Impact Assessment of Natural Resource Management Policy Research: A case study of the contribution of the Sustainable Wetlands Adaptation and Mitigation Project to the effectiveness of the Indonesian Forest Moratorium

Nicole L. Flores

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Bradford Mills, Chair
Jeffrey Alwang
George Norton

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Abstract

The complexity of interactions that inform policy-making poses several challenges to evaluating the impact of policy research. Two key obstacles to policy-oriented research impact assessment (PORIA) are determining the degree of influence that can be claimed by a knowledge-generating entity and quantifying the impact of a policy-oriented research program. This thesis builds upon prior PORIA efforts to develop a framework for the evaluation of the impact of the Sustainable Wetlands Adaptation and Mitigation Program (SWAMP), an environmentally-focused, policy-oriented research project led by the Center for International Forestry Research (CIFOR). We examine a case study of the Indonesian Forest Moratorium policy to determine the policy's impact on emissions from peat deforestation. Results indicate that the policy has been largely ineffective in decreasing deforestation to date and has in fact been associated with increased deforestation above business-as-usual trends. Nevertheless, our analysis shows that if the moratorium were to achieve full protection, Indonesia could avoid the release of 10 – 20 million tons of carbon dioxide over the next 15 years, which corresponds to a mean social value of $402 – 805 million using a $40/ton social cost of carbon. With SWAMP's timely knowledge generation on tropical wetland carbon dynamics we estimate that $4.03 – 40.26 million of these social benefits can be attributed to CIFOR. Furthermore, through its involvement in the IPCC Wetlands Supplement and the Blue Carbon Initiative, SWAMP stands to positively influence outcomes of the 45 billion tons of carbon stored in non-Indonesian tropical peatlands and the global extent of mangroves, further increasing the impact of CIFOR.

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Acronyms

PORIA	Policy-oriented research impact assessment
CIFOR	The Center for International Forestry Research
SWAMP	The Sustainable Wetlands Adaptation and Mitigation Program
TWINCAM	Tropical Wetlands Initiative for Climate Adaptation and Mitigation
UNFCCC	United Nations Framework Convention on Climate Change
REDD	Reducing Emissions from Deforestation and Forest Degradation
IUCN	International Union for Conservation of Nature
IPCC	Intergovernmental Panel on Climate Change
IWG	Interworking Group
SCC	Social Cost of Carbon
IAM	Integrated Assessment Model
PAGE	Policy Analysis of the Greenhouse Effect
FUND	The Climate Framework for Uncertainty, Negotiation, and Distribution
DICE	The Dynamic Integrated Climate-Economy model

CHAPTER 1: INTRODUCTION

1.1 Problem Statement: Understanding the Value of Policy-Oriented Research

Policy-oriented research intends to influence policy decisions by providing credible and objective information to decision makers and other key stakeholders (Herrick & Sarewitz, 2000; Clark et al., 2002). Each year, millions of dollars are committed to this type of research with the aim to enhance environmental, social, or economic welfare through the improvement of regulations, systems, or institutions (Norton & Alwang, 1998; CGIAR Science Council, 2008). To justify and attract continued allocation of funds toward policy-oriented research, the field of policy-oriented research impact assessment (PORIA) has emerged as a way to evaluate the success of research programs in achieving their stated goals and intended impacts.

However, there exist inherent difficulties in understanding how generated knowledge is transferred to stakeholders and many challenges remain in determining the impact of policy-oriented research. First, links between policy-oriented research and policy changes are often non-linear and indirect, as policy-making is an ongoing, multi-stage process that not only incorporates scientific knowledge but also relies heavily on momentum in public opinion and the political environment, among other factors (Weiss, 1980; Healy & Ascher, 1995). Second, because the causal links between policy-oriented research and policy changes are unclear, tracing the impacts of policy changes back to research is challenging.

Nevertheless, funding for PORIA is rising in relation to funding for research measuring the impact of technology-driven research (CGIAR Science Council, 2008). PORIA is attracting attention from various stakeholders interested in measureable results. While donors may be interested in the return on their investment, PORIA also yields a number of benefits for research institutions. For example, researchers gain a better understanding of how their findings travel through the information space to ultimately influence political action. Research centers gain insight into comparative returns on projects, allowing for wise allocation of resources between different research programs.

This paper lays out a framework that seeks to build on past PORIA efforts. We focus on the impact assessment of environmentally-focused, policy-oriented research, a particularly challenging field to evaluate due to the nature of the policy outcomes. Environmentally-focused, policy-oriented research aims to influence policies that sustain ecosystem services, which are often intangible and immeasurable in the traditional market. The difficulties in quantifying non-market impacts of environmental policy add an additional layer of complexity to PORIA beyond the difficulties in tracing knowledge dispersion.

In this thesis we estimate the societal value of research conducted under the Sustainable Wetlands Adaptation and Mitigation Program (SWAMP), an environmentally-focused, policy-oriented research program integrated within the Center for International Forestry Research (CIFOR) which aims to fill the knowledge gap in measuring carbon stocks in tropical peatlands and mangroves, and in doing so, enable the carbon accountability of tropical wetlands in policy-making. SWAMP's project activities run from 2012 to 2015, but sustainable wetland management research in CIFOR began in 2009 with the Tropical Wetlands Initiative for Climate Adaptation and Mitigation (TWINCAM). Following a PORIA framework, this thesis analyzes the Indonesian Forest Moratorium, a policy that could have feasibly been influenced by SWAMP research. Enacted in 2011, the Indonesian Forest Moratorium restricts licensing of primary and peat forests for commercial use. We analyze the effect of the Indonesian Forest Moratorium on peat deforestation and use attribution scenarios to trace the economic impact of the policy back to SWAMP efforts.

1.2 Objectives

This thesis aims to understand the societal value and broader impacts of the policy-oriented research undertaken through CIFOR SWAMP by estimating the impact of the Indonesian Forest Moratorium. The policy impact will be quantified by estimating changes in peat deforestation trends and associated carbon emissions. These impacts will then be traced back to CIFOR through attribution scenarios. Lastly, the social value of CIFOR SWAMP research will be predicted using estimates of social cost of carbon (SCC).

Objectives of this thesis are as follows:

(1) develop a framework to assess the environmental impact of Indonesia's Forest Moratorium. In doing so, we will:

   a. document trends in peat deforestation across various land use categories during two time periods, 2000-2010 (before policy) and 2011-2013 (after policy);
   b. document the differences in the BAU scenario versus projected trends to estimate the quantity of avoided deforestation and avoided carbon emissions attributable to the moratorium;
   c. estimate the social and economic benefits attributable to the Indonesian Forest Moratorium using the social cost of carbon;

(2) present potential scenarios of attribution to CIFOR drawing from verified findings from the CIFOR SWAMP Outcome Assessment;

(3) estimate the value of CIFOR SWAMP's policy-oriented research using results from part (2) and (1d).

1.3 Organization of Thesis

This thesis is organized as follows: Chapter 2 reviews methods used in PORIA, prior PORIA efforts within CIFOR, and an overview of SWAMP and SWAMP research topics; Chapter 3 outlines the theoretical framework used to trace (a) SWAMP research to policy change and (b) policy change to policy impact, and also details the dataset and variables used in the study; Chapter 4 presents the empirical strategy used to estimate the effectiveness of the Indonesian Forest Moratorium; Chapter 5 discusses findings from the five models specified; Chapter 6 explores the economic implications of our findings; and Chapter 7 builds upon these findings to present scenarios of attribution to CIFOR.

CHAPTER 2: LITERATURE REVIEW

2.1 The Impact Assessment of Policy-Oriented Research

PORIA seeks to understand the broader impacts policy-oriented research programs. It is an increasingly attractive field for research institutions and donors alike. Research institutions benefit from PORIA through advancing their understanding of the role research plays in influencing policy and improving societal welfare. By highlighting the pathways between research outputs and policy formation, PORIA provides insight into how these causal links can be strengthened. Donors interested in PORIA can use findings to justify investments or compare the returns of various research programs.

However, the methods used in PORIA are characterized by a high degree of uncertainty due to the inherent difficulties in tracing knowledge dispersion and in some cases, identifying a without research scenario. The following sections further detail these difficulties and present possible solutions to address issues.

2.1.1 Determining Attribution

While past studies have discussed the ways in which research can influence policy-making, there remain many limitations in determining the degree to which research impacts policy decisions (Weiss, 1979; Lindquist, 2000; Spilsbury & Kaimowitz, 2000). Complicating matters, the influence of policy-oriented research on policy-making is rarely direct or immediate. For example, there is evidence that effective policy-oriented research does not necessarily change one's views but is able rather to influence the overall political environment by changing the manner in which technical knowledge is discussed in decision-making (Weiss, 1979; Lindquist, 2001). The pathway between research and decision makers often travels through other spheres of influence before reaching decision makers. Policy-oriented research tends to have a greater influence on public knowledge and conversations, gradually shifting opinion as the public is increasingly exposed to scientifically verified findings (Weiss, 1980). As ideas gain momentum in the public sphere, decision makers are driven to take action. This impetus generates a reinforcing feedback between research and the political environment, with increased interest from policy makers driving increased funding for research and vice versa (Spilsbury & Kaimowitz, 2000). These entangled and indirect pathways of influence pose barriers to tracing a policy change back to policy-oriented research.

Further complicating attribution efforts are the multitude of actors generating knowledge around any one issue. It is not uncommon for a network of stakeholders to become engaged in a shared objective. These overlapping efforts make it difficult to isolate the influence of any one actor, as the process of policy-making lacks the transparency required to draw conclusions on causal relationships between individual actors and outcomes (Norton & Alwang, 1998; Wooding et al., 2007). However, the degree of difficulty in assigning attribution to one influential entity is largely dependent on the type of policy outcome being investigated. For example, tracking the key influential stakeholders involved in the formation of a locally implemented policy is more straightforward than a policy realized at the national or international stage where stakeholders are diverse and not necessarily at the forefront of the process.

To address challenges to attribution, an impact pathway or a theory of change is frequently utilized to facilitate understanding of the complex link between research and policy (Hewitt, 2008; Raitzer & Ryan, 2008). The theory of change traces how information may move from the initial research outputs to policy formation, taking into account the non-linear pathways through which knowledge tends to move. The theory of change also serves to identify key stakeholders who constitute the targeted audience for research outputs and who can serve as interviewees in the development of attribution scenarios. Conducting interviews with these stakeholders provides evidence for proposed pathways and can serve to assess how research outputs were perceived (Hewitt, 2008). Interviews provide an opportunity for stakeholders to communicate their perception of the credibility, influence, quality, and rigor of the research in question (Jones et al., 1999). While most interviewees provide context for the policy change process, key decision makers can provide subjective probabilities regarding counterfactual scenarios, or what they believe would have happened in the absence of the research in question (Schimmelpfenning & Norton, 2003).

As the theory of change provides grounds for testing and verifying causal links between research outputs, stakeholders, policy change, and policy outcomes, it is a critical piece in the overall impact assessment. Without this method, the links of causality between research outputs, policy action, and policy impacts are weak at best and would strain the validity of the estimated policy impact attributable to the policy-oriented research program.

2.1.2 Measuring the impact of policy-oriented research

While many PORIA efforts focus on qualitative methods to determine the degree of influence a research program may have on policy change, they often fail to quantify this influence (Boaz et al., 2008). One barrier to quantifying impact is the difficulty in identifying a valid and sensible counterfactual. In the case of policy-oriented research, the counterfactual is the state of the world in the absence of knowledge generated by the research program. Knowledge is just one factor that affects a program's intended outcome, a change in policy. Because policy change is such a multifaceted concept, replicating a scenario in which just one of the numerous enabling conditions for policy change is removed, is difficult.

Often, PORIA efforts make use of case studies to quantify policy-oriented research impacts. For example, if there is a policy that can be traced back to the research efforts, the case study will focus on estimating the impacts of the aforementioned policy. The logic behind this method is based on the idea that the value of research undertaken can be derived by the societal and welfare benefits generated by the policy (Gardner, 1999). This approach overcomes the challenge of explicitly identifying a counterfactual. The counterfactual in the PORIA study is substituted by the counterfactual in the case study, which is the state of affairs in the absence of the policy in question. After identifying a counterfactual, an empirical model is used to measure the policy's impacts. Then, the theory of change is used to determine what portion of the estimated policy impacts can be attributed to the policy-oriented research program. The value of policy-oriented research is therefore a function of 1) the degree to which the research influences policy change and 2) the social benefits resulting from the policy change.

In this thesis, another challenge to PORIA is the nature of research undertaken through SWAMP. As mentioned, SWAMP research aims to understand the carbon dynamics in tropical wetlands, develop methods to measure carbon stocks, and ultimately promote carbon accountability in decision-making. The intention of SWAMP research is to promote the wise use and management of tropical wetlands through international, national, and subnational policy change. A major benefit from potential SWAMP influenced policies is the retention of environmental services provided by tropical wetlands. A non-exhaustive list of tropical wetland services includes carbon storage and accumulation, coastal protection, and forest products. The challenge to estimating policy impact is that these environmental services are often not directly observed in the marketplace and changes may be observed only in a long and more complex timeframe.

Fortunately, with access to panel data on deforestation trends, we are able to measure the impact of the moratorium policy on our chosen indicator for impact, carbon stocks in tropical peatlands. We choose carbon stocks in tropical peatlands as an indicator for several reasons. First, carbon accountability of tropical wetlands in decision-making is one of the main objectives of SWAMP research. Second, tropical peatlands are one of the two focus ecosystems in SWAMP research. Third, we can reliably estimate changes in carbon retention using SWAMP generated knowledge and Indonesian deforestation data. By documenting differences in deforestation trends before and after the Indonesian Forest Moratorium implementation, we can determine how changes in deforestation translates into changes in carbon emissions. Lastly, we can estimate the social impacts of the Indonesian Forest Moratorium by drawing from recent efforts to internalize carbon sequestration benefits provided by forests.

2.1.3 Economic Implications of Impact: The Social Cost of Carbon

This study will utilize estimates of the social cost of carbon (SCC) to assign an economic value to the estimated emission reductions resulting from the moratorium. The SCC is an economic measure of global climate damages resulting from a marginal increase in carbon dioxide emissions. When used by policy makers and stakeholders, the SCC value can have immense implications for future outcomes. For example, the SCC can influence the strength of policy and investment in emission reductions when used in the regulatory process and in cost benefit analyses.

Estimates of the SCC are based in integrated assessment models (IAMs), which take into consideration changes in economic, social, and ecological states resulting from climate change (Hope, 2011; Nordhaus, 2011; Waldhoff et al., 2014). Since SCC estimates can be highly influential on long run outcomes and their use in policy formation can yield high net social benefits, there is a great amount of emphasis on the makeup of IAMs (Howarth et al., 2014). For this reason, IAMs are the subject of a robust literature.

