# Exploring tropical ecosystem drivers of productivity using GIS, remote sensing and meta-analysis

Stephan J. Gmur

A dissertation

submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

University of Washington

2014

Reading Committee:

Daniel J. Vogt, Chair

Kristiina A. Vogt

Asep S. Suntana

Program Authorized to Offer Degree:

School of Environmental and Forest Sciences

# Dedication

This dissertation and the work therein are dedicated to my family who supported me through this journey. My parents Renee and Dennis Gmur who each supported my decision to continue with graduate school with the completion of each degree. Also to my brother Craig Gmur who was taken from us before he got a chance to give me a hard time about being a perpetual student.

## Acknowledgements

I would like to thank my major professor Daniel Vogt and my committee for assisting me in this research. A special thanks to SUCOFINDO of Indonesia, whose staff provided spatial information for many of the independent variables used in this study. Also to University of Washington's Center for Studies in Demography & Ecology (CSDE) and the University of Washington's Student Technology Fee for providing Computing support for the statistical analyses used in this research. Additional thanks to my Bloedel 178 lab mates for distracting me when needed and my friends who 'almost' never asked when I would be done with school.

# Abstract

Exploring tropical ecosystem drivers of productivity using GIS, remote sensing and meta-analysis

Stephan J. Gmur, M.S.

Chair of Supervisory Committee:
Daniel J. Vogt
School of Environmental and Forest Sciences

Many research studies have characterized the primary productivity of tropical forests and contributed to highlighting the complexity of underlying drivers of the ecological system. However, few studies have explored how productivity changes across multiple scales and how the drivers controlling productivity might differ depending on climatic and edaphic factors. Most know that modeling of the earth's surface using remote sensing within a geospatial format is limited by the spatial resolution of the technology and also the relative small temporal resolution of forestry inventory information. However even when we construct our models from this information knowing errors have probably been incorporated, we have a tendency to overlook those limitations because we generally don't have access to information containing fewer errors. This is especially critical to remember and understand when trying to model a system which is not completely understood or where robust information may not exist. Therefore it is helpful to be able to identify any critical thresholds of productivity so that one can determine when tipping points may occur in complex ecosystems. Determining the critical thresholds and tipping points for productivity would therefore allow us to then recognize the empirical indicators that may trigger a system or its components to shift from one state to another. This would then allow us to better understand the heterogeneity that exits in productivities at the local scales.

To search for potential thresholds and tipping points for productivity across scales, a study was designed to search for any relationships between empirical productivity data from tropical forest studies and other parameters such as climatic and edaphic variables. This study used the tools provided by meta-analysis, spatial modeling and quantification of human impacts at the local level to identify which combination of variables might reveal potential thresholds of the productivity. The performance of these variables was then used within a modeling environment to understand the underlying assumptions and how forest cover at the local scale is impacted by anthropogenic activities in relation to policy implementations.

At the global level those variables that best explain the spatial heterogeneity of total productivities at plot scales was based on using a meta-analysis of aggregated field data from 96 natural forests from the American, Asian and African tropics. These data suggested that 73% of the variance in total net primary productivity (NPPt) could be explained by different combinations of four variables: soil-order, soil-texture, precipitation group and mean air temperature. If variations in NPPt by soil order, soil texture, precipitation group, and mean air temperature are not factored into modeling activities, regional estimates could over- or under-estimates total productivity potentials.

At the regional level, underlying assumptions about a modeling environment were tested to determine how 20, 15, 10, five and one-km sampling resolutions using different occupancy selection criteria altered the distribution and importance of input variables as well as which variables were significant within the prediction model. Variances explained by predictive models were similar across cell sizes although relative importance of variables differed by sampling resolution. Partial dependence plots were used to search for potential thresholds or tipping points of NPP change as affected by an independent variable such as minimum daytime temperature.

Applying different cell occupancy selection rules significantly changed the overall distribution of NPP values. Finally, policy additionality was measured by investigating anthropogenic activities within the Mount Halimun Salak National Park in reducing deforestation by implementing spatially explicit use zones. Results showed that for the period 2003 – 2013, strict conservation areas had a 6.2% lower rate of deforestation relative to all other use zones combined. The relative rate of deforestation was higher in the Special Research & Training zone, which is a designated area for local communities to acquire livelihood resources. Deforestation was lowest in the Rehabilitation zone which are forests designated as areas to restore lands characterized as degraded and deforested.

Table of Contents

# List of Acronyms

| | |
|---|---|
| AG | Aspect Group |
| AGD | Aspect Group Description |
| AP | Annual Precipitation |
| Asp | Aspect |
| Elv | Elevation |
| EZ | Elevation Zone |
| FPAR | Fraction of Absorbed Photosynthetically Active Radiation |
| GLOBE LC | European Space Agency Global Land Cover Map |
| LAI | Leaf Area Index |
| MaxDT | Maximum Daytime Temperature |
| MaxNT | Maximum Night-Time Temperature |
| MeanDT | Mean Daytime Temperature |
| MeanNT | Mean Night-Time Temperature |
| MHSNP | Mount Halimun Salak National Park |
| MinDT | Minimum Daytime Temperature |
| MinNT | Minimum Night-Time Temperature |
| MinP | Minimum Precipitation |
| MnP | Mean Precipitation |
| MODIS LC | Moderate Resolution Imaging Spectroradiometer Land Cover Map |
| MxP | Maximum Precipitation |
| NPP | Net Primary Productivity |
| NPPa | Above Ground Net Primary Productivity |
| NPPb | Below Ground Net Primary Productivity |
| NPPm | Modelled Net Primary Productivity |
| NPPt | Total Net Primary Productivity |
| PG | Precipitation Group |
| REDD+ | Reducing Emissions from Deforestation and Degradation Plus |
| Slope | Slope |
| SO | Soil Order |
| SRTM | Shuttle Radar Topography Mission |
| SubTex | Subsurface Soil Texture |
| SurTex | Surface Soil Texture |

# List of Figures

## List of Tables

# Chapter 1

# Introduction

The yearly accumulation of woody biomass within tropical forests or Net Primary Productivity (NPP) is measured by many applications often using the units tons per hectare per year. The measurement in itself is simple but the implications of this measurement in terms of economic value, carbon sequestration potential, habitat quality, provisions of resources for people, conservation importance, aesthetic value and many other facets are only beginning to be quantified. Underlying processes which drive NPP are not fully understood and has led to the development of numerous models and the creation of a diversity of conservation policies aimed at preserving forested landscapes.

A great amount of attention has been put forth in quantifying the potential sequestration of carbon within tropical forests. Discussion of potential carbon uptake by tropical forests, which has been estimated to account for almost half global terrestrial NPP (Brown and Lugo 1982), has been shaped by estimates derived from a number of models (Solomon 2007). There is still much to be understood about quantifying the entire process that produces productivity estimates across multiple scales, from the global to local level. Tropical forests across the entire globe are interconnected with climatic and edaphic variables often determining site specific productivity. Models seek to represent as many environmental variables as possible to accurately predict field-based conditions controlling the achievable productivity. Models have made strides in beginning to reflect field based conditions but assumptions about model parameters can bias results. Often models do not properly capture the anthropogenic impacts at the local level. This dissertation seeks to understand how climatic and edaphic conditions affect productivity at sites across the tropical zone, and then use predictive methods at the regional scale to understand how model assumptions of spatial sampling and occupancy criteria alter variable distribution. Variations of productivity at the local scale exhibit less variability based on climatic and edaphic conditions but are impacted by resource extraction activities to meet daily economic and vitality needs.

Here I first undertake a meta-analysis approach to understand the significant drivers of productivity and the thresholds of productivity based on a survey of over 96 sites distributed across the tropical zone (Chapter 2). Use of this methodology identified significant climatic and edaphic variables which determined thresholds affecting the rate of growth within tropical forests. By understanding the significant drivers of productivity derived from field based observations, a comparison can be conducted to understand how underlying assumptions of prediction models can alter the outcomes. Comparing prediction models against field-based observations helps identify where existing models are deficient in capturing a component of the overall environment, over generalization using certain sampling resolutions, or cell occupancy selection rules (Chapter 3).

Models which explore productivity at the global or landscape level often are unable to quantify the anthropogenic influences on the landscape, such as uses of forest products by local people or to measure policy additionality. A case study of Mount Halimun Salak National Park was conducted to understand how policies using spatially explicit use zones balanced the resource needs of local people with the conservation goals of sensitive habitat areas (Chapter 4).

### 1.1. Measuring Net Primary Productivity

Net primary productivity provides a single unit of measurement and is logical to use since it records the state of an ecosystem and its responses to disturbances (Vogt et al. 1997). NPP captures the accumulation of carbon dioxide by vegetative through the process of photosynthesis minus how much carbon dioxide is released during respiration over a year’s time within specified area (often reported in hectares). Predictive productivity models generally under-estimate total tree growth rates because they are based on data from only a few sites and derived from aboveground parameters. For example, when Phillips *et al.* (1998) used field data collected from 153 long-term tropical forest sites to determine carbon sequestration rates, they used aboveground tree growth and mortality data, and root biomass estimates were calculated using a ratio. They derived an estimate NPPt of 0.71 Mg C $ha^{-1}$ $yr^{-1}$ as the annual carbon sequestration rate for tropical forests. This estimated productivity is about ten times lower compared to field studies measures of above-and below-ground net primary production (NPPa and NPPb, respectively; e.g., Vogt *et al.*, 1996; Clark *et al.*, 2001; Malhi *et al.*, 2009). The higher NPPt measured at plot scales reflects changes in annual growth rates between the above- and below-ground tree components at the scale where trees adapt to their diverse micro-climatic and soil environments, i.e., roots and mycorrhizas are the response variables sensitive to soil constraints (Vogt *et al.*, 1996). Since NPPa is poorly linked to NPPt, aboveground measures are generally ineffective at detecting productivity changes in response to stress or disturbances.

### 1.2. Modeling Net Primary Productivity

Since ecological processes can be altered due to climate change or land use, it is prudent to model at the scale that would enable the capture of that local variability in NPP, and this would provide a common metric allowing comparisons among different landscape units (Vogt et al. 2010). Currently there exists a global model from NASA using the satellite platform Moderate Resolution Imaging Spectroradiometer (MODIS) which estimates daily productivity then using additional model parameters such as respiration and litter fall, a yearly NPP product is derived. Daily NPP is derived from a combination of other MODIS products, including temperature, fraction of photosynthetically active radiation (FPAR), leaf area index (LAI) and radiation conversion efficiency parameters from biome properties look-up-table (BPLUT) as outlined in 'algorithm theoretical basis' documentation (Running et al. 1999). Many studies have validated the MOD-17 algorithm for different field sites in biomes around the globe (Running et al. 2004; Zhao et al. 2005; Turner et al. 2006). The independent variables included, but were not limited to, those parameters from the MOD-17 algorithm such as LAI, minimum temperature and FPAR.

### 1.3. Protected Areas

Often areas which exhibit high levels of productivity also have the attribute of great biological diversity in plant and animal species which multiple stakeholders have interests in preserving. Policy has served as a mechanism to limit the number of users of specific land areas with the goal of reducing the degradation or utilization of the land from other uses. The total number of protected areas within the tropics has continued to increase over the last 20 years but remains a bias in the creation of protected areas (PA) towards higher elevations farther from roads and cities (DeFries et al., 2005; Joppa & Pfaff, 2009). Conservation of forest areas as PAs has been the primary tool used to retain tropical forests and the ecosystem services they produce (Potapov et al., 2008; Joppa & Pfaff, 2011). A survey of 93 tropical forest plot-scale protected areas, where significant human land-use pressure exists, suggested a majority of these sites were sustaining or helping to increase the amount of forest cover (Bruner, 2001). Protected areas lowering deforestation rates have also been reported by a host of satellite-based studies of PA effectiveness (Sanchez-Azofeifa *et al.*, 2003; DeFries *et al.*, 2005; Nepstad *et al.*, 2006, Scullion *et al.*, 2014). A case study conducted an analysis of the policy additionality of a PA within Indonesia to reduce deforestation within specific areas of the park using spatially explicit land-use zones.

### 1.4. Data

Multiple sources of spatial and tabular data were collated within these chapters to undertake the study of understanding drivers of productivity across multiple scales. For the meta-analysis sources were compiled together to create a data-base which was composed of: published papers (refereed, non-refereed), theses, and dissertations, and field site research reports. Data were only included when direct measures of both NPPa (foliage, branches and bole) and NPPb were reported. For the meta-analysis, only NPPt data were used in the regression analyses. When authors reported NPPt as Mg C ha-1 yr-1, the value was doubled to estimate dry biomass (i.e., mass of C was assumed to be 50% of the dry biomass).

To understand the effect of different spatial sampling scales and occupancy criteria assumptions imposed on models, multiple spatial themes were collected to create a library of spatial data. Collecting spatial datasets that represented the terrestrial, climatic and biophysical conditions of the study area allowed for the creation of a common database (Table 2.1). Datasets were obtained from spatial data gateways maintained by USA federal agencies (NASA [National Aeronautics and Space Administration] 2013*a*, *b*, *c*), the European Space Agency (ESA 2013) and Indonesian ministries that create geographic information systems (GIS) databases (Kementerian Kehutanan 2011; BIG 2011). Datasets which originated from NASA were delivered in 10° × 10° tiles in hierarchical data format (HDR), with many different layers representing satellite conditions and data quality of each pixel. Soils and land-use vector datasets were supplied by the Indonesian federal government in tiled format which were collated and translated into English

Studying how policy applied to a protected area within Indonesia reduced deforestation across the entire park through the use of spatially explicit use zones utilized both remote sensing information and different administrative themes. A collection of spatially explicit datasets created from a variety of sources, including NGOs, such as RMI-the Indonesian Institute for Forest and Environment and JKPP (Jaringan Kerja Pemetaan Partisipatif/Indonesian Community Mapping

Network), working on MHSNP related issues, and the United States. Creation of spatial layers such as distance from boundaries, distance from deforestation or enclaves was calculated using the Spatial Analyst tool Euclidian Distance in ArcGIS 10.2 (ESRI, 2014). Classified land cover maps across the study area were created using LANDSAT scenes for the dates 1997 (TM), 2003 (ETM+) and 2013 (OLI_TIRS) (Path/Row 122/65). Those years with scenes exhibiting partial cloud cover obscuring portions of the study area were composited using multiple scenes from the same year to create the most complete cloud free image. Imagery was obtained from the USGS GLOVIS data portal (USGS, 2014) and radiometric correction was performed within ENVI (ENVI, 2014).

### 1.5. Analysis

Statistical methods used within this dissertation included analysis of variance (ANOVA), classification and regression trees (CART), randomForest and Matching. Within the meta-analysis of tropical forest sites, a multivariate statistical method, which utilizes binary division of sample populations to create tree-like regression models, was used to determine the correlations and thresholds of total productivity (Therneau et al., 2011). To build a regression tree, the sample population was split into two unique groups based on an identified significant division of the data by choosing one of the predictive factors. This process was then applied again, treating each new group as its own unique entity and finding the next set of variables which best divides the input population into two new groups. The process was carried out continually or recursively until a minimum size was reached or a subgroup could no longer be subdivided (Therneau et al., 2011).

To understand the effect of different spatial sampling scales and occupancy criteria assumptions imposed on models the common database of spatial datasets used the GIS software ESRI ArcGIS Desktop (Environmental Systems Research 2013), in combination with the programming language Python, to create automated tools for data processing. Those tiles from NASA's MODIS satellite platform which cover the study area were obtained, layers from each tile were extracted, and then values were transformed from integer values to floating point data using conversions provided by data documentation. Using Python, tools were created which automated processing tasks, ensuring consistent processing of all spatial information.

Equality of means between the populations of values created by the different spatial sampling resolutions and occupancy selection criteria were tested using a one-way analysis of variance (ANOVA). *Post hoc* pairwise comparisons between individual sampling resolutions and cell occupancy selection criteria (Table 33) used a multiple comparisons Tukey HSD ($\alpha = 0.05$; Zar 1999). Testing of prediction methods to identify significant variables used the *randomForest* method within the R program environment (Breiman 2001). Binary trees were created using recursive partitioning where a random sample of dependent variables at each possible split were selected using an out-of bag method, breaking the data into increasingly smaller pieces (Berk 2011). The creation of a binary tree on a random sample from the training data and 3000 binary trees for each prediction model were used to create a forest. Once the forest was created, the importance of each variable was assessed by surveying all nodes and where each was used in the trees (Garzón *et al.* 2006).

Measurement of policy performance to reduce deforestation between park areas (1997 – 2003, 2003 – 2013) and between zone designations within the park (2003 – 2013) used the statistical method called Matching. Matching is a treatment or policy evaluation method where sample populations of treatment and control unit distributions are constructed to be similar to provide an 'apple to apples' comparison (Joppa & Pfaff, 2011; Blackman, 2013). Comparisons between relative deforestation rates of different policy implementations used the 'Matching' package within the R environment (Sekhon, 2011). Sample populations were first balanced using the ‘GenMatch’ algorithm which is a multivariate Matching where a genetic search algorithm determines the weight and cumulative probably distributions. The balanced sample populations were examined using the ‘matchbalance’ command to determine the quality of the resulting match then a match was performed to obtain the casual estimate of relative deforestation between the control and treatment areas.

### 1.6. Dissertation Structure

A meta-analysis which collected field based observations from tropical forest plots distributed across the tropical forest zone to understand the drivers of productivity (Chapter 2). The identified edaphic and climatic site characteristics which drive productivity within an unmanaged landscape revealed thresholds or tipping points where vegetation communities could become altered in the event of land cover or climate change. A binary regression tree is used to represent these relationships between edaphic and climatic factors, where no single variable is used to describe productivity but in fact a combination of factors determines site productivity. Using this prediction model the following questions were examined:

1. What are the multiple combinations of individual edaphic factors and climatic conditions which best explain the variance in NPPt levels?
2. Will an updated data-base identify new combinations of variables driving productivity thresholds help to refine estimates of carbon sequestration rates?
3. Can thresholds of productivity for tropical forests be used to create better models as opposed to the more frequent creation of an ecosystem carbon model?

From the edaphic and climatic variables identified as being significant for determining productivity at the global tropical zone scale a regional study was conducted to understand how underlying assumptions within prediction models modify the resulting outputs (Chapter 3). Using the hypothesis that models predicting NPP are sensitive to the spatial sampling resolution and occupancy selection criteria used to represent the inputs, the relationships between different variables to NPP were explored. Often models are built at coarse scales which over generalize a landscape, five different spatial sampling resolutions to predict NPP using climatic, terrestrial and biophysical variables to examine how model outputs would be altered.

Extending from the global and landscape level analysis, a case study of the Mount Halimun Salak National Park (MHSNP) on the Island of Java in Indonesia explores the local scale dynamic of deforestation when native people's needs for resources must be balanced against conservation goals (Chapter 4). Policy as a method for preserving conservation is implemented in many forms including "exclusion and fine methods", community based inclusion and participatory strategies (Kubo, 2010a). Policy implementation within MHSNP to understand the influence on deforestation of park management practices inside MHSNP, three research questions were explored:

1. How did the park expansion in 2003 change deforestation within each park area?
2. Was deforestation lower inside lands designated for strict conservation verses other land designation?
3. Were their differences in the levels of deforestation between different land-use designations?

This work takes a multi-scale approach to understanding the dynamics of productivity within tropical forests. The objectives of this study was to explore drivers of productivity changes at global tropical zones, limitations of prediction models based on the underlying assumptions at the regional level, and policy which aims to measure policy additionality of land-use zones within protected a protected area.

# Chapter 2

## Pan-tropical natural forests assessed from above and belowground: A meta-analysis of soil and climatic influences on total net primary productivity

*This work is adapted from work originally submitted as:* Vogt, K.A., Gmur, S.J., Vogt, D.J., Scullion J.J., Nackley, L.L., Suntana, A.S., Patel-Weynanad, T., Daryanto, S. (2014) Pan-tropical natural forests assessed from above and belowground: A meta-analysis of soil and climatic influences on total net primary productivity. *Global Ecology and Biogeography.*

### 2.1. Summary

This study identifies what variables best explain the spatial heterogeneity of total productivities at plot scales in tropical forest landscapes. Using a Meta-analysis of aggregated field data from 96 natural forests from the American, Asian and African tropics a database was created. A multivariate statistical method, utilizing binary division of sample populations to create "tree-like" regression models, was used to identify climatic and edaphic variables correlates with 1) total productivity, 2) low, medium and high total productivity thresholds, and 3) total productivity grouped by wet, moist and dry precipitation groups. The multivariate regression model identified combinations of variables that estimated total Net Primary Production (NPPt) and resulted in three significant productivity threshold groups. 73% of the variance in NPPt was explained by different combinations of four variables: soil-order, soil-texture, precipitation group and mean air temperature. A meta-analysis of plot-level research, using a binary regression tree analysis approach, can be used to identify different combinations of soil and climatic factors that may be significantly correlated to total productivity potentials in tropical forests. If variations in NPPt by soil order, soil texture, precipitation group, and mean air temperature are not factored into modeling activities, regional estimates will over- or under-estimates total productivity potentials.

Climatic and soil factors can all contribute to producing thresholds in the total productive capacity and biomass sequestration potential of a tropical forest.

## 2.2.Introduction

In 1973, Lieth published the first global terrestrial productivity ranges using a model in which temperature and precipitation explained 73% of the variance in productivity levels at a biome scale. This study was based on aboveground productivity estimates from a few sites and did not include soil (edaphic) factors or other variables that drive processes at the smaller scale. Many subsequent plot-scale studies have revealed a diversity of different but significant relationships between climatic/edaphic factors and forest productivity shifts between the above- and the below-ground in response to stress or disturbances (reviewed by Vogt et al., 1995). Plot-scale studies, however, may inadequately represent the heterogeneity of possible growth environments across a forest landscape when intensive data collection only occurs at a few research sites. This is supported by the inconsistent identification of variables that explain productivity thresholds. A statistically robust data-base should include data from multiple sites representative of the heterogeneity in edaphic and climatic conditions regulating forest growth rates. It also needs to measure carbon allocation shifts between above- and belowground tree components to increase the accuracy of model predictions of forest total net primary productivity (NPPt).

Predictive productivity models generally under-estimate total tree growth rates because they are based on data from a few sites and derived from aboveground parameters. For example, when Phillips et al. (1998) used field data collected from 153 long-term tropical forest sites to determine carbon sequestration rates, they used aboveground tree growth and mortality data, and root biomass estimates were calculated using a ratio. They derived an estimate NPPt of 0.71 Mg C ha-1 yr-1 as the annual carbon sequestration rate for tropical forests. This estimated productivity is about ten times lower compared to field studies measures of above- (NPPa) and below-ground net primary production (NPPb; e.g., Vogt et al., 1996; Clark et al., 2001; Malhi et al., 2009). The higher NPPt measured at plot scales reflects changes in annual growth rates between the above- and below-ground tree components at the scale where trees adapt to their diverse micro-climatic and soil environments, i.e., roots and mycorrhizas are the response variables sensitive to soil constraints (Vogt et al., 1996). Since NPPa is poorly linked to NPPt, aboveground measures are ineffective at detecting productivity changes in response to stress or disturbances.

The first objective of this study was to identify what multiple combinations of individual edaphic factors and climatic conditions best explain the variance in NPPt levels found in a forest landscape. If these drivers produce significant and different thresholds or tipping points for NPPt, it supports thresholds being a result of a combined effect as opposed to individual phenomena associated with one variable.

The second objective of this study was to determine whether an updated data-base can be used to identify new combinations of variables driving productivity thresholds to help refine estimates of carbon sequestration rates in tropical forests. In fact, the wide variability in NPPt reported in published studies suggests the need to analyze and aggregate tropical forest data by combinations of climatic and soils information (e.g., Brown & Lugo, 1982; Vogt et al., 1996; Gmur et al., 2013). Until recently, an insufficient number of field-based measures of both NPPa and NPPb, coupled to their edaphic and climatic growth factors, were available to adequately characterize the heterogeneity represented in total productivity across a forest landscape.

The third objective was to identify thresholds of productivity for tropical forests growing under diverse edaphic and climatic conditions as opposed to the more frequent creation of an ecosystem carbon model. To search for thresholds of productivity, we compiled a data-base of 96 pan-tropical forests published in refereed journals.

A multivariate statistical method, which utilizes binary division of sample populations to create tree-like regression models, was used to address our three objectives. Such an approach helps to identify which edaphic and/or climatic factors regulate and produce thresholds in forest productivity. It focuses on the identification of local-level (i.e., stand-level) productivity indicators, as opposed to global biome-level comparisons, to detect significant differences in total productivity and to reveal productivity thresholds. The ability to identify critical thresholds of productivity can help to determine when tipping points may occur in complex ecosystems and to identify which empirical indicators may trigger a system or its components to shift to another state (Dai et al., 2012). This allows us to detect thresholds of productivity based on a specific range of environmental conditions and facilitate the detection of the resilience of a forest to disturbances, e.g., will a forest be pushed to a tipping point and transition to another forest or vegetation type?

## 2.3. Methods

### 2.3.1. Data-base creation

Multiple data sources were used to compile the data-base used in our analyses: published papers (refereed, non-refereed), theses, and dissertations, and field site research reports. Data were only included when direct measures of both NPPa (foliage, branches and bole) and NPPb were reported. For this paper, only NPPt data were used in the regression analyses. When authors reported NPPt as Mg C ha-1 yr-1, the value was doubled to estimate dry biomass (i.e., mass of C was assumed to be 50% of the dry biomass).

The NPPb includes coarse and fine root data. Studies typically estimate coarse root biomass using a ratio developed from allometric relationships particular to a species (e.g., Kenzo et al., 2009). Reported fine root NPP data were direct measures of fine root growth based on a “diverse suite of field” sampling methods (e.g., root cores, in-growth cores, mini-rhizotrons, etc). A few fine root NPP values reported were indirect estimates of fine root growth calculated by the authors using correlations between direct measures of root NPP and other ecosystem metrics, such as soil respiration and litterfall (e.g., Clark et al., 2001).

This study did not attempt to standardize or exclude any data from studies due to the methodologies used to collect or to calculate NPPa and NPPb. Despite limitations of having variable sampling protocols to estimate NPPa or NPPb (e.g., Clark et al., 2001; Malhi et al., 2011), these data are useful to examine trends and patterns of change in NPPt and to explore how edaphic and climatic factors produce productivity thresholds.

### 2.3.2. Variables included in the meta-analysis

A total of 96 case data entries were collated from natural tropical forests reported as mature or having a closed canopy (Appendix A). The geographic distribution of the field sites are presented in Figure 2.1. Missing values about specific sites were supplemented from other studies reporting this information (e.g., Vogt et al., 1995; Clark et al., 2001; Phillips et al., 1998; Malhi et al., 2011).

For each site, data were separately recorded by forest region, forest age, climatic variables, by elevation and elevation groupings, by soil orders and soil texture classes according to the USDA soil taxonomy system (Soil Survey Staff, 1999) (Table 2.1, Appendix C). The authors recognize that many tropical areas may have at least three distinct climatic seasons because of monsoons, but these analyses were limited to the annual data since that is generally reported in publications.

### 2.3.3. Meta-analysis statistical approach

A multivariate statistical method, which utilizes binary division of sample populations to create tree-like regression models, was used to determine the correlations and thresholds of total productivity (Therneau et al., 2011). To build a regression tree, the sample population was split into two unique groups based on an identified significant division of the data by choosing one of the predictive factors. This process was then applied again, treating each new group as its own unique entity and finding the next set of variables which best divides the input population into two new groups. The process was carried out continually or recursively until a minimum size was reached or a subgroup could no longer be subdivided (Therneau et al., 2011).

