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Forest carbon management in mangroves and monoculture plantations

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Forest carbon management in mangroves and monoculture plantations

by

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Abstract

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Restoring forest cover is a prominent strategy for offsetting emissions of greenhouse gases. When done appropriately, restoring forest cover can remove atmospheric carbon dioxide and confer non-carbon benefits such as biodiversity conservation, ecosystem service provisioning, or direct economic returns to local communities. Although a range of pathways exist for restoring forest cover, two prominent avenues have caught the attention of decision-makers and investors across the globe: blue carbon and plantations. The three chapters of my dissertation consequently examine the degree to which mangroves, a prominent blue carbon ecosystem, and monoculture plantations, the dominant approach for restoring forest cover, can meet our climate change goals.

In the **first chapter** of my dissertation, I compare and critically assess estimates of carbon stocks in mangroves using i) empirical field data, and ii) outputs of predictive models at global scales. Global maps of carbon stocks are increasingly used to inform environmental management, policy, and decision-making, but may produce biased estimates of mangrove carbon stocks at local scales. My findings suggest that although global maps of mangrove carbon perform well at regional scales, comparison with empirical field data at local scales identifies statistically significant differences in carbon stocks. The results suggest that despite recent advances in computing power, compilation of global datasets, and remote sensing, empirical measurements of mangrove carbon stocks will remain key to informed decision-making at local scales.

My **second chapter** examines a critical question for mangrove conservation and restoration policy-making: are the carbon stocks of deforested mangroves recoverable over time scales meaningful for mitigating climate change? Deforestation of mangroves induces massive carbon emissions from the soil organic carbon pool; however, the pace at which these soil organic carbon stocks are recovered following reforestation is unclear. Using high resolution spatial datasets of land cover and land use change over the last 20 years and models of carbon stock loss and gain in mangroves, I use scenario analysis to examine the net balance of carbon

stocks associated with mangrove gain and loss within Thailand. My findings indicate that in areas where regenerating mangroves are commonly re-cleared, carbon stock losses may be four-fold greater than what net change in mangrove extent statistics would otherwise suggest.

Finally, my **third chapter** turns to monoculture plantations, the dominant approach for restoring forest cover globally. Approximately two thirds (66%) of high-level commitments in the tropics for forest restoration involve planting and almost half (45%) involve the establishment of monoculture plantations. Despite the prominence of this approach, the science and policy communities lack systematic understanding of the degree to which monoculture plantations can meet climate change mitigation goals. Thus, my colleagues and I compiled a database of approximately 3,500 empirical estimates of aboveground carbon in monoculture plantations across the globe. I then used this database to examine variation in growth patterns as well as the key drivers that mediate this growth. I used nonlinear growth curves to more accurately model the accumulation of aboveground carbon stocks with time, which I found to vary substantially by genus of tree and plant functional type. Furthermore, I found factors such as genus, endemism, prior land use, and plant traits to strongly mediate carbon accumulation in monoculture plantations, whereas factors such as biome were found to have little effect.

Taken comprehensively, the chapters of my dissertation critically assess the scientific datasets and approaches that are guiding actions and commitments within the reforestation space. The chapters employ data that have been collected through in situ forest inventories, predictive modeling, and government programs, as well as methodological approaches such as statistical modeling and data synthesis. The findings provide key insights such as i) improved understanding of a critical uncertainty (i.e., the recoverability of mangrove carbon stocks) for investors in reforestation of blue carbon ecosystems, as well as ii) improved understanding of carbon accumulation patterns in global monoculture plantations. I anticipate that these findings will facilitate improved environmental outcomes from reforestation efforts, which are rapidly scaling across the globe.

For my dad.

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Acknowledgments

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Matthew Potts has been both an unwavering source of encouragement and a sounding board for the development of my ideas over the last five years. I am enormously grateful for him for his quick, insightful feedback and his open-ears approach to all the requests I have made of him. My intellect has grown enormously under his watch and I look forward to continuing our work in future collaborations. Thank you also to Greg and Iryna, for their support, advice, and feedback on my work over the last five years. They have given generously with no expectations in return and have always been encouraging as I have sought out different approaches to my research.

Thanks to the many collaborators who have been instrumental to both this dissertation as well as my professional development: Mark Ashton, Jeremy Broadhead, Susan Cook-Patton, Angie Elwin, Jim Enright, David Ganz, Shabbir Gheewala, Uromi Goodale, Tim Gregoire, Rich Mackenzie, Wijarn Meepol, Colin Strine, and Jeff Vincent, among others. Each of these individuals has taken a chance on me and I am enormously grateful for the support and opportunities that they have given me. In particular, thank you to Tim G. and Mark for all of their support and guidance during my Master's degree, which has been formative for my doctoral work. Thank you also to David for taking a chance on me and giving a leg-up to a random field tech chasing snakes in Northeast Thailand. Though he may not know it, the constant support and opportunities he has provided me have not only shaped this dissertation, but also my development as a scientist.