Due to the sensitivity of climate to greenhouse gas emissions, the uncertainty of the pace of global warming, and the unpredictability of climate change impacts, there is great discrepancy in what is included in IAMs. These discrepancies are evident when considering the range of SCC estimates resulting from IAMs. Estimates can be as low as $2/tC (dollars per ton of carbon) and as high as $1500/tC, though the mean estimate is about $23/tC (Tol, 2005; Hope, 2006; Tol, 2008).

One widely debated variable is climate sensitivity, which measures the severity of climate impacts in relation to marginal temperature changes. Some models assume a linear relationship between temperature and climate damages, implicitly suggesting that the marginal cost of carbon dioxide emissions is independent of the state of the environment (Nordhaus, 2007). This assumption neglects the possibility of temperature increases triggering extreme climate events, which are poorly understood (Weitzman, 2009). Extreme events can result in irreversible damage and overwhelmingly large costs to society. The prominent Stern Report is especially criticized for failing to account for potentially irreversible non-market damages of climate change, specifically damages to essential support functions of ecosystems, which are often insubstitutable or costly to replace (Neumayer, 2007; Watkiss & Downing, 2008)

GDP growth is another highly influential, though often excluded, factor in IAMs. GDP growth is an exogenous factor in both the PAGE (Policy Analysis of the Greenhouse Effect) and FUND (The Climate Framework for Uncertainty, Negotiation, and Distribution) models, though climate changes have the potential to permanently decrease GDP growth (Hope, 2006; Anthoff and Tol, 2012). The probable relationship between GDP growth and extreme climate events lies in possible dramatic changes in labor supply, diversion of resources, or loss in the return on investments (Dell et al., 2012). When considered endogenously, GDP growth increases the SCC dramatically, with estimates of up to $220 (Moore & Diaz, 2015).

The discount rate, which is a percent value that reflects the relative importance placed on present and future conditions, is another key variable in IAMs that yields a high degree of influence on SCC estimates and one that is a source of consistent disagreement (Tol, 2008). On one hand, advocates for use of a low discount rate argue that the SCC should be based on the moral premise of intergenerational equity (The Stern Review, 2007). On the other hand, the use of low discount rates is criticized for failing to utilize discount rates based in actual economic behavior and decisions (Nordhaus, 2007). A meta-analysis of carbon emission costs reveals that publications that make use of low discount rates, which place higher value on future outcomes, consistently estimate higher SCC estimates than publications that utilize high discount rates (Tol, 2005; Tol, 2008).

As evidenced by the preceding discussion, IAMs are often criticized for making assumptions that lead the models to severely underestimate the true social cost of GHG emissions. Despite the wide range of estimates and disagreement over which variables are included in IAMs, the SCC is nonetheless a practical and useful contribution to the climate change mitigation and adaptation field. It is widely agreed upon that use of the SCC in policy and decision-making will help society address the issue of climate change immediately and will help to avoid catastrophic outcomes at a relatively moderate cost (Mendelsohn, 2008; Howarth, 2013). Assigning a monetary metric to historically non-traded ecosystem services allows these important services to be considered in the context of decision-making and provides an approach to determine the optimal path for emission reductions. The SCC ultimately allows environmental concerns to enter the terrain of global negotiations.

The IAMs most frequently employed in analysis and policy are the work of three prolific authors: Chris Hope, William Nordhaus, and Richard Tol. Their respective models – PAGE, DICE, and FUND – serve as the basis for the SCC estimates published by the Interagency Working Group (IWG) of the United States Government. Due to the high sensitivity of SCC estimates to discount rates, the IWG presents SCC using three rates, 2.5, 3, and 5 percent, which are based on the discount rates of the three models mentioned (IWG, 2015). The report also includes values for a 3% discount rate for the 95th percentile of the SCC from all three models, which represents the SCC value under the likelihood of above average costs (IWG, 2015). The dollar amounts listed in Table 1 are presented in 2014 Dollars and show the SCC per metric ton. In 2015, the SCC estimates range from \$12 using the 5% discount rate to \$117 when using the 95th percentile value (Table 1). In this study we will report estimates using each IWG discount rate in order to reflect upper and lower bound estimates.

Table 1. Social Cost of CO2, 2015-2050[a] (in 2014 Dollars per metric ton CO2), adapted from IWG, 2015

	Discount Rate and Statistic			
Year	**5% Average**	**3% Average**	**2.5% Average**	**3% 95th percentile**
2015	12	40	62	117
2020	13	47	69	140
2025	16	51	76	150
2030	18	56	81	170
2035	20	61	87	190
2040	23	67	93	200
2045	26	71	99	220
2050	29	77	106	240

[a]The SC-CO2 values are dollar-year and emissions-year-specific and have been rounded to two significant digits. The 2007\$ estimates were adjusted to 2014\$ using GDP implicit price deflator (108.289) from the National Income and Product Accounts Tables, Table 1.1.9.

2.2 Prior Assessments of CIFOR Research

Prior to this study, CIFOR conducted one impact assessment on its policy-oriented research. This research program focused on the political economy of the Indonesian pulp and paper sector (Raitzer & Ryan, 2008). The impact assessment utilized a variety of techniques to determine CIFOR attribution and the value of the policy-oriented research program. An impact pathway was developed to trace how knowledge generated by the research travelled from CIFOR to stakeholders and eventually to policy change. Information gathered from stakeholder interviews was used to develop counterfactual scenarios and to develop potential attribution scenarios. An econometric analysis determined the social value of avoided consumption of forest products resulting from the case study policy.

The study found that CIFOR's research accelerated the timeline for improvements in pulp and paper production practices. The most conservative estimate finds a positive return on investments in CIFOR research. This first impact assessment of CIFOR provides a model on which to base future PORIA studies and serves to provide insight into the importance of conducting similar studies.

2.3 The Sustainable Wetlands Adaptation and Mitigation Program

2.3.1 The Global Significance of Tropical Wetlands

Over the past two decades, tropical wetland forests have become progressively more threatened by deforestation, especially in Indonesia, where potential agricultural land values and profit-driven motives incentivize conversion over conservation (Margono et al., 2014). The essential and intangible services provided by wetland forests are often overlooked in land use decisions as short term aims prevail and opportunities to derive direct monetary benefits from these services have in the past been few and far between.

Both peat swamps and mangroves are especially notable for their long term carbon sequestration capacity. In order to incentivize conservation, the social benefits from the protection of wetlands must be made accessible. Globally funded forest conservation mechanisms now offer opportunities for developing countries to overcome the financial discontinuity between exploitation and preservation in favor of preserving carbon rich ecosystems. However, these mechanisms often require monitoring and verification of carbon stocks before monetary benefits are distributed. This requirement poses a large barrier to leveraging the carbon benefits of tropical wetlands.

Despite the knowledge of the significant carbon storage held in tropical wetlands, there is inadequate scientific understanding of the carbon dynamics in these ecosystems. This lack of scientific knowledge prevents wetland dense countries from both creating verified accounts of carbon stocks and emissions from tropical wetlands and benefitting from global financial conservation mechanisms. This information barrier must be overcome if countries are to incorporate wetlands in national greenhouse gas reports or develop plans for emission reductions.

It was in this environment that CIFOR's Sustainable Wetlands Adaptation and Mitigation Program was launched. The goal of SWAMP is to *"provide policy makers with credible scientific information needed to make sound decisions relating to the role of tropical wetlands in climate change adaptation and mitigation strategies"* (CIFOR, 2015). SWAMP supports this goal by conducting research on carbon stocks and dynamics in tropical peat swamp and mangrove forest ecosystems. The research undertaken by CIFOR SWAMP spans the global distribution of wetlands, with projects in Latin America, Africa, and Southeast Asia. The following sections will provide background on the ecological importance of peat swamps and mangrove forests in the context of SWAMP research.

2.3.2 Peat Swamp Forests

Globally, peatlands contain more than twice the carbon stock of total forest biomass in the world despite covering only 3% of total landmass (Immirzi et al., 1992). Peat is formed over thousands of years by the accumulation of fallen organic matter. Characterized by anaerobic, waterlogged conditions, peat swamps delay decomposition of organic debris, fostering ideal conditions for the formation of a long-term carbon storage system (Andriesse, 1988). The imbalance between continued production and negligible decay of matter makes peatlands into net carbon sinks so long as the deposits remain undisturbed (Rieley et al., 2008).

In tropical peatlands alone, thick deposits of underground biomass account for 3% of the global soil carbon (Page et al., 2007). Although biomass accumulation is slow at 1-2 mm per year, peat deposits over 4 meters are common in Southeast Asia, with reported layers of up to 20 meters (Anderson, 1983). Tropical peatlands are differentiated from their boreal and temperate counterparts by their exposure to high temperatures and abundant rainfall, which increase production of biomass and the rate of carbon accumulation in peat soils. Tropical peatlands are also distinguished by high-reaching forest cover, further adding to their carbon stores, whereas low shrubs and sedges are more typical of boreal peatlands.

Despite the considerable environmental services provided through the carbon storage and accumulation functions, the draw of lucrative crops such as oil palm is threatening the preservation of intact peat swamp forests and increasing pressures to convert peatland for agricultural use (Koh & Ghazoul, 2010; Page et al., 2011). Crude palm oil derived from oil palm is one of the most widespread and affordable vegetable oils on the market, serving as an ingredient in a variety of products including cosmetics, foodstuffs, soaps, and biodiesel. Indonesia has benefitted from the skyrocketing prices of crude palm oil in recent years and is now the world's largest exporter of crude palm oil, producing up to half of global supply (World Growth, 2011).

Beginning in the 1980's, plantation developers began to turn to peatlands for cultivation due to the diminishing availability of easily accessible and arable dry land and the rising demand for agricultural production (Miettinen et al., 2011). However, peatlands in their pristine form are less than ideal environments for agricultural production, and it is thus necessary to alter the fragile landscape to prepare for production. Undergoing conversion and creating dry land apt for agriculture often involves irreversibly damaging procedures that are detrimental to the health and function of the delicate wetland peat ecosystems. The conversion process drastically alters sensitive habitat and disrupts the hydrological stability required for provision of ecosystem services (Jauhiainen et al., 2012). Clearing peatlands removes the main inputs of organic matter, mainly tree roots and leaf litter. Additionally, removing aboveground biomass alters the microclimate of the area, impairing the water retention capability of peat.

The loss of aboveground carbon from a disturbance is relatively insignificant compared to the loss of soil carbon, which accounts for 90% of carbon in peat forests. Draining practices expose previously inundated organic matter to oxygen, initiating the decomposition of underground biomass and prompting the release of the exceptionally large stores of carbon (Couwenberg et al., 2010; Hooijer et al., 2010; Kurnianto et al., 2015). The majority of carbon is lost in the first five years after drainage, primarily from aeration, compaction, and consolidation.

While improved water management in plantations is thought to moderate the impacts of conversion by reducing peat oxidation and subsidence, the reduction is estimated to be at most 20% of total carbon loss. Therefore, even under the best case scenario, the majority of negative impacts from conversion are unavoidable (Hooijer et al. 2012).

Furthermore, deforestation and drainage practices used during conversion can intensify negative feedbacks in carbon emissions. Once disturbed, the biogeochemical properties of peatlands are difficult to restore and peatlands become net carbon sources (Page et al., 2009). Lowering the water table not only disturbs the sensitive hydrological balance but also increases the risk of fire in peatlands (Furukawa et al., 2005). Peatland fires are not just a possible side effect of conversion but are often intentionally used in the conversion process as an inexpensive means of clearing vegetation. Peat fires are notoriously difficult to extinguish and can lead to severe environmental, economic, and health damages as exemplified by the pervasive effects of the 1997 Indonesian Forest Fires, which were the source of an estimated 13-40% of global greenhouse gas emissions in that year (Page et al., 2002; Varma, 2003; van der Werf et al., 2010).

Since 1997, extreme peat fires are an almost biannual occurrence, the extent and severity of which is exacerbated by the onset of El Niño (Ballhorn et al., 2009). This pattern of fire outbreak has emerged only recently, though it now occurs even in non-drought years due to the increasing rate at which pristine peat swamp systems are transformed into zones of high fire susceptibility (Gaveau et al. 2014). Given its role as a major carbon sink and its current status as a major source of GHG emissions, tropical peat swamp forests offer an efficient and cost effective option for decreasing emissions from deforestation. Indonesia, which accounts for 65%

of tropical peat carbon stock, has the opportunity to emerge as a leader in conservation if peat loss is addressed.

2.3.3 Mangrove Forests

Mangrove forests are primarily situated in tropical and subtropical areas characterized by saline waters, high temperatures, oxygen deprived soils, and sharp tidal changes (Giri et al., 2011). These limiting conditions have led mangrove plants to develop distinct structural adaptations that permit growth of vegetation. Exposed above-ground roots, or pneumatophores, facilitate respiration in anoxic conditions, and reproduction is made possible by buoyant, water resistant seeds that are capable of successful establishment in wetlands. The unique makeup of these forests provides key ecosystem services that support abundant life systems (Robertson & Duke, 1987; Alongi, 2002).

With its position on coastlines, mangroves straddle saline and freshwater ecosystems and are widely recognized for their role in ensuring the health of surrounding ecosystems (Walters et al., 2008; Gillis et al., 2014). A mangrove's emblematic entanglement of aerial roots provides a barrier against incoming waves, protecting coastal establishments against major damages from tsunamis and storms (Dahdouh-Guebas et al., 2005). Dense mangrove forests support income generating opportunities for coastal communities. Wood products extracted from mangroves are used for fuel and charcoal and provide quality resources for construction. Food, medicine, and other forest products are often harvested for trade or sale.

Numerous marine species rely on mangroves for their productive habitat and their protection for juvenile development (Rönnbäck, 1999). Aquatic nurseries are able to flourish under mangroves by taking advantage of the abundance of food resources which include fish, crustaceans, and mollusks. The breeding grounds in mangroves provide crucial support to many off-shore commercial fisheries. The sustained health of mangroves is critical if commercial fisheries are to continue to benefit from the mangroves' role as breeding grounds. In Southeast Asian nations, where all shrimp catches and one-third of fish catches are reliant on mangroves, the economic implications of a decline in mangrove services could be drastic (Singh et al. 1994).

Mangrove forests have largely been overlooked in global climate change strategies although they are among the most carbon rich forests in the world. Total carbon storage per hectare is more than 1000 tC and a disproportionate amount of that carbon (49-98%) is stored in belowground biomass (Donato et al., 2011). Production rates in mangroves exceed those in any terrestrial or marine biome, with the rate of carbon accumulation continuing at 5 mm per year if undisturbed (Alongi, 2012). However, if disturbed or drained, the soil chemistry is subject to drastic change, which leads to significant greenhouse gas emissions (Granek & Ruttenberg, 2008; Donato et al., 2011).