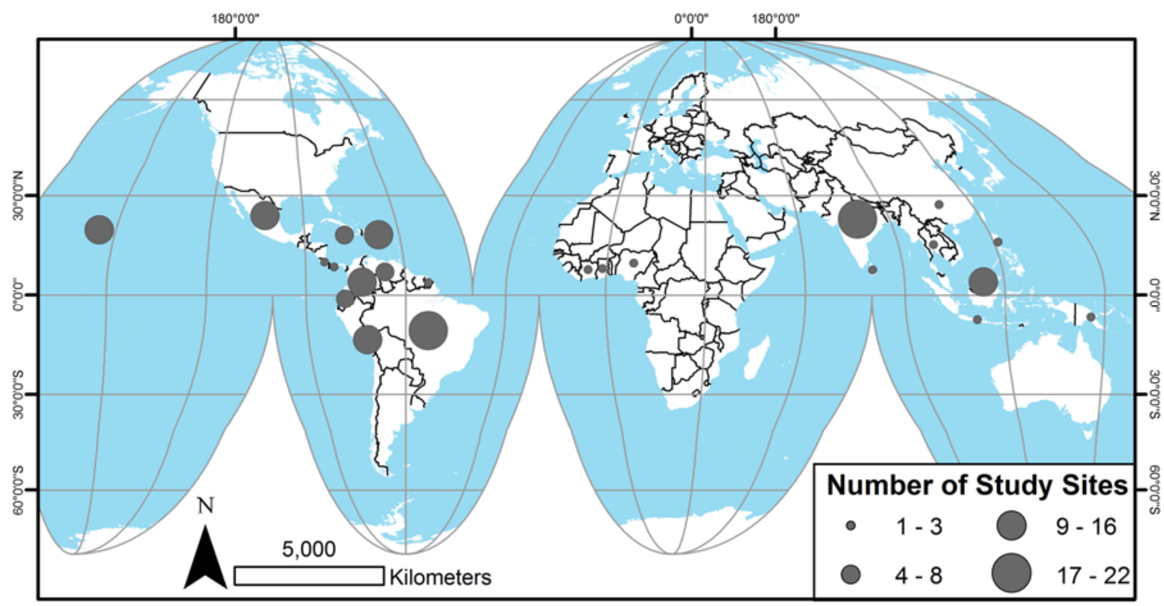


**Figure 2.1.** Geographic distribution of pan-tropical forest sites field sites in our database.

The model’s relative error was used to assess and ensure that a regression was not over-fitted to the data. Regression trees with a relative error close to 0 produce a good prediction while a relative error around or greater than one produce a poorer prediction (Cukjati et al., 2001).

**Table 2.1.** Variables included in our database used to create tree like regression models using data reported by the authors or collated from research field site reports for 95 pan-tropical forest sites.

| **Variable Key** | **Groups** |
|---|---|
| Global forest region | 1 = America; 2 = Asia; 3 = Africa |
| Stand age classes, years | 1 = Exact age; 2 = Mature or closed canopy forest |
| Elevation groups, m asl (e.g., Hertel *et al.*, 2009) | 1 = Lowland zone = <400; 2 = Pre-montane zone = 400 to 1200, 3 = Montane = >1200 |
| Precipitation, mm $yr^{-1}$ | Forest groups by rainfall (Chave *et al.*, 2005): 1 = Wet forests - evapotranspiration exceeds rainfall during less than a month; usually high-rainfall lowland forests (rainfall greater than 3,500 mm $yr^{-1}$ and no seasonality; 2 = Moist forests - evapotranspiration exceeds rainfall during more than a month but less than 5 months; forests with marked dry season (one to 4 months), sometimes semi-deciduous canopy and 1,500-3,500 mm $yr^{-1}$ rainfall for lowland forests; 3 = Dry forests - pronounced dry season, plants suffer serious water stresses (below 1,500 mm $yr^{-1}$, over 5 months dry season)<br><br>Additional subgroups by rainfall: 1 = H wet, > 4500 mm $yr^{-1}$; 2 = L wet, >3500-4500 mm $yr^{-1}$; 3 = H moist, >3000-3500 mm $yr^{-1}$; 4 = M moist, >2000-3000 mm $yr^{-1}$; 5 = L moist, >1500-2000 mm $yr^{-1}$; 6 = moist-dry, >1000-1500 mm $yr^{-1}$; 7 = dry-dry, <1000 mm $yr^{-1}$ |
| Air temperatures, °C | 1 = Mean annual air temperature; 2 = Minimum air temperature; 3 = Maximum air temperature |
| Soil texture classes - standard soil texture class matrices based on amount of sand, silt, clay (Soil Survey Staff 2010) | 1= sand; 2= loamy sand; 3= sandy loam; 4= fine sandy loam; 5= very fine sandy loam; 6= loam; 7= silt loam; 8= silt; 9= sandy clay loam; 10= silt clay loam; 11= clay loam; 12= sandy clay; 13= silty clay; 14= clay [**Appendix 2.B.** Percent sand, silt and clay in each soil texture class] |
| Soil types; Soil orders (Soil Survey Staff 2010) | 1= Mollisols; 2= Alfisols; 3= Andisols; 4= Histosols; 5= Inceptisols; 6= Ultisols; 7= Entisols; 8= Spodosols; 9= Oxisols; 10= Aridisols; 11= Vertisols [**Appendix 2.C.** US soil orders and equivalent international nomenclature] |
| Net Primary Productivity, Mg $ha^{-1}$ $yr^{-1}$ | 1 = Aboveground NPP (NPPa); 2 = Belowground NPP (NPPb); 3 = Total NPP (NPPt) |

The number of nodes or splits to be used within the regression tree is determined by choosing a complexity parameter which minimizes the cross-validation prediction error. The complexity parameter may increase as additional splits are introduced to the fitted tree. This value is expressed within the RPART library (Therneau & Atkinson, 2011) using the printcp command which will print a table showing the unique complexity parameter, the number of splits and the associated cross-validation error (Everitt & Torsten, 2010). Each regression tree was cross-validated 10,000 times and pruned to ensure the replication in trees fit for all response variables. Classification and regression trees are non-parametric with no assumptions made about the underlying distribution of the predictor variables (Lewis, 2000; Tittonell et al., 2008).

## 2.4. Results

### 2.4.1. Binary regression trees for NPPt

The significant independent variables used to create binary regression trees for the dependent variable NPPt are shown in Figure 2. How data were aggregated identified different variables causing NPPt threshold splits. Our meta-analyses suggested that by using a tree-like regression model to identify variables causing thresholds of NPPt, one can bracket NPPt levels based on the local limiting factors that determine forest growth rates and drive carbon allocation shifts between the above- and below-ground portions of a tree. The regression tree prediction model identified: (1) different variable combination groups at the regression tree terminal nodes, and (2) different and multiple combinations of variables that explained similar NPPt levels found in our data (Figure 2.2). Walking down one branch of the tree highlights how a unique set of variable factors were generated compared to walking down a different branch. The first two significant threshold splits resulted from variables that integrated and indexed multiple attributes of any site, i.e., mean air temperature, precipitation group, and soil order. But these variables became less indicative of site specific causal factors controlling forest productivity at the site scale (Figure 2.2).

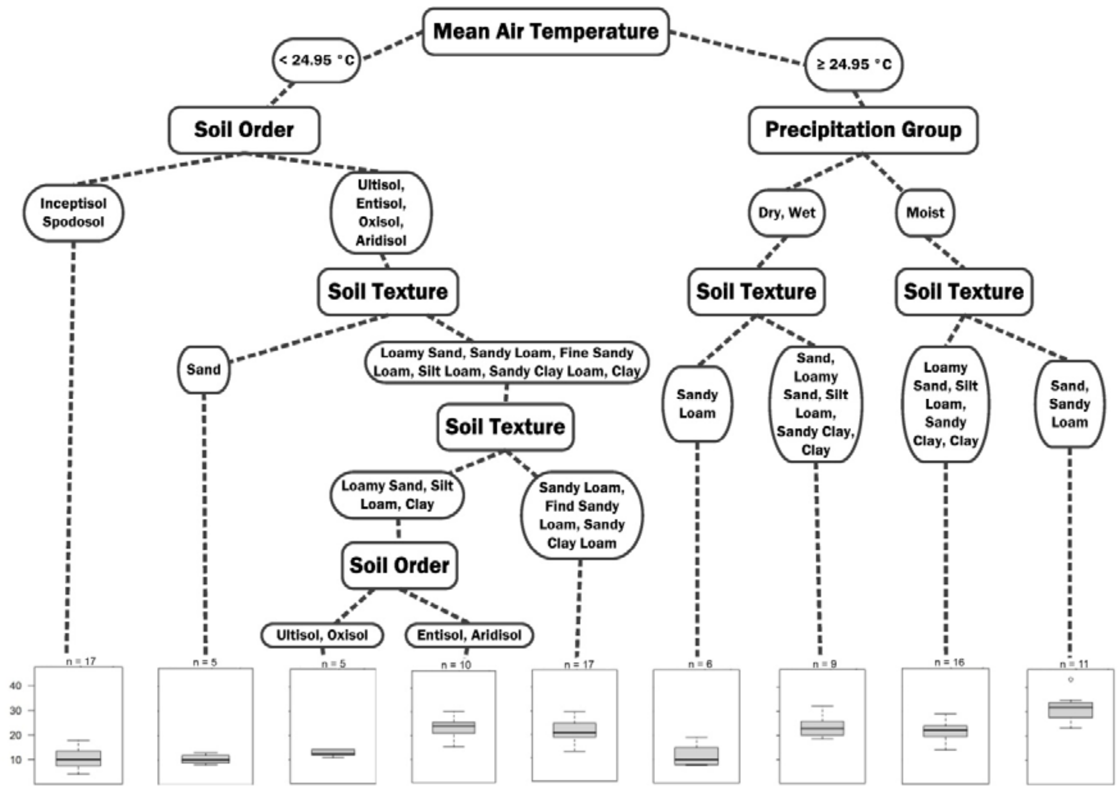


**Figure 2.2.** Selected regression tree prediction model for NPPt of mature or closed canopy unmanaged pan-tropical forests (*n* = 96).

When all forests were analyzed as a group, ~73% of the variance in NPPt was explained by four variables: soil order, soil texture, precipitation, and mean annual air temperature (Table 2.2). However when forests grew in areas with >3500 mm yr-1 precipitation (Wet Forest group), soil texture and the precipitation group explained 79% of the variance in NPPt. The Moist Forest group (1500 – 3500 mm yr-1) had elevation, soil texture and minimum air temperature explaining 78% of the variance in NPPt. The Dry Forest group had one variable (i.e., soil order) explaining 62% of the variance in NPPt.

**Table 2.2.** Selected regression tree model results for NPPt for all natural forest sites by all sites and sites grouped by precipitation groups (p-values were <0.01).

| Sample Population | Significant Independent Variables | $R^2$ | Sample Size |
|---|---|---|---|
| All sites | Soil Order, Soil Texture, Precipitation Group, Mean Air Temperature | 0.73 | 96 |
| Wet Forest >3500 mm $yr^{-1}$ | Soil Texture, Precipitation Group | 0.79 | 26 |
| Moist Forest 1500-3500 mm $yr^{-1}$ | Elevation, Soil Texture, Minimum Air Temperature | 0.78 | 53 |
| Dry Forest <1500 mm $yr^{-1}$ | Soil Order | 0.62 | 17 |

### 2.4.2. Binary regression trees for Low, Medium and High NPPt

The regression analyses were capable of detecting what factors contributed towards explaining Low, Medium, or High NPPt thresholds. The regression tree produced clear breaks, or tipping points, between 10.3 – 12.7 Mg $ha^{-1}$ $yr^{-1}$ for the Low NPPt group, 20.8 – 23.8 Mg $ha^{-1}$ $yr^{-1}$ for the Medium group and >31.0 Mg $ha^{-1}$ $yr^{-1}$ for the High NPPt group. Grouping results by Low, Medium and High NPPt categories showed the importance of mean annual temperature and soil order or soil texture in explaining the productivity levels reached by trees growing at each site. However, there was no consistency in how a temperature or soil variable combination determined what forest growth rate would be reached and therefore which NPPt group it would be found. For example, whether the mean annual temperature was above or below 25°C determined whether the second split would be explained by soil order or soil texture for forests found in the Low NPPt group (Table 2.3).

**Table 2.3.** Statistically significant threshold splits (in order) for the selected regression tree (RTTS) prediction model for NPPt for unmanaged pan-tropical forests grouped by three NPPt groups (Low = <12.7 Mg ha$^{-1}$ yr$^{-1}$, n = 28; Medium = 20.8 – 23.8 Mg ha$^{-1}$ yr$^{-1}$, n = 19; High = >31 Mg ha$^{-1}$ yr$^{-1}$, n = 11). (The designation of A:, B: or C: in each NPPt group is a different combination of variables producing the x NPPt value; NPP includes above- and belowground NPP) [p-values were <0.01]

| **- - Low NPPt Group - -** | | **- - Medium NPPt Group - -** | | **- - - High NPPt Group - - -** | |
|---|---|---|---|---|---|
| **RTTS (in order)** | $\bar{x}$ NPPt (*n*) | **RTTS (in order)** | $\bar{x}$ NPPt (*n*) | **RTTS (in order)** | $\bar{x}$ NPPt (*n*) |
| A:<br>1) Mean Air Temperature - <25°C<br>2) Soil Order – Inceptisols, Spodosols | A: 10.3<br>(17) | A:<br>1) Mean Air Temperature - <25°C<br>2) Soil Order – Ultisols, Entisols, Oxisols, Aridisols<br>3) Soil Texture – Sandy Loam, Fine Sandy Loam, Silt Loam, Clay | A: 23.8<br>(10) | A:<br>1) Mean Air Temperature - >25°C<br>2) Precipitation - 1500 – 3500 mm yr$^{-1}$<br>3) Soil Texture – Sand, Sandy Loam, Silty Clay, Clay | A: 31.2<br>(11) |
| B:<br>1) Mean Air Temperature - <25°C<br>2) Soil Order – Ultisols, Entisols, Oxisols, Aridisols<br>3) Soil Texture - Sand | B: 10.5<br>(5) | B:<br>1) Mean Air Temperature - >25°C<br>2) Precipitation - <1500 and >3500 mm yr$^{-1}$<br>3) Soil Texture – Sand, Loamy Sand, Silt Loam, Sandy Clay | B: 23.5<br>(9) | | |
| C:<br>1) Mean Air Temperature - >25°C<br>2) Soil Texture – Sand, Sandy Loam | C: 11.5<br>(6) | | | | |

Note: 38 sites were not included in the significant regression tree threshold splits that produced the Low, Medium and High NPPt groups

When the binary regression tree prediction model was used to analyze the data-base by grouping information into the Low, Medium or High NPPt groups, the regression tree model identified mean annual air temperature (at 25°C) as the first threshold split determining the growth rates of forests in all three NPPt groups (Table 2.3). A total of three different variable combinations explained the productivities found in the Low NPPt group, two variable combinations described forest productivities in the Medium NPPt group and one variable combination explained productivities reached in the High NPPt group.

The mean annual temperatures of the growing environment had to be higher than 25°C to find forests growing at rates that would place them in the High NPPt group. Furthermore for forests to be placed in the High NPP group, forests need to grow where precipitation rates are to not be too dry (<1500 mm yr-1) or too wet (>3500 mm yr-1) and they need to grow on sand, sandy loam, silty clay or clay textured soils. When precipitation rates were at the two extremes (dry or wet), forests only grew at rates that placed them in the Medium NPPt group. When mean air temperatures were higher than the 25°C threshold level, forest growth rates found in the Low NPPt group were not explained by precipitation rates but by soil texture (i.e., sandy loam).

When growth temperatures were lower than the 25°C temperature threshold, two- to three-threshold split combinations explained the productivities recorded in the Low and Medium NPPt groups, respectively. Under these lower mean air temperatures, forests growing on loamy-textured soils (e.g., sandy loam, fine sandy loam, silt loam) had growth rates that placed them in the Medium NPPt group while those growing on sandy-textured soils were found in the Low NPPt group.

### 2.4.3. Binary regression trees by NPPt and precipitation groups

When data from all sites were aggregated by precipitation groups (e.g., Wet, Moist, Dry), fewer and different variables combinations explained the variance in NPPt including which variable or variable combinations were responsible for NPPt threshold splits (Table 4). The highest total productive capacities occurred when forests were growing in the Moist Forest group (33.1 Mg $ha^{-1}$ $yr^{-1}$), at elevations <950 m, and when growing in sand or sandy loam textured soils (Table 2.4). Forests growing in the Moist Forest group, but at elevations higher than 950 m, only grew at rates that placed them in the Low or Medium NPPt groups. The Wet and Dry Forest groups had no forests that reached productivities found in the High NPPt group. When forests received <1500 mm $yr^{-1}$ precipitation (i.e., Dry Forest group), no significant regression tree splits resulted for our data-base. Forests with low productivity, i.e., Low NPPt group, were found in each of the three precipitation groups group but different variables explained the productivity levels reported in each group (Table 2.4). The Wet Forest group was the only group where precipitation significantly explained part of the variance in NPPt.

## 2.5. Discussion

### 2.5.1. Regression tree NPPt and edaphic/climate thresholds

Most plants do not reach their genetically ordained potential productive capacity in part because of the local environmental limits to productivity (Geiger & Servaites, 1991). It has been shown that even crops grown under intensive management regimes only reach 30% of the yields that the genetics of the plants would suggest (Boyer, 1982). Measuring changes in productivity levels may be used to assess whether a plant is resilient to its environment before visual symptoms of wide spread mortality occurs (Phillips et al., 2010; Zelazowoski et al., 2011). However, estimating potential NPPt in forest ecosystems is challenging since plants have a diversity of different adaptations to their growing environment (e.g., carbon shifts between the above- or below-ground parts; changes in resource-use-efficiencies; forming symbiotic associations; Field et al., 1983; Vogt et al., 1996). Since the productive capacity and shifts in carbon allocation within a plant species determine how well that species is able to respond to anthropogenic or natural

**Table 2.4.** Statistically significant NPPt regression tree threshold splits (in order) for the selected regression tree (RTTS) prediction model for NPPt grouped by Wet, Moist and Dry Forest groups and by three NPPt groups (Low = <12.7 Mg ha$^{-1}$ yr$^{-1}$, n = 27; Medium = 20.8 – 23.8 Mg ha$^{-1}$ yr$^{-1}$, n = 16; High = >31 Mg ha$^{-1}$ yr$^{-1}$, n = 7) in unmanaged pan-tropical forests. (NPP includes above- and belowground NPP) [p-values were <0.01]

| **Forest Precipitation Group (mm year$^{-1}$)** | **- - Low NPPt Group - -** | | **- Medium NPPt Group -** | | **- - High NPPt Group- -** | |
|---|---|---|---|---|---|---|
| | **RTTS (in order)** | $\bar{x}$ NPPt (*n*) | **RTTS (in order)** | $\bar{x}$ NPPt (*n*) | **RTTS (in order)** | $\bar{x}$ NPPt (*n*) |
| **Wet Forests** (**>3500 mm yr$^{-1}$**) | A:<br>1) Soil Texture – Sand, Sandy Loam, Silt Loam, Clay<br>2) Precipitation - >4500 mm | A: 9.6 (9) | A:<br>1) Soil Texture – Sand, Sandy Loam, Silt Loam, Clay | A: 21.8 (8) | No High NPPt sites produced significant regression tree threshold splits | |
| **Moist Forests** (**1500 – 3500 mm yr$^{-1}$**) | A:<br>1) Elevation >950 m<br>2) Minimum air temperature >9.9°C | A: 11.7 (9) | A:<br>1) Elevation >950 m<br>2) Minimum Air Temperature <9.9°C<br>3) Soil Texture – Loamy Sand, Sandy Loam | A: 23.6 (8) | A:<br>1) Elevation <950 m<br>2) Soil Texture – Sand, Sandy Loam | B: 33.1 (7) |
| **Dry Forests** (**<1500 mm yr$^{-1}$**) | A:<br>1) Soil Order - Entisols | A: 9.2 (9) | No Medium NPPt sites produced significant regression tree threshold splits | | No High NPPt sites produced significant regression tree threshold splits | |

NOTE: For our database using the multivariate statistical method, 46 sites did not meet the significant threshold splits generated by the significant regression tree threshold splits that produced the Medium and High NPPt groups (the highest NPPt by precipitation group was 26.2 Mg ha$^{-1}$ yr$^{-1}$ in the Wet Forest and 18.3 Mg ha$^{-1}$ yr$^{-1}$ in the Dry Forest).

stressors, understanding site-level drivers of productivity provides a tool to measure resilience at the scale where trees adapt to their environment. Identifying critical thresholds of productivity, and the empirical indicators that cause a complex forest ecosystem to reach a productivity tipping point, help to determine when an ecosystem may shift to another state (Dai et al., 2012).

In this study, the binary regression tree identified from two to five significant variable combination splits and distinctive multiple combinations of variables that explained the resulting

NPPt thresholds identified for our data-base. When mean air temperatures were lower than 25°C, all of the significant splits were formed by soil variables, i.e., soil order and texture. In contrast when mean annual temperatures were higher than 25°C, the second split was formed by the precipitation group and the third split by soil texture. Soil order only created a significant threshold split in forests that grew at mean air temperatures lower than 25°C. When a split produced by soil order, it suggests soil characteristics other than soil texture (e.g., soil nutrient status, concentrations of Fe and Al oxides, degree of soil weathering, available soil water; Appendix S2-S3) explain the growth rates reached by trees.

This regression analysis showed how a combination of variables needs to be included as input variables to explain the variance in NPPt found at a given location. It also shows how soil variables contribute significantly to explaining the variability in NPPt, although the significance varies based on temperature and precipitation thresholds at a site. The role of soil factors in contributing to explaining tree species distribution and total forest growth rates at a plot level are well documented for the Asian and American tropics (Steege et al., 1993; Oliveira-Filho et al. 1998; Palmiotto et al., 2004; Russo et al., 2005; Malhi et al., 2006 and others). These studies reported the significance of utilizing a combination of soil and non-soil factors to determine forest growth rates. However, the results of these plot scale studies cannot be readily transferred to estimate the productive capacity of other forest plots found in other parts of the forest landscape scale since there is no consistency between studies in the predictive variables developed and each study only represents part of the heterogeneity of the growing environment for forests.

### 2.5.2. Climatic/edaphic factors and NPPt tipping points

A key objective of this study was to detect NPPt thresholds and to identify which variable combinations correlate with low or high NPPt. The regression tree analyses resulted in three NPPt threshold groups (Low, Medium, High) where tipping points for total productivity occurred. Furthermore, the meta-analysis and the regression tree approach identified multiple and different variable combinations (e.g., soil order, soil texture, precipitation group, mean air temperature) that explained the distinct NPPt thresholds produced. Most forests in our data-base were found in either the Low (n = 27) or Medium (n = 27) NPPt group and only 11 of the sites had NPPt levels high enough to place them in the High NPPt group.

The importance of a temperature in creating the first threshold split is suggested by no forests in our data-base growing at high growth rates when mean air temperatures were lower than 25°C. Our meta-analysis suggested that certain edaphic and climatic variable combinations need to exist for a tropical forest to reach the higher NPPt potentials namely, mean annual air temperatures higher than 25°C with precipitation levels between 1500 – 3500 mm $yr^{-1}$ (i.e., Moist Forest group), and a growth medium consisting of sand or sandy loam textured soil. However, temperatures >25°C did not automatically place a forest in the High NPPt group since forests growing on sandy or sandy loam textured soils sites only reached productivity levels found in the Low NPPt group. This pattern suggests that if forests currently located in the Moist Forest group experience lower precipitation rates and are growing on sand or sandy loam textured soils, productivity levels may decrease and shift that forest into the Low NPPt group.

The binary regression tree analyses also showed how an individual driver identified by a plot-scale study does not transfer across the landscape to explain the variance in NPPt at other locations. For example, forests growing on sand textured soils were found in each of the three NPPt groups depending on how the sample population in the data-base split in the regression tree. When mean air temperatures were lower than 25°C, sand textured soils grew stands with low total productivity. But when mean air temperatures were higher than 25°C, these same soil textures had forests growing at rates that placed them in the Medium or High NPPt group.

Furthermore, similar NPPt values may result from several different multiple combinations of site conditions. For example, a forest can achieve total annual growth rates of 23-24 Mg $ha^{-1}$ $yr^{-1}$ (Medium NPPt) under multiple combinations of site conditions. Two variable combinations produced forest growth rates at this level: namely, (1) Mean annual air temperature is lower than 25°C, a specific soil type (i.e., Ultisols, Entisols, Oxisols or Aridisols), and/or soil texture (i.e., sandy loam, fine sandy loam, silt loam, or clay); or (2) Mean annual air temperature is higher than 25°C, precipitation is either <1500 mm or >3500 mm annually, and a soil texture of sand, loamy sand, silt loam, sandy clay or clay. This suggests that a correlation produced at the plot scale will not explain a productivity potential of an adjacent forest with different variable combinations driving productivity changes.

Once the temperature threshold sets the first significant limit to plant growth, the soil nutrient delivery capacity and soil water availabilities (as indexed by soil order and texture classes) combine to constrain the optimal growth rates achievable for forests in our data-base. For all the NPPt groups, soil variables were important in indexing the growth rates of forests in our data-base. Trees with higher growth rates appear to have fewer soil nutrient limitations to growth but are impacted by low or too high soil water availabilities. This contrasts trees that grow slowly or at moderate rates and are typically adapted to low soil availabilities of limiting nutrients or the presence of toxic elements in the soil. When soil nutrient conditions are poor for forest growth, trees adapt by shifting carbon allocation to those organs, e.g., roots and mycorrhizas, which increase the acquisition of limiting resources that allows trees to maintain their productive potentials (Vogt et al., 1996).

This study shows that climatic and soil factors can all contribute to producing thresholds in total productive capacity and the biomass sequestration potential of a tropical forest. However, local site conditions have a significant impact on the optimal NPPt that can be reached at any site. Also it suggests that multiple variable combinations can produce similar NPPt at different sites. In general, this study suggested that trees growing in different locations but on the same soil texture may occur in the Low, Medium or High NPPt groups. This suggests managers mitigating climate change impacts on their forests need to know whether temperature, soil texture and precipitation drive productivity changes in their forest to reduce the risk of reaching a tipping point of productivity.

### 2.5.3. Regression tree NPPt and Wet, Moist and Dry Forest groups

Grouping data in the tropics using precipitation is common since the temperature variance is lower while the variance in precipitation rates is higher. In 1947, Holdridge sorted vegetative biomes by their precipitation, mean annual biotemperature, and evapotranspiration rates (Holdridge, 1947). The Holdridge categories have been a very useful tool for grouping vegetative communities, especially for tropical forests. It is specifically useful because the coarse-scale climatic constraints require different adaptive strategies, which also helps to indirectly index differences in soil development rates related to annual precipitation (Brown & Lugo, 1982; Sanchez, 1982; Chave et al., 2005).

This study suggested that the regression-derived grouping of data by precipitation groups (i.e., Wet, Moist and Dry Forest) increase the detection of NPPt thresholds. The influences of very low or very high precipitation rates impacting tree growth rates can be seen in the results of the data analysis where no variable fit was found between forest NPPt in the Medium and High NPPt groups growing under very wet (Wet Forest) or very dry conditions (Dry Forest) (Table 4). Forests have different adaptations to very dry and very wet conditions (Phillips et al., 2010; Zelazowski et al., 2011) and these adaptations might not be detected by an assessment approach that does not identify multiple combinations of variables to predict NPPt at any given site.

In the Wet Forest group, both precipitation levels and soil texture determined the level of total forest productivity attained. Despite similar soil texture groups explaining NPPt changes in the Wet Forest group, when precipitation rates were >4500 mm $yr^{-1}$, NPPt was only half of what occurred when precipitation rates were between 3500 and 4500 mm $yr^{-1}$. This comparison suggests that very high precipitation rates may decrease total plant productivity potential either due to greater competition by microbes for nutrients (Anaya et al., 2007), low P desorption by plants (Yuan & Chen, 2009), high rates of soil nitrate leaching or anaerobic conditions for tree roots which may experience limited nutrient uptake (Schuur & Matson, 2001).

In contrast to the Wet and Dry Forest groups, the Moist Forest group had the highest NPPt recorded for a forest (33.1 Mg $ha^{-1}$ $yr^{-1}$). The high NPPt forest sites were all found growing on clay and sandy loam textured soils at elevations lower than 950 m, and where precipitation levels ranged between 1500 – 3500 mm $yr^{-1}$. Indeed Aragão et al. (2009) reported that the amount of the total NPP allocated to the belowground was highly correlated ($R^2 = 0.52$) to the soil clay content in the Amazon forests.

