then attributed a mean biomass value. However, using the radar data, a biomass value can be attributed to each of the individual pixels in the study area, therefore providing much finer resolution of forest biomass.

11.5 Limitations of the thesis

This thesis makes a number of contributions to empirical study of tropical forests and monitoring methods. Yet the work is not without its limitations. These are now addressed generally, and then with respect to each individual chapter.

11.5.1 General limitations

One of the main limitations of the thesis is that it uses a short time scale to assess changes in deforestation rates in both the assessment of all the protected areas across Jambi and South Sumatra, and for the assessment of the impact of the first year of activities at the Berbak project site. This raises the risk that the changes observed are due to random annual variations. A further issue is that the study area was restricted by the spatial extent of the PALSAR radar data. So only a sub-section of Sumatra's forest was analysed. This reduces the extent to which the findings can be generalised. This applies in particular to the assessment of the performance of protected areas: only a subset of Sumatra's protected areas are included in the analysis.

11.5.2 Biodiversity assessment

The camera trapping data presented the first comprehensive assessment of the mammalian diversity at the Berbak Carbon Initiative. This provides a baseline against which project performance can be measured in the future. The assessment of tiger population provided very low occupancy estimates however. Only 21 photographs were taken of tigers during the study period. One problem may be the be the distribution of the cameras in the study area. Grid cells of 2.5 x 2.5 km were used to space the cameras out. However other studies have used 17 x 17km grid cells (Wibisono et al., 2011), which means that the sampling grid used may have been too small to capture the home ranges of animals ranging in other parts of the forest.

11.5.3 Below ground biomass

In the below ground biomass estimation, the Berbak Carbon Initiative was treated as discrete landscape. Whilst this appropriate from the project development perspective in terms of quantifying the carbon stored at the site, this is probably invalid from an ecological perspective. The peat may constitute a hydrologically connected 'blanket' across the alluvial plains of eastern Sumatra, and so parts of that cannot be managed in isolation. However, the most comprehensive approach to measuring peatland in Indonesia (the QANS assessment) was unable to model the distribution of peat around Berbak. This provided the justification for the spatial interpolation used in this thesis simply to make a baseline estimate. Finally, the fact that Berbak is a part of broader landscape of peatland means that changes in ecology of peat neighbouring, but not under the control of the project could have major impacts on the ecology of Berbak itself.

11.5.4 Forest Biomass

Issues with the above ground biomass estimation derived from the technology used, and from the field plot data. On the technological side, one of the most significant limitations is the fact that the radar signal saturates at higher biomass levels. The solution provided here was to integrate lidar data into the analysis, the signal from which does not saturate until much higher biomass levels. Yet this solution has its own limitations, because there is only one available lidar data set that intersects with this area, and so which can be used for calibration: the GLAS Ice data. This means that the further the in time each successive radar data set is in time from collection of the lidar data (2003 to 2007), the greater the possibility that the lidar reading of Lorey's height no longer reflects the actual situation on the ground, because of deforestation. This will cause increased errors in the regression relationships. Nonetheless, this is research and development work: these limitations can be overcome given continued investment in technology and availability of new data.

In the field plot data, a first problem was that tree heights were not measured by the field team, so these had to be modelled using relationships from elsewhere in Indonesia. Yet the morphology of trees in peat swamp forests is less well known than for *terra firme* forests because there has historically been less research in this ecosystem. This will have introduced further errors into the final biomass calculations. In addition, the field plot data from Berbak was used to developed a relationships between the lidar data, then radar backscatter, which was extrapolated across the whole landscape. Not all the forests in the landscape are peat swamp forests, but the relationships established at Berbak do not reflect the heterogeneous ecologies of the island. One solution might be to partition the study area into known forest types and develop discrete relationships for each forest type. However, this would have required the establishment of forest plots across the island, each requiring the establishment of new research relationships with local authorities: the bureaucratic requirements of which made this infeasible in the scope of a PhD thesis.