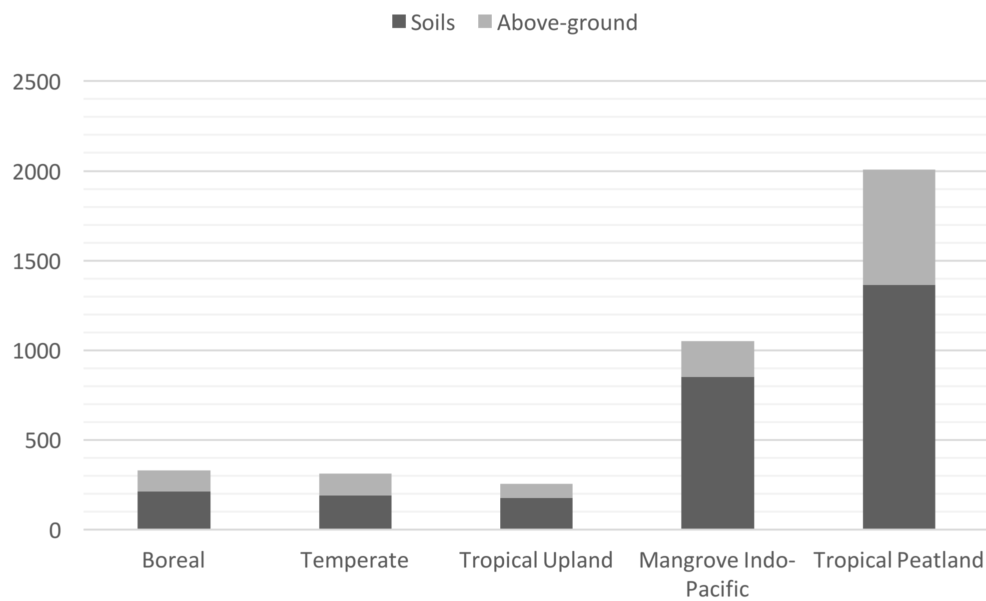
Mangroves are among the most threatened ecosystems in the world, and experts estimate that mangroves may functionally disappear in the next 100 years (Duke et al., 2007). Over the past 50 years, total mangrove area declined by one-third to one-half due to population pressures, conversion to aquaculture, and logging in coastal areas (Valiela et al., 2001; Alongi, 2002; Polidoro et al*.,* 2010). The already rare biome suffers from an alarmingly high deforestation rate that surpasses that of other forest types by three to five times (Alongi, 2002). The average annual loss in mangrove forests represents up to 10% of emissions from deforestation in tropical forests though representing just 0.7% of forest area (FAO, 2007; Spalding et al., 2010; Donato et al., 2011).

Murdiyarso et al. (2015) estimate that completely suspending mangrove deforestation in Indonesia, the world's most mangrove rich country, would reduce annual land use emissions by 10-31%. At an estimated abatement cost of $10 per ton of CO_2, mangrove conservation is one of the least costly methods to reduce carbon emissions compared to other emitting sources (Siikamaki et al., 2012). The cost of damages from wetland emissions is estimated at $41 per ton of CO_2. The clear imbalance between the $41/ton damage costs and the $10/ton abatement cost indicates that mangrove conservation should be prioritized in international climate change negotiations as a socially and economically beneficial strategy (Pendleton et al., 2012).

2.3.4 Summary

SWAMP research focuses on two important tropical wetland ecosystems: peatlands and mangroves. Both are noted for their numerous environmental services and are especially regarded for their status as large carbon sinks. With inundated conditions and high rates of primary production characteristic of tropical areas, forested tropical wetlands harbor some of the largest carbon stores of any forested biome. The average carbon stores per hectare in tropical wetland forests are four to eight times greater than boreal, temperate, and tropical dryland forests (Figure 1; Donato et al., 2011; Page et al., 2011). While these large carbon storage ecosystems can play an important role in climate change mitigation strategies, current trends in altering the natural state of tropical wetlands threaten this potential. In researching carbon dynamics in tropical wetlands and developing methods to measure carbon content, SWAMP aims to change the trajectory of tropical wetland alteration as a major contributor to greenhouse gas emissions.

Figure 1. Mean C Storage (tons/ha) comparison of major forest ecosystems
Adapted from Donato et al., (2011) and Page et al., (2011)



CHAPTER 3: THEORETICAL FRAMEWORK AND DATA

3.1 Theoretical Framework and the Theory of Change

As SWAMP has only a few years of operation to date, this is the first effort to quantify the impact of the research carried out through SWAMP, though the second effort to conduct PORIA of CIFOR research. While this paper will focus on connecting policy change to policy impact, it is only one component of a broader impact assessment. The research to policy assessment (outcome assessment) explores the impact pathways through which information disseminated by CIFOR has been transferred to stakeholders. This outcome assessment seeks to understand both how outputs are disseminated and how outputs have been used by target audiences. To achieve this, the CIFOR Monitoring, Evaluation, and Impact Assessment team has developed a theory of change which traces the probable flow of SWAMP outputs to broader project goals (Appendix, Figure 2). The theory of change is a central component of the SWAMP outcome assessment, enabling a better understanding of information flows and related outcomes. The next section will highlight the outcome assessment process and findings.

3.1.1 Research to Policy: The SWAMP Outcome Assessment

Through the development of the theory of change and stakeholder interviews, the SWAMP outcome assessment determines how well SWAMP achieved their end goal. SWAMP's end-of-program goal is for policy makers on the international, national, and sub-national level to use SWAMP's scientifically-verified information (i.e. carbon content and dynamics) in their decisions regarding tropical wetlands. It is assumed that extending carbon accountability for tropical wetlands into the decision-making process will strengthen protection for these high carbon reservoirs.

CIFOR's role in influencing policy is through the production of high quality research. SWAMP researchers primarily engage in quantifying carbon stocks in tropical wetlands and GHG fluxes resulting from climate change and land use change. SWAMP scientists have also developed GHG measuring tools for stakeholder use. By highlighting the carbon density of tropical wetlands and developing cost-effective techniques for monitoring them, SWAMP scientists have played a crucial role in increasing consideration of these biomes in climate change mitigation strategies.

Stakeholder engagement is necessary for developing influential policy-oriented research. To this end, the SWAMP team has been actively involved in advocating for carbon accountability of tropical wetlands through publishing in scientific journals and producing policy briefs intended for decision makers. In the last decade, CIFOR has played a key role in contributing to the emerging literature focused on the extensive global distribution of wetlands and the carbon dynamics from alteration (Murdiyarso et al., 2012).

Most notably, SWAMP scientists have contributed to the Intergovernmental Panel on Climate Change (IPCC) 2013 Wetlands Supplement, which has raised the prominence and potential for tropical wetland conservation on a global scale. The IPCC draws on scientific findings and expert review to create uniform guidelines for countries to use in their National Greenhouse Gas Inventories. The guidelines cover all economic sectors, including agriculture and forestry, and serve as a tool to verify GHG stores and emissions. These verified values are central to developing countries' ability to leverage carbon reservoirs and GHG emission reductions for monetary compensation through global financing mechanisms. Prior to the adoption of the 2013 Wetlands Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, there was insufficient scientific data to publish standardized emission factors for various wetland management practices. SWAMP scientists directly contributed to UNFCCC Task Force on National Greenhouse Gas Inventories (TFI) effort to develop specific emission factors for monitoring tropical peat swamp and mangrove forest stocks. SWAMP scientists Louis Verchot and Daniel Murdiyarso served respectively as Cooordinating Lead Authors of Chapters 2 and 3 (Drained Inland Organic Soils and the Rewetted Organic Soils) in the drafting of the Wetlands Supplement (IPCC, 2014).

The tailored products mentioned (publications, policy briefs, IPCC Wetlands supplement) are targeted toward stakeholders which include policy makers, research organizations, donors, media, and government agencies. By engaging with stakeholders through discussions, trainings, and capacity building workshops, SWAMP has made progress to achieve its intermediate outcomes. Specifically, SWAMP has improved capacity of researchers and government agents to further research tropical wetlands and has spurred knowledge-sharing at the global, national, and local levels. The subsequent widespread awareness of the high carbon storage in tropical wetland ecosystems provides a stepping stone for the evolution of carbon accountability in policy-making, SWAMP's end of program goal.

The outcome assessment uses a simplified collaborative outcomes reporting technique (CORT) approach to determine the degree to which SWAMP research contributed to the outcomes and goals outlined in the theory of change (CIFOR, 2015). CORT is a participatory approach that utilizes qualitative data and contribution analysis to map data against a theory of change to create impact stories. Qualitative data was collected through literature reviews of CIFOR publications and interviews with key stakeholders who are engaged in wetland research and policy. A total of 30 potential respondents spanning national and international policy realms, academia, technical staff, donor agencies, and NGOs were proposed by the research team and the assessment team. Interviews were conducted in July and August 2015.

Two sets of interview questions were created, one for policy makers and knowledge-sharing organizations and the second for technical staff and researchers. Both sets followed a similar outline. Interview questions first focused on collecting background information on the respondent and the respondent's familiarity with the topic. Second, respondents elaborated on important advancements in wetland management and named particular organizations that have played an influential role in affecting change. The final questions focused on CIFOR influence. These questions asked whether respondents are aware of CIFOR contributions, the importance of

CIFOR’s activities, and how influential CIFOR products have been on the respondent’s organization.

The outcome assessment report finds that SWAMP has achieved both its intermediate and end-of-program outcomes (CIFOR, 2015). Stakeholder interviews revealed that respondents were aware of SWAMP research and have used and shared this research with other parties. There is further evidence that negotiators, policy makers, and donors utilize SWAMP research in decision-making. There are three pieces of evidence specifically: 1) formal notes from the UNFCCC Workshop in Bonn, Germany cite CIFOR and refer to its knowledge output; 2) donors use SWAMP research in policy papers and manuals to support their efforts in advocating for improved mangrove and peatland management policies; and 3) Indonesian policy makers and technical staff reference CIFOR studies when calculating the country’s Forest Reference Emission Level (FREL) for national reporting (CIFOR, 2015).

3.1.2 Policy to Impact: Indonesia’s Forest Moratorium Case Study

Trailing only the United States and China, Indonesia is the third largest emitter of greenhouse gas emissions, with 85% of emissions stemming from deforestation (Sari et al., 2007; Houghton, 2012). A large proportion of these emissions stem from the degradation of carbon rich peatlands. Indonesia’s 21 million hectares (Mha) of peatlands cover more than 10% of the country’s land surface and represents 65% of the total volume of tropical peat in the world (Jaenicke et al., 2008; Page et al., 2011; Gumbricht, 2012). However, peatlands are disappearing rapidly. To date, total decline in peat swamp forest area in Indonesia is over 45%, with a historical deforestation rate estimated at 2.2% per year (Margono, 2012). Past development initiatives in Indonesia such as the Mega Rice Project have further exacerbated the issue by encouraging investment in oil palm and pulpwood industries. In the last two decades alone, oil palm plantation area has increased by 600%, often at the cost of peat deforestation and destruction (Carlson, 2012).

To address such high rates of deforestation and emissions, Indonesia's former president Susilo Yudhoyono set a national goal to reduce emissions by 26% below business as usual levels by 2020 (Fogarty, 2009). In 2010, Norway committed $1 billion in funding to support Indonesia's forest conservation efforts contingent on Indonesia achieving verified emission reductions (Government of Norway, 2010).

Acting on the emissions reduction goal and the Norway partnership, President Yudhoyono instructed a moratorium in May 2011. The moratorium bans granting new concessions to oil palm, timber, and logging plantations in all primary forests and peatlands (Government of Indonesia, 2011). Although SWAMP did not directly influence decisions to undertake the forest moratorium policy, CIFOR scientist Daniel Murdiyarso was a key contributor to the development of Indonesia's REDD+ strategy which encourages the sustainable management of mangroves and peatlands and precedes the announcement of the moratorium. Thus, the moratorium strategy can be traced back to the influence of CIFOR scientists, who produced timely research and developed frameworks which subsequently guided the direction of the moratorium policy and decision to include peat forests in the conservation efforts. Since the moratorium offers protection to Indonesia's remaining peatlands, it is a policy that is indicative of the type of impact that SWAMP research is expected to have. Additionally, through engagement and further research, SWAMP is likely to reinforce Indonesia's commitment to the moratorium. For these reasons, we use the moratorium as a case study to measure CIFOR SWAMP's value and impact.

As the moratorium was adopted recently in 2011, the body of peer-reviewed literature evaluating the impact of the policy on carbon emissions is limited. To date, two studies have investigated the overall impact of the moratorium on forest loss, though generate opposing results (Margono et al., 2014; Busch et al., 2015). Using a Poisson quasi-maximum likelihood estimator, Busch et al. (2015) provide support for an effective moratorium policy, finding that had the moratorium been in place from 2000-2010, emissions from deforestation would have been 2.5-6.4% lower. On the other hand, Margono et al., (2014) find that deforestation rates during the first full year under the moratorium were the highest recorded over the 2000-2012 period, countering the intended goal of the moratorium. While both papers consider the effect of the moratorium policy on dryland and peatland forests, the two studies differ significantly in their findings for several reasons. First, Busch et al. (2015) indirectly estimate the effect of the moratorium by simulating a hypothetical moratorium during the decade preceding the policy while Margono et al. (2014) consider pre- and post-moratorium forest cover data. Second, Busch et al. (2015) consider both primary and secondary forest loss while Margono et al., (2014) focus explicitly on primary forest loss. Lastly, Busch et al., (2015) are reliant on the estimated effect of concessions, which are the target of the moratorium, while Margono et al., (2014) do not consider concession effects and present universal trends in forest cover.

In deriving CIFOR's societal value from this major national policy, this thesis will combine aspects of the aforementioned two studies to estimate the effectiveness of the moratorium. We will estimate the effect of concessions and protected areas on primary forest cover and loss using pre- and post-moratorium data. Concessions include any land that is formally licensed by the Indonesian government as an oil palm, logging, or timber plantation. A protected area is a clearly defined area that is managed for the long-term conservation of nature, as recognized by the International Union for Conservation of Nature (IUCN). Most importantly, we center attention on the moratorium's effect on deforestation specifically in primary peat forests and will not consider the effect on dryland primary forests as previous studies have done. This subject matter has yet to be explored in such a degree of specificity. Focusing solely on peat swamps allows us to isolate the effectiveness of the moratorium in conserving peat forests, which are considered to be especially high conservation priority areas.

Indonesia holds a total of 21 Mha (million hectares) of peatland, one-third (7.1 Mha) of which was under prior lease or concession when the moratorium was enacted. The claimed area under moratorium protection therefore totaled 13.7 Mha, though 6.1 Mha of that area had already been exempt from concessions under prior conservation laws (UNEP/GRID-Arendal, 2011). The additional protection granted to peatlands by the moratorium is thus estimated at 7.6 Mha (Saxon & Sheppard, 2011). Although additional protection is more limited than originally claimed, the moratorium nevertheless offers the opportunity to substantially reduce emissions from deforestation given the high concentration of carbon in peatlands. The moratorium protects 4948.8 Mt (million metric tons) of peat carbon, which constitutes 19% of Indonesia's total peat carbon stock (Saxon & Sheppard, 2011).