Trees growing in the Moist Forest group had more variable combinations explaining similar NPPt values compared to what was found for the Wet and Dry Forest groups. Forests growing in precipitation ranges between 1500 and 3500 mm $yr^{-1}$ appeared to adapt to a greater number of site factors than trees growing in the Wet and Dry Forest groups. The Moist Forests group is also located in zones with relatively stable yearly rainfall. However, the Moist Forests group was also the only group where minimum air temperatures and elevation were associated with NPPt thresholds suggesting forest growth rates are constrained by low temperatures. Clark et al. (2003) also reported a negative correlation between daily minimum temperature and diameter increment of old-growth tropical trees in Costa Rica.

The only variable fit found in the Dry forest group (<1500 mm precipitation) occurred for the Low NPPt group where soil order caused a threshold split. For forests growing in dry conditions, trees are generally adapted to low water levels by senescing leaves, reducing transpiration and photosynthetic rates (McDowell et al., 2008). These drought adaptations may enhance forest survival in the short-term but lower productive capacities may decrease forest resilience to additional stresses or disturbances, e.g., increased tree mortality rates and their susceptibility to insects and pests.

### 2.5.4. Plot-Scale Drivers of Forest Productive Capacity at Landscape Scales

Many researchers have acknowledged the difficulty of deriving NPPt estimates for tropical forests since our knowledge of the spatial variability in productivity and what controls productivity rates was historically inadequate to conduct simulation models for these forests (Vogt et al., 1996; Phillips et al., 1998; Clark et al., 2001; Aragão et al., 2009; Tan et al., 2010; Aguiar et al., 2012). Castanho et al. (2013) stressed the need to move beyond the use of a single value approach to index ecological conditions and to focus on the bio-physical factors that limit tree growth. Many studies conducted in tropical forests further support exploring the multiple links between edaphic and climate factors and tree growth rates (e.g., Vogt et al., 1996; Palmiotto et al., 2004; Castilho et al., 2006; Paoli et al., 2008; Aragão et al., 2009; Ferry et al., 2010). The challenge is to take plot-scale studies to explain the heterogeneity in NPPt that is found at the landscape scale. This study suggests a meta-analysis of plot-level research can be used to identify different combinations of soil and climatic factors and how they are correlated to total productivity potentials.

Total NPP baselines provide thresholds of productivity for each site and factor in inter-annual variability and its impacts on NPPt (i.e., Cao et al., 2004). The baselines derived from this study will be useful to identify sites where maximum productivity, sequestration and carbon storage may be possible. It also identifies sites in a landscape where the growing environment constraints will not allow a forest to achieve higher productive capacities and where the sites are more susceptible to land-uses. A meta-analysis of plot-level research, using a binary regression tree analysis approach, suggested that forest adaptation to climatic variability and change is less detectable if the site-specific multiple adaptation variables are not identified. The results in this study should reduce the potential for models to over- or under-estimate total forest productivity when transferring correlative relationships between predictive variables and NPPt data beyond the boundaries of the original research plots. Such an approach will facilitate assessments of climate change impacts on tropical forests and to estimate their carbon sequestration potentials (e.g., Jha & Singh, 1990; Vogt et al., 1995; Laurance et al., 1999; Girardin et al., 2010).

Since photosynthetic carbon is needed by plants to grow and respond to environmental stresses, detecting the multiple variable drivers of total productive capacity provides a tool to measure forest resilience to environmental stresses and disturbances. Site-specific knowledge of forest growth rates in many different ecosystems is needed to identify which combination of factors and under what environmental conditions will forest productivity decrease. This knowledge may then be used to estimate productivity changes under altered precipitation and temperature scenarios to identify tipping points when a forest becomes less resilient to these changes. It is also invaluable information for predictive NPP models to credibly estimate carbon for Reducing Emissions from Deforestation and Degradation Plus (REDD+) initiatives for different regions or jurisdictions. Site or stand-level forest data based on NPPt estimations could therefore be used to identify sites for REDD+ interventions.

## 2.A. Appendix A

**Table 2.A.1:** Site information and NPPt for natural tropical forests in our data-base. [NPPt is Mg ha$^{-1}$ yr$^{-1}$, air temperature is in °C, Elev (elevation) is in m, Precip (precipitation) is in mm yr$^{-1}$]

| | | | | | | | | | Air temperature | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country & Location | Forest Type | Stand Age | Elev | Soil Type | Soil Order Code | Soil Texture Code | Precip | Precip Group | Mean | Min | Max | TNPP | Refer-en ces |
| Brazil - Egler Reserve | terra firme forest of Leguminosae, Euphorbiaceae, Sapotaceae, Vochysiacea | mature | 50 | nutrient-poor, clay-rich yellow oxisols | 9 | 14 | 1771 | Moist | 27.2 | . | . | 26.8 | 1, 2, 3 |
| Brazil - Fazenda Gaviao, Manaus (Biological Dynamics of Forest Fragments Project - BDFF) | terra firme forest | mature | 50 | xanthic ferrasols, nutrient-poor, clay-rich yellow oxisols | 9 | 12 | 2300 | Moist | 26.7 | . | . | 32.0 | 1, 4 |
| Brazil - Fazenda Dimona Manaus (Biological Dynamics of Forest Fragments Project - BDFF) | terra firme forest | mature | 50 | nutrient-poor, clay-rich yellow oxisols | 9 | 12 | 2300 | Moist | 26.7 | . | . | 31.8 | 1, 4 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Brazil - Fazenda Cabo Frio Manaus (Biological Dynamics of Forest Fragments Project - BDFF) | terra firme forest | mature | 50 | clayey latosol | 9 | 12 | 2300 | Moist | 26.7 | . | . | 25.8 | 1, 4 |
| Brazil – Fazenda Porto Alegre Manaus (Biological Dynamics of Forest Fragments Project - BDFF) | terra firme forest | mature | 50 | clayey latosol | 9 | 12 | 2300 | Moist | 26.7 | . | . | 23.2 | 1, 4 |
| Brazil - Paragominas | evergreen primary forest | mature | 0 | clayey, red-yellow Oxisols | 9 | 13 | 1750 | Moist | 25 | 22 | 28 | 27.8 | 1, 5, 6 |
| Brazil | primary wet forest | mature | 50 | Oxisols | 9 | 14 | 3521 | wet | 26.2 | 22 | 28 | 7.5 | 7, 8 |
| Brazil | secondary wet forest | young | 50 | Oxisols | 9 | 14 | 3521 | wet | 26.2 | 22 | 28 | 8.4 | 7, 8 |
| Brazil | secondary wet forest | 50 | 50 | Oxisols | 9 | 14 | 3521 | wet | 26.2 | 22 | 28 | 7.8 | 7, 8 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Brazil - CAX-03 Caxiuanã National Forest, Para State, Caxiuanã drought experiment control plot | tall primary forest | mature | 15 | sandier site; Vetic Acrisol (Alumic, Hyperdystric), loamy sand, 75% sand, 10% silt, 15% clay | 9 | 2 | 2314 | Moist | 26.9 | 22 | 28 | 23.2 | 4, 9, 10, 11, 12 |
| Brazil - CAX-06 Caxiuanã National Forest, Para State, Caxiuanã flux tower site | tall primary forest | mature | 15 | Clay ferralsol or oxisol; Geric Acric Ferralsol (Alumic, Hyperdystric, Clayic), loamy sand, 32.54% sand, 10% silt, 53.76% clay | 9 | 14 | 2314 | Moist | 26.9 | 22 | 28 | 21.8 | 4, 9, 10, 11, 12 |
| Brazil - CAX-08 Caxiuanã National Forest, Para State, Caxiuanã Terra Preta site | late successional forest | mature | 15 | archaeo-anthrosol; Hortic Archaeo-Anthrosol (Ebonic, Clayic, Mesothropic, Mesic, Ferralic, loamy sand, 41.41% clay | 9 | 2 | 2314 | Moist | 26.9 | 22 | 28 | 21.2 | 4, 9, 10, 11, 12 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Brazil - MAN-05 Manaus | old growth terra firme forests | mature | 60 | clay-rich ferrasols & frequent waterlogged podzol; Geric Ferralsol (Alumic, Hyperdystric, Clayic), 20.97% sand, 12.81% silt, 66.21% clay | 9 | 14 | 2272 | Moist | 27.1 | 22 | 28 | 20.2 | 4, 9 |
| Brazil - TAP-04 Tapajós National Forest, Pará State, Tapajós flux tower site | old growth terra firme forests | mature | 90 | clay-rich Belterra clay ferralsols interspersed sandier soil patches; Geric Ferralsol (Alimic, Hyperdystric, Clayic, Xanthic), 2.86% sand, 7.89% silt, 89.25% clay | 9 | 14 | 1968 | Moist | 26.1 | 22 | 28 | 28.8 | 4, 9 |
| China- Xinkou Experimental Forestry Centre, Sanming Nature Reserve, Fujian | subtropical evergreen broadleaved forest of Castanopsis | 41 | 393 | red soils (humic planosols in FAO system), silty loam oxisols | 9 | 7 | 1749 | Moist | 19.1 | . | . | 22.5 | 45 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| China - Menglun Nature Reserve in Xishuangbanna, Southwestern Yunnan | seasonal rain forest | mature | 639 | rhodic ferralsol; lateritic derived from siliceous rocks (granite, gneiss) limestone derived soils | 9 | | 1487 | dry | 21.7 | 15.9 | 25.7 | 17.6 | 46, 47 |
| China | montane evergreen broadleaved | 100 | 1130 | ultisol, acid, from granite, dark colour & fine texture | 6 | 14 | 1744 | Moist | 19.6 | -6.1 | 38.8 | 29.6 | 48 |
| Columbia - Porce region | premontane primary forest | mature | 900 | derived granitic rocks with low fertility & high acidity; Grouped into Entisol & Inceptisol | 5 | 3 | 2078 | Moist | 22.7 | 21.3 | 24.1 | 29.0 | 13, 14 |
| Columbia - Araracuara (Magdalena Terrace) | evergreen seasonal forest | mature | 200 | Infertile acid, surface water gleys | 9 | 14 | 3000 | Moist | 27.5 | 26 | 28 | 21.2 | 1, 8 |
| Columbia - AGP-01 Amacayacu National Natural Park Aqua Pudre plot E | primary old-growth terra firme forest | mature | 102 | fertile clay plinthosols or aquic entisols; Endostagnic Plinthosol (Alumic, Hyperdystric), clay loam, 42.12% clay | 7 | 11 | 2723 | Moist | 25.5 | | | 22.6 | 9, 15 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Columbia - AGP-02 Amacayacu National Natural Park Aqua Pudre plot U | primary old-growth terra firme forest | mature | 102 | fertile clay plinthosols or aquic entisols; Endostagnic Plinthosol (Alumic, Hyperdystric), clay loam, 43.10% clay | 7 | 11 | 2723 | Moist | 25.5 | | | 23.4 | 9, 15 |
| Columbia - ZAR-01 Rio Calderon Forest Reserve Zafire, Varillal | primary forest | mature | 80 | white sand podzol or spodosols, impermeable hardpan layer at ~100 cm; Ortseine Podzol (Oxyaquic), loamy sand, 0.64% clay | 8 | 2 | 2723 | Moist | 25.5 | | | 18.6 | 9, 15 |
| Ecuador - Stand 1 provinces of Zamora-Chinchipe & Loja, Podocarpus National Park, South Ecuador | pre-montane forests | mature | 1050 | Alumic Acrisol or ultisols | 6 | 14 | 2230 | Moist | 19.4 | 11.5 | 30.2 | 13.1 | 16 |
| Ecuador - Stand 2 provinces of Zamora-Chinchipe & Loja, Podocarpus National Park, South Ecuador | pre-montane forests | mature | 1540 | Alumic Acrisol or ultisols | 6 | 14 | 2300 | Moist | 17.5 | 11.2 | 26.7 | 12.8 | 16 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ecuador - Stand 3 Reserva Biológica San Francisco, South Ecuador | montane forests | mature | 1890 | Gleyic Cambisol or inceptisol, 35.77% sand, 49.3% silt, 14.9% clay | 5 | 6 | 1950 | Moist | 15.7 | 7.9 | 29.4 | 12.4 | 16, 17, 18 |
| Ecuador - Stand 4 Reserva Biológica San Francisco, South Ecuador | montane forests | mature | 2380 | Gleyic Cambisol histosols | 4 | 1 | 5000 | wet | 13.2 | 7 | 25.1 | 7.9 | 16, 17 |
| Ecuador - Stand 5 Cajanuma area of Podocarpus National Park, South Ecuador | stunted upper montane forest, elfin forest | mature | 3060 | Podzol | 8 | 1 | 4500 | wet | 9.4 | 3.1 | 18.8 | 13.0 | 16 |
| Hawaii, USA - Laupahoehoe | primary *Metrosideros polymorpha* forest | mature | 1170 | histosols or lithic tropofolists, Typic Hydrandept | 4 | 7 | 2500 | Moist | 16 | . | . | 16.0 | 1, 19, 20 |
| Hawaii, USA - Kohala | primary *Metrosideros polymorpha* forest | mature | 1122 | histosols or lithic tropofolists | 4 | 7 | 2500 | Moist | 16 | . | . | 17.8 | 1, 19, 20 |
| Hawaii, USA - Kokee | primary *Metrosideros polymorpha* forest, disturbed by hurricane in 1982, 1992 | mature | 1134 | histosols or lithic tropofolists, Plinthic Acrudox | 4 | 7 | 2500 | Moist | 16 | . | . | 14.2 | 1, 19, 20 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Hawaii, USA - Mauna Loa (site2, 136yr soil) | mountain volcanic *Metrosideros polymorpha* forest | young | 700 | hydrous, isothermic, Acrudoxic Hydrudand in Akaka serieshistosols or lithic tropofolists | 4 | 7 | 5750 | wet | 19.3 | . | . | 10.0 | 20, 21 |
| Hawaii, USA - Mauna Loa (site4, 136yr soil) | mountain volcanic *Metrosideros polymorpha* forest | young | 1660 | shallow histosols or lithic tropofolists overlyaing pahoehoe bedrock | 4 | 7 | 2600 | Moist | 13 | . | . | 12.7 | 20, 21 |
| Hawaii, USA - Mauna Loa (site5, 3400yr) | mountain volcanic *Metrosideros polymorpha* forest | mature | 700 | histosols; lithic tropofolists acid very dark brown friable slightly sticky strongly smeary mucks | 4 | 7 | 5750 | wet | 19.3 | . | . | 5.8 | 1, 20, 21 |
| Hawaii, USA - Mauna Loa (site6, 3400yr) | mountain volcanic *Metrosideros polymorpha* forest | mature | 1660 | shallow histosols or lithic tropofolists overlyaing pahoehoe bedrock | 4 | 7 | 2600 | Moist | 13 | . | . | 7.4 | 1, 20, 21 |
| India - Western Ghats Site 1 (Pattighat) | tropical wet evergreen | mature | 1000 | oxisol | 9 | 6 | 2800 | Moist | 26.6 | 8 | 36 | 22.4* | 14, 49 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| India - Western Ghats Site 2 (Brahamagiri) | tropical wet evergreen | mature | 1500 | oxisol | 9 | 6 | 3200 | wet | 24.6 | 8 | 36 | 27.7 | 49 |
| India - Western Ghats Site 3 (Padnailkannad) | tropical wet evergreen | mature | 1100 | oxisol | 9 | 6 | 2800 | Moist | 26.6 | 8 | 36 | 18.8 | 49 |
| India - Western Ghats Site 4 (Kadmakal) | tropical wet evergreen | mature | 1300 | oxisol | 9 | 6 | 3000 | wet | 25.6 | 8 | 36 | 25.8 | 49 |
| India - Western Ghat mountains, Karnataka State (Site Agumbe) | evergreen rainforests, dipterocarps dominant | 50 | 575 | oxisols developed from hornblendic bedrock, 87.8% sand, 5.9% silt, 6.3% clay | 9 | 2 | 7670 | wet | 22.2 | 32 | 10 | 24.7 | 50 |
| India - Western Ghat mountains, Karnataka State (Site Bannadpare) | evergreen rainforests, dipterocarps dominant | 50 | 200 | oxisols developed from hornblendic bedrock, 70.1% sand, 7.2% silt, 22.7% clay | 9 | 9 | 5310 | wet | 27 | 32 | 10 | 20.1 | 50 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| India - Western Ghat mountains, Karnataka State (Site Kagneri) | evergreen rainforests, dipterocarps dominant | 50 | 500 | oxisols developed from hornblendic bedrock, 86.5% sand, 2.1% silt, 11.4% clay | 9 | 2 | 6100 | wet | 28.6 | 32 | 10 | 22.6 | 50 |
| India - Western Ghat mountains, Karnataka State (Site South Bhadra) | evergreen rainforests, dipterocarps dominant | 50 | 800 | oxisols developed from hornblendic bedrock, 45.8% sand, 42.1% silt, 12.1% clay | 9 | 6 | 6520 | wet | 22 | 32 | 10 | 20.7 | 50 |
| India - Mirzapur district in Uttar Pradesh, Marihan range, East Mirzapur Forest Division, Site 1 Summit | mixed, dry deciduous forest | mature | 280 | ultisols derived from Kaimur sandstones, reddish-brown in colour, sandy loam texture, sand (56-69 %), silt (24-28 %) & clay (4-16 %) | 6 | 3 | 821 | dry | 27 | 17.5 | 35.7 | 19.2 | 51, 52 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| India - Marihan range, East Mirzapur Forest Division, Site 2 Slope | mixed, dry deciduous forest | mature | 280 | ultisols derived from Kaimur sandstones, reddish-brown in colour, sandy loam texture, sand (56-69 %), silt (24-28 %) & clay (4-16 %) | 6 | 3 | 821 | dry | 27 | 17.5 | 35.7 | 14.8 | 51, 52 |
| India - Marihan range, East Mirzapur Forest Division, Site 3 Hill Base | mixed, dry deciduous forest | mature | 280 | ultisols derived from Kaimur sandstones, reddish-brown in colour, sandy loam texture, sand (56-69 %), silt (24-28 %) & clay (4-16 %) | 6 | 3 | 821 | dry | 27 | 17.5 | 35.7 | 11.3 | 51, 52 |
| India - Central Himalaya | *Quercus lanuginosa*/*Q. floribunda*, Tilonj-dominated mixed-oak | mature | 2200 | quartzite and slates | 6 | 2 | 2488 | Moist | 15 | 6.4 | 42 | 27.9 | 53, 54, 55 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| India - Central Himalaya | *Quercus lanuginosa*/*Q. floribunda*, Rianj-dominated mixed-oak | mature | 2150 | ultisol, dolomite limestone & conglomeratic sandstone, loamy sand | 6 | 2 | 2488 | Moist | 15 | 6.4 | 42 | 20.9 | 53, 54, 55 |
| India - Central Himalaya | Mixed oak/ chir pine | mature | 1850 | mica schist and gneisses | 6 | 2 | 1313 | dry | 15.8 | 6.4 | 42 | 18.9 | 53, 54, 55 |
| India - Central Himalaya | *Pinus roxburghii*/ *Myrica esculenta* | mature | 1750 | ultisol, slates and dolomite, loamy sand | 6 | 2 | 2185 | Moist | 15.8 | 6.4 | 42 | 19.0 | 53, 54, 55 |
| India - Central Himalaya | *Shorea robusta*/ *Mallotus philippensis* | mature | 300 | ultisol, sandstone associated with slates | 6 | 2 | 2076 | Moist | 23 | 6.4 | 42 | 18.8 | 53, 54, 55 |
| Indonesia - Central Sulawesi (Lore Lindu National Park | paleotropical natural forest, premontane rain forest, evergreen | mature | 1050 | ferralsol derived from metamorphic bedrock, well drained camisols, 63.7% sand, 24.6% silt, 11.7% clay | 9 | 3 | 3543 | wet | 20.8 | . | . | 15.2* | 56, 57, 58 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ivory Coast | premontane, Banco | mature | 50 | ferrallitique fortement desature, well drained | 9 | 1 | 2095 | Moist | 26.7 | . | . | 34.8 | 1, 8 |
| Ivory Coast | premontane, Yapo *Dacryodes klaineana*, *Allanblackia floribunda*, *Coula edulis* | mature | 70 | ferrallitique fortement desature, gravelly, poor drainage | 9 | 1 | 1739 | Moist | 26.7 | . | . | 30.0 | 1, 8 |
| Jamaica - Blue Mountain Mor Ridge | montane rain forest, ridge; *Lyonia spp*, *Octandra spp*, *Chaetocarpus globosus*, *Cyrilla racemiflora* | mature | 1550 | Peat podzol | 8 | 3 | 2500 | Moist | 15 | 8.5 | 24 | 25.4 | 1, 8, 22 |
| Jamaica - Blue Mountain Mull Ridge | montane, *Cyrilla racemiflora*, *Clethra occidentalis*, *Podocarpus urbanii*, *Hedyosmum arborescens* | mature | 1600 | Peat podzol | 8 | 3 | 2230 | Moist | 15.5 | 8.5 | 24 | 21.0 | 1, 22 |
| Jamaica - Blue Mountain Gap Forest | montane rain forest, *Cyathea pubescens*, *Clethra occidentalis*, *Solanum punctulatum* | mature | 1590 | Peat podzol | 8 | 3 | 2230 | Moist | 15.3 | 8.5 | 24 | 23.6 | 1, 22 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Jamaica - Blue Mountain Wet Slope b Forest | montane, *Clethra occidentalis*, *Podocarpus urbanii* | mature | 1570 | Peat podzol | 8 | 3 | 2230 | Moist | 15.3 | 8.5 | 24 | 21.0 | 1, 22 |
| Malaysia - Borneo (North), Bako National Park, Sarawak | montane tropical: *Oncosperma tigillaria*, *Salacca conferta*, *Artocarpus kemando* | mature | 2590 | aquic paleudult | 6 | 9 | 4000 | wet | 25 | . | . | 32.2 | 1.0 |
| Malaysia - Pasoh | dipterocarp evergreen lowland | mature | 100 | oxisol, 30%sand, 21% silt, 49% clay | 9 | 9 | 2054 | Moist | 25 | . | . | 24.2 | 1, 3, 14, 59 |
| Malaysia | lowland dipterocarp | mature | 100 | ultisol, sandy clay loam-clay | 6 | 9 | 1800 | Moist | 26 | . | . | 14.0 | 60 |
| Malaysia - Pasoh Forest Reserve, Negri Sembilan | lowland evergreen forest of *Shorea spp*, *Dipterocarpus spp*, *Koompassia spp*. | mature | 100 | oxisol, 30% sand, 21% silt, 49% clay | 9 | 9 | 2054 | Moist | 25 | . | . | 18.2 | 1, 29, 38, 61 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mexico - El Eden Ecological Reserve Quintana Roo (La Pantera site) Yucatan | seasonally dry forest | 5 | 20 | Derived from limestone bedrock, no soil formed and shallow 20 c, lithic rendolls | 7 | 3 | 1650 | dry | 24.2 | . | . | 7.6 | 23, 24 |
| Mexico - El Eden Ecological Reserve Quintana Roo (La Pantera site) Yucatan | seasonally dry forest | 9 | 20 | Derived from limestone bedrock, no soil formed and shallow 20 c, lithic rendolls | 7 | 3 | 1650 | dry | 24.2 | . | . | 7.1 | 23, 24 |
| Mexico - El Eden Ecological Reserve Quintana Roo (La Pantera site) Yucatan | seasonally dry forest | 15 | 20 | Derived from limestone bedrock, no soil formed and shallow 20 c, lithic rendolls | 7 | 3 | 1650 | dry | 24.2 | . | . | 5.4 | 23, 24 |
| Mexico - El Eden Ecological Reserve Quintana Roo (La Pantera site) Yucatan | seasonally dry forest | 29 | 20 | Derived from limestone bedrock, no soil formed and shallow 20 c, lithic rendolls | 7 | 3 | 1650 | dry | 24.2 | . | . | 4.0 | 23, 24 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mexico - El Eden Ecological Reserve Quintana Roo (La Pantera site) Yucatan | seasonally dry forest | mature | 20 | Derived from limestone bedrock, no soil formed and shallow 20 c, lithic rendolls | 7 | 3 | 1200 | dry | 24.2 | . | . | 9.4 | 23, 24 |
| Mexico - Watershed 1 (Control) Upper Plot, Biological Station Chamela | deciduous dry forest | mature | 150 | weakly developed entisols on rhyolite and basalts, Sandy loam with gravely structure, 60% sand, 14% silt, 26% clay | 7 | 9 | 707 | dry | 24.9 | 15.9 | 32.2 | 11.2 | 3, 8, 25, 26, 27 |
| Mexico - Watershed 1 (Control) Middleplot, Biological Station Chamela | lowland high evergreen forest | mature | 130 | weakly developed entisols on rhyolite and basalts | 7 | 3 | 707 | dry | 24.9 | 15.9 | 32.2 | 11.5 | 1, 25 |
| Mexico - Watershed 1 (Control) Lowerplot, Biological Station Chamela | lowland high evergreen forest | mature | 70 | weakly developed entisols on rhyolite and basalts | 7 | 3 | 707 | dry | 24.9 | 15.9 | 32.2 | 13.5 | 1, 25 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mexico - Chamela-Cuixmala Biosphere Reserve, Pacific Coast | secondary deciduous dry forest | 50 | 500 | Sandy loam with gravely structure, lithic rendolls, 80% sand, 8% silt, 12% clay | 7 | 3 | 748 | dry | 24.9 | 14.8 | 32 | 13.4 | 8, 26, 28 |
| New Guinea - Mt Kerigomma, Papua New Guinea | lower montane forest of *Planchonella firma*, *Caldcluvia nymanii*, *Dacryocarpus cinatus*, *Podocarpus archiboldii* | mature | 2500 | Humic brown, deeply weathered clay, humic clay loam, gabbritic alluvium and lots volcanic ash | 9 | 11 | 4000 | wet | 13 | 5 | 22 | 27.0 | 1, 29, 30 |
| Nigeria - Olokemeji Forest Reserve | moist semi-deciduous forest of *Ricinodendron heudelotii*, *Triplochiton scleroxylon*, *Chrysophyllum albidum*, *Chlorophora excelsa* | mature | 100 | ferrunginuous or plinthic cambisol, mainly kaolinitic type clay, loam to sandy loam, 70.6% sand, 7.5% silt, 21.9% clay | 6 | 9 | 1330 | dry | 26.4 | 19 | 35 | 20.2 | 1, 63, 64, 65 |
| Peru - TAM3 Tambopata III, Tambopata reserve, Tambopata Province, Dept of Madre de Dios | lowland evergreen seasonal rain forest | mature | 210 | clay-rich sediments formed from alluvial deposits, 74.2% sand, 7.4% clay | 8 | 3 | 2730 | Moist | 26.4 | 24.4 | 28.4 | 33.8 | 31, 32 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Peru - TAM4 Tambopata IV, Tambopata reserve, Tambopata Province, Dept of Madre de Dios | lowland evergreen seasonal rain forest | mature | 194 | clay-rich sediments formed from alluvial deposits, 74.2% sand, 7.4% clay | 8 | 3 | 2730 | Moist | 26.4 | 24.4 | 28.4 | 27.2 | 31, 32 |
| Peru - TAM-05 Tambopata Biological Reserve, Madre de Dios Region, Tambopata RAINFOR plot 3 | lowland evergreen seasonal rain forest | mature | 200 | infertile Pleistocene cambisols or inceptisols; Haplic Cambisol (Alumic, Hyperdystric, Clayic), 7.41% clay | 5 | 1 | 2417 | Moist | 25.2 | 23.2 | 27.2 | 33.8 | 9, 11 |
| Peru - TAM-06 Tambopata Biological Reserve, Madre de Dios Region, Tambopata RAINFOR plot 4 | lowland evergreen seasonal rain forest | mature | 200 | alisol or ultisols on fertile Holocene alluvial terrace; Haplic Alisol (Hyperdystric, Siltic), 9.66% clay | 6 | 2 | 2417 | Moist | 25.2 | 23.2 | 27.2 | 27.6 | 9, 11, 31 |
| Peru - TON Tono, Kosnipata valley, Province of Paucartambo, Deptment of Cusco, Southern Peruvian Andes | premontane rain forest | mature | 1000 | Fluvic claysol, clay-rich sediments formed from alluvial deposits | 8 | 2 | 3087 | Moist | 20.7 | 20.7 | 20.7 | 14.1 | 14, 31, 32 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Peru - SPD San Pedro Kosnipata valley, Province of Paucartambo, Deptment of Cusco, Southern Peruvian Andes | montane rain forest | mature | 1500 | Umbric Gleysol, clay-rich sediments formed from alluvial deposits | 8 | 2 | 2631 | Moist | 18.8 | 18.8 | 18.8 | 14.1 | 14, 31, 32 |
| Peru - TU8 Trocha Union VIII Kosnipata valley, Province of Paucartambo, Deptment of Cusco, Southern Peruvian Andes | montane rain forest | mature | 1855 | Umbric Gleysol, granite batholith | 8 | 2 | 2472 | Moist | 18 | 18 | 18 | 11.9 | 14, 31 |
| Peru - TU7 Trocha Union VIIKosnipata valley, Province of Paucartambo, Deptment of Cusco, Southern Peruvian Andes | montane rain forest | mature | 2020 | Palaeozoic shales-slates, inceptisols, sandy | 5 | 1 | 1827 | Moist | 17.4 | 17.4 | 17.4 | 9.0 | 31.0 |
| Peru - TU4 Trocha Union IVKosnipata valley, Province of Paucartambo, Deptment of Cusco, Southern Peruvian Andes | montane rain forest | mature | 2720 | Histic Lithosols, Palaeozoic shales-slates | 5 | 1 | 2318 | Moist | 13.5 | 13.5 | 13.5 | 12.0 | 14, 31 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Peru - TU3 Trocha Union IIIKosnipata valley, Province of Paucartambo, Deptment of Cusco, Southern Peruvian Andes | montane rain forest | mature | 3020 | Histic Lithosols, Palaeozoic shales-slates | 5 | 1 | 1776 | Moist | 11.8 | 11.8 | 11.8 | 8.2 | 14, 31 |
| Peru - WAY Wayqecha Kosnipata valley, Province of Paucartambo, Deptment of Cusco, Southern Peruvian Andes | montane rain forest | mature | 3025 | Histic Lithosols, Palaeozoic shales-slates | 5 | 1 | 1706 | Moist | 12.5 | 12.4 | 12.6 | 10.2 | 14, 31 |
| Puerto Rico - Guanica State Forest Reserve | dry forest, deciduous: *Gymnanthes lucida*, *Exostema caribaeum*, *Pisonia albida* | 50 | 175 | limestone soils, mollisol soil, dark brown clay loam or clay | 10 | 11 | 860 | dry | 25.1 | . | . | 18.6 | 1, 33 |
| Puerto Rico - Luquillo Forest | broadleaf secondary forest | 12 | 350 | Epiaquic palehumults, clayey, mixed, isothermic tropohumult, 27% sand, 41% silt, 32% clay | 6 | 11 | 3920 | wet | 22.3 | 21 | 25.3 | 19.4 | 34.0 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Puerto Rico - Luquillo Exp Forest Biosphere Reserve, El Verde (EVNF) | secondary forest | mature | 200 | Tropeptic haplorthox,oxidic, isohyperthermic, clayey, 30% sand, 26% silt, 44% clay | 6 | 14 | 3920 | wet | 22.3 | 19.3 | 25.3 | 21.4 | 8, 14, 35 |
| Puerto Rico - Luquillo Mountains (Bisley Stream 3) | subtropica evergreen forest with wood addition | mature | 265 | clay & silty clay loam Ultisols in Los Guineos soil series | 6 | 14 | 4500 | wet | 22.3 | 21 | 24 | 13.3 | 35, 36, 37, 38 |
| Puerto Rico - Luquillo Mountains Bisley Watershed 1-2 | Tabonuco forest | mature | 375 | Ultisols, typic tropohumults, ~70% clay | 6 | 14 | 3500 | wet | 23 | 21 | 24 | 21.4 | 8, 14, 35, 36 |
| Puerto Rico - Luquillo Experimental Forest | *Prestoea montana* palm floodplain forest | mature | 750 | inceptisol, fine sandy loam | 5 | 4 | 3725 | wet | 19.7 | 18.3 | 21.1 | 30.2 | 1, 38, 39 |
| Puerto Rico - Luquillo Mountains | Colorado Forest permplots, montane forests | mature | 725 | inceptisol, fine sandy loam | 5 | 4 | 3725 | wet | 21.1 | 19 | 23 | 24.2 | 40, 41 |
| Puerto Rico - Luquillo Mountains Pico del Este | dwarf cloud forest | mature | 1050 | lithic tropaquents deep clay | 5 | 11 | 5000 | wet | 19 | 18 | 20 | 10.8 | 36, 42 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Thailand - Khao Chong Forest Reserve, Southern Thailand | little disturbed tropical rain forest | mature | 175 | sandy texture of granitic origin soil, sandy loam 14.31% clay | 7 | 3 | 2700 | Moist | 27 | . | . | 43.4 | 1, 62 |
| Venezuela - San Eusebio | montane humid | mature | 2250 | silty and clayey sedimentary rocks, humitropepts | 6 | 13 | 1500 | dry | 14 | . | . | 25.6 | 1, 2 |
| Venezuela - San Carlos de Rio Negro, Amazon | low Bana or evergreen sclerophyllous woodland | mature | 119 | oxisols, on bleached sands | 9 | 1 | 3500 | wet | 26 | 22 | 31.5 | 22.8 | 8, 14, 38, 43 |
| Venezuela - San Carlos de Rio Negro, Amazon | tall caatinga, sclerophyllous forest | mature | 119 | spodosols, alluvial quartizitic sands | 8 | 1 | 3500 | wet | 26 | 22 | 31.5 | 23.2 | 1, 8, 43 |