11.5.5 Assessment of the performance of protected areas in Jambi and South Sumatra

This chapter provided an opportunity to assess the extent to which protected areas had actually been effective in reducing deforestation. The results produced here confirmed the findings of the only other study to make an assessment of Sumatra's protected areas: they do appear to be working, as measured against matched unprotected pixels. However there are three key issues with this conclusion. The first is that study area only covers a sub-section of Sumatra and hence only a sample of Sumatra's protected areas. The interpretation should be limited to the protected areas in the study scene. Second, the problem with the limited extent of the study area constrains the selection of pixels to match against. For instance, better comparisons may have been found further to the north of the Berbak in Riau province, where extensive peat forests are also still found. This means that selection of matched pixels only from within the boundaries may give a false degree of confidence. In addition, the short study period (2007:2009) provides only a small sample of the changes which are occurring over the medium term. As such, the underlying trend in deforestation may be obscured by the short term annual fluctuations in deforestation. Nonetheless, the collection of the radar data used in this study was only started in 2007, which limits its utility for analysing historical deforestation, as compared against optical LANDSAT data for example.

11.5.6 Assessment of project impact

. The chapter on the assessment of the project impact provided an exciting empirical analysis since it is probably the first assessment of a pilot REDD+ project. The potential limitations relate to both the analytical approach and to the actual events on the ground. On the analytical side, the same criticisms of the limitations of the matching procedure described above equally apply to this chapter: the matched pixels may not represent ideal matches for the study site: there are no other such large peat swamp forests in the study scene. Nonetheless, that is a constraint of the available data. Other limitations relate to the nature of the intervention and the time frame involved: building the new ranger base and providing permanent staffing is only the first step in the implementation of the pilot REDD+ project. It would be too ambitious to conclude that the changes observed in the study period are an end result of REDD+ implementation: this is why the chapter is careful to set out that the analysis is of one year of project implementation. In addition, it is not possible know what processes are occurring socially without new data collection from the villages bordering the park. However, interviewing people about the REDD+ project for PhD research was deemed too sensitive by the project manager, so this option was not available. Nonetheless, lack of information on the social processes in the area does not of course change the results measured by the remote sensing. A more fundamental problem with the assessment is that it is hard to distinguish the protective effect of the national park from the impact of the NGO intervention in the national park. Since the park was protected anyway, and appeared in the analysis to be reducing deforestation then the final estimation of the project impact is actually the change in protection performance of the national park, which is quite convoluted. This is likely to continue to remain a problem for REDD+ projects which are established in areas which are already protected.

11.6 Synthesis and implications: Deforestation on Sumatra

Whilst Indonesia's high deforestation rate has been documented recently by Margono et al. (2012), the change observed during two years period is nonetheless very high. Forest conversion has major impacts on natural and human systems. In theory, forest clearance and plantation development can provide jobs and infrastructure for the rural poor; foreign exchange from timber, pulp and oil palm; and tax revenue. Yet this is naïve: three decades ago, a researcher wrote: 'if one could argue that the people of Sumatra had benefited, especially those who once used and lived near those resources, maybe the [forest] loss would be felt less acutely (Whitten et al., 1984). Little seems to have changed: murky business and corruption blight Indonesia's forestry sector (Palmer, 2005; Obidzinski et al., 2006; Indrarto and Murharjanti, 2012). These entrenched institutional problems complicate the implementation of mitigation activities like REDD+ (Collins et al., 2011a). A striking case in point is the legally protected forest described in (hutan lindung) in which little biomass remains (see chapter 8). Unfortunately, the clearance of Indonesia's legally protected forests is not uncommon, as shown for example in Sulawesi by Macdonald et al. (2011). The loss of these forests imposes costs not measured in price systems. These externalities include the loss of vital ecosystem services, crucial for climate change adaptation. Forests provide *inter alia*: local and global climate regulation; soil fertility and clean water supplies. Furthermore, Sumatra is in the Sundaland hotspot, one of earth's most species-rich regions (Myers et al., 2000). Some of the world's last tigers (*Panthera tigris sumatrae*) are found here (Chapter 5). In addition the world's tallest and largest flowers are found here (*Amorphophallus sp.* and *Rafflesia sp.* respectively). Reducing deforestation and forest degradation here is necessary to help conserve forest-dependent species, though it is not sufficient (Collins et al., 2011b). In addition, this thesis has demonstrated that the implementation of REDD+ activities may lead to perverse outcomes, including increases in deforestation locally. This in turn has implications for the implementation of the carbon project at Berbak national park.