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Chapter 1

Introduction

1.1 Motivation

Mitigating climate change through the conservation and expansion of forests is a long-standing idea that has taken various forms over the last few decades. Two key reasons drive the interest in using forests to mitigate greenhouse gas emissions. First, conversion of forest to non-forest land cover types induces large emissions of organic carbon that are currently sequestered in biomass and soils. Second, the continued or new growth of forests sequesters carbon in biomass and soils, producing a large draw-down of atmospheric carbon dioxide at relatively low cost. Most recently, interest in the climate change mitigation potential of forests has focused on quantifying the potential climate benefits associated with forest conservation and expansion at global scales.

Within the current forests and climate arena, two types of actions are prominent: first, the conservation and restoration of mangroves, a ”blue carbon” ecosystem; and second, expansion of forest cover with monoculture plantations. Mangroves, the intertidal forests that exist along most tropical and subtropical coastlines, are carbon-rich ecosystems that have disproportionate impacts on the climate relative to their spatial extent. As a result of this, there is widespread interest in investing in their conservation and restoration [152]. Monoculture plantations, on the other hand, are less carbon rich ecosystems; however, establishment of monoculture plantations is currently the dominant commitment to restoring forest cover across the globe [92]. Furthermore, monoculture plantations are controversial because they can adversely impact local environments when poorly implemented and have relatively minor biodiversity value relative to naturally regenerated forests.

Despite the prominence of these two actions, there remains substantial uncertainty around the degree to which mangroves and monoculture plantations can meet the climate change mitigation goals of the international community. For example, while it is relatively well-understood that the conversion of mangroves to other land uses, such as shrimp farming, can induce massive emissions of organic carbon to the atmosphere, it is currently unclear how quickly carbon stocks are recovered upon reforestation. While some suggest that restored mangroves may recover the same carbon stocks as reference forests within 7-17 years [117], others suggest that recovery of carbon stocks in organic soils may take centuries [79]. For monoculture plantations, one key uncertainty is whether these systems sequester carbon faster than naturally regenerating forests, which is a reforestation pathway that is commonly lower cost that planting and therefore potentially easier to scale.

Given this context, the overarching goal of this dissertation was to improve our understanding of the degree to which mangroves and monoculture plantations might meet international goals to mitigate climate change. Specifically, I sought to answer three key research questions:

1. *How accurate are predictive models of standing carbon stocks in extant mangroves?*
2. *Are ecosystem carbon stocks in deforested mangroves recoverable over meaningful timeframes for climate change mitigation?*
3. *How quickly does carbon accumulate in monoculture plantations and how variable are these rates of accumulation across the globe?*

Answers to these questions are of direct relevance for actors and decision-makers in both the public and private sectors. As such, the major findings of this dissertation are highly applied in nature. In recognizing this, I have tried to situate my results by commenting on their implications for environmental management and policy-making as much as possible.

1.2 Structure

The three chapters that form the body of my dissertation correspond to each of the three key research questions listed above. Chapters 2 and 3 are focused on mangrove ecosystems, whereas Chapter 4 is focused on monoculture plantations. Each of these chapters is focused at broad, but varying, geographic scales: Chapter 2 is focused at the site level for five mangrove forests spread across the globe, Chapter 3 is focused on the whole of Thailand, and Chapter 3 is focused on global patterns in monoculture plantations. The scale of each chapter not only reflects that of the research question, but also the decision-making community that would be most interested in the results.

In Chapter 2, I compared and critically assessed two approaches for estimating baseline carbon stocks in mangroves. Specifically, I compared estimates of ecosystem carbon stocks that have been derived from field-based forest inventories versus global maps of carbon stocks that have been produced by predictive modeling. Understanding of how estimates of carbon stocks vary between the two approaches is critical for forest carbon programs. On the one hand, field-based estimates are the conventional approach and are typically seen to be more accurate than other methods; however, they are resource intensive given accessibility constraints in mangrove ecosystems. On the other hand, global maps of mangrove carbon stocks may be less accurate than field-based inventories, but are highly valuable for countries or programs that do not have the resources to run field-based inventories. The accuracy of these global maps is consequently of high interest for the development of mangrove forest carbon programs, as their use could help reduce costs in the development and establishment of such programs. I conducted this analysis using the three-tier framework of the Intergovernmental Panel on Climate Change, the foremost authority on carbon accounting within the land use sector.

In Chapter 3, I examine the climate impacts of land use and land cover change in Thailand's mangroves. Mangroves are among the most carbon rich ecosystems globally and their deforestation induces large emissions of carbon to the atmosphere, mostly from their soils. However, it is less clear how quickly these dense carbon stocks can be recovered if areas that were formerly mangroves are reforested. Although others have examined this question, they have used carbon stock recovery curves that are derived from data in all blue carbon ecosystems (i.e. including sea grasses and salt marshes) that are unlikely to accurately represent carbon stock recovery in mangroves. Thus, I re-examined these dynamics for the case of Thailand, a country that has lost large extents of mangrove and is interested in their reforestation as part of their Nationally Determined Contribution to the 2015 Paris Agreement. The specific objectives of this study were to i) assess whether data specific to carbon stock recovery in mangrove ecosystems produced different findings relative to blue carbon ecosystems more broadly, ii) assess whether net loss-of-area statistics for changes in mangrove extent mask greenhouse gas emissions in areas of dynamic land use change, and iii) quantify the potential of mangrove reforestation to contribute to Thailand's Nationally Determined Contribution.