4

## 2.B. Appendix B

**Table 2.B.1:** Percent sand, silt and clay in each soil texture class designation used in our statistical analyses (from Soil Survey Staff, 2010).

| Textural Class | Texture Code | Maximum Clay, ≤ % | Minimum Clay, ≥ % | Maximum Sand, ≤ % | Minimum Sand, ≥ % |
|---|---|---|---|---|---|
| Sand | 1 | 10.0 | 0.0 | 100.0 | 85.0 |
| Loamy Sand | 2 | 15.0 | 0.0 | 90.0 | 70.0 |
| Sandy Loam | 3 | 20.0 | 0.0 | 85.0 | 45.0 |
| Sandy Loam (fine) | 4 | 20.0 | 0.0 | 85.0 | 45.0 |
| Sandy Loam (very fine) | 5 | 20.0 | 0.0 | 85.0 | 45.0 |
| Loam | 6 | 27.5 | 5.0 | 52.5 | 22.5 |
| Silt Loam | 7 | 27.5 | 0.0 | 50.0 | 0.0 |
| Silt | 8 | 12.5 | 0.0 | 20.0 | 0.0 |
| Sandy Clay Loam | 9 | 35.0 | 20.0 | 80.0 | 45.0 |
| Silty Clay Loam | 10 | 40.0 | 27.5 | 20.0 | 0.0 |
| Clay Loam | 11 | 40.0 | 27.5 | 45.0 | 20.0 |
| Sandy Clay | 12 | 55.0 | 35.0 | 65.0 | 45.0 |
| Silty Clay | 13 | 60.0 | 40.0 | 20.0 | 0.0 |
| Clay | 14 | 100.0 | 40.0 | 45.0 | 0.0 |

**2.C. Appendix C**

**Table 2.C.1:** Soil taxonomy and the United Nation Food and Agriculture Organization equivalent (Batjes, 1997; Soil Survey Staff, 1999; Kang & Tripathi, 2014)

| US Taxonomic classification | FAO classification | Taxonomic description of US taxonomic classification |
|---|---|---|
| Mollisols | Rendzinas, Phaeozems | Thick, dark surface horizon rich in organic matter derived from long-term accumulation of plant roots. Soils moderate to high fertility. |
| Alfisols | Luviosols, Eutric Nitosols, Planosols | Subsurface accumulation of silicate clays from surface horizons. Soils are moderate to high fertility. |
| Andisols | Andosols | Soils originated from volcanic materials and dominated by allophane or aluminum-humic complexes. |
| Histosols | Histosols | Soils that consist of a minimum 20-30% organic matter by weight and mostly occur in wetland and peatland areas. |
| Spodosols | Podsols | Subsurface accumulation of Al- and Fe-oxides and generally complexed with humus. |
| Inceptisols | Gleysols | Soils that have minimal horizon development. Although they are more developed than Entisols, they have few diagnostic features. |
| Ultisols | Acrisols, Dystric, Nitosols | Strongly leached. They have a subsurface horizon of accumulated clay. Moderate to very low soil fertility. |
| Entisols | Gleysols | Newly developed soils with only surface A horizon but no developed subsurface horizons. |
| Oxisols | Ferrasols | Highly weathered soils commonly found in the tropics. They are rich in Fe and Al oxides, which often make P unavailable to plants, Moderate to very low soil fertility. Well drained soils. |
| Aridisols | Solonchacks | Dry soils with a surface horizon generally low in organic matter and sometimes an accumulation of clays in subsurface horizon. |
| Vertisols | Vertisols | Soils high in shrink/swelling types of clays. |

References: Batjes NH. 1997. A world dataset of derived soil properties by FAO-UNESCO soil unit for global modeling. Soil Use and Management 13, 9-16; Soil Survey Staff (1999) Soil taxonomy: A basic system of soil classification for making and interpreting soil surveys. 2nd Edition. United States Department of Agriculture. 436p; Kang, B.T. & Tripathi, B. (2014) Technical Paper 1: Soil classification and characterization. http://www.fao.org/wairdocs/ilri/x5546e/x5546e04.htm (accessed 13 January 2014)

Chapter 3

# Effects of different sampling scales and selection criteria on modelling net primary productivity of Indonesian tropical forests

*This work is adapted from work originally submitted as:* Gmur, S.J., Vogt, D.J., Vogt, K.A., Suntana, A.S (2014) Effects of different sampling scales and selection criteria on modelling net primary productivity of Indonesian tropical forests. *Environmental Conservation.*

## 3.1. Summary

The availability of spatial data sourced from either field-derived or satellite-based systems has created new opportunities to estimate and/or monitor changes in carbon sequestration rates, climate change impacts or the potential habitat alterations occurring across large landscapes. However, an effort to create models is not standardized, in part, due to different needs and data sources available for the models. For example, data may have different spatial resolutions with varying degrees of complexity in regards to inputs and statistical methods. This study determines effects of 20, 15, 10, five and one km sampling resolutions on detection of changes in modelled net primary productivity (NPPm), occupancy selection criteria for areas to be included in the sample and identification of significant variables impacting NPPm in Indonesia forests. Production forest designated for selective harvest was used to define the sampling areas. Variances explained by predictive models were similar across cell sizes although relative importance of variables was different. Partial dependence plots were used to search for potential thresholds or tipping points of NPPm change as affected by an independent variable such as minimum daytime temperature. Applying different cell occupancy selection rules significantly changed the overall distribution of NPPm values. The magnitude of those changes within a cell size varied with changes in cell size. The mean estimated NPPm for production forests across Indonesia differed significantly at every sampling resolution and occupancy selection criteria.

## 3.2. Introduction

Invaluable information can be gained from modelling environments to explore different scenarios associated with changing climatic conditions (Cramer et al. 2001) or modelling vegetation dynamics across different scales (Moorcroft et al. 2001). Models represent the surface of the Earth across a range of spatial resolutions, breaking up the surface into a regularly gridded pattern in which a single value of some parameter is assigned to each grid cell to represent a process or phenomena. Collections of geospatial data have been used within a multitude of applications to assess habitat (Carollo et al. 2009), map ecosystem services and conservation priorities (Naidoo et al. 2008), estimate vegetation community impacts due to global changes (Barbosa et al. 2012) measurement and monitoring of deforestation and forest degradation (Korhonen-Kurki et al. 2012), and to also monitor net primary productivity (NPP) as a complex model of multiple controlling parameters on a global scale (Field et al. 1995; Cramer et al. 1999).

Geospatial data have great utility when combined with multiple parameter simulation models to solve complex problems and where data are lacking to conduct an exploratory interpolation exercise (Field et al. 1995; Cramer et al. 1999; Gmur et al. 2012). Geospatial data have been linked to complex models to monitor and estimate NPPm across multiple ecological space and time scales. For example, models used to assess the impacts of climate change and alternative land-uses on ecosystem productive capacity. Since the resolutions of geospatial data can range from 10º x 10 º to 1-km2 cell sizes, the output of these studies could potentially introduce data inconsistencies, depending on the spatial sampling resolutions and occupancy selection criteria used by each study.

Discussion of potential carbon uptake by tropical forests, which has been estimated to account for almost half global terrestrial NPP (Brown & Lugo 1982), has been shaped by estimates derived from a number of models (Solomon 2007). A partnership between spatial data and field collected information can provide insight into the relationship of NPP to climate and terrestrial conditions (Vogt et al. 2010). Before geospatial data and models become a common approach in landscape assessments, there is a need to know whether these data overestimate or underestimate NPP at any site, and what is the influence of the use of inconsistent resolution scales and occupancy selection criteria on the estimated NPPm.

The spatial resolution of models has continued to increase, capturing greater amounts of local variability through a more detailed representation of the Earth's surface. This can be seen in models predicting CO2 sequestration in vegetation due to climate change, where cell sizes were 0.5º latitude (55.5 km at equator) by 0.5º longitude (Melillo et al. 1993) or 3.75º longitude (416.5 km at equator) by 2.5º latitude (277.5 km at equator) (Cramer et al. 1999), but changing satellite technologies with resolutions of 1-km2 cell sizes have increased the complexity of carbon models (Running et al. 2004; Richardson et al. 2012). Sizes of individual grid cells within a modelling domain determine the amount of local variation captured, increasing the overall variance and noise of the data distribution as the cell size decreases. Accordingly larger cell sizes generalize spatial variations across a sampling area (Bellehumeur et al. 1997).

Use of environmental models has gained momentum as a method of predicting changes in global ecosystems due to climate change or land-use alterations, including detection of local changes, upscaled to a country level. To facilitate these analyses, environmental models have evolved from simple process-based models of coarse resolution into multiple parameter simulation models. These multiple parameter simulation models are now able to integrate information from field-based observations, literature values and, more recently, spatial information derived from satellite observations.

These multiple parameter simulation models diverge in spatial sampling resolutions and vary considerably between studies. For example, the resolutions can range from 10° (c. 1100 km at the equator) down to 1-km cell sizes. Since ecological processes can change due to climate change or land use, it would be prudent to model at the scale that would enable the capture of that local variability in NPPm, and this would provide a common metric allowing comparisons among different landscape units (Vogt et al. 2010). NPP would be logical to use as one such unit of measurement since it records the state of an ecosystem and its responses to disturbances (Vogt et al. 1997). We hypothesize that models predicting NPPm are sensitive to the spatial sampling resolution and occupancy selection criteria used to represent the inputs which can affect the significant variables identified across prediction models. Here we report the results of a study which used five different spatial sampling resolutions to predict the NPPm using climatic, terrestrial and biophysical variables. The objective was to examine whether variables identified as significant when predicting NPPm would vary with the spatial resolution or cell size used, and whether sampling across the cell sizes or applying different occupancy selection criteria significantly changed the distribution of NPPm values.

This study was restricted to analyzing tropical forest areas in Indonesia that are designated as 'production forests', which are unfertilized natural forest areas under selective harvest management (Suntana et al. 2013a). We used the randomForest statistical method (Liaw & Wiener 2002) to identify at each scale the significant variables in the predictive models.

## 3.3. Methods

### 3.3.1. Study Area

Indonesia comprises 17 504 islands (Biro Pusat Statistik 2012) and is located between 6º N and 11º S and between 95º and 141º E (Figure 3.1). It has three prevailing climatic zones (equatorial, tropical and monsoon). The geomorphology is variable, with mountain ranges, volcanic features and expansive plains. Vegetation is generally a reflection of the different climatic conditions, being described as tropical rainforest, tropical monsoon forest and tropical savannah forest (Tan 2008).

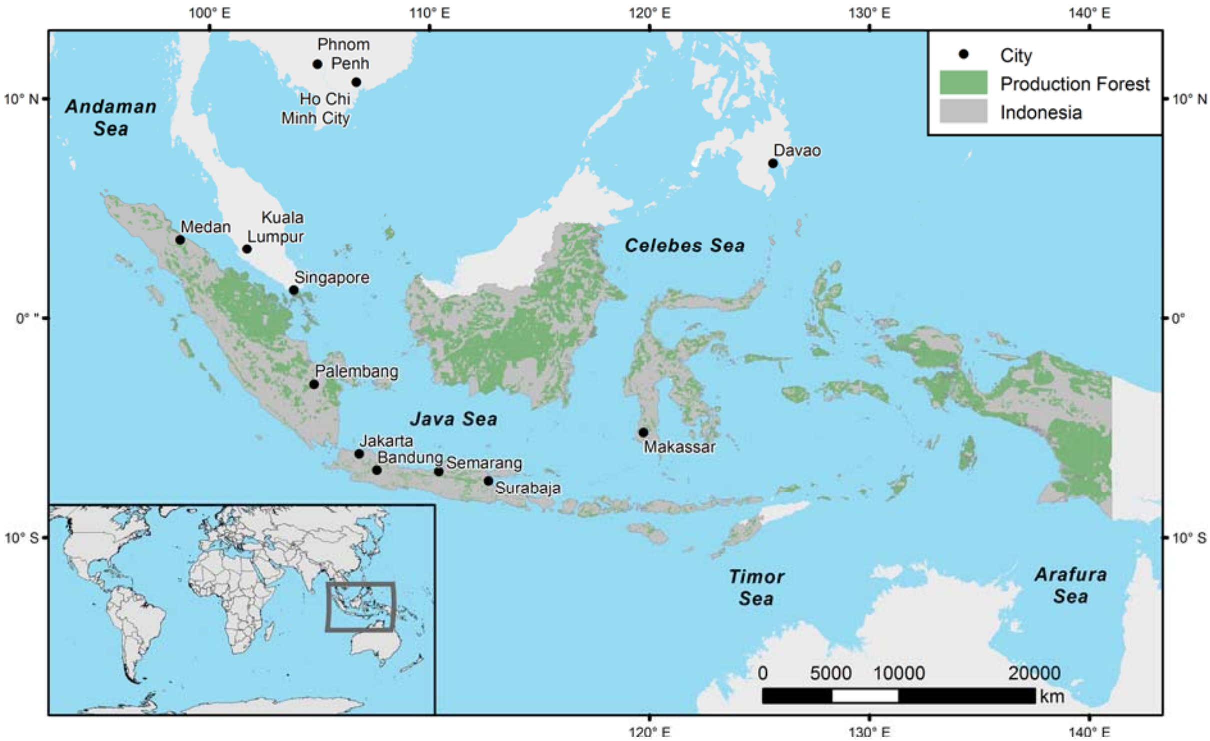


**Figure 3.1** Map indicating locations of production forest areas in Indonesia.

### 3.3.2. Spatial Datasets

Collecting spatial datasets that represented the terrestrial, climatic and biophysical conditions of the study area allowed for the creation of a common database (Table 3.1). Datasets were obtained from spatial data gateways maintained by USA federal agencies (NASA [National Aeronautics and Space Administration] 2013*a*, *b*, *c*), the European Space Agency (ESA 2013) and Indonesian ministries that create geographic information systems (GIS) databases (Kementerian Kehutanan 2011; BIG 2011). Datasets which originated from NASA were delivered in 10° × 10° tiles in hierarchical data format (HDR), with many different layers representing satellite conditions and data quality of each pixel. Soils and land-use vector datasets were collated and translated into

English, and then rasterized to the smallest common unit with the other spatial datasets in the database. Translation of datasets from the source formatting into a rasterized format was undertaken using tools that summarized values across the different spatial sampling resolutions.

### 3.3.3. Dependent and Independent Variables

The MODIS (Moderate Resolution Imaging Spectroradiometer) Net Primary Productivity model (MOD-17) was chosen as the dependent variable (NASA 2013c). Daily NPPm was derived from a combination of other MODIS products, including temperature, fraction of photosynthetically active radiation (FPAR), leaf area index (LAI) and radiation conversion efficiency parameters from biome properties look-up-table (BPLUT) as outlined in ‘algorithm theoretical basis’ documentation (Running *et al.* 1999). Many studies have validated the MOD-17 algorithm for different field sites in biomes around the globe (Running *et al.* 2004; Zhao *et al.* 2005; Turner *et al.* 2006). The independent variables included, but were not limited to, those parameters from the MOD-17 algorithm such as LAI, minimum temperature and FPAR. Additional variables, such as elevation, precipitation, land cover and soil characteristics (Table 3.1), were added as independent variables based on data availability and relation to ecological processes. Expanded temperature variables such as night-time/daytime: maximum, mean and minimum values were used to capture effects of temperature on dark and daytime respiration as night-time temperatures affect tree growth (Larcher 1975; Kramer & Kozlowski 1979). Variables which reflect topographic features, such as aspect and slope, were calculated using surface analysis tools within the ESRI spatial analyst toolbox (Environmental Systems Research 2013). Ecological elevation zones were calculated using the elevation ranges: lowland (< 400m), pre-montane (400–1200m), montane (1200–3000m) and alpine (> 3000m) (Hertel *et al.* 2009).

**Table 3.1** Spatial datasets used to create a common database from which sample populations were drawn (acronyms: LAI: leaf area index; FPAR: fraction of absorbed photosynthetically active radiation; NPP: modelled net primary productivity; NASA: National Aeronautics and Space Administration; SRTM: Shuttle Radar Topography Mission; TRMM: Tropical Rainfall Measuring Mission; MODIS: Moderate Resolution Imaging Spectroradiometer; ESA: European Space Agency).

| *Data theme* | *Factors* | *Scale/ raster resolution* | *Source* |
|---|---|---|---|
| Elevation | Elevation, elevation zones, aspect and slope | 90 m | NASA SRTM (NASA 2013*b*) |
| Precipitation | Minimum, mean, maximum and annual | 4 km | NASA TRMM (NASA 2013*c*) |
| Modelled Net primary productivity | Mean NPPm | 1 km | NASA MODIS (MOD17A2) (NASA 2013*c*) |
| GlobCover | Land cover | 300 m | ESA (2B31) (ESA 2013) |
| Land cover | Land cover | 500 m | NASA MODIS (MCD12Q1) (NASA 2013*c*) |
| Daytime/night-time surface temperature | Minimum, mean, maximum | 1 km | NASA MODIS (MOD11C2) (NASA 2013*c*) |
| Night-time surface temperature | Minimum, mean, maximum | 1 km | NASA MODIS (MOD11C2) (NASA 2013*c*) |
| LAI / FPAR | Mean | 1 km | NASA MODIS (MOD15A2) (NASA 2013*c*) |
| Soil | Order, surface texture, subsurface texture | 1:250 000 | Badan Informasi Geospasial (BIG 2011)( |
| Production forest areas | Define sampling area | 1:250 000 | Kementerian Kehutanan (2011) |

### 3.3.4. Spatial sampling resolution

The study area was gridded into cells using a fishnet function, with the coordinate system for the study area being an Albers equal area conic projection for South Asia. Five different grid cell sizes (20, 15, 10, 5 and 1 km) were used for the spatial sampling (Figure 3.2), and a single value for each grid cell area was extracted for input into the models. Three different occupancy selection criteria methods were used to filter which grid cells were to be included in each analysis. The first sample was composed of every cell intersecting an area defined as containing production forest, while cells without production forest areas were exempted from analyses. The second sample consisted of cells where > 60% of the cell area was occupied by production forest. In the third approach, analyses only included cells where > 95% of the cell area was occupied by production forest.

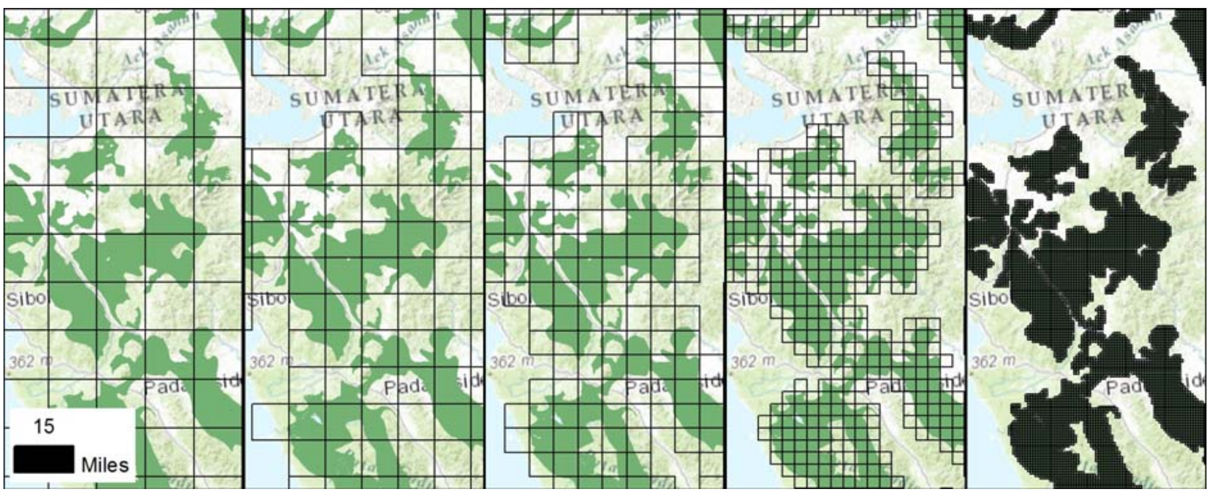


**Figure 3.2** Five maps illustrating how the different spatial sampling resolutions capture the area of a selected production forest. The grid cell sizes are (from left to right) 20, 15, 10, 5 and 1 km.

### 3.3.5. Software environment and data processing

The common database of spatial datasets used the GIS software ESRI ArcGIS Desktop (Environmental Systems Research 2013), in combination with the programming language Python, to create automated tools for data processing. Those tiles from NASA's MODIS satellite platform which cover the study area were obtained, layers from each tile were extracted, and then values were transformed from integer values to floating point data using conversions provided by data documentation. Using Python, tools were created which automated processing tasks, ensuring consistent processing of all spatial information. The land surface temperature (MOD-11A2) values reported as averages for eight day intervals were obtained for years 2000 through 2012 (NASA 2013c). Maximum, minimum and mean daytime and night-time temperatures were calculated for each 1-km pixel from the 12-year data. The same procedures were used to extract data on precipitation and temperature, resulting in raster spatial datasets representing the variability in climate. Terrestrial conditions were obtained using elevation sourced from NASA's Shuttle Radar Topography Mission (SRTM) dataset (NASA 2013*b*) creating ecological elevation zone, aspect and slope datasets.

Processing of these data resulted in the creation of a spatial database representing the dependent and independent variables from which the sample populations were drawn. Using the ESRI Zonal Statistics as Table tool, mean values from each numerical raster or the majority from each categorical raster was obtained in a cell-by-cell operation to derive a single value for each grid cell. This operation was repeated for each input layer across the five different spatial sampling resolutions resulting in five flat files. Themes such as temperature or precipitation, which have temporal variability, were captured using the mean, minimum and maximum values across the lifetime of that data product. For example temperature was derived from the MODIS land surface temperature and emissivity (MOD 11A2 version 005) dataset (NASA 2013c). All graticules covering the area of study were downloaded, layers one and five were extracted from the HDF file, tiles were mosaicked together and multiplied by 0.02 to convert to Kelvin. From all the processed mosaics, the minimum, mean and maximum values were calculated for each 1-km grid cell for the period 2000–2012 across the study area.

**Table 3.2** A complete list of variable acronyms and their full name description used within the NPPm prediction model.

| *Variable abbreviation* | *Full name* |
|---|---|
| AG | Aspect group |
| AGD | Aspect group description |
| EZ | Elevation zone |
| FPAR | Fraction of absorbed photosynthetically active radiation |
| GLOBE LC | ESA global land cover map |
| LAI | Leaf area index |
| MODIS LC | MODIS land cover map |
| NPPm | Mean modelled net primary productivity |
| AP | Annual precipitation |
| PG | Precipitation group |
| MxP | Maximum precipitation |
| MnP | Mean precipitation |
| MinP | Minimum precipitation |
| SO | Soil order |
| Asp | Aspect |
| Elv | Elevation |
| Slope | Slope |
| SubTex | Subsurface soil texture |
| SurTex | Surface soil texture |
| MaxDT | Maximum daytime temperature |
| MeanDT | Mean daytime temperature |
| MinDT | Minimum daytime temperature |
| MaxNT | Maximum night-time temperature |
| MeanNT | Mean night-time temperature |
| MinNT | Minimum night-time temperature |

### 3.3.6. Prediction model variables

A library of spatial datasets was assembled and used to create prediction models for NPPm (Table 3.2).