3.2 Data Sources

Data were collected through the Global Forest Watch platform, an online facility providing Landsat 7ETM images that detail global forest cover, gain, and loss at a 30-meter spatial resolution (Hansen et al., 2013). We classify forest cover using the Indonesian Ministry of Forestry definition, a contiguous area of woody vegetation greater than 0.25 ha (hectares) with a tree cover threshold of at least 30% (MoF, 2008). Tree cover is defined as foliage with a minimum height of 5 meters. Forest loss is a change from forest state to non-forest state.

The official definition of primary forest is a patch of mature forest stands that is undisturbed by human activity and has retained undisturbed ecological processes (UNEP/CBD/SBSTTA, 2001). Secondary forest growth includes growth that can be attributed to plantation activity, for example oil palm tree growth. Since Global Forest Watch images include both primary and secondary forest cover, we overlay a dataset created by Margono et al. (2014) to isolate Indonesian primary forest. Eliminating secondary forests from the dataset removes observances of forest and plantation regrowth, a necessary consideration if we are to capture the true effect of concessions on the destruction of pristine peat forest.

As SWAMP research focuses on carbon rich peat forests, we further restrict our dataset to exclude non-peat forest cover. Wetlands International provides three maps detailing the extent of peat on the Indonesian islands of Sumatra, Kalimantan, and Papua. (Wahyunto et al., 2003; Wahyunto et al., 2004a; Wahyunto et al., 2004b). It is important to note that peatland in Indonesia is not restricted to forested areas. Peatlands without high vegetation cover are excluded from the dataset using our definition of forest. Consequently, our estimate may underestimate the effect of the moratorium as we only consider a subset of total peatland and do not consider the impact of the moratorium on non-forested peat.

The forest cover, forest loss, primary forest, and peat coverage maps are intersected in ArcGIS to create a dataset that details primary peat forest cover and loss in Indonesia. The combined dataset at the given 30-m resolution is prohibitive in size as this study covers the entirety of Indonesia, so we aggregate data at a coarser resolution. We overlay a grid of 1-km x 1-km cells (equal to 100 hectares) to create 139,274 grid cell units covering the entirety of

Indonesia's primary peat forest (Table 2). These grid cells collectively represent 9.27 million hectares (Mha), or about 44.14% of total peatland in Indonesia (Wahyunto et al., 2003; Wahyunto et al., 2004a; Wahyunto et al., 2004b; Page et al., 2011).

Each grid cell is categorized according to its land use designation. As large scale plantation activity poses a major threat to peatlands and is the focus of the moratorium on concessions, we account for the three major industries for which land use data is publicly available; oil palm, logging, and wood fiber plantations. These datasets account for large scale industrial plantations but do not include smallholder plantations, which are defined as a production area of less than 50 hectares (RSPO, 2013). Oil palm, logging, and wood fiber concession data are obtained through the Global Forest Watch platform and provided by the Indonesian Ministry of Forestry (World Resources Institute, 2014a, 2014b, 2014c). Licensing information, which includes license date, is included when available, though these data are far from complete.

Table 2. Summary Statistics

	All	**Non-designated**	**Protected**	**Concession**
# Cells, 2000	139,274	67,229	16,709	56,409
# Cells Converted to Protection after 2000	6,314	6,314	-	0
# Cells Converted to Concession after 2000	4,305	4,305	0	-
# Cells Converted to Moratorium in 2011	58,653	58,653	0	0
Avg. Forest Cover per grid cell (ha), 2000	66.53	64.3	73.11	67.50
Slope (degrees)	1.27	1.24	1.36	1.27
Elevation (m)	31.15	30.26	50.62	26.49
Distance from road (km)	78.53	82.80	11.90	60.92
Distance from city (km)	107.53	103.45	114.77	109.82
Proportion of sample in Region				
Sumatra	0.314	0.249	0.285	0.408
Kalimantan	0.319	0.363	0.163	0.310
Papua	0.367	0.388	0.552	0.282

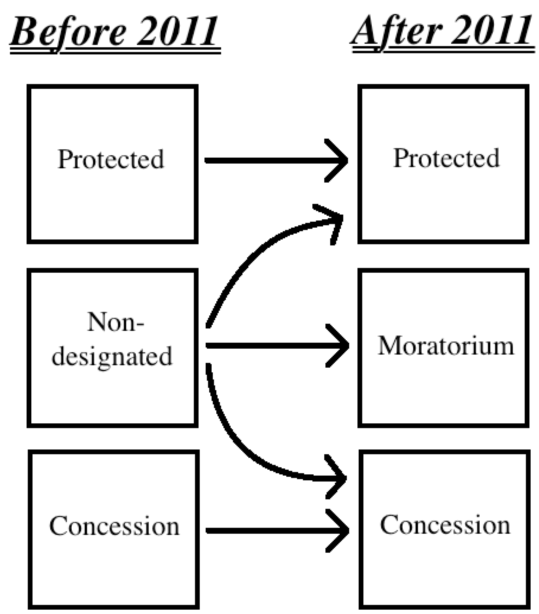
Protected area maps were obtained from the World Database on Protected Areas (IUCN and UNEP-WCMC, 2015) and include complete information on category of protection, total area, and designation year.

We use the first version of the Indicative Moratorium Map released in May 2011 to determine peatlands that are protected under the moratorium (MoF, 2011). The moratorium map published by the Indonesian government is updated every 6 months as a strategy to permit land holders to dispute categorizations they believe are incorrect. In the majority of the revised moratorium maps from 2011 to 2015, the maps have shown a decrease in the area of peat considered under protection. In using the first published map, we are estimating the originally intended impact. It is possible, therefore, that our model overestimates the effect of the moratorium.

We modify the moratorium map to account for overlapping designation statuses. The original moratorium map claims protection in areas that have already been licensed to concession or protected prior. This overlap is erased in order to isolate the additional protection offered by the moratorium. Using ArcGIS, we erase the intersections between moratorium and protected areas and the intersections between moratorium and concession areas from the original moratorium map. The resulting moratorium map isolates the additional protection offered to peatlands under the moratorium policy. Though the moratorium policy technically protects all non-designated peatlands after 2011, there are a small number of grid cells that are neither protected, concession, or moratorium that will be excluded from our study.

Therefore, grid cells initially categorized as non-designated followed three possible paths before moratorium implementation in 2011 in our dataset. Non-designated grid cells could only be converted to concession or protection, or would remain non-designated. Of the 67,229 grid cells categorized as non-designated in 2000, the number of grid cells converted to concession before 2011 totaled 4,305 (6.4%) (Table 2). The number of grid cells converted to protected areas after 2000 and before 2011 numbered 6,314 (9.4%) (Table 2). The 58,653 (87.2%) non-designated grid cells remaining in 2011 were re-categorized as moratorium (Table 2). Plainly, all peatlands were either protected, under moratorium, or under concession after 2011. Figure 3 illustrates the possible designation changes. Note that the total number of post-2011 grid cells is greater than the number of grid cells pre-2011 due to the potential for one grid cell to be assigned to multiple designations (Table 2).

Figure 3. Possible designation categorizations before and after moratorium implementation



3.3 Variables

In the following we further specify key outcome and explanatory variables included in our models. The outcome variable is the logged value of forest cover. The explanatory variables include dummy variables for protection designation and concession designation. Therefore, the benchmark group for comparison are non-designated grid cells. We also include a temporal dummy variable to separate the periods before and after the moratorium policy.

3.3.1 Outcome Variable

FOREST COVER: $Log(FC)_{it}$

The dependent variable is the logged value of primary peat forest cover in grid cell *i* in year *t,* measured in hectares (ha). By logging the value of forest cover, we are able to interpret the empirical model parameter estimates as the percent change in forest cover resulting from changes in designation status. Forest cover is recorded at the end of each year *t*, with the first observation in *t*=2000. Forest cover in each subsequent year is calculated by subtracting forest loss in year *t* from forest cover in the previous year, *t-1.*

3.3.2 Explanatory Variables

PROTECTED DESIGNATION: $PROT_{it}$

We include a binary variable to denote whether a grid cell is under protection or not. We use the (IUCN) definition of protected areas, which are recognized areas set aside for the long-term conservation of nature. Using the designation dates provided in the WDPA database, we assign grid cells as protected if the area had been granted protection in year

t or earlier. For example, the variable $PROT_{it=2004}$ equals 0 and $PROT_{it=2005}$ equals 1 if a grid cell i is within a protected area granted in 2005. A grid cell is labelled under protection if any fraction of the cell falls within a protected area. This allows for the possibility that grid cells fall under protection when only a miniscule area is actually protected. We assume that the impact of this designation strategy on overall designation effects is minimal, as research on protected area effectiveness shows a positive spillover effect in areas immediately outside protected boundaries (Gaveau et al., 2009).

CONCESSION DESIGNATION: $CONC_{it}$

The binary variable $CONC_{it}$ equals to 1 if a grid cell in year t falls within the boundaries of either oil palm, logging, or wood fiber concessions, and equals 0 otherwise. Concessions are nationally recognized production areas, typically surpassing 50 hectares. As mentioned prior, licensing dates are not provided for all concessions. This limits our ability to analyze the moratorium's impact on forest cover as we cannot estimate the the effect of designation on forest cover before the moratorium if we do not know when a plantation was established. Of the 1845 oil palm concessions listed, the license date is known for only 263 (14.3%) concessions. Logging plantation license dates are known for 553 of the 557 (99.3%) concessions listed. The wood fiber plantation dataset does not indicate license year for any of the 542 wood fiber plantations.

We will assume that all concessions with missing designation dates were licensed in 2000. By assuming designation in the earliest year within our dataset we are likely assuming grid cells fall within concession boundaries before they are actually designated, and therefore underestimating the concession effect. For example, if we assume a grid cell is licensed in 2001 when the correct license date is in 2007, we attribute any deforestation or lack thereof between these years to concessions instead of correctly attributing the data to non-designated areas. Logic would have us expect lower rates of deforestation in non-designated areas, so early categorization of non-designated cells instead as concession cells likely underestimates the concession effect.

As with protected designations, a grid cell is labelled under concession designation if any fraction of the cell falls within concession boundaries. With fractional designations resulting in full grid cell categorization, there is the potential for overlapping designations. In the case that multiple designations are assigned to the same grid cell, the grid cell will be considered under both categories. For example, a grid cell can be categorized as both protected and concession.

TEMPORAL DESIGNATION: $AFTER_t$

The variable $AFTER_t$ is a temporal variable that segments the data into two periods. The variable equals 0 in the first period, 2000-2010. The first period encompasses all years before the moratorium was implemented. During this first period, there were no restrictions on concession licenses. Non-designated peat forests could be titled into either concession or protection designations. $AFTER_t$ equals 1 in the second period, 2011-2013, encompassing years during which the moratorium was implemented. The moratorium offered protection to all remaining non-designated peatlands, effectively prohibiting all concessions during this time. Peatlands could technically be designated under official protection after 2011, though protection would be redundant given moratorium protection.

CHAPTER 4: EMPIRICAL STRATEGY

4.1 Methods

With no non-designated peatlands remaining after 2011, there is no obvious control group to use in constructing a counterfactual scenario. If non-designated peatlands remained after 2011, we could compare the post-2011 outcomes in moratorium grid cells to the post-2011 outcomes in non-designated grid cells to estimate moratorium effectiveness, assuming selection into groups is random, which is unlikely. Without this control group it is difficult to know how non-designated peatlands would have fared after 2011 in the absence of the moratorium.

With access to panel data on forest cover change before and after moratorium implementation, we can overcome the control group limitation. We estimate the effect of the moratorium on the dependent variable forest cover by comparing pre-2011 non-designated to post-2011 moratorium forest cover outcomes. We assume that in the absence of the moratorium, post-2011 moratorium forest cover trends would have continued at the same rate as pre-2011 non-designated rates. Therefore, a significant difference in temporal forest cover trends implies that the moratorium significantly changed the expected trajectory of non-designated peatlands.

Forest cover change can be influenced by various time and location specific factors. Exchange rates or political instability, variables associated with time, can sway motivations of commodity producers by altering levels of production and investment in new land opportunities. For example, diminished returns on investment would likely result in a decrease in land use change and activity. Similarly, certain site-specific factors have a large influence on the magnitude of forest cover change by determining the feasibility of commodity production. For example, studies find that forest patches closer to roads are more likely to be deforested, and land in high elevations and with steep slopes are less likely to be chosen for commercial production (Gerold et al., 2004). The robust literature finding correlations between site-specific variables and forest cover suggests that disregarding external influences in a model would result in inaccurate estimates.

We control for external influences on the outcome in question by employing a fixed effects econometric model. Time trends and aggregate year effects control for unobservable time influences, while fixed effects control for site-specific, time-invariant variables that may affect the amount of deforestation observed in a given area. The fixed effects model separates the influence of time and site-specific characteristics on forest cover change from the influence of the explanatory variable of interest, in this case land use designation.

As mentioned, our models initially classify peat forest grid cells into three land use designations; protected, concession, or non-designated. With binary variables included in our model as indicators of protected and concession areas, non-designated peatlands become the benchmark group for comparison. Our models account for the moratorium policy change with the inclusion of a temporal variable, $AFTER_t$. This temporal dummy variable separates the trends in forest cover into two periods, the first from 2000-2010 and the second from 2011-2013. The second period, 2011-2013, represents years when the moratorium policy is binding.