I turn to monoculture plantations in my fourth chapter. Monoculture plantations are controversial because they can have adverse impacts on local environments when implemented poorly and may have limited biodiversity value relative to natural forests. However, they currently account for the vast majority of commitments by global actors to expand forest cover, including up to 45% of those in the tropics. Although understanding of growth rates and the factors that mediate this growth are well-known for localized systems (e.g., slash pine in the Southern United States), we lack synthetic understanding of growth rates in monoculture plantations, variation in these rates, and the factors that mediate these rates of growth at global scales. Understanding of this is key because mitigating climate change is a primary motivation for expanding monoculture plantations globally and rates of growth directly describe the rate at which carbon accumulates within plantation systems. I therefore compiled a large database of aboveground carbon estimates in monoculture plantations across the globe and used this database to i) fit theoretically defensible growth curves to describe the accumulation of carbon in monoculture plantations across time, ii) examine how this carbon accumulation varies across geographic regions, genus of tree crop, and type of tree, and iii) examine the factors that mediate variation in growth rates across spatial scales. The results provide foundational understanding of the degree to which widespread investments in planting forests can meet our climate change goals.

Finally, in Chapter 5, I provide concluding thoughts on the key results of this dissertation as well as their implications for forest carbon management and decision-making. Taken comprehensively, they represent a synthetic examination of two key avenues for mitigating climate change with forests: conservation and reforestation of mangroves and the expanded planting of monoculture plantations. As with most research projects, the findings of the chapters have opened more questions than those that they have answered. I consequently conclude my dissertation by providing thoughts on future research directions that would continue to refine our understanding of forest carbon management at a range of geographic scales.

1.3 Other relevant work

The chapters in this dissertation directly respond to the objectives described above. However, I have also undertaken a number of other research collaborations during my doctoral studies that parallel the goals of this dissertation. These studies have taken the form of peer-reviewed publications, working papers for international forestry agencies, and a special issue collection for the *Journal of Sustainable Forestry.*

The publications that support this dissertation but are not directly included are:

- Rovai, A.S., Twilley, R.R., Castañeda-Moya, E., Midway, S.R., Friess, D.A., Trettin, C.C., **Bukoski, J.J.**, et al. 2020. Macroecological patterns and drivers of mangrove forest structure and carbon stocks across biogeographic regions and coastal morphologies. *Global Ecology and Biogeography* 30(5): 1000-1013. doi: /10.1111/geb.13268
- Elwin, A., **Bukoski, J.J.**, Jintana, V., Robinson, E.J.Z., and J. Clark. 2019. Preservation and recovery of mangrove ecosystem carbon stocks in abandoned shrimp ponds. *Scientific Reports* 9: 18275. doi: 10.1038/s41598-019-54893-6
- Sanderman, J., Hengl, T., Fiske, G., Solvik, K., Adam, M.F., Benson, L., **Bukoski, J.J.**, et al. 2018. A global map of mangrove forest soil carbon at 30 m spatial resolution. *Environmental Research Letters*. doi: 10.1088/1748-9326/aabe1c
- **Bukoski, J.J.**, Drazen, E., Johnson, W.R., and Swamy, L. 2018. Tropical forests for sustainable development: Shaping the 2030 Agenda for Sustainable Development with knowledge from the field. *Journal of Sustainable Forestry* 37(2): 77-81. doi: 10.1080/10549811.2018.1418255
- Swamy, L., Drazen, E., Johnson, W.R., and **Bukoski, J.J.** 2017. The future of tropical forests under the United Nations Sustainable Development Goals. *Journal of Sustainable Forestry* 37(2): 221-256. doi: 10.1080/10549811.2017.1416477
- **Bukoski, J.J.**, Broadhead, J.S., Donato, D.C., Kauffman, J.B., Murdiyarso, D., and Gregoire, T.G. 2017. The use of mixed effect models for obtaining low-cost ecosystem carbon stock estimates in mangroves of the Asia-Pacific. *PLoS ONE* 12(1): e0169096. DOI: 10.1371/journal.pone.0169096

- Broadhead, J.S., **Bukoski, J.J.** and Beresnev, N. 2016. Mangrove carbon stock estimator and monitoring guide. United Nations Food and Agricultural Organization, Regional Office for the Asia Pacific (UN FAO-RAP) & International Union for the Conservation of Nature (IUCN).

Additionally, the first chapter of my thesis has been published in *Environmental Research Letters* with minor differences from the version that is published here.