### 3.3.7. Statistical model

Equality of means between the populations of values created by the different spatial sampling resolutions and occupancy selection criteria were tested using a one-way analysis of variance (ANOVA). *Post hoc* pairwise comparisons between individual sampling resolutions and cell occupancy selection criteria (Table 3.3) used a multiple comparisons Tukey HSD ($\alpha = 0.05$; Zar 1999). Testing of prediction methods to identify significant variables used the *randomForest* method within the R program environment (Breiman 2001). Binary trees were created using recursive partitioning where a random sample of dependent variables at each possible split were selected using an out-of bag method, breaking the data into increasingly smaller pieces (Berk 2011). The creation of a binary tree on a random sample from the training data and 3000 binary trees for each prediction model were used to create a forest.

Once the forest was created, the importance of each variable was assessed by surveying all nodes and where each was used in the trees (Garzón *et al.* 2006). Using standard methodology, the number of variables selected at each node when performing a split in creating the binary regression trees was chosen randomly using the *tuneRF* method with a *mtry* value of three (Liaw & Wiener 2002). The algorithms within the *randomForest* library store the forest of binary trees with attributes such as node impurity (variable importance) and decrease in accuracy (mean squared error). These attributes were derived using a vote method, which tallied where each variable appeared within all binary tees, how many times it was used and strength of the split. Using the voting method, tallies were taken for each variable then ranked against all other variables used within the model. Due to the dimensionality of the prediction models and complex interactions between variables, the *randomForest* model creates independent trees which characterize the true importance of individual variables (Cutler *et al.* 2007). Using this importance value, all other values were normalized to this highest score so that importance values were ranked between zero and one. This step was then applied to the other four models using different spatial sampling resolutions. Thus full models using all input variables compared the importance of variables between the five different grid cell sizes with the occupancy selection criteria set at > 0%.

In addition to the importance of each variable, the amount of variance explained by each variable when added to a binary tree was reported by *randomForest*. Those variables which were added at or near the first split explained a greater amount of variance, increasing the mean squared error (MSE) or $R^2$ compared to those variables added later to the same binary tree. Averaged over many trees using an out-of-bag variable selection method, the MSE of a particular variable was normalized by using a large number of binary trees creating the prediction model. Again, as with the node impurity normalization, the MSEs were normalized to the highest MSE and were ranked between zero and one.

## 3.4.Results

### 3.4.1. Variable spatial scaling effects on NPP estimates

The 20, 15, 10, 5 and 1 km sampling resolutions showed initial differences in the variance explained by each full model. The spatial data used to create the sample population for the statistical models were the same, but the variance explained by the prediction models varied by spatial sampling resolution (Table 3.3). The variance explained by each prediction model ranged from 48.3 to 55.1%. The detailed representation of each production forest area showed that the area decreased as the spatial sampling resolution decreased. ANOVA and Tukey HSD pairwise comparisons among spatial sampling resolutions indicated mean NPPm were significantly different. ANOVA indicated occupancy selection criteria were significantly different, but Tukey HSD pairwise comparisons were not all significantly different at the 0.01 level. For example all sample populations created from occupancy selection criteria for the 1-km spatial sampling resolution were significantly different. NPPm was significantly different between all three occupancy selection criteria of intersection (namely > 0%, ≥ 60% and ≥ 95%) at all spatial sampling resolution populations (20, 15, 10, 5 and 1 km) (Table 3.4).

**Table 3.3** Descriptions of the predictive models from each of the spatial sampling resolutions, highlighting the variance explained by each *randomForest* model. The size of the training dataset and number of cells that are (1) > 0% = include any production forest (PF) land areas, (2) > 60% = consist of at least 60% PF, (3) >95% = consist of at least 95% PF.

| *Spatial sampling resolution* | *Number of trees* | *Training sample size* | *Total number of cells* | | | *Number of variables tried at each split* | *Variance explained (%)* |
|---|---|---|---|---|---|---|---|
| | | | *>0%* | *>60%* | *>95%* | | |
| 20 km | 3000 | 1924 | 3847 | 1519 | 581 | 3 | 48.3 |
| 15 km | 3000 | 3234 | 6465 | 2790 | 1312 | 3 | 49.8 |
| 10 km | 3000 | 6619 | 13222 | 6709 | 3743 | 3 | 55.1 |
| 5 km | 3000 | 22483 | 45119 | 28981 | 20062 | 3 | 53.4 |
| 1 km | 3000 | 40000 | 870425 | 768100 | 694478 | 3 | 49.9 |

### 3.4.2. Independent variables affecting NPP (importance)

#### 3.4.2.1. Node Impurity

As anticipated, some type of temperature variable may be important in affecting NPPm. For example, outcomes from determining the variable importance from the five randomForest prediction models found the minimum daytime temperature variable from the 20, 15 and 10-km spatial sampling resolution models had the highest node impurity score or highest importance value. However, for the 5-km model, the mean daytime temperature had the highest importance value and for the 1-km model the mean night-time temperature had the highest importance value. Comparing this across the different models, minimum daytime temperature remained the most important variable for the 20, 15 and 10-km grid cell sizes but then decreased to the third and tenth most important variable for 1-km and 5-km grid cell sizes, respectively. Besides the different temperature variables, other variables that showed somewhat high importance in affecting NPPm were elevation, fraction of absorbed photosynthetically active radiation and leaf area index; however, none of these variables were as important as the temperature variables (Plot can be viewed in Appendix 3.A, Figure 3.A.1).

**Table 3.4** Mean modelled net primary productivity (NPPm) estimates by sampling resolution for production forests (PFs) in Indonesia. Cell selection methods were (1) > 0% = inclusion for any cell intersecting PF land areas, (2) > 60% = model only considers cells consisting of at least 60% PF, (3) >95% = model only considers cell consisting of at least 95% PF. We assumed 50% C for biomass. Total PF area in Indonesia is *c*. 47 707 000 ha (Suntana *et al*. 2013*b*). Tukey HSD comparisons across columns (*) are significantly different, Tukey HSD comparisons across rows (+) cells with same letter are not significantly different.

| *Sampling resolution* | *Mean NPP (kg C $m^{-2}$ $yr^{-1}$)* | | | *Mean NPP (t biomass $ha^{-1}$ $yr^{-1}$)* | | | *Mean NPP × $10^6$ (t biomass $yr^{-1}$ $PF^{-1}$)* | | |
|---|---|---|---|---|---|---|---|---|---|
| | *>0%$^{i*}$* | *>60%$^{ii*}$* | *>95%$^{iii*}$* | *>0%* | *>60%* | *>95%* | *>0%* | *>60%* | *>95%* |
| 20 km $^{+}$ | $1.245^{A}$ | $1.207^{B}$ | $1.189^{B}$ | 24.9 | 24.1 | 23.7 | 1188 | 1152 | 1135 |
| 15 km $^{+}$ | $1.213^{A}$ | $1.191^{B}$ | $1.173^{B}$ | 24.3 | 23.8 | 23.4 | 1157 | 1136 | 1119 |
| 10 km $^{+}$ | $1.168^{A}$ | $1.164^{AB}$ | $1.155^{B}$ | 23.4 | 23.2 | 23.1 | 1114 | 1111 | 1102 |
| 5 km $^{+}$ | $1.127^{A}$ | $1.136^{B}$ | $1.134^{B}$ | 22.5 | 22.7 | 22.6 | 1075 | 1084 | 1082 |
| 1 km $^{+}$ | $1.107^{A}$ | $1.118^{B}$ | $1.121^{C}$ | 22.1 | 22.3 | 22.4 | 1056 | 1067 | 1070 |

#### 3.4.2.2. Mean squared error

For the spatial sampling resolutions of 20 and 10 km, the variable with the greatest MSE (explaining more NPPm variance) was minimum daytime temperature. The MSE for spatial sampling resolutions of 1-km and 5-km grid cell size did not identify one single variable as being the most significant, but showed an overall effect of multiple variables. In the case of MSE, the explained variance of NPPm by each variable was similar to variable importance. Prediction models using cell sizes of 20, 15 and 10 km identified two to five significant variables from the model. Prediction models using 5-km and 1-km cell sizes captured local variability, thus nine or more significant variables were identified in these models (Plot can be viewed in Appendix 3.A, Figure 3.A.2).

### 3.4.3. Partial dependence plots

A partial dependence plot displays the relationship between the dependent variable NPPm and single independent variables, given all other variables are in the prediction model. The plot can be used to compare the performance of a variable between the five models to understand how spatial sampling resolution changes a model. Five variables (minimum daytime temperature, mean daytime temperature, mean night-time temperature, elevation and FPAR) had the greatest change in importance across the five spatial sampling resolutions (Figure 3).

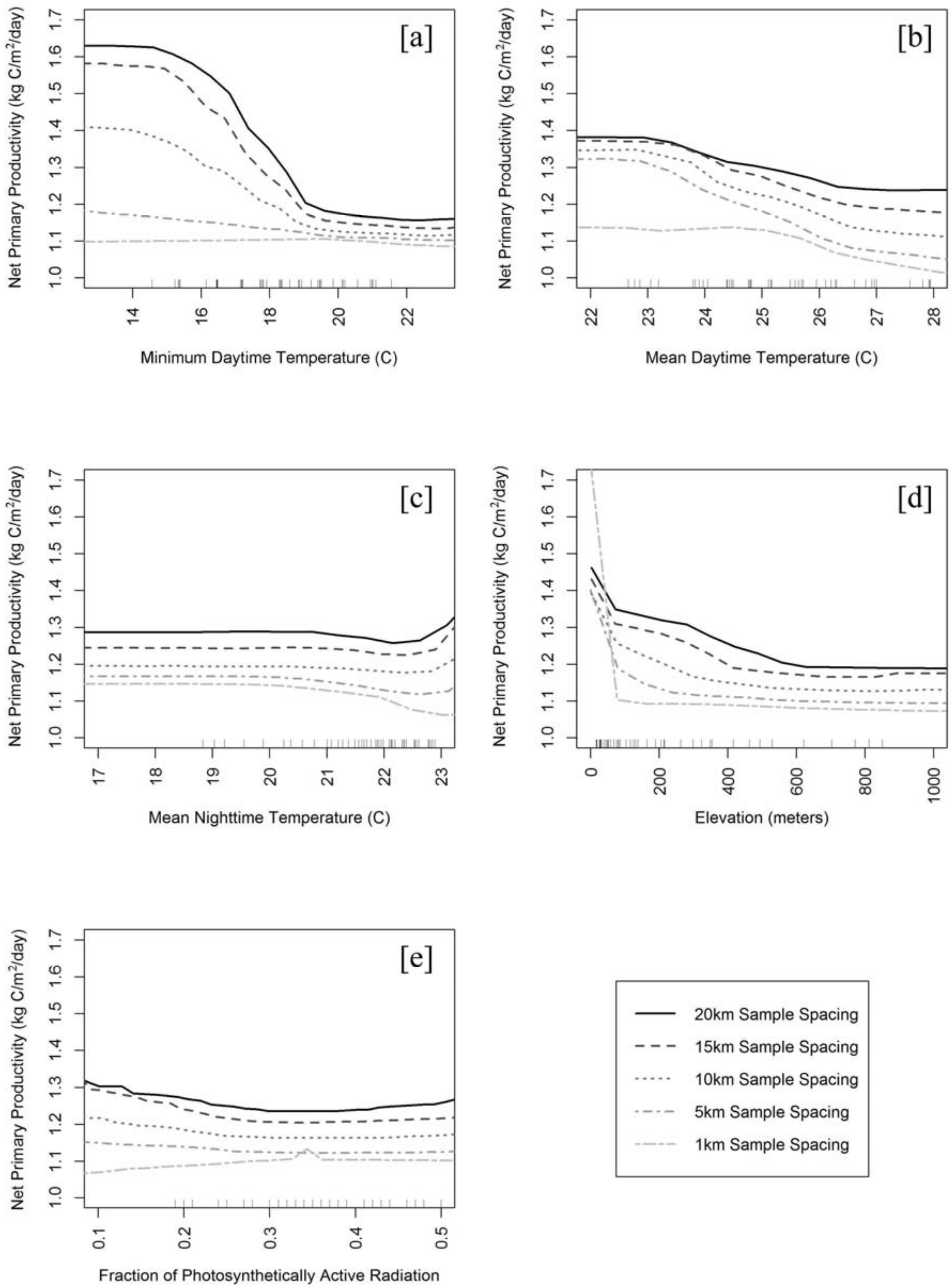


**Figure 3.3** Partial dependence plots between NPPm and (*a*) minimum daytime temperature, (*b*) mean daytime temperature, (*c*) mean night-time temperature, (*d*) elevation and (*e*) fraction of photosynthetically active radiation for each of the five different spatial sampling resolutions.

#### 3.4.3.1. Minimum daytime temperature

The partial dependence plot between minimum daytime temperature and NPPm showed NPPm decreased as the minimum daytime temperature increased (Figure 3.3$a$). While the 20-km model highlighted a significant decrease in productivity as the minimum daytime temperature increased, the 1-km and 5-km models removed that significant relationship and showed almost no change in productivity as the daytime minimum temperature increased.

#### 3.4.3.2. Mean daytime temperature

The partial dependence plot for NPPm and mean daytime temperature showed an increase in temperature with a decrease in NPPm (Figure 3.3$b$). The mean daytime temperature was a variable ranked as being least important at the 20-km spatial sampling resolution. However, it increased in importance as the grid cell size decreased. It was ranked as having the highest importance variable for the 5-km grid cell size and was among the top four in the 1-km grid cell size. Compared to the 1-km grid cell size, the 20-km spatial sampling resolution showed a consistent decrease in NPPm as there was an increase in temperature; this created a valley-shaped relationship that was more defined at the smaller grid cell size.

#### 3.4.3.3. Mean night-time temperature

The partial plot between NPPm and mean night-time temperature shows variability in predictions of variable behaviour at different sampling cell-sizes (Figure 3.3$c$). The 1-km cell size prediction model showed a decrease in NPPm at higher night-time temperatures, while 20-km grid cell model showed little to no change in NPPm at higher night-time temperatures. The mean night-time temperature had a similar behaviour to mean daytime temperature, gaining importance as the spatial sampling resolution size decreased the grid cell size. This variable was ranked as most important for the 1-km grid cell size and third most important for the 5-km grid cell size.

#### 3.4.3.4. Elevation

Elevation was a variable that had a low importance in the 20-km spatial sampling resolution model, but gained importance through the other four grid cell sizes. There was a sharp decrease in productivity as there was a gain in elevation (Figure 3.3*d*). Depending on the grid cell size used, NPPm appeared to decrease rapidly as elevations increased to *c.* 100–600 m. The spatial sampling resolution defined a sharper drop-off in productivity for smaller grid cell sizes than found for the 15-km or 20-km spatial sampling resolution models.

#### 3.4.3.5. Fraction of absorbed photosynthetically active radiation

FPAR, which is a component of the MODIS NPP model (Running *et al.* 1999), did not rank as a significant variable in the 20-km spatial sampling resolution, but gained importance as the grid cell size decreased. In the 5-km NPPm model, FPAR was the third most important variable. The partial dependence plot of NPPm and FPAR showed there was no consistent relationship across the different grid cell sizes (Figure 3.3*e*). The 15-km and 20-km spatial sample spacing showed a decreasing relationship between NPPm and FPAR initially, but this relationship disappeared as the available photosynthetically active radiation increased. This behaviour might be because the study area was located near the equator and therefore was not subject to large variations in the angle of the sun.

### 3.4.4. Change in grid cell size

The differing spatial sampling resolutions (the five different cell sizes) affected variable importance, MSE ranking and individual variable interactions with NPPm. The change in grid cell size affected which production forest areas were sampled. In addition to the change in variable importance and MSE rank, the partial dependence plots had significantly higher NPPm values for larger grid cell sizes than smaller grid cell sizes (1.245 versus 1.107 kg C $m^{-2}$ $yr^{-1}$). These comparisons translated into about 1188 × $10^6$ versus 1056 × $10^6$ t vegetative biomass annually for all of Indonesia's production forest in 20-km and 1-km grid cell sizes, respectively. Therefore an annual biomass difference of up to 131.6 × $10^6$ t could occur depending upon which cell size is used (Table 3.4).

## 3.5. Discussion

### 3.5.1. Sampling scale and NPPm estimates

This study suggested that NPPm estimates will vary with the sampling resolution used and cell occupancy selection criteria chosen. For example, the lowest mean NPPm estimate (1.107 kg C $m^{-2}$ $yr^{-1}$) was found for the 1-km sampling scale using the intersecting method (if > 0% cell occupancy occurs, the cell is retained for analyses), while the highest mean NPP (1.245 kg C $m^{-2}$ $yr^{-1}$) was found at the 20-km sampling resolution (Table 3.4). Hence the higher resolution 1-km sampling scale had 11% lower mean NPPm compared to the 20-km sampling resolution scale. If the 1-km sampling resolution is found to have the more realistic total NPPm estimate, the 20-km sampling resolution provides an example of how generalization can alter model results.

Determining what sampling resolution scale should be used to estimate NPPm values cannot be established from the results in this study. A comprehensive field study that systematically measured total productivity and the various drivers of productivity at each of the sampling scales used in this analysis is required. Since a comprehensive field study was not possible for this research, value can still be obtained by knowing if and how NPPm changes with respect to changing scales or cell occupancy selection criteria, and this can be used to provide insights into the potential range of carbon sequestration found in Indonesian forests.

Several reasons might explain the different estimates found for NPPm from using the different sampling resolutions. The 20-km scale may: (1) include other land use or forest types, such as plantation forests for producing: (*a*) timber, such as teak forest plantation; (*b*) pulp and paper (mostly acacia in Indonesia), and (*c*) energy, and/or (2) the operation of averaging values over a variable area size will change the overall distribution. Trees respond to small changes in microclimate or soil nutrient thresholds, which are probably muted at the larger sampling resolutions because of their inherent variability across a larger geographic area.

The change in grid cell size can impact the magnitude of non-production forest values outside of the production forest areas that is integrated into the sample grid. If this occurs, it would impact the overall mean. In contrast, a smaller grid cell size would have a greater likelihood of sampling values predominately solely from the production forest areas. This reduces sampling from surrounding areas under different land-use management practices that are nonetheless still forests. In addition to the change in variable importance and MSE rank, the partial dependence plots showed significantly higher NPPm values for larger grid cell sizes than for smaller grid cell sizes.

In this study, for the partial dependence plot of elevation to NPPm within the tropical production forests of Indonesia, the greatest changes in NPPm were observed for forests growing below 500 m elevation. This decrease in NPPm with increasing elevation is not as pronounced at the 1-km sampling resolution as it is at the 20-km sampling resolution, where NPPm decreased from 1.35 to 1.2 kg C $m^{-2}$ $yr^{-1}$ with increasing elevation to 500 m. Most of the sampling resolutions used in this study showed that higher elevations have lower rates of productivity and changed very little after 500 m elevation. A survey of the tropical forests in the Andes of Ecuador revealed productivity decreased with elevation (Moser *et al.* 2011), which supports the trend found in a survey comparing sites across an altitudinal transect in Borneo, where aboveground NPP decreased in relation to elevation (Kitayama & Aiba 2002). Our results indicate that increasing elevations above 500 m would have little effect on NPPm. Indonesian elevations recorded by SRTM varied between 0 m and 4805 m, with a mean value of 340 m and standard deviation of 525m. Based on this distribution, and because there are so few data points above 1000 m in the Indonesian tropics, the previous statement would be subject to caution. However from sea-level to *c.* 750 m elevation, we observed elevation had a significant effect on NPP at all grid cell sizes, excluding perhaps the 1-km cell size.

### 3.5.2. Scale-dependent drivers of productivity change

We explored how different site specific variables may interact with NPPm. We had hypothesized that NPPm, which is derived from an algorithm having its own assumptions, is sensitive to spatial sampling at different grid cell sizes and that a prediction model would identify variables of significance not originally used in the original NPPm algorithm. The objective of this study was to detect how the predictors of NPPm would change with scale and also how NPPm itself would change with scale and sampling criteria.

In this study, the dependent variable NPPm did not have the same significant independent variables across the different spatial sampling resolutions. For example, the minimum daytime temperature was ranked most important for 10, 15 and 20-km sampling resolutions but not at 5-km and 1-km sampling resolutions. Studies of tropical forests have had varied results in quantifying what temperature parameter best corresponds with productivity. A meta-analysis of 113 tropical sites statistically showed the strongest correlation with aboveground NPPm was mean annual temperature (Cleveland *et al.* 2011), while in Costa Rica, tree-ring growth was negatively correlated with annual means of daily minimum temperature (Clark *et al.* 2003).

Scale is an especially relevant issue for studies using satellite observations since these are typically obtained at very large scales where resolution is dictated by technology. It is important to determine what resolutions can adequately detect ecological changes occurring at smaller scales. Since field studies have shown that ecological and physiological processes, and therefore indicators of change, vary by scale (Lovejoy *et al.* 1986; Levin 1993), varying the scale of analysis will produce different estimates of an ecosystem's productive capacity and the drivers that control or modify it. This explains why field studies may identify a greater number of variables needed as input data to explain changes in NPPm, compared to satellite observations using larger scales of NPPm estimation. The number of indicators needed to explain ecological processes across scales was recognized more than 20 years ago by ecologists studying ecological changes in space and time (Gosz 1992). In a similar manner, our ecological research suggests that multiple parameter simulation models might not encompass all the available variables or, more specifically, the variables may not being selected at the scale at which they are statistically significant.

### 3.6. Conclusions

This study suggested that plotting the relationship of NPPm to different climatic and terrestrial variables may provide the ability to refine multiple parameter-simulation models for estimating NPP. This study on Indonesian tropical production forests highlighted the multitude of driving variables that are part of the complex relationships that may be used to predict changes in productivity. This means that any multiple parameter simulation models must be able to determine the scale at which NPP changes are occurring to realistically model the impact of climate change and land-use changes on productivity. The use of randomForest enabled us to highlight how varying spatial sample resolutions can change the significance of different variables generated from the same source datasets. The use of different occupancy selection criteria may change the distribution of the sample population. Defining the sample set in different ways can impact the overall results of a statistical analysis, reinforcing the need for variability to be introduced into a model. Models continue to be the primary way to estimate climate scenarios or carbon sequestration potentials (Parry 2007). Within this study, the variation in variable interaction with differing model cell size highlights the need to test and compare model results at different spatial sampling resolutions and using different cell occupancy criteria.

## 3.A. Appendix A

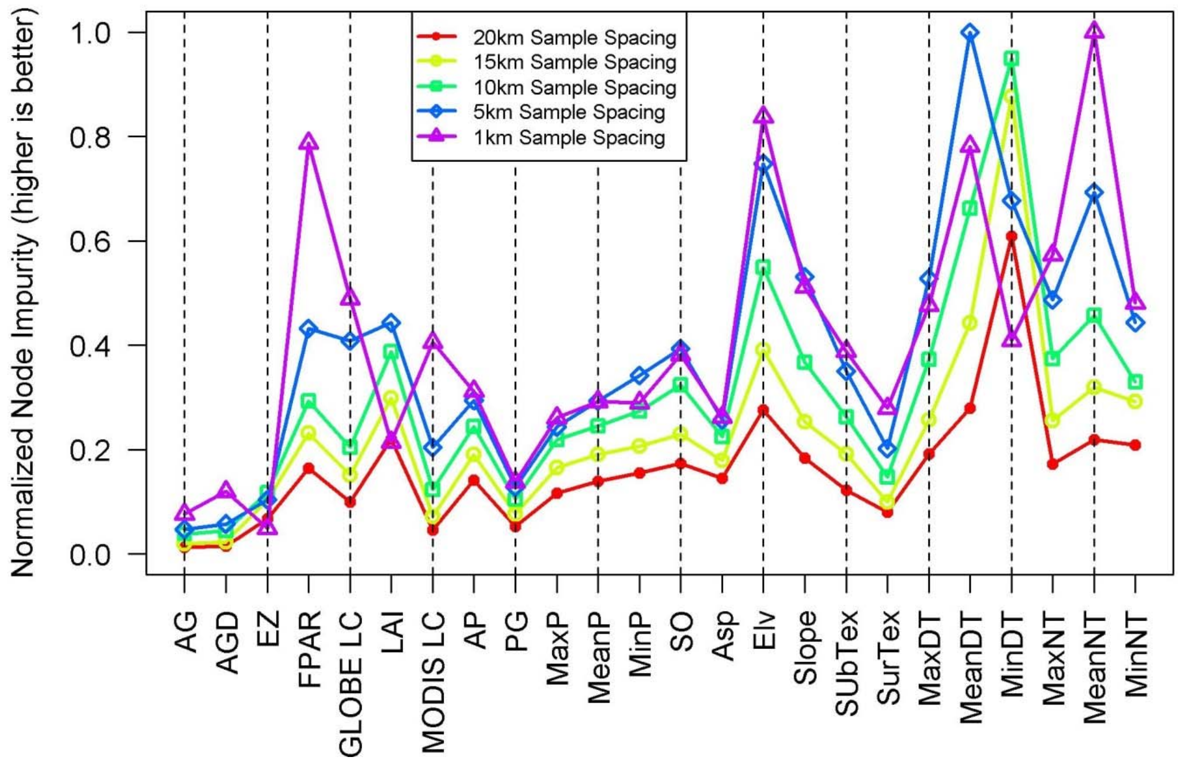


**Figure 3.A.1** Normalized variable importance as ranked by *randomForest* for the five different spatial sampling resolutions. Those variables that ranked higher received a greater number of votes when creating the forest of binary trees. The shortened variable names on the x axis are explained in Table 3.2.

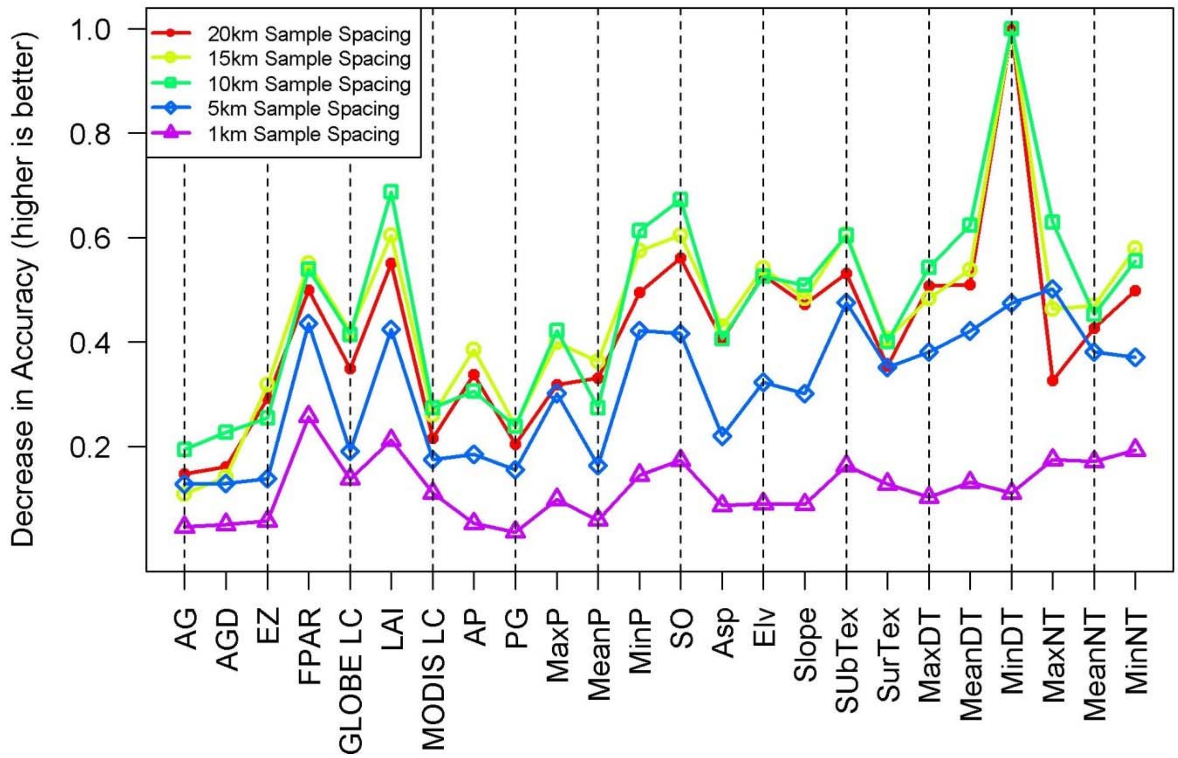


**Figure 3.A.2** Normalized increase in the mean squared error of a variable when used in the creation of a binary tree for the five different spatial sampling resolutions. Those variables that ranked higher explained a greater amount of the variance when used in the *randomForest* binary trees. The shortened variable names on the x axis are explained in Table 3.2.