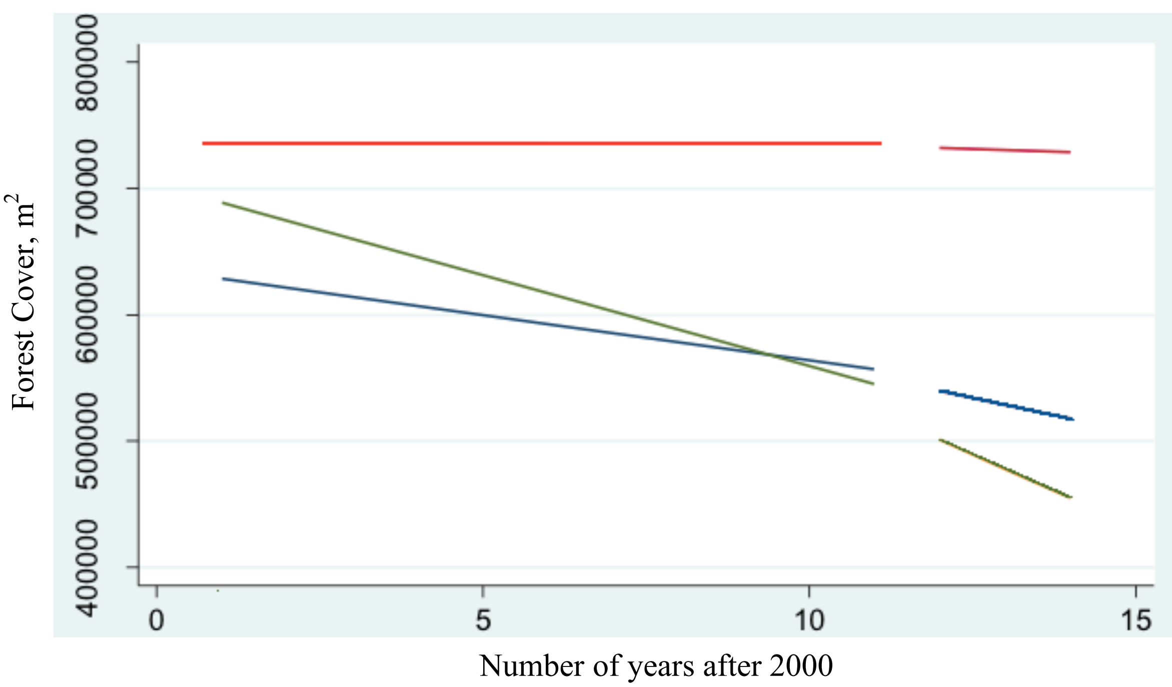
If the moratorium is effective to some degree, we would expect a positive temporal effect, evidenced by a positive $AFTER_t$ coefficient. A positive temporal effect indicates that rates of forest retention in the second period are higher than in the first period. This would be expected if the moratorium truly offered protection to former non-designated areas. A negative temporal effect would indicate accelerating rates of deforestation after 2011, a result contrary to the moratorium's intended effect. An insignificant effect would signify that post-2011 trends are continuing at the same pace as before the policy change. This would represent a business-as-usual (BAU) scenario, an indication that the moratorium had no effect on forest cover trends.

We include interactions between the variable $AFTER_t$ and each designation variable to allow for variation in the temporal effect between each designation group. For example, in the case where the model predicts a negative $AFTER_t$ coefficient, which describes an overall acceleration in deforestation rates after 2011, the interaction term between the concession variable and the temporal variable, $CONC_{it} * AFTER_t$, specifies whether that accelerating rate is different in concession areas compared to the benchmark group, former non-designated areas. Similarly, the variable $PROT_{it} * AFTER_t$ assesses the temporal variation between protected and benchmark areas. For example, an insignificant protection interaction coefficient would indicate that the difference in the $AFTER_t$ effect between protected and benchmark areas is not significant. Therefore, an insignificant protection interaction term would indicate that forest cover trends in protected and benchmark areas change similarly after the moratorium implementation in 2011.

These interaction terms offer insight into differential designation effects, allowing us to see how the designation effect changes from the first period to the second period. If there is a significant variation between designations in the effect of $AFTER_t$, we know that the designation effect is strengthening or weakening, depending on the direction of significance. This reveals how deforestation shifts between designations. It also reveals whether the moratorium generates unintended spillover effects on areas not protected by the policy. For example, if our model estimates a negative differential concession effect, we know that the change in forest cover trends after 2011 was more negative in concession areas than in benchmark (non-designated) areas. In other words, deforestation increased more in concession areas than in benchmark areas after 2011. This finding alludes to a negative spillover effect resulting from the moratorium.

Our identification strategy isolates the effects of three different land use categories on forest cover 1) non-designated areas which are re-categorized to moratorium areas after 2011, 2) concession areas, and 3) protected areas. Figure 4 illustrates forest cover trends within each of the three land use categories separated by the period before moratorium implementation, 2000-2010, and the period after moratorium implementation, 2010-2013. Figure 4 shows how forest cover generally declines after 2010, particularly within concession areas. Our models use the temporal effect, designation effects, and differential designation effects to estimate the magnitude of effectiveness of the moratorium and determine how deforestation trends change between designations. Section 4.2 furthers discusses how these identifications allow for estimating the impact of the moratorium.

Figure 4. Forest cover trends before and after moratorium implementation in 2011. Protected areas = red; Concession areas = green; Non-designated/moratorium = blue



4.2 Models

4.2.1 Models 1-3

The first model specification estimates the differential effect of protected or concession designation on forest cover at the 1-km^2 grid cell level. This model is given in equation (1).

(1) $$log(FC_{it}) = \beta t + \vartheta_1 PROT_{it} + \vartheta_2(PROT_{it} * AFTER_t) + \delta_1 CONC_{it} + \delta_2(CONC_{it} * AFTER_t) + \pi AFTER_t + \alpha_i + u_{it}$$

The variable FC_{it} is the recorded forest cover in grid cell *i* at the end of year *t*. For example, with t=2000, FC_{it} is the observed forest cover on December 31, 2000. The term βt represents a linear time trend with the year 2000 normalized to 0. The linear time trend assumes that the effect of time on forest cover is constant over the study period and therefore does not allow for any variation in year-specific effects. The variable α_i accounts for any unobserved heterogeneity which includes grid-specific time invariant variables like slope, elevation, distance to the nearest road or city, or distance to forest edge. The variable u_{it} is the idiosyncratic error term.

The variable $PROT_{it}$ equals 1 if grid cell *i* is within a designated protected area in year *t*, and equals 0 otherwise. Likewise, $CONC_{it}$ equals 1 if grid cell *i* is within a governmentally recognized oil palm, logging, or timber concession in year *t*, and equal to 0 if not within one of these concession designations. Observations that fall under neither protection or concession designation (i.e., $PROT_{it}$ and $CONC_{it}$ are jointly equal to 0) are the non-designated peatlands that form the benchmark group. Interpreting the coefficients of $PROT_{it}$ and $CONC_{it}$ allow us to estimate the ceteris parabus difference in forest cover between each designation and the benchmark comparison group. If, for example, the coefficient of $PROT_{it}$ is positive and significant, we can conclude that protection designation results in higher forest cover retention compared to the non-designated areas.

We are especially interested in how forest cover trends change after moratorium implementation in 2011. The variable $AFTER_t$ distinguishes the two time periods of interest. Specifically, $AFTER_t$ equals 0 if the year is between 2000 and 2010 and equals 1 if the year is between 2011 and 2013. The coefficient of $AFTER_t$ tells us if forest cover trends in the second time period, when the moratorium is in effect, differ significantly from the first time period. A significantly positive coefficient suggests the moratorium is effective in increasing the average forest cover retention rate, while a significantly negative coefficient suggests the moratorium accelerates deforestation rates. With a linear time trend, the effect of $AFTER_t$ is interpreted on a yearly basis. That is, the effect is interpreted as the change in the yearly forest cover retention rate.

The model includes the interaction terms $(PROT_{it} * AFTER_t)$ and $(CONC_{it} * AFTER_t)$ to account for the possible variation in the $AFTER_t$ effect between designations. The interaction term $(PROT_{it} * AFTER_t)$ tests whether the the effect of the $AFTER_t$ variable is significantly different between protected and benchmark areas. Similarly, a significant coefficient on $(CONC_{it} * AFTER_t)$ provides support that the effect of $AFTER_t$ is significantly different between concession areas and the benchmark group. We will use these results to determine how forest cover trends change across time and whether the designation effects are strengthened, weakened, or remain the same relative to the benchmark group.

The second model specification, given in equation (2), expands on Model (1) to include aggregate time effects.

$$(2) \qquad log(FC_{it}) = \gamma_t + \vartheta_1 PROT_{it} + \vartheta_2(PROT_{it} * AFTER_t) + \delta_1 CONC_{it} + \delta_2(CONC_{it} * AFTER_t) + \pi AFTER_t + \alpha_i + u_{it}$$

Aggregate time effects γ_t replace the linear time trend in Model (1), βt. By including aggregate time effects, Model (2) accounts for unobservable year-specific variables which may have an effect on forest cover in that year, such as political activity or economic trends. With aggregate time effects, this model estimates a cumulative moratorium effect, unlike Model (1). That is, the $AFTER_t$ effect is interpreted as the change in the average forest cover retention rate from the first period to the second period. The dummy variables for designations and corresponding interaction terms remain the same.

We consider a dynamic panel data model in the third model, given in equation (3). This model includes a lagged dependent variable to consider the likely possibility that the current level of forest cover is influenced by the amount of forest cover in the year prior, *t-1*.

$$(3) \qquad \log(fc_{it}) = \gamma_t + \varphi \log(fc_{i,t-1}) + \vartheta_1 PROT_{it} + \vartheta_2(PROT_{it} * AFTER_t) + \delta_1 CONC_{it} + \delta_2(CONC_{it} * AFTER_t) + \pi AFTER_t + \alpha_i + u_{it}$$

Without inclusion of the lagged dependent variable, the model may suffer from omitted variable bias which would increase the variance of the model and the estimated effect of other independent variables. However, including a lagged dependent variable violates strict exogeneity and estimates inconsistent standard estimators. Since $\Delta\log(fc_{i,t-1})$ and Δu_{it} are correlated, we use an instrumental variable (IV) approach to adjust for endogeneity. The IV approach replaces values of the endogenous variable with fitted values estimated with an instrumented variable. A valid instrumental variable is strongly correlated with the endogenous variable but uncorrelated with the error term. We instrument $\Delta\log(fc_{i,t-1})$ using the second lag of the dependent variable, $\Delta\log(fc_{i,t-2})$. If the error term is independent and identically distributed (i.i.d.), the second lag will be highly correlated with the lagged dependent variable and its difference, but uncorrelated with the error term (Arellano, 1989). Aggregate time effects, designation dummy variables, temporal dummies, and interaction terms remain in this model as with Models (1) and (2). Like Model (2), Model (3) estimates moratorium effects that are cumulative and represent the change in the average effect over a time period rather than year-specific moratorium effects estimated in Model (1).

Our preferred model for analysis is Model (3), as Models (1) and (2) do not account for prior forest cover trends and may overestimate the impact of designation status on forest cover change. The following specifications will therefore focus solely on the lagged dependent variable model.

4.2.2 Allowing for Designation Specific Duration Effects

Models (1), (2) and (3) restrict analysis of the protected and concession effect by assuming that the effect of designation is constant. A constant designation duration effect implies that the rate of forest loss during the first year of designation is equal to the rate of forest loss during the thirteenth year of designation. It is unlikely that the designation effect is constant since commercial plantations tend to develop land in large tracts during a single year or in clustered years. Furthermore, once a plot of land is completely deforested, there is no potential for future primary forest loss. Additionally, a company licensed with a concession may not begin to develop the land until several years after the license is granted. Therefore, the constant designation duration effect assumption may mislead analysis by over or underestimating a single year effect. The extended model shown in equation (4) allows for the designation duration effect to change over time.

$$(4) \qquad \log(fc_{it}) = \gamma_t + \varphi \log(fc_{i,t-1}) + \sum_{n=1}^{13} \vartheta_n \, PAYR\_n_{it} + \vartheta_0(PROT_{it} * AFTER_t) + \sum_{n=1}^{13} \delta_n \, COYR\_n_{it} + \delta_0(CONC_{it} * AFTER_t) + \pi AFTER_t + \alpha_i + u_{it}$$

The protected and concession dummy variables are replaced by variables $PAYR\_n_{it}$ and $COYR\_n_{it}$ respectively, where *n* is a number between 1 and 13. These two variables represent a series of dummy variables that specify for the number of years a grid cell is categorized under a protected or concession designation. For example, $PAYR\_1_{it}$ equals 1 if grid cell *i* in year *t* has been within a protected area designation for one year, and equals 0 if not. The variable $COYR\_2_{it}$ equals 1 if a grid cell *i* at year *t* has been within a concession designation for two years and equals 0 if not. Interpreting interaction terms and determining post-moratorium designation effects then become dependent on designation duration effects. Because Model (4) allows for variation in the designation effect, based on the duration, this model estimates how the effect of the variable $AFTER_t$ changes the year-specific forest cover retention rates. This interpretation is the same as the interpretation in Model (1).

4.2.3 Allowing for Year-specific Designation Effects

The fifth model allows for the designation effect to vary within each given year. This model, presented in equation (5), includes interaction terms between year dummies and the protected and concession designation dummy variables.

$$(5) \qquad log(fc_{it}) = \gamma_t + \varphi \log(fc_{i,t-1}) + \sum_{t=2001}^{2013}(\vartheta_t\, PROT_{it} * \gamma_t) + \vartheta_0(PROT_{it} * AFTER_t) + \sum_{t=2001}^{2013}(\delta_t\, CONC_{it} * \gamma_t) + \delta_0(CONC_{it} * AFTER_t) + \pi AFTER_t + \alpha_i + u_{it}$$

The protected and concession dummy variables in Model (3) are replaced by $(PROT_{it} * \gamma_t)$ and $(CONC_{it} * \gamma_t)$, where γ_t is a dummy variable for each year. These interaction terms allow for a yearly variation in deforestation rates between designation types. For example, the coefficient of $(PROT_{i,t=2005} * \gamma_{t=2005})$ measures how forest cover retention in protected areas differs from the benchmark group specifically in 2005. This model, like Models (1) and (4), estimates an $AFTER_t$ effect that is year-specific, opposed to estimating how the $AFTER_t$ variable changes average forest cover retention rates over an entire period, as in Models (2) and (3). As with Models (1)-(4), the benchmark group encompasses all non-designated areas. All other variables remain the same.

CHAPTER 5: RESULTS

This study estimates the extent to which the moratorium policy offered protection to Indonesian peat forests. We do this by examining how peat forest cover trends changed after the implementation of the moratorium in 2011 compared to a business-as-usual scenario (BAU) under which there is no moratorium. The BAU scenario assumes that in the absence of the moratorium policy, the rate of deforestation from 2011-2013 would be consistent with trends observed in 2000-2010. The temporal variable $AFTER_t$ assesses whether the difference between observed trends and BAU trends is statistically significant. A positive and significant coefficient suggests that the moratorium policy encouraged higher rates of forest cover retention and therefore decreased deforestation relative to BAU. A negative and significant coefficient implies that the moratorium policy decreased forest cover retention compared to BAU.

Our models include interaction terms between each designation variable and the $AFTER_t$ variable. These interaction terms estimate differential designation effects, which are the differences between the initial designation effect before 2011 and the designation effect after 2011. With differential designation effects we can determine whether the designation effect was strengthened or diminished after moratorium implementation. In doing so, the differential designation effects let us assess the variation in responsiveness to the moratorium policy. With this information, we can determine how relative forest cover trends change, and whether the moratorium offers increased protection to the benchmark group. For example, we would expect a negative differential concession effect if the moratorium increased protection in benchmark areas relative to concession areas.

5.1 Models (1) - (3) Results

Results from Models (1), (2), and (3) are reported in Table 3 with robust standard errors which address the issue of heteroscedasticity and serial correlation. Running the models with robust standard errors has no observable effect on the significance or coefficients of variables.