- **Bukoski, J.J.**, Elwin, A., MacKenzie, R.A., Sharma, S., Purbopuspito, J., Kopania, B., Apwong, M., Poolsiri, R., and M.D. Potts. 2020. The role of predictive model data in designing mangrove forest carbon programs. *Environmental Research Letters*. doi: 10.1088/1748-9326/ab7e4e

I anticipate that the second and third chapters will be published in peer-reviewed journals shortly after the completion of this dissertation.

Chapter 2

The role of predictive model data in designing mangrove forest carbon programs

With Angie Elwin, Richard A. MacKenzie, Sahadev Sharma, Joko Purbopuspito, Benjamin Kopania, Maybeleen Apwong, Roongreang Poolsiri, and Matthew D. Potts.

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Abstract

Estimating baseline carbon stocks is a key step in designing forest carbon programs. While field inventories are resource-demanding, advances in predictive modeling are now providing globally coterminous datasets of carbon stocks at high spatial resolutions that may meet this data need. However, it remains unknown how well baseline carbon stock estimates derived from model data compare against conventional estimation approaches such as field inventories. Furthermore, it is unclear whether site-level management actions can be designed using predictive model data in place of field measurements. We examined these issues for the case of mangroves, which are among the most carbon dense ecosystems globally and are popular candidates for forest carbon programs. We compared baseline carbon stock estimates derived from predictive model outputs against estimates produced using the Intergovernmental Panel on Climate Change's (IPCC) three-tier methodological guidelines. We found that the predictive model estimates out-performed the IPCC's Tier 1 estimation approaches but were significantly different from estimates based on field inventories. Our findings help inform the use of predictive model data for designing mangrove forest policy and management actions.

Keywords

blue carbon, climate change mitigation, carbon offsets, carbon accounting, wetlands

2.1 Introduction

Forest carbon offset programs are controversial, partly due to the high levels of uncertainty associated with estimating carbon fluxes from land use change [53, 144, 50]. The validity of these programs for mitigating climate change depends in part upon these estimates and it is therefore important for them to be accurate [51]. One key step in accurately estimating the climate benefits from these programs is the estimation of baseline carbon stocks, or the reference levels upon which potential project interventions are evaluated [10, 52]. Despite their importance, obtaining accurate estimates of baseline carbon stocks can be a barrier for program design due to the costs of implementing statistically valid field inventories. There has consequently been longstanding interest in improving both the accuracy and precision of baseline carbon stock estimates at lower costs [148, 90].

The Intergovernmental Panel on Climate Change (IPCC) is the foremost authority on inventorying ecosystem carbon stocks. The IPCC provides a three-tier system for categorizing the accuracy and uncertainty of baseline carbon stock estimates [68]. Under the IPCC's guidelines, the Tier 1 and Tier 2 approaches use global and regional default parameters, respectively. The Tier 3 approach uses "higher-order methods," which may include models or field data from national forest inventories to meet country-specific conditions. Inventorying baseline carbon stocks under the Tier 3 approach provides the highest data quality but is the most complex and resource-demanding [85].

To better understand global variation in forest carbon and potentially provide baseline carbon stock estimates under a Tier 3 approach, global maps of carbon stocks are increasingly being produced using predictive modeling. Modern classification techniques (e.g., machine learning algorithms), access to remotely sensed data, and larger compilations of empirical data have enabled these models to accurately predict trends in environmental variables from global to sub-regional scales [121, 9, 44]. The benefits of these models include wall-to-wall mappings of environmental variables, which can account for broad-scale variation in forest carbon stocks or land use change [60]. The shortcomings, on the other hand, include relatively coarse spatial resolutions as well as the risk of introducing bias when correlating remotely sensed metrics to field data. Despite their promise, it remains unclear i) whether the estimates are sufficiently accurate for designing forest carbon programs at local scales, and ii) how these global predictive models fit best within the IPCC's three tiers of approaches for estimating carbon stocks [90, 61].

Mangroves are one ecosystem for which accurate estimates of baseline carbon stocks from predictive models would be highly valuable [98]. Mangroves provide many environmental and social benefits, including the stocking of large amounts of organic carbon [45, 35]. Further, conservation of mangroves could help achieve many of the United Nations Sustainable Development Goals [17, 137]. As a consequence, mangrove-holding nations are interested in “blue carbon” projects, or the financing of mangrove conservation and restoration through forest carbon programs [143, 97, 58]. However, quantifying baseline carbon stocks in mangroves is particularly resource demanding due to limited accessibility and the importance of the soil organic carbon pool. Numerous predictive models of mangrove carbon stocks have consequently emerged in recent years, potentially meeting the demand for accurate estimates of baseline carbon stocks [65, 72, 122, 134].