# Chapter 4

# Linking deforestation to policy additionality within Mount Halimun Salak National Park, Indonesia

*This work is adapted from work originally submitted as:* Gmur, S.J., Suntana, A.S., Scullion J.J., Vogt, D.J., Tess, R., Vogt, K.A. (2014) Linking deforestation to policy additionality within Mount Halimun Salak National Park, Indonesia. *Global Environmental Change.*

## 4.1. Summary

Mount Halimun Salak National Park (MHSNP) is the largest protected area on the island of Java, Indonesia. Mount Halimun Salak National Park was first protected by the Dutch colonial administration in 1929 but was only designated by the Indonesian Ministry of Forestry as a National Park in 1992. In 2003, MHSNP was expanded to its current day boundaries followed by a 2005 policy which sought to involve local stakeholders in a collaborative management paradigm to increase conservation effectiveness. To include the local stakeholders in management, several land-use zones were established within the park boundaries: Core, Culture, Rehabilitation, Special Training & Research, Use, and Wildlife. Using a statistical matching approach, this study assessed the influence of land-use zoning regulations on deforestation levels inside the MHSNP. Results show that for the period 2003 – 2013, strict conservation areas had a 6.2% lower rate of deforestation relative to all other use zones combined. The relative rate of deforestation was higher in the Special Research & Training zone, which is a designated area for local communities to provide livelihood. Deforestation was lowest in the Rehabilitation zone which is meant to restore lands that were characterized as degraded and deforested. These results suggest policies geared towards including local people's land-uses within protected areas can meet the conservation goals in a national park and help to reduce deforestation rates. By designating specific zones of land-uses within a protected area, utilization of resources were contained to certain zones and allowed other areas to regenerate back into forest condition.

### 4.2. Introduction

Tropical forests have been recognized as multifunctional in both hosting a rich variety of plant and animal species along with serving the function of storing globally important carbon pools in the face of a changing climate (Parry, 2007; Schmitt et al., 2009). The total number of protected areas within the tropics has continued to increase over the last 20 years but remains a bias in the creation of protected areas (PA) towards higher elevations farther from roads and cities (DeFries et al., 2005; Joppa & Pfaff, 2009). Conservation of forest areas as PAs has been the primary tool used to retain tropical forests and the ecosystem services they produce (Potapov et al., 2008; Joppa & Pfaff, 2011). A survey of 93 tropical forest plot-scale protected areas, where significant human land-use pressure exists, suggested a majority of these sites were sustaining or helping to increase the amount of forest cover (Bruner, 2001). The effectiveness of protected areas in lowering deforestation rates has also been reported by a host of satellite-based studies (Sanchez-Azofeifa et al., 2003; DeFries et al., 2005; Nepstad et al., 2006, Scullion et al., 2014).

However within Indonesia, few published studies exist assessing the effectiveness of protected areas in reducing deforestation. These studies indicate that Indonesia is a country whose protected areas have had varying levels of effectiveness, or policy additionality. For example, Sumatra's PA's have been shown to be more effective than comparable unprotected areas in Indonesia, but interestingly deforestation remains an ongoing concern inside the region's protected areas (Ferraro et al., 2014; Gaveau et al., 2009). In the lowland forests on the island of Borneo, protected areas decreased by more than 56% from 1985 to 2001 (Curran 2004). The history of deforestation and general land degradation across the country of Indonesia has become more complex as logging operations, especially illegal logging, reoccurring fires, and socioeconomic and political issues, become more intertwined with population growth pressures (Nawir et al., 2007). The largest quantities of forested area which remain unprotected are primarily located within commercial logging, mining oil palm or plantation concessions (Abood et al., 2014).

Policies designed to reduce deforestation rates inside Indonesian's PAs, have taken many forms including "exclusion and fine methods" and community based inclusion and participatory strategies (Kubo, 2010a; Mulyana et al., 2010). Research has suggested that involving local people in the planning, management and decision processes may result in a reduction in overall deforestation rates within PAs (Bruner, 2001; Kubo, 2010a; Porter-Bolland et al., 2012). Also, research has suggested that "exclusion and fine methods" can be detrimental to local populations, particularly forest dependent people, by creating deficits in access to resources (Naughton-Treves et al., 2005). In Mount Halimun Salak National Park (MHSNP), located 60 km from the cities of Jakarta and less than ten km from Bogor district, a variety of land-use designations exists with varying degrees of restrictions on resource uses by local people. This approach to the management of MHSNP started in 2003 when the Indonesian Ministry of Forestry issued a decree to formally recognize the involvement of local communities in decisions being made in the park (Kubo, 2010b). This study was designed to understand the impacts of including local people in park management and whether land-use zoning can provide an effective way to balance the resource needs of resource users living in the park while also achieving park management objectives to reduce deforestation rates. Therefore, this study was designed to evaluate land-cover dynamics and policy additionality of different land-use zones inside MHSNP for the period 2003 to 2013.

MHSNP provides a unique opportunity to evaluate the additionality of land-use zoning because the park is virtually a forest island surrounded by human land-use and the nearby megacities of Jakarta and Bogor, which together form the second largest urban area in the world (Kotkin, 2013). Before 2003, MHSNP was smaller in total area and management policies followed the strict conservation approach defined as the “exclusion and fine methods”. In 2003, policies within the park shifted to include local people (including indigenous peoples) in park decision-making and planning. Part of this process was the development of land designations within the park describing what uses would be practiced in each area. Many past studies of MHSNP were designed to understand the needs of local people in regards to forest products, to evaluate the attitudes and interactions between local people and frontline staff, and to evaluate the values that local people place on the forest following education initiatives (Galudra, 2005; Harada, 2005; Gunawan et al., 2007; Kubo, 2008; Kubo, 2010a, b; Prasetyo et al., 2010). However, research did not measure the influence of the park re-zoning efforts, which included local people in management of park lands, on deforestation rates. To detect the influence of park management practices on deforestation rates inside MHSNP, three research questions were explored: (1) How did the park expansion in 2003 change deforestation rates within each park area? (2) Were deforestation rates lower inside lands designated for strict conservation verses other land designation? (3) Were different land-use designations linked to varying levels of deforestation?

## 4.3. Materials and Methods

### 4.3.1. Study Area

MHSNP is located on the island of Java just south of the capital city Jakarta within the country of Indonesia (Figure 4.1). This park was created in 1992 and initially consisted of an area of 40,000 ha that was later expanded to 113,357 ha in 2003 (Figure 4.2). This park contains the greatest amount of intact tropical forest on the island of Java. The initial park area has a history of being protected starting in 1929 under the Dutch colonial administration and continued to be under protective management by different governmental organizations (Wiharisno, 2010). Rainfall within the park averages from 4,000 to 6,000 mm/year with a temperature range of 19.7 ºC to

31.8ºC. Three main volcanic mountain peaks [Salak (2211 m), Halimun West (1929 m) and Halimun East (1750 m] form the parks elevational ecosystem zones from range from sea level to over 2200 meters in elevation. These park ecosystem zones are: Lowland (0 – 500), Colline (500 – 1000 meters), Submontane (1000 – 1500 meters), and Montane (1500 – 2400 meters) (Steenis, 2006). These zones contribute to the high diversity of plant species with at least 1000 species of plants of which 845 are flowering (Wiharisno, 2010). The core tropical forest area of the park also provides critical habitat for many threatened species such as panthers (Steenis, 2006) and Javan Gibbon (Supriatna, 2006).

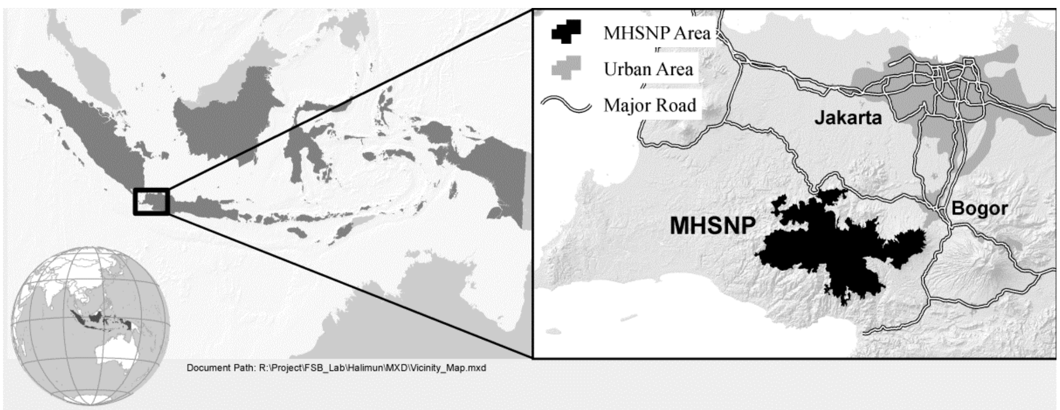


**Figure 4.1:** Location of Mount Halimun-Salak National Park (MHSNP), Island of Java, Indonesia.

### 4.3.2 History of Park Management

Initially the management of MHSNP as a protected area used the legal framework adopted by the national government of Indonesia. This did not allow indigenous peoples living within the national park any formal recognition of their settlements, the ability to harvest resources or use forested areas for production purposes (Kubo, 2010a). A change in management of MHSNP subsequently occurred in phases. The first phase occurred in October of 2004 when a new decree on collaborative management was passed that outlined how local and indigenous peoples and civil society organizations, such as NGOs, are stakeholders in any conservation forest management planning. The second phase was undertaken as a pilot project by the MHSNP office in 2005. This project had a goal of recognizing settlements and agricultural land use within the park and to find a balance between forest resource conservation while providing rural livelihoods for those living within the park (Kubo, 2008). Since mid-May 2013, the management of MHSNP needed to pay more attention to the implementation of the Constitutional Court (Mahkamah Konstitusi/MK) of the Republic of Indonesia, i.e., decision number 35/PUU-X/2012 (TEBTEBBA, 2012). The decision was made following the Judicial Review process of the Law 41/1999 on Forestry that was requested by the Indigenous Peoples Alliance of the Archipelago (AMAN) and two Indigenous Communities. The Constitutional Court confirmed that Customary Forests are forests located in Indigenous territories, and should no longer be considered as State Forests or part of the national park (Aman, 2014).

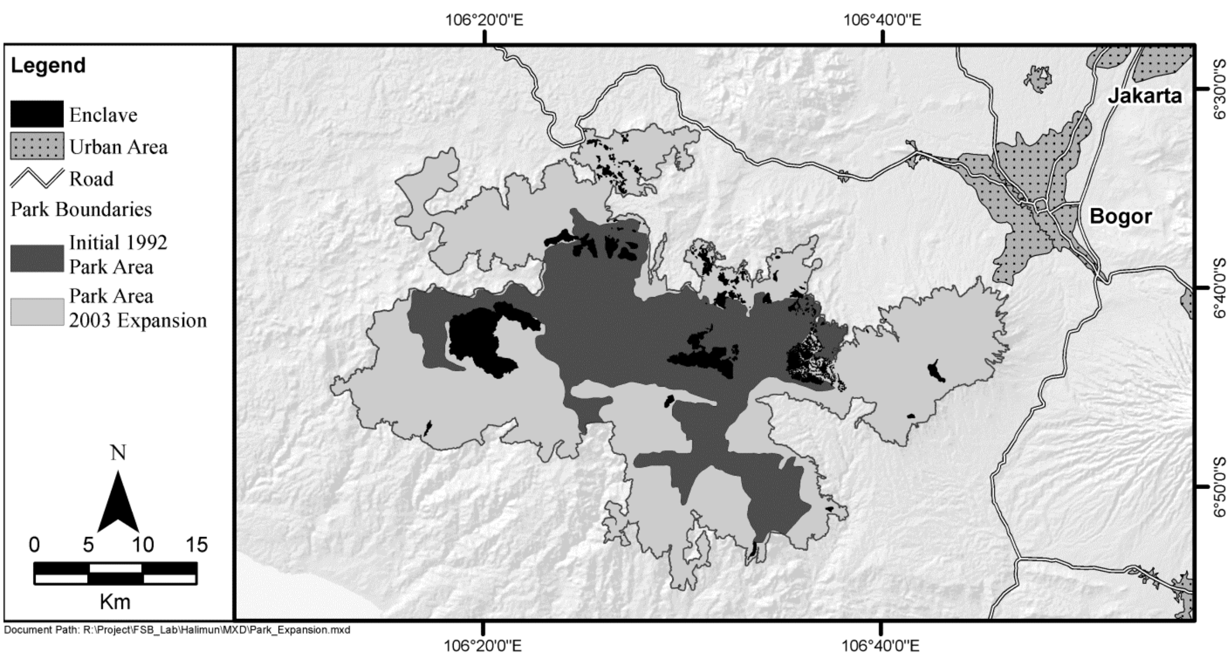


**Figure 4.2:** The initial 1992 Mount Halimun Salak National Park area (40,000 ha) and 2003 park expansion (113,000 ha).

Results from the pilot project highlighted that illegal logging could be reduced when front line field staff, responsible for enforcing use policy of the protected forest, interacted with local people on developing consensus on the values of the forest to be included in management plans. Local populations would often serve as the labor pool during illegal logging operations to generate income for their families. When front line staff took the time to form personal relationships with village elders and understand their livelihood options, park inhabitants gained a greater understanding of the value of forest resources and services. With the expansion of the park boundaries in 2003, many enclaves which had previously been located in production forest areas (Figure 4.2) were no longer able to utilize forest resources they had historically utilized for generations. Also, the enclave parcels were recognized as not being part of a PA and under the ownership by a private party, including community-owned forests/gardens managed under customary laws. This situation created villages situated inside of the park geographically but outside of the administrative control of the park (Harada, 2005). Park inhabitants were suspicious of park staff who needed to enforce conservation forest policies and police their activities. The goal of the pilot project was to redefine the relationships between park staff and park inhabitants.

### 4.3.3. Land use zones within MHSNP between 2003 and 2013

National parks within the country of Indonesia are directed to protect natural ecosystems and are managed by the National Park Agency (Balai Taman nasional or BTN) using a system of spatial zoning. Ministerial Decree P.56 regulates the zoning within national parks to function according to existing ecological, socio-economic and cultural conditions (Mulyana *et al.*, 2010).

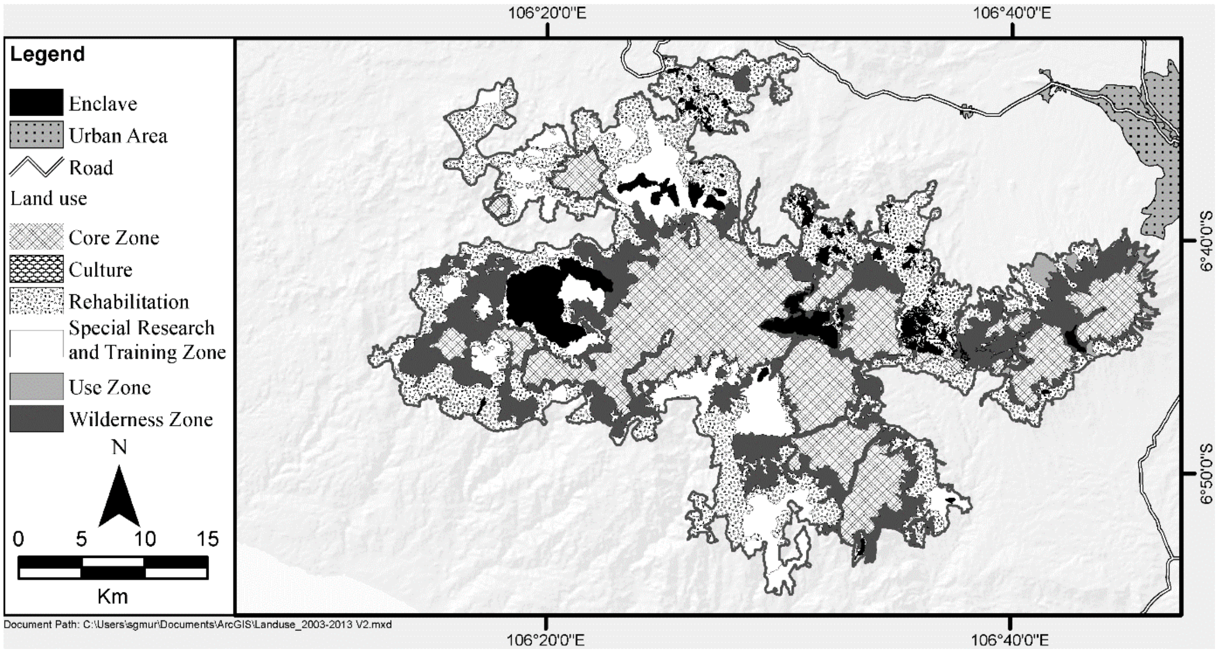


**Figure 4.3:** Land use designations within Mount Halimun Salak National Park after the expansion of the park in 2003.

Delineation of these use zones within parks is an attempt to balance the needs of communities living within national parks, often in communities that were established before the national park with conservation efforts to preserve vegetation and wildlife species. Figure 4.3 outlines the different zones within MHSNP and Table 4.1 outlines the zones, description of each zone and its relative size in hectares.

**Table 4.1:** Description and the area (in hectares) of different land-use designations within Mount Halimun Salak National Park after the expansion of the park in 2003.

| Land use designation | Description | Area (ha) |
|---|---|---|
| Core Zone | Core habitat area for use in feeding, breeding, nesting, escaping and hiding sensitive wildlife species (Gunawan *et al.*, 2007) | 30,192.3 |
| Culture | For protection of culture and history of local people who are living within a national park (Mulyana *et al.*, 2010) | 6.5 |
| Enclave | Areas within MHSNP where sub-villages or settlements are located (Kubo, 2010a) | 7,137.1 |
| Rehabilitation | Restoration of lands which are degraded and deforested (Gunawan *et al.*, 2007) | 32,485.8 |
| Special Research and Training Zone | Designated area for local communities to provide livelihood for local communities through cultivation of degraded land using agro-forestry system for an agreed upon time (Gunawan *et al.*, 2007) | 16,382.8 |
| Use Zone | An area within a national park where local peoples can use it for their own local interests (Mulyana *et al.*, 2010) | 833.6 |
| Wilderness | Habitat extension for species of wildlife foraging outside the core zone (Gunawan *et al.*, 2007) | 27,629.1 |

### 4.3.3. Mapping Forest Cover Change

#### 4.3.3.1. Time Series of Satellite Imagery

Classified land cover maps across the study area were created using LANDSAT scenes for the dates 1997 (TM), 2003 (ETM+) and 2013 (OLI_TIRS) (Path/Row 122/65). Those years with scenes exhibiting partial cloud cover obscuring portions of the study area were composited using multiple scenes from the same year to create the most complete cloud free image. Imagery was obtained from the USGS GLOVIS data portal (USGS, 2014) and radiometric correction was performed within ENVI (ENVI, 2014). Scenes from the years 1997 and 2003 were geo-referenced to the a 2013 LANDSAT band 8 Panchromatic color pan sharpened image through a third order polynomial co-registration technique using over 25 registration points per scene (Jensen, 2005). The spatial precision obtained was smaller than one pixel (900 sq. m) using the coordinate system Universal Transverse Mercator (UTM) projection, Zone 48 South. Atmospheric correction of the scenes used Dark Object Subtraction subtracting the smallest meaning value with a 1% frequency from each band. Land cover for the MHSNP area was mapped to exclude enclave areas and areas obscured by cloud cover which resulted in a study area of 104,419 hectares. Cloud cover present in any of the four scenes obscured 1985 hectares or 1.8% of the park area.

#### 4.3.3.2 Land Cover Classification

Classification of land cover for the four scenes used the supervised classifier Mahalanobis which is a distance classifier that assumes all classes covariances are equal and pixels are classified to the closest region of interest (ROI) (Richards, 2006). Three classes were chosen based on distinguishing characteristics of vegetation: Forest where tree crown expansion has formed a closed canopy by high climax trees 50 years or older with a height of 15 – 30 m high, Secondary Forest where weed trees have rapidly grown characterized by less dense vegetation with ages 10 to 25 year with a height of 10 – 15 m high and the third class are areas lacking vegetation or exposed soil (Steenis, 2006). More than 12 representative ROIs for each class within the 4 scenes were chosen for the ENVI to classify within the study area.

Validation of each resulting classified image was undertaken by a second person creating over 300 ground truth ROIs for each scene, 100 validation points for each class were used to create a confusion matrix to calculate the percent accuracy and kappa values. Overall accuracy for each map was 1997 (95.3% kappa 0.9300), 2003 (95.3% kappa 0.9300), 2013 (95.5% kappa 0.9331). Land-cover change was assessed using the spatial analysis software ArcGIS Desktop 10.2 (ESRI, 2014). The confusion matrices can be seen in Appendix A materials (1997 (Table 4.A.1), 2003 (Table 4.A.2) and 2013 (Table 2.4.3). The resulting mapped land-cover classes for the 4 scenes are presented in Appendix 4.B.

### 4.3.4 Defining variables

#### 4.3.4.1 Dependent Variable Deforestation

Deforestation was determined using the change between time series land cover maps where forested areas in a preceding scene were mapped as either secondary forest or bare ground in the subsequent scene. Using this pixel by pixel change classification method, areas of deforestation across the study area for time series 1997 – 2003 and 2003 – 2013 were mapped. Areas delineated as being deforested over the different time periods can be seen in Appendix 4.C.

#### 4.3.4.2 Deforestation Covariates

The covariate variables used within the statistical analysis of this study were developed from a collection of spatially explicit datasets created from a variety of sources: RMI-the Indonesian Institute for Forest and Environment and JKPP (Jaringan Kerja Pemetaan Partisipatif/Indonesian Community Mapping Network) and NASA.  Creation of spatial layers such as distance from boundaries, distance from deforestation or enclaves was calculated using the Spatial Analyst tool Euclidian Distance in ArcGIS 10.2 (ESRI, 2014). Values were transferred using a cell-by-cell operation to derive values for each 30 x 30 m grid cell area as defined by the 2013 land cover classified LANDSAT scene using the ArcGIS Zonal Statistics tool (Gmur *et al.*, 2013). Covariates used within the statistical analysis are outlined in Table 4.2.

**Table 4.2:** Data sources used to estimate relative policy effectiveness for preventing deforestation in Mount Halimun Salak National Park, Indonesia including the variable name, a description of the source or how the data were derived and the time period in which the specific variable was used.

| Variable Name | Description |
|---|---|
| Elevation | Elevation derived from Shuttle Radar Topography Mission (NASA, 2013) |
| Distance to Enclave | Euclidian distance to nearest enclave |
| Distance to 2003 Boundary | Euclidian distance to the closest 2003 park boundary edge |
| Deforested ‘97 – ‘03 | Binary value indicating forest cover conversion during the time period 1997 – 2003 |
| Distance to Deforestation during ‘97 – ‘03 | Euclidian distance to the closest area of deforestation during the time period 1997 – 2003 |

### 4.3.5. Calculating relative performance of the policies against deforestation

Measurement of policy performance to reduce deforestation between park areas (1997 – 2003, 2003 – 2013) and between zone designations within the park (2003 – 2013) used the statistical method called Matching. Matching is a treatment or policy evaluation method where sample populations of treatment and control unit distributions are constructed to be similar to provide an ‘apple to apples’ comparison (Joppa & Pfaff, 2011; Blackman, 2013). Comparisons between relative deforestation rates of different policy implementations used the ‘Matching’ package within the R environment (Sekhon, 2011). Sample populations were first balanced using the ‘GenMatch’ algorithm which is a multivariate Matching where a genetic search algorithm determines the weight and cumulative probably distributions. The balanced sample populations were examined using the ‘matchbalance’ command to determine the quality of the resulting match then a match was performed to obtain the casual estimate of relative deforestation between the control and treatment areas. Parameters of the model were carried using 1 to 1 Matching with variable sampling ratios to increase the likely number of matches between control and treatment populations. This was especially important when comparing the Core/Wilderness Zones against Use Zones which make up less than 0.1% of the total national park area. A more detailed explanation of using Matching to obtain the casual estimate of deforestation between land parcels under differing policy management is available in Scullion et al. (2014).

**Table 4.3:** Comparisons made using matching between the park areas along with different spatially explicit use zones to measure the relative performance of policy to mitigate deforestation. The comparisons used a control (c) and treatment (t) to measure the relative rate of deforestation between areas.

| Areas Compared | Sampling Ratio |
|---|---|
| 1992 park area (c) verses areas added in 2003 (t) | 3:1 |
| Strict conservation (c) (i.e. Core and Wildlife) verses all other use zones (t) (i.e. Use, Rehabilitation and Special Research & Training) | 1:1 |
| Strict conservation (c) verses Rehabilitation Zone (t) | 4:7 |
| Strict conservation (c) verses Special Research & Training Zone (t) | 2:7 |
| Strict conservation (c) verses Use Zone (t) | 1:70 |

## 4.4. Results

### 4.4.1. Local communities and deforestation within MHSNP

Few studies have addressed the links between the effectiveness of policies aimed at including local people in management decisions and the success of this policy in reducing deforestation rates (Naughton-Treves, 2005; DeFries, 2010). Studies using survey and interview methods have focused on understanding the needs of local people to extract forest resources, to evaluate the attitudes and interactions between local people and frontline staff who implement policies, and whether educational initiatives have been successful in building consensus on values to be derived from protected areas but have not measured how extensively deforestation was reduced (Galudra, 2005; Harada, 2005; Gunawan *et al.*, 2007; Kubo, 2008; Kubo, 2010a, b; Prasetyo *et al.*, 2010). Therefore, this study was designed to determine whether the adoption of pivotal policy changes contributed to decreasing deforestation rates in a protected area in Indonesia. The focus of this study was to explore whether land designation within a park can contribute towards reducing deforestation.

### 4.4.2. Deforestation within MHSNP 2003 expansion area

To understand how the policy intervention of expanding MHSNP from its 1992 boundaries to current day boundaries in 2003 impacted the extent of forest cover, the percent change in forest cover within each area was calculated for the contrasting periods 1997 – 2003 and 2003 – 2013. Matching was also employed to calculate the relative rate of deforestation between the areas. Table 4 reports the change in total forested area, rate of deforestation in hectares per year and the estimated effect of conservation in reducing deforestation within the park as compared to surrounding production forest. During the years 1997 – 2003 the forest area within the park was increasing less than one hectare per year while the production forest areas surrounding the park had a deforestation rate of 5.14 hectares per year. During the years 2003 – 2012 MHSNP expanded its borders to include the former production forest areas and the forested area within the 1992 boundary area grew at a rate of 1.45 hectares per year while the newly incorporated areas grew at a rate of 6.81 hectares per year. During the entire period of 1997 – 2013, the estimated effect of the 1992 park boundary area in reducing deforestation as compared to the 2003 expansion area had an estimated effect of 1.2 %. While the estimated effect of difference in deforestation between the areas remained the same, the loss of tree cover within the production forest area under policy of selective logging was reversed once those areas were incorporated into the park. Forest cover within the 1992 park boundary continued to increase over the entire 1997 – 2013 period.