With a logged dependent variable, the coefficients of each binary independent variable must be transformed using the *exp(β)-1* correction to calculate marginal effects. This correction is applied to coefficients in Models (1), (2), and (3) and presented in Table 4. The following discussion will focus on the marginal effects in Table 4, particularly on results from our preferred Model (3).

Table 3. Models (1)-(3) Regression Results

	A Model 1	B Model 2	C Model 3
PROTECTED	-0.151***	-0.153***	-0.033***
	(0.0075)	(0.0075)	(0.0045)
PROT*AFTER	0.218***	0.220***	0.052***
	(0.0027)	(0.0027)	(0.0016)
CONCESSION	0.198***	0.195***	0.054***
	(0.0115)	(0.0114)	(0.0078)
CONC*AFTER	-0.307***	-0.308***	-0.079***
	(0.0020)	(0.0020)	(0.0012)
AFTER	-0.007***	-0.292***	-0.076***
	(0.0018)	(0.0021)	(0.0014)
Time Trend	-0.035***		
	(0.0001)		
Lagged FC			0.862***
			(0.0006)
Intercept	12.979***	12.894***	1.759***
	(0.0056)	(0.0057)	(0.0094)
Unit fixed effects	yes	yes	yes
Aggregate time effects	no	yes	yes

Note: Numbers in parentheses are standard errors
*p < 0.10, **p < 0.05, ***p < 0.01

Table 4. Models (1)-(3) Marginal Effects

	A Model 1	B Model 2	C Model 3
PROTECTED	-0.140***	-0.142***	-0.032***
PROT*AFTER	0.243***	0.245***	0.053***
CONCESSION	0.219***	0.215***	0.055***
CONC*AFTER	-0.265***	-0.265***	-0.076***
AFTER	-0.007***	-0.253***	-0.073***
Time Trend	-0.034***		
Lagged FC			0.862***
Intercept	433131.94***	397904.57***	4.807***
Unit fixed effects	yes	yes	yes
Aggregate time effects	no	yes	yes

*p < 0.10, **p < 0.05, ***p < 0.01

Model (1), estimates designation effects while controlling for time-specific factors using a linear time trend. The annual rate of forest loss is 3.4%, as indicated by the negative time trend, βt (Table 4, Column A). After the moratorium was implemented in 2011, the annual rate of forest loss increased by 0.7 percentage points above BAU, accelerating the rate of forest loss to 4.1% per year. This finding is supported by the significantly negative $AFTER_t$ coefficient (Table 4, Column A). Model (1) therefore alludes to an ineffective moratorium policy.

Model (2) estimates designation effects and replaces the linear time trend with aggregate time effects, γ_t. Findings from Model (1) are robust to the addition of aggregate time effects in Model (2), with the exception of the temporal trend, $AFTER_t$. Model (2) estimates that average rate of forest loss increases by 25.3 percentage points after the moratorium is implemented in 2011, a much larger estimate in magnitude compared to the 0.7 percentage point difference estimated in Model (1) (Table 4, Column B). However, as Model (2) replaces the linear time trend with aggregate time effects, the large temporal difference estimated in Model (2) is picking up a cumulative effect rather than the year-specific effect estimated in Model (1).

A thorough discussion of the marginal effects will focus on our preferred model, Model (3). Model (3) adds a lagged dependent variable which is instrumented using a two-period lagged dependent variable to adjust for endogeneity. Model (3) also includes aggregate time effects instead of a linear time trend. Results from Model (3) are similar in direction though generally smaller in magnitude compared to estimates from Models (1) and (2) (Table 4, Column C).

The instrumented lagged dependent variable is logged, so the coefficient is interpreted as the percent change in the dependent variable due to a percent change in the lagged independent variable and does not require the exponential transformation. In this case, a 1% increase in forest cover in year *t-2* is associated with 0.862% forest cover in year *t*, holding all else constant (Table 4, Column C). In other words, a grid cell in year *t* retains 86.2% of the observed forest cover in year *t-2.* All other coefficients in Model (3) are interpreted relative to the instrumented lagged dependent variable coefficient.

The coefficient of the variable $AFTER_t$ is significantly negative (-0.073) (Table 4, Column C). This finding is consistent with findings in previous models, showing that forest loss accelerates after moratorium implementation in 2011. Despite claimed protection under the moratorium policy, observed forest loss in moratorium areas is again significantly greater than BAU trends.

The rate of forest loss differs significantly between protected areas and the benchmark group (non-designated areas), evidenced by the variable $PROT_{it}$. The average protection effect is significantly negative (-0.032) at a 1% significance level, suggesting ineffective protection afforded to protected areas, an unexpected outcome (Table 4, Column C). Protected area grid cells are left with just 83% of forest cover from two years prior compared to 86.2% in non-designated areas. However, the protection interaction term ($PROT_{it} * AFTER_t$) is significantly positive at the 1% level. The coefficient of this variable indicates that after 2011, forest retention in protected areas is increased by an average of 5.3 percentage points relative to the pre-moratorium trends (Table 4, Column C). This differential protection effect also provides evidence that the accelerating rate of forest loss observed in moratorium areas is not observed within protected areas. Rather, areas under protection designation experience positive spillover effects from the moratorium, benefitting from higher rates of forest retention after moratorium implementation. These results echo findings from Models (1) and (2), which also find positive spillovers (positive protection interaction terms) in protected areas after moratorium implementation.

The concession effect is significantly positive at a 1% level (0.055), indicating a higher rate of forest retention within concession designations compared to benchmark (non-designated) areas (Table 4, Column C). This finding is contrary to what we may have expected, given the typical association between accelerated land use change and concessions. However, after the moratorium is implemented in 2011, forest loss within concession areas accelerates compared to pre-2011 trends. The concession effect becomes significantly more negative by 7.6 percentage points after the 2011 moratorium implementation, evidenced by the negative differential concession effect (Table 4, Column C). We can conclude then, that concession areas experienced much higher rates of forest loss after the moratorium was implemented compared to what may have occurred in the absence of the moratorium. These relatively higher deforestation rates in concession areas highlight negative spillover effects from the moratorium.

Drawing from Model (3) findings, we can speculate on the underlying reasons for the observed patterns. After the moratorium implementation in 2011, we see an accelerating rate of forest loss in moratorium areas, positive spillovers (increased protection) in protected areas, and negative spillovers (increased deforestation) in concession areas. The accelerating forest loss in moratorium areas is contrary to the policy's objectives. This likely reveals ineffective enforcement on deforestation in moratorium areas. Because this study only considers three years following moratorium implementation, it is possible that we are capturing a transition period associated with the new law, when enforcement and regulation may not be well understood or well executed. In fact, a study conducted by the World Resources Institute reveals that many officials within the local governmental institutions that are charged with implementing the policy did not fully comprehend which lands were protected under the new moratorium (Austin et al., 2012).

Compared to the benchmark group, protected areas have higher rates of deforestation and concession areas have lower rates of deforestation before 2011. After 2011, these trends switch so that protected areas have lower rates of deforestation and concession areas have higher rates of deforestation compared to the benchmark group, which are under moratorium protection from 2011-2013. It is possible that the moratorium is effective in curbing illegal peat deforestation within established protected areas. This explanation is further supported by the negative spillovers observed in concession areas after 2011. The negative spillovers suggest that the moratorium redirects a majority of deforestation activity to within licensed concession borders. It may be the case that the observed decrease in deforestation in protected areas after 2011 is being transferred to concession areas. It is logical then, to suggest that the moratorium does not necessarily decrease deforestation in peat forests, but rather redistributes the activity to occur mainly within concession boundaries.

5.2 Model (4) Results

Model (4) relaxes the assumption of a constant designation effect and includes binary variables that indicate the number of years a grid-cell is under designation. For example, the variable $COYR\_5_{it}$ equals one if grid-cell *i* has been under concession designation for five years in year *t* and equals zero otherwise. The longest designation duration included in this model is thirteen years. Replacing the constant designation effect with designation duration effects accounts for non-linear trends in forest cover change over the span of a designation. In other words, we allow for deforestation rates to change over time following a change in designation.

Model (4) findings are consistent with Model (3) in providing support for an ineffective moratorium policy. Contrary to the moratorium's anticipated impact, deforestation rates accelerated after 2011. Forest loss increased by 6.9 percentage points above BAU trends after the moratorium is implemented (Table 5, Column C).

The protection duration effects, represented by variables $PAYR\_n_{it}$, separate the effect of protection by the number of years a grid-cell is under protected designation. By analyzing the coefficients of the protection duration dummy variables, we can determine not only the direction of the protection effect, but also whether the effect endures over time. Model (4) results reveal protection duration variables that are positive and significant, with the exception of the third designation year effect, which is insignificant (Table 5, Column C). This finding indicates that grid cells under protection designation had higher rates of forest retention compared to the benchmark group immediately following a change in designation status.

Table 5. Model 4 Regression Results and Marginal Effects

	A	B	C
	Model 4	**Std. Err.**	**Marginal Effects**
PROT*AFTER	0.007***	(0.0029)	0.007***
CONC*AFTER	-0.003	(0.0023)	-0.003
AFTER	-0.071***	(0.0018)	-0.069***
Lagged FC	0.858***	(0.0007)	
PA_YR1	0.019***	(0.0050)	0.019***
PA_YR2	0.016***	(0.0042)	0.016***
PA_YR3	0.003	(0.0042)	0.003
PA_YR4	0.023***	(0.0040)	0.023***
PA_YR5	0.038***	(0.0042)	0.039***
PA_YR6	0.040***	(0.0043)	0.041***
PA_YR7	0.054***	(0.0045)	0.056***
PA_YR8	0.056***	(0.0045)	0.057***
PA_YR9	0.062***	(0.0045)	0.064***
PA_YR10	0.073***	(0.0047)	0.076***
PA_YR11	0.076***	(0.0058)	0.079***
PA_YR12	0.110***	(0.0058)	0.116***
PA_YR13	0.076***	(0.0058)	0.079***
CO_YR1	-0.007	(0.0058)	-0.007
CO_YR2	0.030***	(0.0047)	0.030***
CO_YR3	0.037***	(0.0047)	0.038***
CO_YR4	0.009*	(0.0047)	0.009*
CO_YR5	0.011**	(0.0048)	0.011**
CO_YR6	0.017***	(0.0048)	0.017***
CO_YR7	0.022***	(0.0049)	0.022***
CO_YR8	-0.005	(0.0049)	-0.005
CO_YR9	-0.025***	(0.0049)	-0.025***
CO_YR10	-0.059***	(0.0050)	-0.057***
CO_YR11	-0.066***	(0.0058)	-0.064***
CO_YR12	-0.108***	(0.0058)	-0.102***
CO_YR13	-0.067***	(0.0058)	-0.065***
Intercept	1.811***	(0.0090)	5.1144***
Unit fixed effects		yes	
Aggregate time effects		yes	

Note: Numbers in parentheses are standard errors
*p < 0.10, **p < 0.05, ***p < 0.01

The positive protection duration effect increases in magnitude as the number of years under designation increases, suggesting that the benefits of protection accrued the longer a grid cell was under protected designation. For example, a grid cell in the first year of protection designation ($PAYR\_1_{it}$) retained 1.9% more forest cover compared to non-designated areas (Table 5, Column C). The difference in forest cover retention rates widened as the protection duration increased. A grid cell in the eleventh year of protection retained on average 7.9% more forest cover compared to non-designated areas, a 6% increase in protection (Table 5, Column C). Contrary to findings in Model (3), which reveal a negative protection effect before 2011, these findings suggest an immediate, effective, and enduring protection effect within designated protected areas.

The positive differential protection effect ($PROT_{it} * AFTER_t$) is consistent with Model (3), showing that after the moratorium was implemented in 2011, the rate of forest retention in protected areas increased compared to pre-moratorium trends. This finding highlights how protected areas fared relatively better compared to the benchmark group after the policy implementation. In other words, the increase in deforestation after 2011 was not as severe in protected areas as in the benchmark group, and protected areas therefore experienced positive spillover effects from the moratorium. While Model (3) estimates a differential protection effect of 5.3 percentage points, Model (4) estimates a much lower differential protection effect of 0.7 percentage points (Table 5, Column C). The large difference in estimates can be explained by the difference in identification strategies between the two models. Model (3) aggregates the protection effect while Model (4) separates the protection effect by designation duration. The aggregated differential protection effect in Model (3) is therefore interpreted as the difference between the average pre-2011 protection effect and the average post-2011 protection effect. The differential protection effect in Model (4) is interpreted on a yearly basis and illustrates how the protection effect changes for each designation duration year. For example, the first year protection duration effect ($PAYR\_1_{it}$) equaled 1.9% before 2011 and increased to 2.6% after 2011.

As with protection duration effects, concession duration effects provide insight into how the concession effect changed over the span of a designation. Although a licensed concession legally permits land holders to undertake land cover changing practices, our results indicate that rates of forest cover retention were significantly greater in second ($COYR\_2_{it}$) to seventh year ($COYR\_7_{it}$) concessions compared to non-designated areas (Table 5, Column C). The comparatively higher rates of deforestation in non-designated areas suggest that many concession areas laid relatively undisturbed for up to seven years after licensing. The initial development phase in concession areas appears to occur in the ninth year after designation ($COYR\_9_{it}$), when the concession duration effect was first significantly negative (Table 5, Column C). Concessions continue to experience higher rates of forest loss relative to non-designated areas throughout the remainder of the designation. These results describe a concession development timeline characterized by several small-scale clearings over many years rather than a timeline in which land development occurs in a one-time large-scale clearing.

Relative to the benchmark group, concessions after 2011 are neither worse nor better off compared to concessions before 2011, as indicated by the insignificant differential concession effect ($CONC_{it} * AFTER_t$) (Table 5, Column C). This finding is inconsistent with Model (3), which found that concession areas were relatively worse off after 2011. The insignificant differential concession in Model (4) suggests that concession areas responded to the moratorium policy similarly as the benchmark group. The concession effect therefore continued at the BAU rate after 2011.

While Model (3) found that the increased protection effect (positive spillovers) after 2011 was offset by increased deforestation in concession areas (negative spillovers), Model (4) finds that the increased protection effect came at a cost borne equally by concession and moratorium areas. Model (4) therefore provides even stronger evidence for the weak enforcement in moratorium areas and further stresses the need to improve enforcement to achieve the intended outcome.

5.3 Model (5) Results

Model (5) allows for potential variation in designation effect. However, unlike Model (4) which varies the effect by designation duration, Model (5) allows for a yearly variation in designation effect with the inclusion of interaction terms between year dummies and designation dummy variables. Model (5) then makes it possible to compare how forest cover trends differed within each year. Similar to prior findings, results from Model (5) provide evidence for an ineffective moratorium policy, with results showing a significant acceleration in forest loss after 2011.

Compared to a BAU scenario, the rate of forest loss increased by 6.4 percentage points, an estimate on par with findings from Models (3) and (4) (Table 6, Column C). Before 2011, non-designated areas in a given year could expect to retain 85.9% of forest cover from time *t-2*. After 2011, the average percent of forest cover retained after two years dropped to just 79.3%.