Although a number of studies have compared predictive models of forest carbon stocks against empirical data for pan-tropical forests, no study has done this for mangroves despite their explicit inclusion in the 2013 Supplement to the IPCC Guidelines for National Greenhouse Gas Inventories [66]. The lack of such a study is a key gap in the literature as pan-tropical forest carbon maps are often inaccurate for mangroves due to unique ecological conditions. For example, tidal dynamics greatly influence remotely sensed imagery often used to produce these pan-tropical maps, potentially inducing high levels of uncertainty [89]. Operationalizing predictive models of mangrove carbon stocks for forest carbon program design thus requires assessing the accuracy of these datasets as well as guidance on their use.

The goal of this study was to i) compare estimates of baseline carbon stocks in mangroves derived from predictive model data against stock estimates derived through the IPCC’s methods, and ii) assess the accuracy of the predictive model data estimates against statistically valid field inventories. To do so, we compared estimates of baseline carbon stocks built off predictive model data against the IPCC’s approaches for mangroves located along four coastlines of the globe. We compared the four estimates to gain insight into potential biases, shortcomings, and benefits of each of the approaches. While the results are directly relevant for the blue carbon community, the study also provides guidance on the role of predictive models in environmental decision-making.

2.2 Methods

Study sites

We estimated ecosystem carbon stocks for mangroves along four coastlines of the world: a) the northwest coast of the United Arab Emirates, b) the Brazilian coast south of the Amazon river, and both c) the western and d) eastern coasts of peninsular Thailand (Figure 1). The sites were selected to capture a range of mangrove climatic and geomorphological variation (Table 1), including arid mangroves (UAE), sites heavily influenced by fluvial transport of sediment (Brazil and eastern Thailand), and tidally-dominated estuaries (western Thailand). Furthermore, only sites that used standardized methods and had field inventory data not included in the predictive model parameterization were used. Each of the sites were sampled with the primary objective of estimating site-level carbon stocks, and each of the sampling regimes used protocols that were designed specifically to meet the IPCC’s Tier 3 approach. Additional details of the sites and our selection criteria for inclusion are provided in the supplementary material.

Estimation approaches

We compared baseline carbon stock estimates at each site using four different approaches. It is worth noting that there are errors and biases inherent to estimates of baseline carbon stocks derived from both field inventories and predictive models, and objective comparisons of the approaches are limited by the absence of "true" values of extant carbon stocks [61]. However, it is valid to assume that each of the approaches provide independent estimates of the "true" values of site-level baseline carbon stocks, and thus their comparison is informative. We followed each of the IPCC's Tier 1, Tier 2, and Tier 3 approaches for estimating baseline carbon stocks, which are defined in terms of increasing methodological rigor. The Tier 1 and 2 approaches use global default parameters and country-level data on baseline carbon stocks, respectively. The Tier 3 approach uses empirical data that account for site-specific conditions and are collected through statistically valid field inventories. In addition to the Tier 1, Tier 2 and Tier 3 approaches, we also performed site-level pseudo-inventories by extracting carbon stock data from the modeled datasets at each of our field plots. We then compared the plot-level and site-level estimates of baseline carbon stocks using each of the estimation approaches.

Field inventories

Field inventory data were collected using variations of the Kauffman and Donato protocols for sampling forest structure and carbon stocks in mangrove forests [77]. The protocols were designed to fit the IPCC's Tier 3 approach for estimating baseline carbon stocks. We sampled the sites in Thailand and obtained plot level field inventory data for the UAE and Brazilian sites from published datasets that used the same protocols [80, 126]. All field inventories were designed with the stated purpose of estimating site-level ecosystem carbon stocks. The boundaries of the sites under consideration were delineated using geographic information systems software. Transects consisting of five to six circular plots at 25 m intervals were randomly located and placed perpendicular to the shoreline within each mangrove forest, allowing for unbiased estimation of site-level ecosystem carbon stocks. Within each plot, all trees were identified to species and their stem diameters at breast height were recorded. Additionally, soil cores up to 2 m depth were collected from the center of each plot with a Russian peat auger.

Biomass carbon was estimated by converting diameter at breast height measurements to volume estimates using species-specific allometric equations when available. In the absence of species-specific equations, a general allometric equation for mangroves with species-specific wood densities was used [83]. Soil carbon was estimated by coring each plot, collecting 5 cm soil samples at five depth intervals (0-15, 15-30, 30-50, 50-100, and 100-200 cm), and processing the samples for percent organic carbon, bulk density, and soil organic carbon density. Minor variations in the laboratory analyses of soil carbon existed across the studies, but all methods used widely accepted techniques for deriving bulk density (drying until constant mass) and percent organic carbon (dry combustion with an elemental analyzer) [119]. Soil organic carbon density was calculated as the product of percent organic carbon and bulk density. Despite coring to a maximum of 2 m depth, we only examined soil organic carbon stocks in the top meter of soil to match the predictive model data. The field inventory methods are described in full detail in the supplementary information, as well as in the other publications associated with the published datasets [18, 40, 80, 126].