**Table 4.4:** Comparison between the 1992 park area (control) and the 2003 expansion areas (treatment) using matching to measure the relative rate of deforestation between areas, percent change in forest cover within each group and the relative rate of deforestation between groups.

| | Deforestation | | | | |
|---|---|---|---|---|---|
| **Years** | **% change (control)** | **Rate of Change ha/yr (control)** | **% change (treatment)** | **Rate of Change ha/yr (treatment)** | **Estimated Effect (%)** |
| 1997 – 2003 | 1.06 | 0.17 | -26.5 | -5.14 | 1.2 |
| 2003 - 2013 | 15.6 | 1.45 | 97.7 | 6.81 | 1.2 |

### 4.4.3. Relative policy performance (matching results)

For this study, the statistical method matching was used to determine the relative rate of deforestation between different control and treatment groups to understand the success of different policy prescriptions within the context of MHSNP (see Table 4.3). This study focused on key policy changes and examined whether reduced rates of deforestation occurred following policy implementation. Policy intervention impacts on deforestation were examined for the following scenarios: (1) How did the park expansion in 2003 change deforestation within each park area? (2) Was deforestation lower inside lands designated for strict conservation verses other land designations?; and (3) Were there differences in the levels of deforestation between land-use designations?

A comparison between the diverse zone designations during the time period 2003 to 2013 is used to understand the performance of specific use area designations compared to zones with the highest level of protection, i.e. Core and Wildlife zones. This comparison showed that the zone designated as Core and Wilderness areas had 6.2% less deforestation occurring compared to all the other use zones. Three of the zone designations (i.e., Use, Rehabilitation and Special Research and Training zones) were compared against the Core and Wildlife zones (defined in Table 4.1). These comparisons showed that the relative rate of deforestation was compared to the Core and Wildlife zones as shown in Table 4.5.

**Table 4.5:** Comparisons between the different spatially explicit use zones using matching to measure the relative performance of policy to mitigate deforestation between the control and treatment areas, percent change in forest cover within each group and the relative rate of deforestation between groups.

| | | **Deforestation** | | |
|---|---|---|---|---|
| **Control** | **Treatment** | **% change (control)** | **% change (treatment)** | **Estimated Effect (%)** |
| Strict conservation | All other spatially explicit use zones | 12.9 | 262.7 | 6.2 |
| | Rehabilitation Zone | | 221.0 | 3.4 |
| | Special Research & Training Zone | | 575.7 | 11.7 |
| | Use Zone | | 57.6 | 5.2 |

### 4.5. Discussion

Designating areas as protected is the primary tool for increasing conservation efficacy thus a method is needed to determine the capability of policies with a range of approaches, including exclusionary measured aimed at reducing resource extraction in specific areas to reduce deforestation. Since establishing protected areas is an international strategy that frequently has not involved local communities and their resource needs, resource extraction from PAs by local people has become by definition illegal and thus uncoordinated and unlimited. So in a confounding way PAs may be at risk of being further deforested and losing biodiversity in areas designated for protection (DeFries, 2010). However some research has suggested that involving local people in the planning, management and decision processes may result in a reduction in overall deforestation within PAs (Bruner, 2001; Kubo, 2010a; Porter-Bolland *et al.*, 2012). Wang and Wilson (2007) supported this idea by promoting a multi interest forestry as a approach in dealing with institutional aspects of forest management (i.e., who manages forests, managing forests for whom, and how to share the benefits and costs among stakeholders).

The most successful multiple purpose PAs have been those which seek to partner both preservation of ecosystems with user education programs focusing on the ecological values of the resource they collect (Naughton-Treves *et al.*, 2005; Gunawan *et al.*, 2007; Sodhi Ns, 2011). In order to determine if policies are effective, there is a need to develop an objective measure of rates of deforestation in the affected area.

#### 4.5.1. The Additionality of Land-Use Zoning and Management Changes in MHSNP

Establishment of land-use zones within the national parks of Indonesia is based on the effort to balance the need for local peoples to access natural resources for their daily needs and to pursue economic activities while furthering the national interest of increasing conservation efficacy. For this project, zones were defined according to existing spatial arrangement of landscape features based on function and existing ecological, socio-economic and cultural conditions (Mulyana *et al.*, 2010). The distribution of different use zones within MHSNP are shown in Figure 3 which highlights the extent of core habitat and wildlife zones along with all the other use zones within the current day park boundaries. The zones with the highest levels of protection (e.g., Core and Wilderness use zones) had 6.2% less deforestation occurring compared to all the other use zones.

The decrease in deforestation in the Core and Wilderness use areas correlate with the introduction of policies allowing resource extraction from other areas. The policies allow local people to utilize resources within specific designated areas within MHSNP that would divert them from using designated conservation core habitat and wilderness areas providing habitat for more sensitive species requiring a higher area of forest cover. The individual comparisons between strict conservation zones and other use zones suggest that the underlying function of conservation policy within MHSNP is facilitating the maintenance and expansion of forest cover. The Core and Wilderness zones, which are designated to provide habitat for sensitive species of wildlife, had the lowest level of overall deforestation while experiencing an expansion of overall forest area. Within the Rehabilitation zone, deforestation rates resulted in an increase in total forest cover.

The increase in forest cover relates the efforts to restore degraded lands back into a forested condition. Spatially designated Use zones experienced an increase in total forest area by 57.5%; which suggests that allowing local peoples to practice management based on their own interests can expand the total area of forested lands. Special Research and Training zones, designated to provide livelihood for local communities through cultivation of degraded land using agro forestry systems, an increase in total forest area. While all use zones saw some level of deforestation, all saw an overall increase in the total amount of forested area when local people were given designated land use zones that they could manage.

### 4.6. Conclusions

Increasing population growth in countries within the tropical forest zone will increase the demand for conversion or clearing of forested lands to agricultural production or the extraction of natural resources (Wright, 2005). On the island of Java, which has historically seen a dramatic loss of its tropical forests, forest cover has increased within the MHSNP when local communities living in the park were allowed to manage designated zones for their own survival and to pursue economic activities. While there has been a trend for establishing PAs in more remote areas farther from cities and roads, this study measured the rate of deforestation within MHSNP which is near the second largest urban area in the world. Areas which had the strictest conservation protection within MHSNP only lost 81.2 ha of total forested area from 2003 thru 2013 but the overall forested area grew by 12.9% within the spatially designated Core and Wildlife zones. The highest occurrence of deforestation has been within use zones specifically meant for resource extraction (e.g., Use, Rehabilitation and Special Research and Training zones) while those areas meant for strict conservation have the lowest level of deforestation (e.g., Core and Wildlife zones). Policy which localizes specific resource extraction to spatially designated area in MHSNP allowed local people legally living in the park access to additional resources if needed.

This study demonstrated that use of satellite imagery to capture deforestation within a study area can evaluate the effectiveness of policy change and represents a method to continually evaluate the success of that policy. The continued development of policy, which balances use of forested lands by local people with conservation goals of international partners, could provide a successful framework for managing tropical forests to reduce the loss of forest cover. Evolution of policy to balance the goals of conservation with the needs of local peoples to access forest products within PAs can be seen within MHSNP. Targeted policy which localizes gathering of forest products by local people within specific areas helps to relieve pressures on other areas which may have higher biodiversity value.

## 4.A. Appendix A

**Table 4.A.1.:** Confusion matrix to evaluate the accuracy of the 1997 land-cover classification dataset.

**1997 Confusion Matrix**
**Overall Accuracy:** 95.3% & **Kappa** = 0.93

| Land Cover Types | Ground Verification Points | | | | |
|---|---|---|---|---|---|
| | Forest | Secondary Forest | No Forest | Total | User Accuracy |
| Unclassified | 0 | 0 | 0 | 0 | |
| Forest | 91 | 4 | 0 | 95 | **95.8%** |
| Secondary Forest | 9 | 96 | 1 | 106 | **90.6%** |
| No Forest | 0 | 0 | 99 | 99 | **100.0%** |
| Total | 100 | 100 | 100 | 300 | |
| Producer Accuracy | **91.0%** | **96.0%** | **99.0%** | | |

**Table 4.A.2.:** Confusion matrix to evaluate the accuracy of the 2003 land-cover classification dataset.

**2003 Confusion Matrix**
**Overall Accuracy:** 95.3% & **Kappa** = 0.93

| Land Cover Types | Ground Verification Points | | | | |
|---|---|---|---|---|---|
| | Forest | Secondary Forest | No Forest | Total | User Accuracy |
| Unclassified | 0 | 0 | 0 | 0 | |
| Forest | 97 | 4 | 4 | 105 | **92.4%** |
| Secondary Forest | 3 | 96 | 3 | 102 | **94.1%** |
| No Forest | 0 | 0 | 93 | 93 | **100.0%** |
| Total | 100 | 100 | 100 | 300 | |
| Producer Accuracy | **97.0%** | **96.0%** | **93.0%** | | |

**Table 4.A.3.:** Confusion matrix to evaluate the accuracy of the 2013 land-cover classification dataset.

**2013 Confusion Matrix**
**Overall Accuracy:** 95.5% & **Kappa** = 0.93

| **Land Cover Types** | **Ground Verification Points** | | | | |
|---|---|---|---|---|---|
| | Forest | Secondary Forest | No Forest | Total | User Accuracy |
| Unclassified | 0 | 0 | 0 | 0 | |
| Forest | 104 | 1 | 1 | 106 | **98.1%** |
| Secondary Forest | 8 | 99 | 3 | 110 | **90.0%** |
| No Forest | 1 | 0 | 97 | 98 | **99.0%** |
| Total | 113 | 100 | 101 | 314 | |
| Producer Accuracy | **92.0%** | **99.0%** | **96.0%** | | |

## 4.B. Appendix B

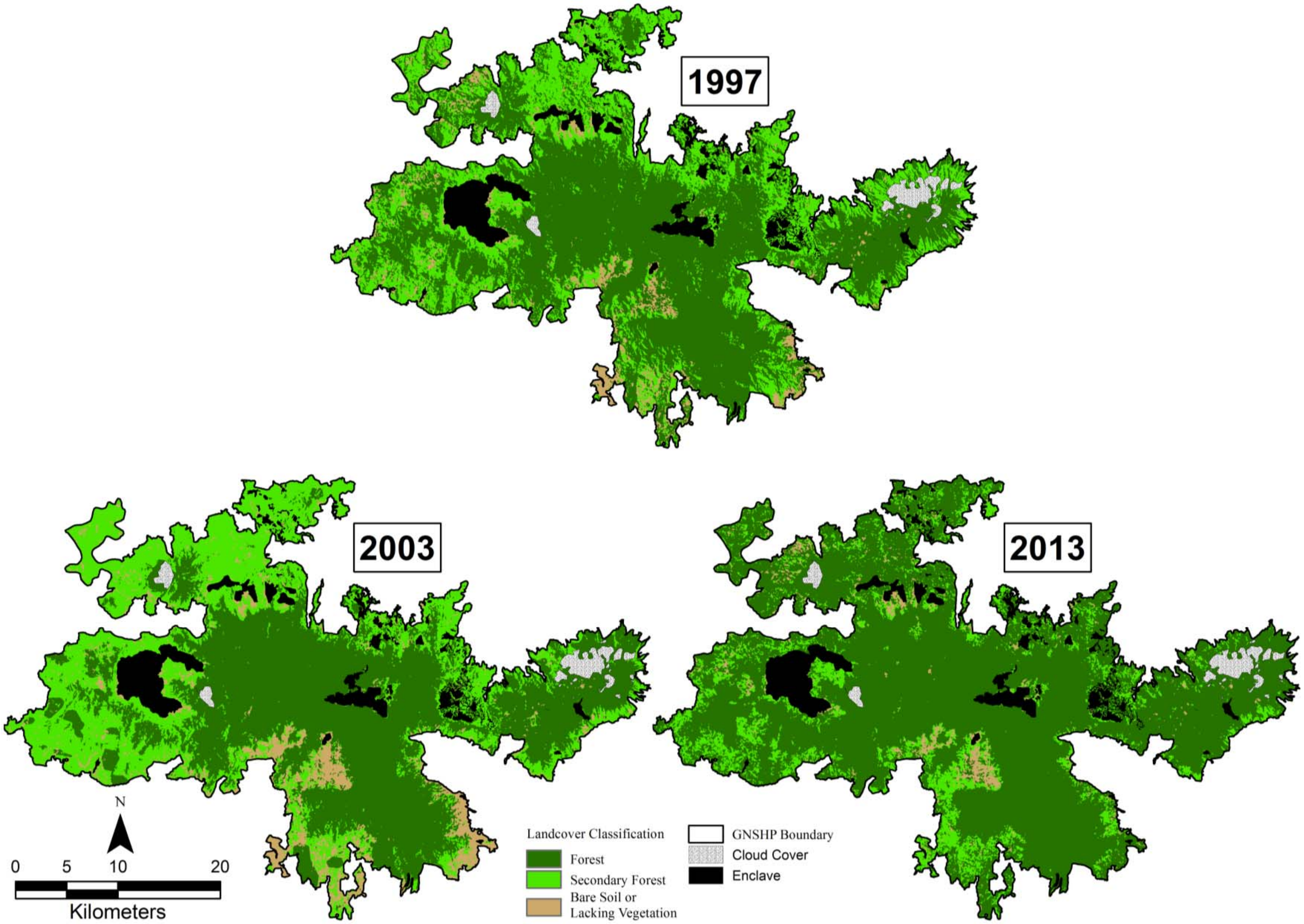


**Figure 4.B.1:** Land cover classifications across Mount Halimun Salak National Park for the years 1997, 2003 and 2013.

## 4.C. Appendix C:

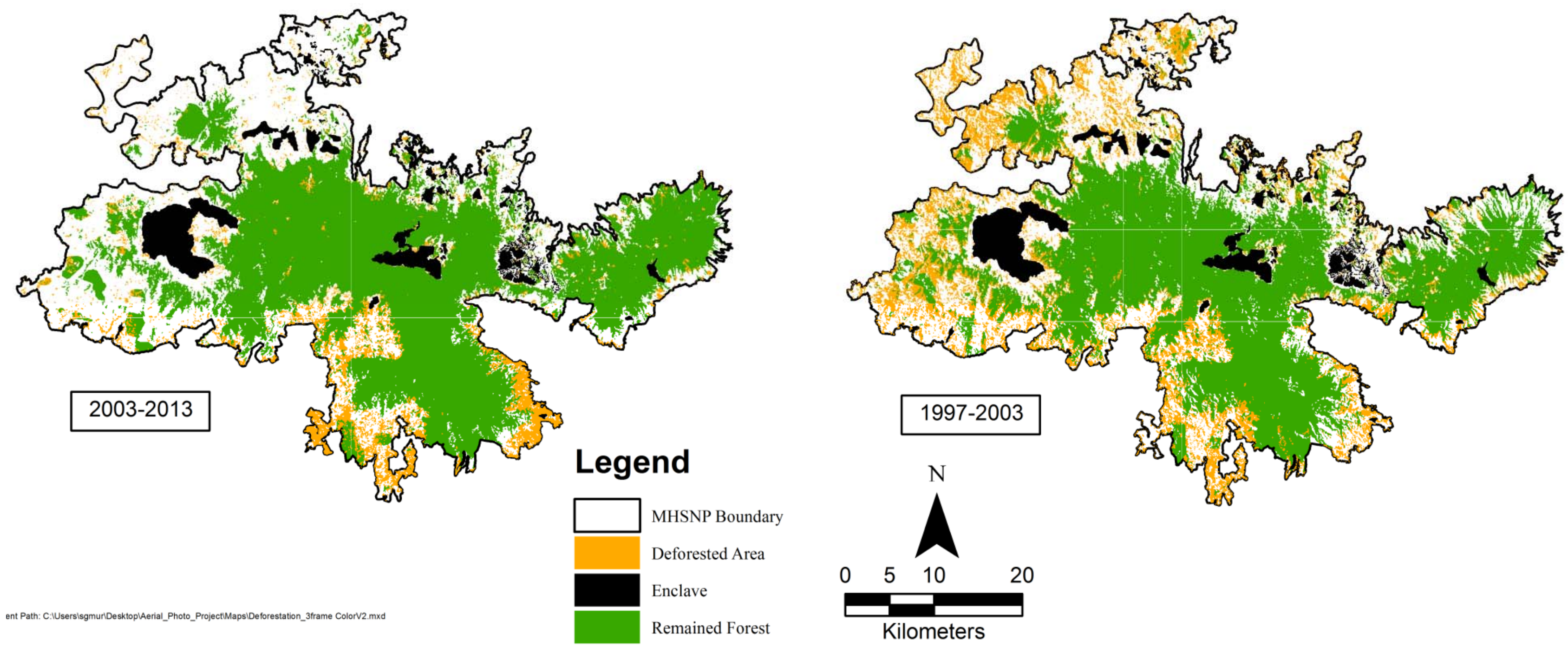


**Figure 4.C.1:** Deforestation across Mount Halimun Salak National Park for the time series 1997 – 2003 and 2003 – 2013. Forest areas which remained intact over the same time period are highlighted.

# Chapter 5

# Conclusions

## 5.1. Overview

Understanding the drivers of changes in total productivity across different scales, from the global tropical zone to the local level, require diverse investigation techniques capable of identifying the significant drivers of productivity at each reference scale. The growth of tropical forests still account for nearly half of the carbon emitted through anthropogenic activities each year but these forest communities continually face degradation from potential climate and land–use changes. Through studying of this ecosystem and the underlying processes, scientist can begin to identify those thresholds or tipping points where changes in site characteristics will alter the vegetation community of that site, resulting in a change in overall productivity and the potential loss of that forest and the habitats it supports. Often landscape level modeling neglects to integrate anthropogenic impacts within forested areas, only using climatic and edaphic conditions to predict productivity. Use of the local scale to detect human activity within a forested landscape, often represented and measured using rate of deforestation provides insight on how forested areas are impacted.

To determine the drivers of productivity over these different scales, from the global tropical zone to the local level, first a meta-analysis was conducted to identify site level conditions which determine productivity from a sample population distributed across the global tropical zone (Chapter 2). This research then explored the underlying assumptions which are imposed through the construction of a model to predict productivity across the country of Indonesia. This was important to explore since researchers use multiple resolution scales to assess the role of tropical forests in sequestering carbon. By varying the spatial sampling resolution and cell occupancy criteria, this research was able to understand how the distribution of dependent and independent variables were altered depending on the resolution scale of analysis (Chapter 3). Finally this research focused on the protected area of Mount Halimun Salak National Park in Indonesia to understand how anthropogenic activities impact the forested areas of the park. It also supported the idea that policy focusing on conservation planning developed with park inhabitants can result in conservation additionality when designating spatially explicit use zones for resource utilization activities by native peoples living within the park area (Chapter 4).

**5.2. Findings**

In the second chapter, edaphic and climatic variables were explored in order to identify changes in total productivity. It was hypothesized that a meta-analysis of tropical data would select a different set of multiple combinations of variables to explain changes in NPPt compared to focusing on analyzing data sorted into already presorted into groups with common modes of adaptation to precipitation gradients. The hypothesis that forests adaptation to climate change is less detectable if the multiple adaptation variables are not identified that are site specific. This means that different combinations of variables will detect changes in NPPt depending on the climatic and soil properties.

The creation of a binary regression tree using meta-data suggested that multiple combinations of variables are needed to detect NPPt thresholds where a forest becomes more or less resilient. Since plants do not respond to environmental stress as a whole plant but as changes in allocation to different parts of the plant, resilience has to measure plant adaptation to multiple variables and should be based on total production changes. Global forest data collected at the site or stand level should be used to identify optimal areas for REDD intervention (Harris et al. 2008) or REDD+ intervention, which is REDD which also includes conservation, sustainable forest management and enhancement of forest carbon stocks.

Results from Chapter 3 suggested that plotting the relationship of NPP to different climatic and terrestrial variables may provide the ability to refine multiple parameter-simulation models for estimating NPP. The study in Indonesian tropical production forests highlighted the multitude of driving variables that are part of the complex relationships that may be used to predict changes in productivity. This means that any multiple parameter simulation models must be able to determine the scale at which NPP changes are occurring to realistically model the impact of climate change and land-use changes on productivity. The use of *randomForest* enabled us to highlight how varying spatial sample resolutions can change the significance of different variables generated from the same source datasets. The use of different occupancy selection criteria may change the distribution of the sample population. Defining the sample set in different ways can impact the overall results of a statistical analysis, reinforcing the need for variability to be introduced into a model. Models continue to be the primary way to estimate climate scenarios or carbon sequestration potentials (Parry 2007). Within this study, the variation in variable interaction with differing model cell size highlights the need to test and compare model results at different spatial sampling resolutions and using different cell occupancy criteria.

Chapter 4 explored how continuing population growth in countries within the tropical forest zone will increase the demand for conversion or clearing of forested lands to agricultural production or for the extraction of natural resources (Wright, 2005). On the island of Java, which has historically seen a dramatic loss of its tropical forest area, the overall forest cover increased within MHSNP when local communities living in the park were allowed to manage designated zones for their own survival and to pursue economic activities. Areas which had the strictest conservation protection designations within MHSNP only lost 81.2 ha of total forested area from 2003 thru 2013 but the overall forested area grew by 12.9% within the spatially designated Core and Wildlife zones. The highest occurrence of deforestation have been within use zones specifically meant for resource extraction (e.g., Use, Rehabilitation and Special Research and Training zones) while those areas meant for strict conservation have the lowest level of deforestation (e.g., Core and Wildlife zones). Policy which localizes specific resource extraction to spatially designated area in MHSNP allowed local people legally living in the park access to additional resources if needed.

Chapter 4 demonstrated that use of satellite imagery to capture changes in forest area within a study area can evaluate the effectiveness of policy change and represents a method to continually evaluate the success of that policy. The continued development of policy, which balances use of forested lands by local people with conservation goals of international partners, could provide a successful framework for managing tropical forests that reduces the loss of forest cover. Evolution of policy to balance the goals of conservation with the needs of local peoples to access forest products within PAs can be seen within MHSNP. Targeted policy which localizes gathering of forest products by local people within specific areas helps to relieve pressures on other areas which may have higher biodiversity value.

### 5.3. Future Research

Future research on this topic would be the extension of the knowledge about thresholds or tipping points of tropical forest ecology to create scenario based models to understand potential impacts of climate and land cover change. The building of these scenarios would form a vulnerability assessment framework which could be used at the landscape level to address concerns of multiple stakeholder groups. This type of work would inform and affect the policy and management of natural resources using geospatial analysis methods, ecosystem sciences (e.g., integrating published meta-data with spatial data representing climatic and edaphic phenomena to define tipping points of forest productivity), physical sciences (e.g., hydrologic modeling, climate change outputs) and social/cultural inputs to develop an innovative communications protocol for distributing scientific information to the wider public using cloud based technologies. The creation of this framework would allow the synthesis of disparate data sources from across multiple scales to be evaluated using value systems from various stakeholder groups that include knowledge of ecosystem mechanisms. It will create and deliver actionable information directly to citizen scientists using emerging technologies from the computer sciences. It would also build upon this research using spatially-linked intensive science data sets to identify thresholds of productivity within social and natural systems, and to reveal system-level vulnerabilities in the face of disturbances and climate change. The tool would combine data intensive vulnerability assessments in a cloud-based infrastructure platform that can be queried and the results visualized. Access to such a tool by local decision-makers, managers and community members will allow them to work together using the same databases to identify vulnerable social/environmental hotspots and make appropriate scale-dependent decisions. A new framework could be crucial in further developing tools which would replace existing cumbersome analysis methods which are often unable to address social conflicts when science facts produce different conclusions.

## References


Abood, S.A., Lee, J.S.H., Burivalova, Z., Garcia-Ulloa, J., Koh, L.P. (2014) Relative contributions of the logging, fiber, oil palm, and mining industries to forest loss in Indonesia. *Conservation Letters*, Early View, 1-10

Aguiar, A.P.D., Ometto, J.P., Nobre, C., Lapola, D. M., Almeida, C., Vieira, I. C., Soares, J. V., Alvala, R., Saatchi, S., Valeriano, D., Castilla-Rubio, J. C. (2012) Modeling the spatial and temporal heterogeneity of deforestation-driven carbon emissions: the INPE-EM framework applied to the Brazilian Amazon. *Global Change Biology*, **18**, 3346-3366.

Aman. (2014). "Petition for MK No.35 Ruling and Indigenous Peoples Bill." Available at: http://www.aman.or.id/petition-for-mk-no-35-ruling-and-indigenous-peoples-bill/.

Anaya, C.A., García-Oliva, F., Jaramillo, V.J. (2007) Rainfall and labile carbon availability control litter nitrogen dynamics in a tropical dry forest. *Oecologia*, **150**, 602-610.

Aragão, L.E.O.C., Malhi, Y., Metcalfe, D.B., Silva-Espejo, J.E., Jiménez, E., Navarrete, D., Almeida, S., Costa, A.C.L., Salinas, N., Phillips, L.O. (2009) Above- and below-ground net primary productivity across ten Amazonian forests on contrasting soils. *Biogeosciences*, **6**, 2759-2778.

Barbosa, J.P.R.A.D., Rambal, S., Soares, A.M., Mouillot, F., Nogueira, J.M.P., Martins, G.A. (2012) Plant physiological ecology and the global changes. *Ciência e Agrotecnologia* **36**: 253–269.

Bellehumeur, C., Legendre, P., Marcotte, D. (1997) Variance and spatial scales in a tropical rain forest: changing the size of sampling units. *Plant Ecology* **130**(1): 89–98.

Berk, R.A. (2011) *Statistical Learning From a Regression Perspective*. New York, USA and London,UK: Springer.

BIG (2011) Badan Informasi Geospasial [www document]. URL http://www.bakosurtanal.go.id/

Biro Pusat Statistik (2012) *Statistical Yearbook of Indonesia.* Jakarta, Indonesia: BPS.

Blackman, A. (2013) Evaluating forest conservation policies in developing countries using remote sensing data: An introduction and practical guide. *Forest Policy and Economics Forest Policy and Economics*, **34**, 1-16.

Boyer, J.S. (1982) Plant productivity and environment. *Science*, **218**, 443-448.

Breiman, L. (2001) Random forests. *Machine Learning* **45**(1): 5–32.

Brown, S., Lugo, A.E. (1982) The storage and production of organic matter in tropical forests and their role in the global carbon cycle. *Biotropica*, **14**, 161-187.

Bruner, A.G. (2001) Effectiveness of Parks in Protecting Tropical Biodiversity. *Science*, **291**, 125-128.

Cao, M., Prince, S.D., Small, J., Goetz, S.J. (2004) Remotely sensed interannual variations and trends in terrestrial net primary productivity 1981-2000. *Ecosystems*, **7**, 233-242.

Carollo, C., Reed, D.J., Ogden, J.C., Palandro, D. (2009) The importance of data discovery and management in advancing ecosystem-based management. *Marine Policy* **33**(4): 651–653.

Castanho, A.D.A., Coe, M.T., Costa, M.H., Malhi, Y., Galbraith, D., Quesada, C.A. (2013) Improving simulated Amazon forest biomass and productivity by including spatial variation in biophysical parameters. *Biogeosciences*, **10**, 2255-2272.

Castilho, C.V., Magnusson, W.E., de Araújo, R.N.O., Luizao, R.C.C., Luizao, F.J., Lima, A.P., Higuchi, N. (2006) Variation in aboveground tree live biomass in a central Amazonian forest: Effects of soil and topography. *Forest Ecology and Management*, **234**, 85-96.

Chave, J., Andalo, C., Brown, S., Cairns, M.A., Chambers, J.Q., Eamus, D., Fölster H., Fromad, F., Higuchi, N., Kira, T. Lescure, J.P., Nelson, B.W., Ogawa, H., Puig H., Riéra, B., Yamakura T. (2005) Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia*, **145**, 87-99.

Clark, D.A., Brown, S., Kicklighter, D.W., Chambers, J.Q., Thomlinson, J.R., Ni, J., Holland, E.A. (2001) Net primary production in tropical forests: An evaluation and synthesis of existing field data. *Ecological Applications*, **11**, 371-384.

Clark, D.A., Piper, S.C., Keeling, C.D., Clark, D.B. (2003) Tropical rain forest tree growth and atmospheric carbon dynamics linked to interannual temperature variation during 1984-2000. *Proceedings of the National Academy of Sciences*, **100**, 5852-5857.

Cleveland, C.C., Townsend, A.R., Taylor, P., Alvarez-Clare, S., Bustamante, M.M.C., Chuyong, G., Dobrowski, S.Z., Grierson, P., Harms, K.E., Houlton, B.Z., Marklein, A., Parton, W., Porder, S., Reed, S.C., Sierra, C.A., Silver, W.L., Tanner, E.V.J., Wieder, W.R. (2011) Relationships among net primary productivity, nutrients and climate in tropical rain forest: a pan-tropical analysis. *Ecology Letters* **14**(9): 939–947.