Reinforcing findings from Model (3), protected areas experienced higher rates of forest loss compared to non-designated areas prior to moratorium implementation. The year-specific protection interaction terms, $(PROT_{it} * \gamma_t)$, which highlight the protection effect in any given year, show that observed forest loss in protected areas is greater than in non-designated areas every year between 2002 and 2008 (Table 6, Column C). However, there is a gradual shift in deforestation away from protected areas toward non-designated areas, evidenced by a diminishing negative protection effect during this period and the positive protection effect in 2010 (Table 6, Column C).

The positive differential protection effect $(PROT_{it} * AFTER_t)$ shows that relative protection offered to protected areas was increased even further after 2011 (Table 6, Column C). This positive spillover in protected areas, which increased the protection effect by 1.4 percentage points, is consistent with Models (3) and (4). Similar to Model (4), Model (5) separates the protection effect by year, so the differential protection effect is interpreted as the difference in each year-specific effect.

We observe higher rates of forest retention in concession areas compared to non-designated areas in every year between 2002-2009, evidenced by the positive year-specific concession effects $(CONC_{it} * \gamma_t)$ (Table 6, Column C). The year-specific concession effect diminishes over this period, suggesting that as the decade progressed, concession deforestation increased relative to non-designated areas. For example, deforestation in non-designated areas was 9.2% higher than in concession areas during the 2002 year (Table 6, Column C). In 2009, the year-specific concession effect, $(CONC_{i,t=2009} * \gamma_{t=2009})$, indicates that deforestation in non-designated areas was just 2.6% higher than concession areas (Table 6, Column C).

Table 6. Model 5 Regression Results and Marginal Effects

	A Model 5	B Std. Err.	C Marginal Effects
PROT*AFTER	0.014***	(0.0046)	0.014***
CONC*AFER	-0.018***	(0.0025)	-0.018***
AFTER	-0.066***	(0.0018)	-0.064***
Lagged FC	0.859***	(0.0007)	
***PROT**2002**	-0.053***	(0.0053)	-0.051***
***PROT**2003**	-0.052***	(0.0053)	-0.050***
***PROT**2004**	-0.040***	(0.0052)	-0.040***
***PROT**2005**	-0.023***	(0.0052)	-0.023***
***PROT**2006**	-0.022***	(0.0052)	-0.022***
***PROT**2007**	-0.025***	(0.0052)	-0.024***
***PROT**2008**	-0.020***	(0.0051)	-0.020***
***PROT**2009**	0.001	(0.0051)	0.001
***PROT**2010**	0.010**	(0.0051)	0.010**
***PROT**2012**	0.044***	(0.0031)	0.045***
***PROT**2013**	0.006**	(0.0031)	0.006**
***CONC**2002**	0.088***	(0.0033)	0.092***
***CONC**2003**	0.095***	(0.0033)	0.100***
***CONC**2004**	0.061***	(0.0033)	0.062***
***CONC**2005**	0.062***	(0.0033)	0.064***
***CONC**2006**	0.067***	(0.0033)	0.069***
***CONC**2007**	0.068***	(0.0033)	0.070***
***CONC**2008**	0.041***	(0.0033)	0.041***
***CONC**2009**	0.026***	(0.0033)	0.026***
***CONC**2010**	-0.004	(0.0033)	-0.004
***CONC**2012**	-0.028***	(0.0024)	-0.028***
***CONC**2013**	0.004	(0.0024)	0.004
Intercept	1.787***	(0.0088)	4.973***
Unit fixed effects		yes	
Aggregate time effects		yes	

Note: Numbers in parentheses are standard errors

*p < 0.10, **p < 0.05, ***p < 0.01

This shift toward more deforestation within concession areas was further exacerbated by the moratorium implementation. The differential concession effect ($CONC_{it} * AFTER_t$) indicates that concession areas fared worse after 2011, with the rate of deforestation in concession areas increasing by an additional 1.8 percentage points compared to BAU (Table 6, Column C). Therefore, after 2011 deforestation in concession areas accelerated at a faster rate compared to the benchmark group, demonstrating negative spillovers.

Overall, Model (5) supports Models (3) and (4) in illustrating an overall increase in deforestation and positive spillovers in protected areas after moratorium implementation in 2011. Negative spillover effects in concession areas are consistent with Model (3) findings, although Model (5) estimates negative spillovers of a lower magnitude. Again, the lower estimates in Model (5) can be explained by the differences in identification strategy. Model (3) estimates aggregated concession effects while Model (5) separates the concession effect by year. Nonetheless, these results support the idea that the moratorium did not decrease deforestation overall and perhaps directed a greater proportion of deforestation away from protected areas to concession areas.

All models discussed find that the moratorium was largely ineffective in decreasing deforestation in peatlands protected under the moratorium policy. In fact, contrary to the policy's objective, deforestation rates actually increased compared to BAU trends. While the models are inconsistent in determining how deforestation was redistributed, it is clear that in all cases enforcement and implementation of the policy was insufficiently carried out. The following section presents simulated scenarios under which adequate protection is provided to moratorium areas in order to estimate the reasonable potential of the moratorium to reduce peat deforestation and associated emissions.

CHAPTER 6: THE ENVIRONMENTAL AND ECONOMIC IMPACT OF INDONESIA'S FOREST MORATORIUM

6.1 Economic implications

We can determine the impact of the moratorium by comparing the post-moratorium (post-2011) observed outcomes to the BAU scenario in which the moratorium is not implemented. Results from our models offer considerable support for an ineffective moratorium policy. Contrary to the policy's intended goals, rates of deforestation actually increased following the moratorium implementation. Therefore, in the three-year period after moratorium implementation, emissions from peat deforestation were greater than what we may have expected in the absence of the moratorium.

Although our results show that deforestation increased after the moratorium was implemented, we can infer what the moratorium is capable of achieving by estimating how much deforestation and emissions could be avoided if the moratorium policy offered full protection to peatlands. Because we do not assume that full protection is synonymous with zero deforestation, we define full protection as the level of additional protection afforded to peatlands under official protection designation after 2011. We are then able to use the differential protection effect as a proxy for estimating full protection and the potential moratorium impact. This approach assumes that under full protection, grid cells falling under the moratorium are equally responsive to the moratorium policy as protected areas.

To simulate a scenario in which moratorium grid cells are exposed to the post-2011 protection effect, we first determine the average forest loss within moratorium grid cells from

2011-2013. Multiplying this value by the estimated differential protection effect tells us how much forest loss we would have expected had the moratorium offered full protection. We use the differential protection effect estimates derived from Models (4) and (5) and exclude estimates from Model (3) because Models (4) and (5) estimate year-specific designation effects. Year-specific differential effects allow us to project effects over time to estimate the long-term potential of the moratorium. These scenarios are presented in Table 7. The differential protection effect in Model (3) is not used because it picks up the average change in the protection effect over the entire three-year post-moratorium period. Since the average effect groups the effect of a number of years and any individual year effect could be higher or lower, Model (3) estimates cannot be used additively and would not provide accurate estimates in an extended time frame analysis.

Average annual grid level forest loss in moratorium areas between 2011 and 2013 is 1.10 ha. Using a differential protection effect of 0.7% from Model (4), a full protection scenario decreases annual forest loss from 1.10 ha to 1.09 ha, a decrease of 0.01 ha per grid cell (Table 7, Column B). With a differential protection effect of 1.4%, Model (5) estimates a 0.02 ha decrease in annual deforestation per grid cell (Table 7, Column B). We calculate annual grid level emissions associated with each full protection scenario following Murdiyarso et al. (2010) who estimate the average emissions from the conversion of one hectare of peat swamp forests to oil palm is 1486 tCO_2/ha (tons of carbon dioxide per hectare) (Table 7, Column C). With this calculation, we are implicitly assuming that deforestation of primary peat forest involves processes that subject the land to drainage practices common to the oil palm conversion practice and release underground biomass carbon. To determine additional annual emission reductions associated with each protection scenario, we subtract the emissions associated with each scenario from the observed emissions (Table 7, Column D). Additional annual emission reductions are projected to the national level by multiplying grid level estimates by the total number of grid cells categorized under moratorium protection (Table 7, Column E). Table 7, Column 7 shows the total emission reductions over the 2011 – 2013 period. Our calculations show that the moratorium could have decreased emissions from peat deforestation by 2.01 – 4.02 MtCO2 (million tons of carbon dioxide) during the three-year period if full protection were realized.

Table 7. Full Protection Scenarios, 2011-2013

	A	B	C	D	E	F
	Protection Effect	**Annual Grid Level Forest Loss (ha)**	**Annual Grid Level Emissions (t)**	**Grid Level Emission Reductions (t)**	**Annual Nationwide Emission Reductions (Mt)**	**Total Emission Reductions, 2011 - 2013 (Mt)**
Observed	0	1.10	1634.60	0	0	0
Model 4	0.007	1.09	1623.16	11.44	0.67	2.01
Model 5	0.014	1.08	1611.72	22.88	1.34	4.02

Calculations

Column B = 1.10 – (A*1.10)

Column C = B*1486 , where Average Peat Carbon Storage =1486 tCO2e/ha (Murdiyarso et al., 2010)

Column D = 1634.60 - C

Column E = (D*58653)/1000000 , where Total Moratorium Grid Cells = 58653

Column F = E*3

As the protection effect is persistent and accumulates over time, the potential moratorium effect will be greater the longer it is in place. Table 8, Column A provides an estimate of the projected potential moratorium effect. After 15 years, a fully enforced moratorium decreases emissions from deforestation by 10.5 – 21.0% compared to the observed outcome (Table 8, Column A). We repeat computations used to derive values in Table 7 in order to calculate emission reductions under an extended 15-year analysis. Results are presented in Table 8.

Table 8. Full Protection Scenarios, 15 Year Projection

	A	B	C	D	E	F
	15 Year Projected Concession Effect	**Grid Level Forest Loss (ha)**	**Grid Level Emissions (t)**	**Grid Level Emissions Reductions (t)**	**Nationwide Emissions Reductions (Mt)**	**Percent of 26% Reduction Goal**
Model 4	0.105	0.98	1462.97	171.63	10.07	1.7
Model 5	0.210	0.89	1291.33	343.27	20.13	3.4

Calculations

Column B = 1.10 – (A*1.10)

Column C = B*1486 , where Average Peat Carbon Storage =1486 tCO2e/ha (Murdiyarso et al., 2010)

Column D = 1634.60 - C

Column E = (D*58653)/1000000 , where Total Moratorium Grid Cells = 58653

Column F = (E/594.5) , where a 29% emissions reduction = 594.5

In the second national communication report to the UNFCCC, Indonesia's emissions baseline in 2005 is estimated at 2.05 $GtCO2_e$ (gigaton, or billion tons of carbon dioxide equivalent) (MoE, 2010). Therefore, if Indonesia is to reach its originally committed 26% emissions reduction goal, the country would need to decrease emissions by 533 million tons. In the most optimistic scenario presented by Model (5), the 15-year projection achieves 3.4% of the 26% emissions reduction goal (Table 8, Column F).

We calculate the value of potential avoided emissions from deforestation using the social cost of carbon estimates provided by the Interagency Working Group on Social Cost of Carbon (IWG, 2015). Using a 3% discount rate and the corresponding SCC of $40/tCO2, the estimated value of potential avoided emissions between 2011-2013 ranges from $80.40 – 160.80 million

(Table 9, Column D). Over 15 years, the value of avoided emissions at this \$40 SCC estimate ranges from \$402.80 – 805.20 million (Table 10, Column D). Using a low discount rate of 2.5%, which corresponds to a high SCC of \$62/tCO2e, the estimated value of avoided emissions under a full protection scenario over 15 years, ranges from about \$0.62 – 1.25 billion (Table 10, Column E).

Table 9. Economic Value of Avoided Emissions, 2011-2013

	A	B	C	D	E	F
	Full Protection Effect	**Total Emissions Reductions (Mt)**	**Economic Value using Stated SCC (Millions \$)**			
			\$12/tCO2	**\$40/tCO2**	**\$62/tCO2**	**\$117/tCO2**
Model 4	0.007	2.01	24.12	80.40	124.62	235.17
Model 5	0.014	4.02	48.24	160.80	249.24	470.34

Table 10. Economic Value of Avoided Emissions, 15 Year Projection

	A	B	C	D	E	F
	Full Protection Effect	**Total Emissions Reductions (Mt)**	**Economic Value using Stated SCC (Millions \$)**			
			\$12/tCO2	**\$40/tCO2**	**\$62/tCO2**	**\$117/tCO2**
Model 4	0.105	10.07	120.84	402.80	624.34	1178.19
Model 5	0.210	20.13	241.56	805.20	1248.06	2355.21

6.2 Related Research

Although prior research has estimated that the moratorium has decreased Indonesia's emissions from deforestation by 1-2.5 percent since its inception, this study shows that the moratorium was ineffective in reducing emissions from the deforestation of peat swamp forests when centering attention solely on carbon dense peat swamp forests (Busch et al., 2015). This finding is contrary to what we anticipated. We would expect the moratorium to be more effective in decreasing deforestation in peatlands than in dryland areas because of the additional effort and costs associated with converting wet peatland to agriculturally suitable land. However, peatlands may have inherently higher land values, which increases the draw to peatland conversion.

Preliminary studies offer insight into challenges the Indonesian government faces in effectively implementing the moratorium. Interviews with local forest officials reveal that the officials often showed a lack of clear understanding of moratorium protection boundaries within their own district (Austin et al., 2014). Enforcement in localities and routine implementation activities are crucial to the performance of the moratorium in achieving its intended outcomes but seem to have been overlooked in the planning phases of the moratorium. Austin et al. (2014) predict that in the absence of centrally administered technical management and guidance the moratorium would likely fall short of its goals. In fact, several instances of encroachment were observed within moratorium boundaries during the first months after the adoption of the moratorium (Austin et al., 2012).

Although the moratorium has fallen short of its intended goals there remain opportunities for its continual improvement. Firstly, closing existing loopholes, which allow for concession licenses to be granted on peatlands and primary forests if a project is in support of national food and energy security, will increase the effectiveness of the moratorium. Notably, these loopholes allow exceptions for granting licenses to palm oil plantations given that production is allocated to biofuel. Closing these loopholes and focusing instead on increasing yields within existing plantation land would dually achieve emission reductions and food and energy security. Secondly, a permanent and indisputable forest protection policy would reduce the confusion currently characterizing the sub-national implementation activities. The current moratorium lacks permanency, requiring renewal of the policy every two years. Although strengthening and institutionalizing the moratorium is dependent on Indonesia's commitment and efforts, it also relies heavily on external influences, particularly that of international climate agreements. Internationally funded mechanisms and other forms of support can provide the framework for Indonesia to move forward to effective conservation. It is these national and international pathways, which CIFOR SWAMP has positive influenced, that provide a source of optimism for future outcomes.