Pseudo-sampling using predictive model data

We performed a pseudo-inventory of each site using the locations of the field inventory plots by substituting predictive model data for field data. We used two raster maps at 30 x 30 m spatial resolution to extract modeled estimates of aboveground biomass and soil organic carbon to 1 m depth using the Simard et al and Sanderman et al datasets, respectively [134, 122]. The Simard et al mangrove biomass data were produced by extracting mean canopy height from synthetic aperture radar data and converting the measurements to biomass estimates using allometric equations. The Sanderman et al dataset of soil organic carbon was produced using the random forest algorithm to predict soil organic carbon in mangroves as a function of globally coterminous covariates. Additional details of the predictive models are provided in the supplementary information.

We used the plot-specific coordinates to extract the modeled estimates of aboveground biomass and soil organic carbon from each sampling plot. We excluded plots whose geographic coordinates either could not be confirmed or did not align with the extents of the modeled data. Aboveground biomass was converted to aboveground biomass carbon using the IPCC's conversion factor of 45.1% dry-weight biomass to biomass carbon. Accurate estimates of belowground biomass are lacking due to the difficulties of field sampling root biomass, and predictive models of belowground biomass in mangroves consequently do not exist [4]. While we excluded belowground biomass from our statistical tests, we calculated rough estimates using a simple root-to-shoot factor for mangroves of 27.8% and a belowground dry-weight biomass to biomass carbon ratio of 39% for a more complete picture of ecosystem level carbon stocks [35, 77]. Others have recommended the adjustment of belowground biomass based on salinity and stem density; however, these variables are absent for our plots and we did not apply this correction [4]. For those plots that were less than 1 m in soil depth, we adjusted the predictive model estimates of soil organic carbon to the actual soil depth of the plot given that the modeled soil organic carbon data are estimated at 1 m depth.

Calculation of Tier 1 and Tier 2 estimates

We calculated Tier 1 and Tier 2 estimates of ecosystem carbon stocks using global and regional default factors, respectively. For the Tier 1 estimates, we used default parameters for mangroves specific to different climatic zones from the IPCC Guidelines [66]. While the

IPCC Guidelines were recently updated, the specific guidance for wetlands were not refined [96]. Losses from the soil organic carbon pool under shifting forest management practices are assumed to be non-existent under the Tier 1 approach, and we therefore omitted the soil organic carbon pool from our Tier 1 estimates. The IPCC's Tier 2 methods are analogous to Tier 1 methods but use country- or region-specific estimates of ecosystem carbon stocks to reduce uncertainty. For the Tier 2 estimates, we used ecosystem carbon stock estimates from published studies out of the same region. Specifically, we used a regional inventory from Southeast Asia, an inventory from mangroves in Northeastern Brazil, and two studies quantifying biomass and soil organic carbon stocks for mangroves from the Red Sea [35, 78, 6, 1]. Additional details of these studies and the Tier 2 approach are provided in the supplementary information.

Statistical analyses

We calculated mean baseline carbon stocks for all sites using each of the four approaches. For those approaches that allowed estimation of uncertainty, we also report the standard error of the mean. Normality in the field inventory and model-derived data were assessed using Shapiro-Wilk tests and quantile-quantile plots. We tested for significant differences in baseline carbon stocks between the field inventory and model-derived estimates. To account for spatial autocorrelation within transects, biomass carbon and soil organic carbon from all plots within the same transect were averaged for both the field inventory and model-derived data prior to the statistical tests. The statistical tests were performed with one-way analysis of variance for normally distributed data and non-parametric Kruskal-Wallis analysis of variance for non-normally distributed data.

2.3 Results

The estimates of baseline carbon stocks varied by both site and estimation approach. Figure 2 shows the ecosystem carbon stocks for the individual sites using each of the four estimation approaches. The Tier 1 estimates do not incorporate soil organic carbon and therefore differed substantially from the other estimation approaches at an ecosystem level. Given that the sites only fell within two of the IPCC's climatic classes for mangroves, only two Tier 1 parameters were used (33.8 Mg C ha^{-1} for the UAE site, and 86.6 Mg C ha^{-1} for all others). The Tier 2 estimates (regional defaults) both over- and under-estimated baseline ecosystem carbon stocks relative to the Tier 3 field data (Table 2). Visual comparison of baseline carbon stock estimates using the field inventory vs. predictive model data revealed significant biases, particularly for aboveground biomass carbon.

Pooling the data across all sites, we did not find a significant difference in aboveground biomass carbon for the field inventory versus predictive model data (Kruskal Wallis Test, χ^2 = 0.114, p-value = 0.7). However, for the soil organic carbon data, we found a significant difference between the field inventory and predictive model data when pooling across all sites

(Kruskal-Wallis test, χ^2 =11.4, p-value = <0.001). The results were variable for individual sites. One of the five sites showed a significant difference for aboveground carbon stock estimates whereas four of the five sites had significant differences in soil organic carbon estimates (Table 3).