Cramer, W., Kicklighter, D.W., Bondeau, A., Moore, B., Churkina, G., Nemry, B., Ruimy, A., Schloss, A.L. (1999) Comparing global models of terrestrial net primary productivity (NPP): overview and key results. *Global Change Biology* **5**(4): 1–15.

Cramer, W., Bondeau, A., Woodward, F.I., Prentice, I.C., Betts, R.A., Brovkin, V., Cox, P.M., Fisher, V., Foley, J.A., Friend, A.D., Kucharik, C., Lomas, M.R, Ramankutty, N., Sitch, S., Smith, B., White, A., Young-Molling, C. (2001) Global response of terrestrial ecosystem structure and function to $CO_2$ and climate change: results from six dynamic global vegetation models. *Global Change Biology* **7**(4): 357–373.

Cukjati, D., Robnik-Sikonja, M., Rebersek, S., Kononenko, I., Miklavcic, D. (2001) Prognostic Factors in the Prediction of Chronic Wound Healing by Electrical Stimulation. *Medical, Biological Engineering and Computing*, **395**, 542-550.

Curran L.M., Trigg S.N., Mcdonald A.K., Astiani D., Hardiono Y.M., Siregar P., Caniago I., Kasischke E. (2004). Lowland forest loss in protected areas of Indonesian Borneo. *Science*, **303**, 1000-1003

Cutler, D.R., Edwards, T.C., Beard, K.H., Cutler, A., Hess, K.T., Gibson, J., Lawler, J.J. (2007) Random forests for classification in ecology. *Ecology* **88**(11): 2783–2792.

Dai, L., Vorselen, D., Korolev, K.S., Gore, J. (2012) Generic indicators for loss of resilience before a tipping point leading to population collapse. *Science*, **336**, 1175-1177.

DeFries, R., Hansen, A., Newton, A.C., Hansen, M.C. (2005) Increasing isolation of protected areas in tropical forests over the past twenty years. *Ecological applications : a publication of the Ecological Society of America.*, **15**, 19.

DeFries, R., Karanth, K.K., Pareeth, S. (2010) Interactions between protected areas and their surroundings in human-dominated tropical landscapes. *Biological Conservation*, **143**, 2870-2880.

ENVI (2014) *Exelis Visual Information Solutions*. Exelis Visual Information Solutions.

Environmental Systems Research (2013) ESRI GIS, mapping software [www document]. URL http://www.esri.com/

ESA (2013) GlobCover [www document]. URL http://due.esrin.esa.int/globcover/

Everitt, B., Torsten, H. (2010) A Handbook of Statistical Analyses Using R. Boca Raton, CRC Press.

Ferraro, P.J., Hanauer, M.M., Miteva, D.A., Canavire-Bacarreza, G.J., Pattanayak, S.K., Sims, K.R.E. (2013) More strictly protected areas are not necessarily more protective: evidence from Bolivia, Costa Rica, Indonesia, and Thailand. *Environmental Research Letters* **8**,2.

Ferry, B., Morneau, F., Bontemps, J.D., Blanc, L., Freycon, V. (2010) Higher treefall rates on slopes and waterlogged soils result in lower stand biomass and productivity in a tropical rain forest. *Journal of Ecology*, **98**, 106-116.

Field, C., Merino, J., Mooney, H.A. (1983) Compromiser between water-use efficiency and nitrogen-use efficiency in five species of California evergreens. *Oecologica*, **60**, 384-389.

Field, C.B., Randerson, J.T., Malmstrom, C.M. (1995) Global net primary production. Combining ecology and remote-sensing. *Remote Sensing of Environment* **51**(1): 74–88.

Galudra, G. (2005) Land tenure conflicts in Halimun area: what are the alternative resolutions for land tenure conflicts? International Land Coalition, 10.

Garzón, M.B., Blazek, R., Neteler, M., Dios, R.S.d., Ollero, H.S., Furlanello, C. (2006) Predicting habitat suitability with machine learning models: the potential area of *Pinus sylvestris* L. in the Iberian Peninsula. *Ecological Modelling* **197**(3): 383.

Gaveau, D. L. A., Epting, J., Lyne, O., Linkie, M., Kumara, I., Kanninen, M., Leader-Williams, N. (November 01, 2009). Evaluating whether protected areas reduce tropical deforestation in Sumatra. *Journal of Biogeography*, **36**, 11, 2165-2175.

Geiger, D.R., Servaites, J.C. (1991) Carbon allocation and response to stress. In: Response of Plants to Multiple Stresses (ed. by H.A. Mooney, W.E. Winner, E.J. Pell, E. Chu), pp. 103-127. Academic Press, Inc. San Diego, New York, Boston.

Girardin, C.A.J., Malhi, Y., Aragão, L.E.O.C., Mamani, M., Huaraca Huasco, H., Durand, L., Feeley, K.J., Rapp, J., Silva-Espejo, J.E., Silman, M., Salinas, N., Whittaker, R.J. (2010) Net primary productivity allocation and cycling of carbon along a tropical forest elevational transect in the Peruvian Andes. *Global Change Biology*, **16**, 3176-3192.

Gmur, S., Vogt, D., Zabowski, D., Moskal, L.M. (2012) Hyperspectral analysis of soil nitrogen, carbon, carbonate, and organic matter using regression trees. *Sensors* **12**(12): 10639–10658.

Gmur S.J., Vogt D.J., Vogt K.A., Suntana A.S. (2013) Effects of different sampling scales and selection criteria on modelling net primary productivity of Indonesian tropical forests. *Environmental Conservation*, **41**, 2, 187-197

Gosz, J.R. (1992) Gradient analysis of ecological change in time and space: implications for forest management. *Ecological Applications* **2**(3): 248–261.

Gunawan, H., Chumsangsri, T., Lastini, T., Gunawan, W. (2007) *Policy in Compromising Ecological and Social Aspects for Establishing Halimun-Salak Corridor* Available at: http://www.helsinki.fi/vitri/research/Educational_Projects/forrsa/GIS_AL2_course%20proceedings/cd/Group%20report/gibbon%20group.pdf

Harada, K. (2005) Local use of agricultural lands and natural resources as the commons in Gunung Halimun National Park, West Java, Indonesia. *International Journal of Sustainable Development & World Ecology*, **12**, 34-47.

Hertel, D., Moser,G., Culmsee, H., Erasmi, S., Horna, V., Schuldt, B., Leuschner, C. (2009) Below- and above-ground biomass and net primary production in a paleotropical natural forest (sulawesi, Indonesia) as compared to neotropical forests. *Forest Ecology and Management* **258**(9): 1904–1912.

Holdridge, L.R. (1947) Determination of world plant formations from simple climatic data. *Science*, **105**, 367-368.

Inhibición de Deforestación e Incendios por Parques y Terrenos Indígenas en la Amazonia. *Conservation Biology*, **20**, 65-73.

Inoue, M., Isozaki, H. (2003) *People and forest : policy and local reality in Southeast Asia, the Russian Far East, and Japan*. Kluwer Academic, Dordrecht; Boston.

Jensen, J.R. (2005) *Introductory digital image processing : a remote sensing perspective*. Prentice Hall, Upper Saddle River, N.J.

Jha, C.S., Singh, J.S. (1990) Composition and dynamics of dry tropical forest in relation to soil texture. *Journal of Vegetation Science*, **1**, 609-614.

Joppa, L.N., Pfaff, A. (2009) High and Far: Biases in the Location of Protected Areas. *Plos One*, **4**, 6.

Joppa, L.N., Pfaff, A. (2011) Global protected area impacts. *Proceedings of the Royal Society B: Biological Sciences*, **278**, 1633-1638.

Kang, B.T., Tripathi, B. (2014) Technical Paper 1: Soil classification and characterization. http://www.fao.org/wairdocs/ilri/x5546e/x5546e04.htm (accessed 13 January 2014)

Kementerian Kehutanan (2011) Interactive Map Index of production forest [www document]. URL http://appgis.dephut.go.id/appgis/petaarahanpemanfaatan2.html

Kenzo, T., Ichie, T., Hattori, D., Itioka, T., Handa, C., Ohkubo, T., Kendawang, J.J., Nakamura, M., Sakaguchi, M., Takahashi, N., Okamoto, M., Tanaka-Oda, A., Sakurai, K., Ninomiya, I. (2009) Development of allometric relationships for accurate estimation of above- and below-ground biomass in tropical secondary forests in Sarawak, Malaysia. *Journal of Tropical Ecology*, **25**, 371-386.

Kitayama, K., Aiba, S.I. (2002) Ecosystem structure and productivity of tropical rain forests along altitudinal gradients with contrasting soil phosphorus pools on Mount Kinabalu, Borneo. *Journal of Ecology* **90**(1): 37–51.

Korhonen-Kurki, K., Brockhaus, M., Duchelle, A.E., Atmadja S., Thuy, P.T. (2012) Multiple levels and multiple challenges for REDD. Report. CIFOR. Analysing REDD+, 91, Chapter 6..

Kotkin, J. (2013) The World's Fastest-Growing Megacities. In: *Forbes*, Washington.

Kramer, P.J., Kozlowski, T.T. (1979) *Physiology of Woody Plants*. Orlando, FL, USA: Academic Press.

Kubo, H. (2008) Diffusion of policy discourse into rural spheres through co-management of state forestlands: two cases from West Java, Indonesia. *Environmental management*, **42**, 80-92.

Kubo, H. (2010a) From fence-and-fine to participatory conservation: mechanisms of transformation in conservation governance at the Gunung Halimun-Salak National Park, Indonesia. *Biodiversity and Conservation*, **19**, 1785-1803.

Kubo, H. (2010b) Understanding Discretionary Decision Making of Frontline Bureaucrats in State Forestland Management: A Case from Java, Indonesia. *Society & Natural Resources*, **23**, 240-253.

Larcher, W. (1975) *Physiological Plant Ecology*. Berlin, Germany: Springer-Verlag.

Laurance, W.F., Fearnside, P.M., Laurance, S.G., Delamonica, P., Lovejoy, T.E., Rankin-de Merona, J., Chambers, J.Q., Gascon, C. (1999) Relationship between soils and Amazon forest biomass: a landscape-scale study. *Forest Ecology and Management*, **118**, 127-138.

Lewis, R.J. (2000) An Introduction to Classification and Regression Tree (CART) Analysis. In: 2000 Annual Meeting of the Society for Academic Emergency Medicine, pp. 14.

Levin, S.A. (1993) 2: Concepts of scale at the local level. In: *Scaling Physiological Processes*, ed. R. Jacques, Ehleringer, J.R., Field, C.B.,, pp. 7–19. San Diego, CA, USA: Physiological Ecology, Academic Press.

Liaw, A., Wiener, M. (2002) Classification and regression by randomForest. *R News* **2**(3): 18–22.

Lieth, H. (1973) Primary production: terrestrial ecosystems. *Human Ecology*, **1**, 303-332.

Lovejoy, T., Bierregaard, R., Rylands, A., Malcolm, J., Quintela, C., Harper, L., Brown, K., Powell, A., Powell, G., Schubar, H., Hays, M. (1986) Edge and other effects of isolation on Amazon South America forest fragments. In: *Conservation Biology: The Science and Scarcity and Diversity*, Sinauer, p. 256. MA, USA: Sunderland.

Malhi, Y., Wood, D., Baker, T.R., Wright, J.S., Philips, O.L., Cochrane, T., Meir, P., Chave, Almeida, S., Arroyo, L., Higuchi, N., Killeen, T., Laurance, S., Laurance, W.F., Lewis, S.L., Monteagudo, A., Neill, D., Nunez Vargas, Pitman, N., Quesada C.A., Slamao, Silva, J. N., Torres-Lezama, A., Terborgh, J., Vasquez, M. R., Vinceti, B.(2006). The regional variation of aboveground live biomass in old-growth Amazonian forests. *Global Change Biology*, **12**, 1107-1138.

Malhi, Y., Aragão, L.E.O.C., Metcalfe, D.B., Paiva, R., Quesada, C.A., Almeida, S., Anderson, L., Brando, P., Chambers, J.Q., Da Costa, L.A.C., Hutyra, L.R., Oliveira, P., Patiño, S., Pyle, E.H., Robertson, A.L., Teixeira, L.M. (2009) Comprehensive assessment of carbon productivity, allocation and storage in three Amazonian forests. *Global Change Biology*, **15**, 1255-1275.

Malhi, Y., Doughty, C., Galbraith, D. (2011) The allocation of ecosystem net primary productivity in tropical forests. Philosophical Transactions of Royal the Society B: *Biological Sciences*, **366**, 3225-3245.

McDowell, N., Pockman, W.T., Allen, C.D., Breshears, D.D., Cobb, N., Kolb, T., Plaut, J., Sperry, J., West, A., Williams, D.G., Yepez, E.A. (2008) Mechanisms of plant survival and mortality during drought: why do some plants survive while others succumb to drought? *New Phytologist*, **178**, 719-739.

Melillo, J.M., McGuire, A.D., Kicklighter, D.W., Moore, B., Vorosmarty, C.J., Schloss, A.L. (1993) Global climate change and terrestrial net primary production. *Nature* **363**(6426): 234–240.

Moorcroft, P.R., Hurtt, G.C., Pacala, S.W. (2001) A method for scaling vegetation dynamics: the Ecosystem Demography model (ED). *Ecological Monographs* **71**(4): 557–586.

Moser, G., Leuschner, C., Hertel, D., Graefe, S., Soethe, N., Lost, S. (2011) Elevation effects on the carbon budget of tropical mountain forests (S Ecuador): the role of the belowground compartment. *Global Change Biology* **17**(6): 2211–2226.

Mulyana, A., Moeliono, M., Minnigh, P., Indriatmoko, Y., Limberg, G. (2010) Establishing special use zones in national parks. *Center for International Forestry Research Briefs*, 1-6.

Naidoo, R., Balmford, A., Costanza, R., Fisher, B., Green, R.E., Lehner, B., Malcolm, T.R., Ricketts, T.H. (2008) Global mapping of ecosystem services and conservation priorities. *Proceedings of the National Academy of Sciences USA* **105**(28): 9495–9500.

NASA (2013*a*) Earth Observing System Data and Information System [www document]. URL http://reverb.echo.nasa.gov/reverb/

NASA (2013*b*) Shuttle Radar Topography Mission [www document]. URL http://www2.jpl.nasa.gov/srtm/

NASA (2013*c*) Earth Observatory [www document]. URL http://earthobservatory.nasa.gov/

Naughton-Treves, L., Holland, M.B., Brandon, K. (2005) The role of protected areas in conserving biodiversity and sustaining local livelihoods. *Annual Review of Environment and Resources*, pp. 219-252. Annual Reviews, Palo Alto.

Nawir, A.A., Murniati, Rumboko, L. (2007) *Forest rehabilitation in Indonesia: where to after three decades?* Center for International Forestry Research (CIFOR), Bogor, Indonesia.

Inhibición de Deforestación e Incendios por Parques Oliveira-Filho, N., Curi, A., Vilela, E.A., Carvalho, D.A. (1998) Effects of canopy gaps, topography, and soils on the distribution of woody species in a Central Brazilian deciduous dry forest. *Biotropica*, **30**, 362-375.

Palmiotto, P.A., Davies, S.J., Vogt, K.A., Ashton, M.S., Vogt, D.J., Ashton, P.S. (2004) Soil-related habitat specialization in dipterocarp rain forest tree species in Borneo. *Journal of Ecology*, **92**, 609-623.

Paoli, G.D., Curran, L.M., Slik, J.W.F. (2008) Soil nutrients affect spatial patterns of aboveground biomass and emergent tree density in southwestern Borneo. *Oecologia*, **155**, 287-299.

Parry, M.L. (2007) *Climate Change 2007: Impacts, Adaptation and Vulnerability : Contribution of Working Group Ii to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK: Cambridge University Press..

Phillips, O.L., Malhi, Y., Higuchi, N., Laurance, W.F., Nunez, P.V., Vasquez, R.M., Laurance, S.G., Ferreira, L.V., Stern, M., Brown, S., Grace, J. (1998) Changes in the carbon balance of tropical forests: Evidence from long-term plots. *Science*, **282**, 439-442.

Phillips OL, van der Heijden G, Lewis SL, López-González, G., Aragão, L.E.O.C., Lloyd, J.J., Malhi, Y., Monteagudo, A., Almeida, S., Dávila, E.A., Andelman, S., Andrade, A., Arroyo, L., Aymard, G., Baker, T.R., Blanc, L., Bobal, D., de Oliveira, A.C.A., Chao, K.-J., Cardozo, N.D., da Costa, L., Feldpausch, T.R., Fisher, J.B., Fylla, N.M., Freitas, M.A., Galbraith, D., Gloor, E., Higuchi, N., Honorio, E., Jiménez, E., Keeling, H., Killeen, T.J., Lovett, J., Meir, P., Mendoza, C., Morel, A., Vargas, P.N., Patiño, S., Peh, Kelvin S.-H., Cruz, A.P., Prieto, A., Quesada, C.A., Ramírez, F., Ramírez, H., Rudas, A., Salamão, R., Schwarz, M., Silva, J., Silveira, M., Slik, J.W.F., Sonké, B., Thomas, A.S., Stropp, J., Taplin, J., Vásquez, R., Vilanova, E. (2010) Drought-mortality relationships for tropical forests. *New Phytologist*, **187**, 631-646.

Porter-Bolland, L., Ellis, E.A., Guariguata, M.R., Ruiz-Mallén, I., Negrete-Yankelevich, S., Reyes-García, V. (2012) Community managed forests and forest protected areas: An assessment of their conservation effectiveness across the tropics. *Forest Ecology and Management*, **268**, 6-17.

Potapov, P., Yaroshenko, A., Turubanova, S., Dubinin, M., Laestadius, L., Thies, C., Aksenov, D., Egorov, A., Yesipova, Y., Glushkov, I., Karpachevskiy, M., Kostikova, A., Manisha, A., Tsybikova, E., Zhuravleva, I. (2008) Mapping the World's Intact Forest Landscapes by Remote Sensing. *Ecology and Society*, **13**, 16.

Prasetyo, L., Setiawan, Y., Miura, K. (2010) Land-use & Land cover Changes during Regional Decentralization Policy Implementation: Study Case at Halimun National Park, Indonesia. IPB (Bogor Agricultural University

Richards, J.A., Xiuping, J. (2006) *Remote sensing digital image analysis : an introduction*. Springer, Berlin.

Richardson, A.D., Anderson, R.S., Arain, M.A., Barr, A.G., Bohrer, G., Chen, G., Chen, J.M., Ciais, P., Davis, K.J., Desai, A.R., Dietze, M.C., Dragoni, D., Garrity, S.R., Gough, C.M., Grant, R., Hollinger, D.Y., Margolis, H.A., McCaughey, H., Migliavacca, M., Monson, R.K., Munger, J.W., Poulter, B., Raczka, B.M., Ricciuto, D.M., Sahoo, A.K., Schaefer, K., Tian, H., Vargas, R., Verbeeck, H., Xiao, J., Xue, Y. (2012) Terrestrial biosphere models need better representation of vegetation phenology: results from the North American Carbon Program Site Synthesis. *Global Change Biology* **18**(2): 566–584.

Running, S.W., Nemani, R., Glassy, J.M., Thornton, P.E. (1999) MODIS daily photosynthesis (PSN) and annual net primary production (NPP) product (MOD17) Algorithm Theoretical

Basis Document. SCF At-Launch Algorithm ATBD Documents, University of Montana, USA [www document]. URL http://www. ntsg. umt. edu/modis/ATBD/ATBD_MOD17_v21. pdf

Running, S.W., Nemani, R.R., Heinsch, F.A., Zhao, M., Reeves, M., Hashimoto, H. (2004) A continuous satellite-derived measure of global terrestrial primary production. *BioScience* **54**(6): 547–560.

Russo, S.E., Davies, S.J., King, D.A., Tan, S. (2005) Soil-related performance variation and distributions of tree species in a Bornean rain forest. *Journal of Ecology*, **93**, 879-889.

Sanchez, P.A. (1982) Properties and Management of Soils in the Tropics. John Wiley, Sons, New York.

Sanchez-Azofeifa, G.A., Daily, G.C., Pfaff, A.S.P., Busch, C. (2003) Integrity and isolation of Costa Rica's national parks and biological reserves: examining the dynamics of land-cover change. *Biological Conservation*, **109**, 123-135.

Schmitt, C.B., Burgess, N.D., Coad, L., Belokurov, A., Besancon, C., Boisrobert, L., Campbell, A., Fish, L., Gliddon, D., Humphries, K., Kapos, V., Loucks, C., Lysenko, I., Miles, L., Mills, C., Minnemeyer, S., Pistorius, T., Ravilious, C., Steininger, M., Winkel, G. (2009) Global analysis of the protection status of the world's forests. *Biological Conservation*, **142**, 2122-2130.

Schuur, E.A., Matson, P.A. (2001) Net primary productivity and nutrient cycling across a mesic to wet precipitation gradient in Hawaiian montane forest. *Oecologia*, **128**, 431-442

Scullion, J.J., Vogt, K.A., Sienkiewicz, A., Gmur, S.J., Trujillo, C. (2014) Assessing the influence of land-cover change and conflicting land-use authorizations on ecosystem conversion on the forest frontier of Madre de Dios, Peru. BIOC Biological Conservation **171**, 247-258.

Sekhon, J.S. (2011) Multivariate and Propensity Score Matching Software with Automated Balance Optimization: The Matching Package for R. *Journal of Statistical Software*, **42**, 1-52.

Singh, H.S., Gibson, L. (2011) A conservation success story in the otherwise dire megafauna extinction crisis: The Asiatic lion (Panthera leo persica) of Gir forest. Biological Conservation **144**, 1753-1757.

Sodhi, N.S., Butler, R., Laurance, W.F., Gibson, L. (2011) Conservation successes at micro-, meso- and macroscales. Trends in Ecology & Evolution **26**, 585-594.

Soil Survey Staff (1999) Soil taxonomy: A basic system of soil classification for making and interpreting soil surveys. 2nd Edition. United States Department of Agriculture. 436p.

Soil Survey Staff (2010) Keys to Soil Survey. United States Department of Agriculture, Natural Resources Conservation Service. Eleventh Edition, 2010. ftp://ftp-fc.sc.egov.usda.gov/NSSC/Soil_Taxonomy/keys/2010_Keys_to_Soil_Taxonomy.pdf, accessed 12 October 2012.

Solomon, S. (2007) *Climate Change 2007: The Physical Science Basis: Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge, UK: Cambridge University Press.

Steenis, C.G.G.J.V., Hamzah, A., Toha, M., (2006) The mountain flora of Java. Brill, Leiden; Boston.

Suntana, A., Vogt, K., Turnblom, E., Vogt, D., Upadhye, R. (2013*a*) Non-traditional use of biomass at certified forest management units in Indonesia: Forest biomass for energy production and carbon emissions reduction. *Journal of International Forest Research* (in press).

Suntana, A.S., Turnblom, E.C., Vogt, K.A. (2013*b*) Addressing unknown variability in seemingly fixed national forest estimates: aboveground forest biomass for renewable energy. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects* **35**(6): 546–555.

Supriatna, J. (2006) Conservation Programs for the Endangered Javan Gibbon (Hylobates moloch). *Primate Conservation Primate Conservation*, **21**, 155-162.

Steege, H., Jetten, V.G., Polak, A.M., Werger, M.J.A. (1993) Tropical rain forest types and soil factors in a watershed area in Guyana. *Journal of Vegetation Science*, **4**, 705-716.

Tan, K.H. (2008) *Soils in the Humid Tropics and Monsoon Region of Indonesia*. Boca Raton, FL, USA.: CRC Press.

Tan, Z., Zhang, Y., Yu, G., Sha, L., Tang, J., Deng, X., Song, Q. (2010) Carbon balance of a primary tropical seasonal rain forest. *Journal of Geophysical Research*, **115**, 1-17.

TEBTEBBA (2012). Indonesian Constitutional Court's Decision regarding the 1999 Forestry Law Baguio City, Indigenous People's International Centre for Policy Research and Education. Available at: http://www.tebtebba.org/index.php/all-resources2/all-resources-menu-2?download=885:indonesian-constitutional-courts-decision-regarding-the-1999-forestry-law

Therneau, T.M., Atkinson, B., Ripley, B. (2011) *rpart: Recursive Partitioning*. //CRAN.R-project.org/packageIrpart, accessed November 1, 2012.

Therneau, T.M., Atkinson EJ (2011) An introduction to recursive partitioning using the RPART routines. *Mayo Foundation*, January 11.

Tittonell, P., Vanlauwe, B., Shepherd, K.D., Giller, K.E. (2008) Unravelling the effects of soil and crop management on maize productivity in smallholder agricultural systems of western

Kenya-An application of classification and regression tree analysis. *Agriculture, Ecosystems and Environment*, **123**, 137-150.

Turner, D.P., Ritts, W.D., Cohen, W.B., Gower, S.T., Running, S.W., Zhao, M.S., Costa, M.H., Kirschbaum, A.A., Ham, J.M., Saleska, S.R., Ahl, D.E. (2006) Evaluation of MODIS NPP and GPP products across multiple biomes. *Remote Sensing of Environment* **102**(3–4): 282–292.

USGS (2014) *GLOVIS*. Available at: http://glovis.usgs.gov/ (accessed 2013 2013).

Verburg, P.H., Veldkamp, T., Bouma, J. (1999) Land use change under conditions of high population pressure: the case of Java. Global Environmental Change Global Environmental Change **9**, 303-312.

Vogt, K., Vogt, D., Brown, S., Tilley, J., Edmonds, R., Silver, W., Siccama, T. (1995) Forest floor and soil organic matter contents and factors controlling their accumulation in boreal, temperate and tropical forests. In: Advances in Soil Science, Soil Management and Greenhouse Effect (ed. by R. Lal, J. Kimble, E. Levine, B.A. Stewards), pp. 159-178. CRC Press. Boca Raton, Florida.

Vogt, K.A., Vogt, D.J., Palmiotto, P., Boon, P., O'Hara, J., Asbjornsen, H. (1996) Review of root dynamics in forest ecosystems grouped by climate, climatic forest type and species. *Plant and Soil*, **187**, 159-219.

Vogt, K.A., Gordon, J., Wargo, J., Vogt, D., Asbjornsen, H., Palmiotto, P.A., Clark, H., O'Hara, J., Keeton, W.S., Patel-Weynand, T., Witten E., with contributions by Larson, B., Tortoriello, D., Perez, J., Marsh, A., Corbett, M., Kaneda, K., Meyerson, F., Smith D. (1997) *Ecosystems: Balancing Science with Management*. New York, NY, USA: Springer-Verlag.

Vogt, K.A., Patel-Weynand, T., Shelton, M., Vogt, D.J., Gordon, J.C., Mukumoto, C., Suntana, A.S., Roads, P.A. (2010) *Sustainability Unpacked : Food, Energy and Water for Resilient Environments and Societies*. London, UK and Washington, DC, USA: Earthscan.

Wang, S., Wilson, B. (2007) Pluralism in the Economics of Sustainable Forest Management. Forest Policy and Economics 9, 743-750.

Wiharisno, J. 2010. Evaluasi Ketersediaan Data dan Informasi Ekologi untuk Penilaian Kinerja Pengelolaan Taman Nasional Gunung Halimun-Salak (Evaluation on the Availability of Ecological Data and Information for the Performance Valuation of Gunung Halimun-Salak National Park Management). Master Thesis. Graduate School, Bogor Agricultural University (IPB), Bogor.

Wright, S.J. (2005) Tropical forests in a changing environment. *Trends in Ecology & Evolution*, **20**, 553-560.

Yuan, Z.Y., Chen, H.Y.H. (2009) Global-scale patterns of nutrient resorption associated with latitude, temperature and precipitation. *Global Ecology and Biogeography*, **18**, 11-18.

Zar, J.H. (1999) *Biostatistical Analysis*. Upper Saddle River, NJ, USA: Prentice Hall.

Zelazowski, P., Malhi, Y., Huntingford, C., Sitch, S., Fisher, J.B. (2011) Changes in the potential distribution of humid tropical forests on a warmer planet. Philosophycal Transaction of the Royal Society A: *Mathematical, Physical and Engineering Sciences*, **369**, 137-160.

Zhao, M.S., Heinsch, F.A., Nemani, R.R., Running, SW. (2005) Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sensing of Environment* **95**(2): 164–176.