CHAPTER 7: THE SOCIAL IMPACT OF CIFOR SWAMP RESEARCH

7.1 Case Study Impact of SWAMP

The case study undertaken in this thesis confirms that any reduction in peat deforestation from BAU trends will have broad economic and social impacts due to the high carbon content in peatlands. The most conservative full protection effect (Model 4) estimates that improving moratorium protection by 0.7 percentage points results in 2.01 million tons of avoided emissions from peat deforestation over just three years and 10.07 million tons over 15 years. This corresponds to a societal value of \$80.40 million in the short-term and \$402.80 million in the long-term if using a median SCC of \$40/tCO2e. With these estimates, it is clear that efforts to consider tropical wetland conservation in national policies can have an extensive and significant impact.

We can develop scenarios simulating various levels of attribution using evidence from the Outcome Assessment Report of CIFOR's key role in developing frameworks for tropical wetland conservation. We assume across all scenarios that 25% of developments in peat-specific policy decisions, such as the moratorium, can be attributed to research. In the main scenario, we assume that CIFOR is responsible for 10% of the research used by policy makers. Therefore, 2.5% of moratorium outcomes can be attributed to CIFOR. We use sensitivity analysis to explore sources of uncertainty in the attribution values. A conservative scenario assumes that 4% of research can be attributed to CIFOR, which corresponds to 1% of the peat-specific Indonesian Forest Moratorium outcomes attributed to CIFOR SWAMP efforts. The optimistic scenario assumes a 20% CIFOR attribution to research, which corresponds to 5% of moratorium outcomes attributed to CIFOR. These scenarios are illustrated in Table 11.

Table 11. Attribution Scenarios

	A **Research Attribution to Moratorium**	**B** **CIFOR Attribution to Research**	**C** **CIFOR Attribution to Moratorium**
Conservative	25%	4%	1%
Main	25%	10%	2.5%
Optimistic	25%	20%	5%

Table 12 draws from the avoided emissions scenarios from Model (4) and illustrates the estimated returns to SWAMP research. With the median avoided emissions value, which draws from a $40 SCC, a conservative scenario estimates a $0.80 million value to SWAMP research over just the 2011-2013 period (Table 12, Column B), and a $4.03 million value over a 15-year projection (Table 12, Column F). With a 5% optimistic scenario, the $40 SCC values translate to a $4.02 million SWAMP value in the short-run (Table 12, Column B) and a $20.14 value in the long-run (Table 12, Column F). It is important to note that of the 15-year projection estimates, all but the 1% attribution scenario at the $12 SCC value (Table 12, Column E) far surpass the $1.54 million investment in SWAMP.

Table 12. SWAMP Value using Model 4 Economic Value of Avoided Emissions

	A	B	C	D	E	F	G	H
	Economic Value of Avoided Emissions, 2011-2013 (Millions $)*				**Economic Value of Avoided Emissions, 15 Year Projection (Millions $)****			
Attribution Scenarios	**$24.12**	**$80.40**	**$124.62**	**$235.17**	**$120.84**	**$402.80**	**$624.34**	**$1178.19**
1%	0.24	0.80	1.25	2.35	1.21	4.03	6.24	11.78
2.5%	0.60	2.01	3.12	5.88	3.02	10.07	15.61	29.45
5%	1.21	4.02	6.23	11.76	6.04	20.14	31.22	58.91

Note: Values do not account for mangrove benefits
*Values are taken from Table 9
**Values are taken from Table 10

We value SWAMP research using the avoided emissions value estimates from Model 5 and the conservative, main, and optimistic attribution scenarios. Results are shown in Table 13. In the short-term, which captures the three-year period between 2011 and 2013, all estimates of SWAMP research using an SCC of $40 or above exceed the $1.54 million investment (Table 13, Column B, C, D). In the long-term, all estimates show a return to investment in SWAMP research of 150% or higher (Table 13, Column E, F, G, H).

Table 13. SWAMP Value using Model 5 Economic Value of Avoided Emissions

	A	B	C	D	E	F	G	H
	Economic Value of Avoided Emissions, 2011-2013 (Millions $)*				**Economic Value of Avoided Emissions, 15 Year Projection (Millions $)****			
Attribution Scenarios	**$48.24**	**$160.80**	**$249.24**	**$470.34**	**$241.56**	**$805.20**	**$1248.06**	**$2355.21**
1%	0.48	1.61	2.49	4.70	2.42	8.05	12.48	23.55
2.5%	1.21	4.02	6.23	11.76	6.04	20.13	31.20	58.88
5%	2.41	8.04	12.46	23.52	12.08	40.26	62.40	117.76

Note: Values do not account for mangrove benefits
*Values are taken from Table 9
**Values are taken from Table 10

7.2 Global Impact of SWAMP

The SWAMP Outcome Assessment report provides strong evidence that knowledge generated through CIFOR SWAMP has had extensive influence in promoting carbon accountability of tropical wetland ecosystems on policy agendas (CIFOR, 2015). The theory of change, developed by CIFOR, corroborates links between SWAMP activities, engagement, outcomes, and policy change through interviews with global policy makers and donors, researchers, national knowledge sharing partners, and government technical staff involved with wetland policy and research.

According to interview respondents, furthering scientific understanding of the carbon content and dynamics of tropical wetlands is one of the major factors driving the changes in national and international policies. This knowledge elevates the discussion of tropical wetlands as high conservation value ecosystems and priorities for climate change mitigation and adaptation. SWAMP is acknowledged by interviewees as one of the key organizations participating in the surge of research surrounding tropical wetland carbon stores and dynamics. SWAMP has not only increased understanding and awareness but has improved the capacity of academics, researchers, and technical staff in government agencies to incorporate the environmental benefits of tropical wetlands into policy decisions. It is through these knowledge generation and engagement activities that CIFOR has advanced opportunities for tropical wetland conservation and made a positive societal contribution.

In one of CIFOR's most notable contributions to advancing scientific understanding of tropical wetlands, SWAMP scientists contributed their expertise to the process to fill gaps for wetlands in the 2006 IPCC Guidelines for national level greenhouse gas inventories, a global reference product that has potential to play a formative role in future climate change discussions and developments. The 2013 Wetlands Supplement is a pivotal development that enables wetland-rich countries to develop strategies and participate in conservation finance mechanisms, which often rely on verified measurements of carbon stocks and emission reductions.

Furthermore, CIFOR is a collaborator in the Blue Carbon Initiative, a global program formed in 2011 that advances the sustainable management of coastal ecosystems, including mangroves, as a climate change mitigation strategy. By supporting the development of global and national policies for blue carbon, advancing coastal monitoring and management tools, and building capacity of stakeholders, the Blue Carbon Initiative is leading efforts to integrate considerations for blue carbon into international policy frameworks.

Together, the Wetlands Supplement and the Blue Carbon Initiative are paving the road for the sustainable management of mangrove and peatland ecosystems. Given CIFOR's key role in both of these initiatives, it is likely that the impact of SWAMP will likely continue to grow beyond the impact of the Indonesian Forest Moratorium. The societal value of SWAMP research will continue to multiply as international negotiations develop and tropical wetland carbon benefits become increasingly incorporated in national accounting mechanisms. As this thesis only analyzes a fraction of the worldwide distribution of tropical wetlands and does not consider future wetland policy developments, our findings should be considered as a minimum estimate of the global impact of SWAMP research.

In an attempt to estimate the future potential of SWAMP research, we consider the global extent of tropical wetlands and provide a rough estimate of global carbon reserves at risk of land alteration. While Indonesia accounts for a majority of global tropical peatland, with 65% of the carbon storage reserves in tropical peatlands, the remaining 35% is not considered in this study (Page et al., 2011). This leaves about 31.13 GtC (billion tons of carbon) at risk of release under land use changes.

Furthermore, the potential for mangrove conservation worldwide is extensive and unaccounted for in this thesis. Globally, mangroves cover over 13.7 Mha (million hectares) and 93.1% of the total area remains unprotected under the IUCN protected areas network (Giri et al., 2011). This means that over 12.7 Mha of mangroves lie vulnerable to unsustainable and habitat-threatening human pressures. Although conversion to aquaculture, one of the main drivers of mangrove deforestation, has slowed since 2000, there are still high rates of forest loss in Indonesia, where many mangroves remain unprotected (Strong & Minnemeyer, 2015). Using findings from Donato et al. (2011), which estimate the average carbon content of Indo-Pacific mangroves at 1023 tC/ha, the global carbon storage of mangroves totals 14.02 GtC, with 12.99 GtC lying outside of protected areas.

Combined with the 31.13 GtC storage in non-Indonesian peatlands, the total carbon storage in vulnerable tropical peatlands and mangroves that is not considered in this study totals

44.12 GtC. These estimates are shown in Table 14. Note that these values do not account for the loss of the carbon accumulation function of these ecosystems, which have been estimated to store 0.5 – 1.0 tC per year. The value of these global carbon stores is $1.94 billion if using a conservative $12 SCC (Table 14, Column C). A small improvement in the management of tropical peatlands and mangroves could potentially yield large social and economic benefits. Therefore, even if SWAMP is attributed with a small fraction of the benefits from reduced emissions in tropical wetlands, the value added by SWAMP research will indisputably surpass the $1.54 million investment in the two-year project.

Table 14. Estimated Global Carbon Stores and Values of Tropical Peatlands and Mangroves at risk of Land Use Change

	A	B	C	D	E	F
	Global C (Gt)	Global CO2 (Gt)	Economic Value using Stated SCC (Millions $)			
			$12/tCO2	$40/tCO2	$62/tCO2	$117/tCO2
Peatlands (excluding Indonesia)	31.13	114.25	1370.97	4569.88	7083.32	13366.91
Mangroves (unprotected)	12.99	47.67	572.04	1906.80	2955.54	5577.39
Total	44.12	161.92	1943.04	6476.80	10039.04	18944.64

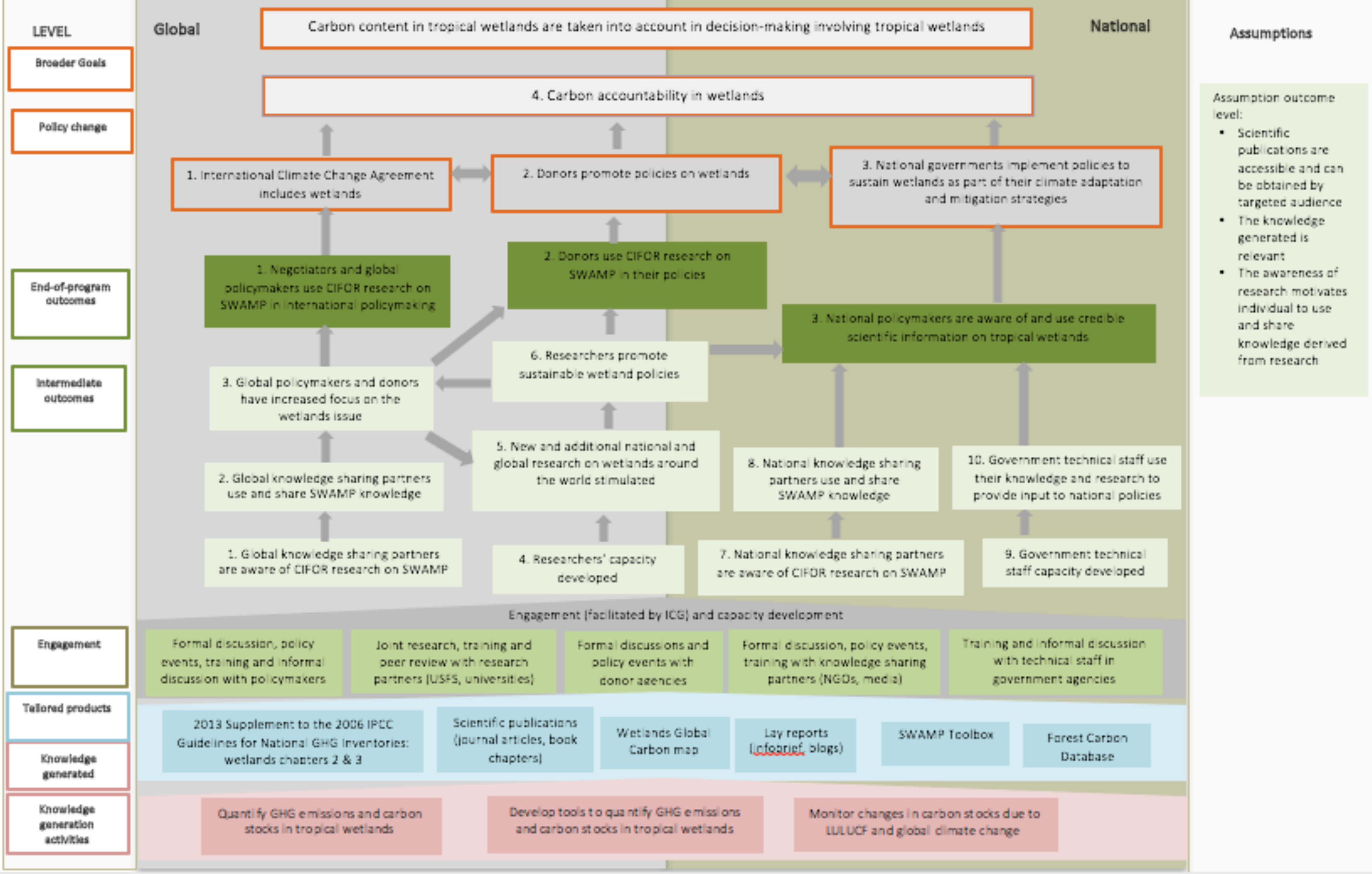
<u>Calculations</u>
Column B = (A*3.67), where 3.67 is the atomic ratio between carbon dioxide and carbon

7.3 Conclusion

There are often numerous contending factors contributing to policy change. Economic, social, and geopolitical conditions must align with research to support the adoption of international and national policies. Research is crucial for raising the prominence of tropical wetlands in national and international climate change agendas. SWAMP's role to further consideration of tropical wetland ecosystems has undoubtedly helped to foster an environment favorable for their conservation. SWAMP has generated awareness tools that have influenced policy and increased donor support for tropical wetland conservation.

Though calculating a precise estimate of the potential global impact of SWAMP research is limited by the availability of accurate spatial and descriptive data and by the lack of binding policies regarding tropical wetlands, the impact of SWAMP will likely grow exponentially as the Blue Carbon Initiative and the Wetlands Supplement become integrated in decision-making. Given the large carbon stores in tropical peatlands and mangroves that are not considered in this study, it is reasonable to surmise that the long-term impact of SWAMP research is positive, significant, and greatly outweighs the investment in the Sustainable Wetlands Adaptation and Mitigation Program.

APPENDIX **Figure 2. SWAMP Theory of Change**



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