2.4 Discussion

Our results reveal substantial differences in baseline carbon stock estimates that arise from the estimation approaches. The results suggest that estimating site-level baseline carbon stocks in mangroves using default factors is inaccurate and does not account for important regional and local variation. If we assume the field inventory data are the most accurate for estimating true carbon stocks (as is widely done), it is clear that the predictive model data better-approximate these estimates compared to the IPCC Tier 1 defaults and may outperform the Tier 2 approach in certain cases. These results parallel similar findings for predictive models of biomass in tropical forests more generally and suggest that the widespread availability of predictive models of biomass may obviate the IPCC's default factors at global scales [90]. We delve more deeply into the differences in results below, offering explanations for apparent contrasts that may emerge due to methodological differences. We then make recommendations for the design of blue carbon programs and situate the estimation approaches within ongoing systematic efforts for space-based monitoring of forest biomass.

Results of the four approaches for estimating baseline carbon stocks in mangroves

Our results reveal substantial differences in baseline carbon stock estimates that arise from the different estimation approaches. For the sites in which the Tier 2 estimates closely approximated the site geomorphology (i.e., neighboring sites rather than regional inventories; Brazil and the United Arab Emirates), the Tier 2 estimates based on field data better approximated site level values than estimates from predictive model data. However, the estimates derived from predictive model data better approximated the field inventory estimates than the Tier 2 estimates for the sites in Thailand. These results suggest that while the predictive models are capable of accounting for regional scale variation in ecosystem carbon stocks, this ability begins to break down at local scales. For mangroves, these differences at sub-regional scales are likely a result of differing mangrove typologies, which may depend upon the particular hydrological, sedimentary, or climatic conditions at a given site [142]. While previous studies have provided country-level estimates of mangrove carbon stocks, a potentially promising and more ecologically-informed update would be to produce country-specific default mangrove carbon stocks by mangrove typology (e.g., lagoon vs. deltaic vs. estuarine sites) [58, 120].

Despite the promise of predictive models for improving default estimates of carbon stocks, our statistical comparisons of field inventory versus predictive model carbon stock estimates at the site level reveal significant differences. The findings emphasize that even with the relatively fine spatial resolution of the predictive models (30 m), caution should be taken in their use at site-level scales. These differences are particularly pronounced at the pixel level, confirming the warnings of model producers against use of products at local scales (panel b of Figure 2). While we acknowledge that direct comparisons of the plot-level field inventory and predictive model estimates of carbon stocks are not valid due to their differing spatial footprints, we visualize the data to further emphasize this point. Visual inspection of plot-level carbon stock estimates against a one-to-one line (i.e., perfect alignment of stocks estimates from field inventory and predictive model data) indicates that the variation in field inventory aboveground biomass at the plot-level was not captured by the predictive models (Figure 2). Estimates of aboveground biomass from the predictive model data fell between <1 to 114.4 Mg C ha^{-1} across all sites whereas the estimates from the field inventories varied from <1 to 490.3 Mg C ha^{-1}. Although it is not possible to say for certain, the use of different allometric equations (regional-level equations based on height for the predictive model vs. species-specific based on diameter at breast height for the field inventories) likely contributed to the differences in plot-level estimates of biomass. Other sources of uncertainty may have included geolocation errors, error propagation and differences in timing of measurements.

Recommendations for the design of blue carbon projects

In considering our results, we recommend the use of predictive model outputs for estimating site-level baseline carbon stocks over global defaults (Tier 1) and regional inventories (Tier 2). The predictive model data can provide large improvements in accuracy and are freely available for those with capacity in geographic information systems (GIS). Free and open source GIS software are sophisticated, well-developed, and provide a readily accessible means to analyze the publicly available maps of mangrove carbon examined here. We further discuss the utility of GIS for designing blue carbon projects in the supplementary information.

However, our results also indicate that Tier 2 estimates may out-perform predictive model estimates when using field data from neighboring sites with similar geomorphological and climatic conditions (e.g., see panel (a) of Figure 2 for the Arabian Gulf and Coast of Para). It is important for blue carbon projects to justify their use of one data type over the other and may be most appropriate to provide both. Additionally, we advise caution in using predictive model data for decision-making at the within-site level despite their high spatial resolution. Methodological differences in producing the datasets may bias estimates of carbon stocks and may ultimately be ill-suited for interventions that are not uniform across space.

A hybrid approach that uses the predictive model outputs for stratifying sampling regimes may hold promise in reducing uncertainty at lower costs. The aboveground biomass model is based on a remotely sensed measure of canopy height, which is an appropriate variable to use for stratifying sampling regimes of mangrove biomass. Should programs have capacity in GIS analyses on hand, significant cost reductions can be achieved by using predictive model data to inform stratified inventories [139]. Ultimately, a combination of modeled-derived data and field inventory data may provide the best combination of cost-efficiency and accuracy in estimating baseline carbon stocks.

It is important to note that the epistemic stance of this paper emerges primarily from the field of predictive modeling. While accurate estimates of carbon stocks are of clear importance for advancing valid forest carbon programs in mangroves, there are other critical barriers that emerge from disciplines such as the field of environmental justice [128]. For example, equitable benefit sharing, assent of local communities, and de-/centralization of governance can be equal, if not larger, barriers to forest carbon programs [95, 43]. Our aim here is not to argue for more complicated measurements of forest carbon in mangroves but rather situate the accuracy of publicly available datasets that may meet this need. While we only note the importance of these additional barriers to carbon forestry programs here, we provide additional discussion of them in the supplementary information.