11.7 Implications for the Berbak project

For project-level REDD+ implementation need to be aware of both of the physical and the institutional landscape in which they operate (Collins et al., 2011a). Aside from the presence of tigers in Berbak which drew ZSL to the site in the first instance, the fact that the core of the project is Berbak national park is significant. National parks are managed by the Ministry of Forestry in Jakarta. Notwithstanding the threat of Law 10 of 2010, National Parks contain the forests least likely to be legally converted to production forest, and as such have the lowest opportunity cost for the Ministry of Forestry in terms of *Retribusi*, the fees, charges and levies which the MoF can charge on new forestry operations. Simultaneously, it allows the Ministry to publicly 'buy-in' to REDD+; most of the areas covered by the forest moratorium are in areas which are already protected e.g. Austin et al. (2012). In addition, supporting REDD+ in a national park allows the Ministry to support other goals such as the the plan to support the recovery of the Sumatran tiger population (Ministry of Forestry, 2010). This may have underpinned the success that ZSL has experienced so far in developing the pilot REDD+ project in Berbak National Park: it is supported by the Presidential instruction on the moratorium; allows buy-in from the MoF at little cost; and moreover is already protected on paper, meaning that multiple institutions and organisations have incentives to support project activities and the enforcement of existing laws. However the Berbak Carbon Initiative includes other forest classes outside the park: hutan lindung, forest park (TAHURA) and limited production forests, and these are the forest classes that fall under the control of local *Bupatis*. The protected forest classes have less infrastructure for protection (having no park office for instance), whilst the production forest is designated for commercial exploitation. Chapter 8 highlights how this land use class has on average the highest forest biomass in the study area. The excision of these forests from Jambi's productive forest estate for REDD+ purposes therefore has much higher opportunity costs than authorising the already-protected Berbak national park. From the perspective of the state, not only is there a loss of *retribusi* for the DINAS Kehutanan (the district and provincial-level MoF offices which administer production forests under autonomy) in addition to MoF in Jakarta, but also the reduction in employment by concessionaires and associated multiplier effects.

From the perspective of the concessionaires with licences to exploit the production forest next to Berbak, there is the loss of revenues from the timber and loss of the opportunity to cover the fixed costs of acquiring the concession. Furthermore, the concessionaires are aware that ZSL wishes to incorporate their concessions within a REDD+ project. Yet agreement on how or whether this will happen has not been made. The options include ZSL subsidising reduced impact logging in the concessions, or even taking over management of the concessions directly, in which case they could either be logged at sustainable levels or retired under PP6/2007 as an Ecosystem Restoration Concession (REKI). These were created under law PP6/2007 and allow for appropriate entities to manage logged land under a 99 year lease with the objective of regenerating forest. The NGOs Royal Society for the Protection of Birds (RSPB) and Birdlife International used this licence to create the Harapan forest in South Sumatra province (Collins et al., 2011a).

In either case the concessionaires should be expected to behave rationally, such that they incur no net loss from the transaction and are able to cover the costs listed above include profits foregone. Yet, over and above these costs, the firms may also seek a surplus on any transaction with ZSL. That is, the concessionaires originally bid for their licences since they saw a viable commercial opportunity in exploiting those forests and will continue to gain from holding their licences. On the other hand ZSL does not gain from the existence of active concessions adjacent to Berbak National Park. Indeed it stands to lose: canals dug into the peat for drainage and access will also affect the water levels and hence carbon stability of Berbak national park. Logging up to the border of Berbak national park in order to fully exploit the concessions will necessitate building more canals and railway tracks to extract logs. These will reduce the transport costs of illegal loggers and individuals hoping to exploit forest resources inside the park, thereby increasing the costs of maintaining the park and carbon stocks. Finally, with the relatively low levels of deforestation at Berbak in comparison with the surrounding landscape, a major component of the additional carbon benefits from the project derive from the inclusion of the production forests. This could put the concessionaires in quite a strong position, and may explain may explain why negotiations between the NGO and concessionaires are moribund. Even aside from the costs and potential speculative behaviour of the firms, the reality of the machinations of the forestry department need also to be addressed: an Indonesian working in the field of REDD+ and who asked not to be named, stated that the reality of getting the MoF to alter forest designations involved extra-legal direct payments to officials involved (see chapter 3 for a discussion of rent-seeking in official positions).

The opportunity costs of allowing ZSL to manage the hutan lindung areas (managed by the district forest office (*DINAS kehutanan*) have also risen in light of Law No.10, SK292, and Permenhut No.18, 2011. Since the legal precedents have now been set for protected areas to be re-zoned for production in east Kalimantan and Aceh, land managers have an incentive to emulate this in their own district and provinces. In practice, this means that forest which agents wish to exploit must seek the support of the Bupati (the political head of the regency *kabupaten*, i.e. a 'regent') and the governor, the head of the province before a representation is made to MoF in Jakarta. This is because, whilst hutan lindung is administered by the district government, only MoF in Jakarta may change land use status.

Whilst the question over the performance of protected areas in chapter 9 addressed questions about the non-random location of protected area, this chapter also raises second-order questions about the non-random location of conservation interventions in protected areas. ZSL was drawn to the Berbak project site because of the presence of tigers. However, the presence of forest and tigers may be due in large part to how remote Berbak is, rather than how effective the national park has been historically in reducing deforestation and conserving biodiversity. That is, that the additional conservation effect of creating a national park will be lowest where there is the lowest risk of deforestation. If this is true then it also suggests that ZSL's intervention follows that bias, that it is making an intervention in an area which was already protected to a large degree by its remoteness and low suitability for agriculture in the first place. Then a park was created at Berbak because of the need to create protected areas to meet international targets under the Convention on Biological Diversity. ZSL is therefore also making a non-random selection on the intervention in this area, because the tigers are present at the site.

On the outset this seems quite logical. Yet it is important to remember the call for novel thinking in environmental economics and impact evaluation (Ferraro, 2009). Consider that Pfaff et al. (2009) found that marginal avoided deforestation impacts are greatest in areas which are under the highest threat. Since biodiversity and habitat conservation are correlated (Collins et al., 2011b), this provides a good reason to believe that intervening in places with the highest loss rates of biodiversity also offer the highest marginal benefits for biodiversity conservation too. So in practice at Berbak, this may mean that greater marginal benefits for both tiger and carbon conservation may be achieved by biasing conservation activities towards those areas with the highest risk of deforestation, rather than inside the national park.

This is not to suggest abandoning law enforcement in the park. In addition there is evidence that conserving forest outside the protected area could help the protected area itself anyway, which is called a conservation spillover effects (Pfaff and Robalino, 2012), a form of a positive spatial externality. However, there is of course the possibility that by increasing conservation activities outside the current project area could simply displace deforestation elsewhere. This is often called 'leakage', and is conversely a negative spatial externality. Yet where this has actually been tested, there is evidence that these leakage effects are negligible Andam et al. (2008).

Choosing the areas of forest at highest risk of deforestation rather than the lowest may therefore offer greater marginal benefits to carbon and biodiversity conservation. However, the challenge is to demonstrate this to funders and land managers who decide where conservation activities are targeted. This is because in the same way that naïve comparisons can lead to the conclusion that intervention in a low deforestation risk area is working, a naïve examination of intervention performance in a high-risk area would suggest that projects are failing.

11.7.1 Concluding remarks

Finally, this thesis was motivated by the ongoing destruction of the world's tropical forests and the associated negative externalities of biodiversity loss and climate change. It demonstrates a range of techniques in an applied setting that allow the quantification of fundamental information required to improve forest management. The results provide a robust basis upon which to build support for the continued conservation of the forests of the Berbak Carbon Initiative. Not only does this thesis show that Berbak's forests supports a population of one of the world's most charismatic and threatened species, the Sumatran tiger. It also shows that the Berbak Carbon Initiative is extremely important for the conservation of above and below ground carbon stocks. In the forest biomass maps, Berbak stands out clearly as one of the last remaining areas of in-tact forest in this part of Sumatra. However its future is not certain, with large scale forest clearance now at the very edge of the borders of the project area, and new laws in place that can - and are - being used to convert the status of protected forests to allow exploitation and land use conversion. The thesis very clearly demonstrates the pace of the change of the region's forests. The methodology used to do this contributes a new approach to monitoring tropical forests that are often covered by cloud and smoke. This may reduce costs for REDD+ implementation, but more optimistically, could contribute to improved tropical forest management, and the support of the protected areas which have contributed to additional forest conservation. Yet the implementation of additional support for protected areas should be undertaken carefully, since the results presented here suggest that over the short run at least an intervention may have an opposite effect to the one desired. Testing whether this effect holds true for the period after 2010 is of paramount importance for the success of the Berbak Carbon Initiative. The possibility to do this may depend on the availability of new data from new satellites being launched by the European Space Agency in 2014, which will provide multiple new opportunities for research on deforestation and forest degradation. So it is exciting then that the analysis of this very data is the focus of the author's first job following the completion of this thesis.

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