Considerations for future field-based vs. model-based approaches

The uncertainty associated with not knowing the "true" value of ecosystem carbon stocks will persist within forest carbon programs and is likely best addressed by a combination of field inventory and model-based data. Given the absence of "true" values of mangrove carbon stocks at our sites, we cannot state that the predictive model data or field inventory data provide more accurate or more valuable estimates of baseline carbon stocks in mangroves. Field inventories provide nuanced measurements of ecosystem variables such as forest structure but are resource-demanding to collect and require the extrapolation of measurements from plot to stand or site-level scales. Conversely, predictive models also provide direct estimates of forest metrics across broad regions but are limited in their ability to account for fine scale variation. While both have their strengths and limitations, they are capable of providing complementary information.

Numerous satellite missions with the primary objectives of estimating and monitoring ecosystem biomass will be launched from 2020-2030 [60]. These missions will be critical for measuring changes in forest biomass over broad scales, but will also need corresponding field inventory data to validate the measurements and calibrate the predictive models based upon them [124, 25]. Although limited in number, networks of large permanent plots exist for other tropical forest types that will facilitate the use of space-based estimates of forest biomass. However, to the best of our knowledge, permanent field plots of mangrove forest structure and biomass are largely absent. While the Kauffman and Donato protocols and the associated widespread collection of mangrove forest structure data have greatly benefited the mangrove community, the next phase of mangrove forest biomass estimation and monitoring would be appropriate in aligning with space-based missions capable of estimating ecosystem structure.

2.5 Conclusion

We tested the utility of predictive models to estimate baseline carbon stocks in mangroves, which are among the most carbon dense ecosystems globally. Our results show that predictive models are capable of providing more accurate estimates of ecosystem carbon stocks at local levels relative to the IPCC's Tier 1 default parameters. However, we also found that estimates of mangrove carbon stocks derived from predictive model data were significantly different from analogs based on comprehensive field inventories (IPCC Tier 3 approach). We recommend the use of predictive models in designing national or regional forest policy and strategies but also recommend caution in using them at local scales.

Acknowledgements

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Data Availability Statement

The predictive model data for mangrove soil organic carbon [122] are available at DOI: 10.7910/DVN/OCYUIT. The predictive model data for mangrove aboveground biomass [134] are available at DOI: 10.3334/ORNLDAAC/1665. The United Arab Emirates field data are available in the DataONE digital repository at DOI: 10.15146/R3K59Z. The field data from Brazil are available through the Center for International Forestry's (CIFOR) Sustainable Wetlands Adaptation and Mitigation Program (SWAMP) Dataverse (https://data.cifor.org/dataverse/swamp) at DOIs:

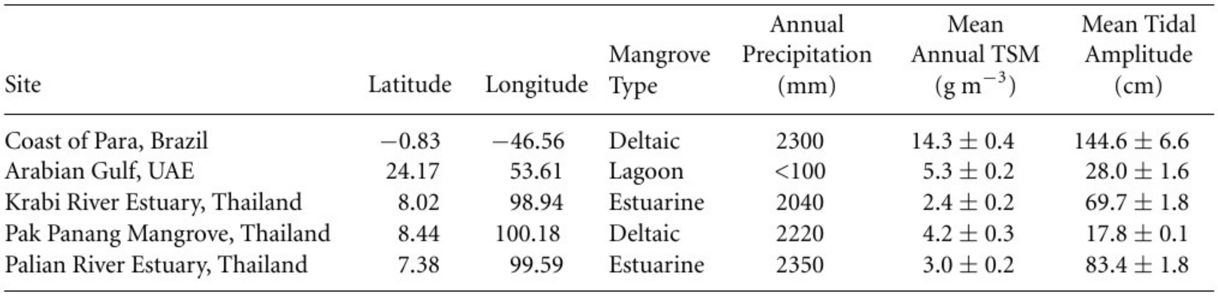
- 10.17528/CIFOR/DATA.00125, 10.17528/CIFOR/DATA.00126,
- 10.17528/CIFOR/DATA.00127, 10.17528/CIFOR/DATA.00128,
- 10.17528/CIFOR/DATA.00129, 10.17528/CIFOR/DATA.00130,
- 10.17528/CIFOR/DATA.00132, 10.17528/CIFOR/DATA.00163,
- 10.17528/CIFOR/DATA.00164, 10.17528/CIFOR/DATA.00165,

- 10.17528/CIFOR/DATA.00166, 10.17528/CIFOR/DATA.00167,
- 10.17528/CIFOR/DATA.00168, 10.17528/CIFOR/DATA.00169.

The Thailand data are not currently available but will be published within six months from the data of publication within the CIFOR SWAMP Dataverse.

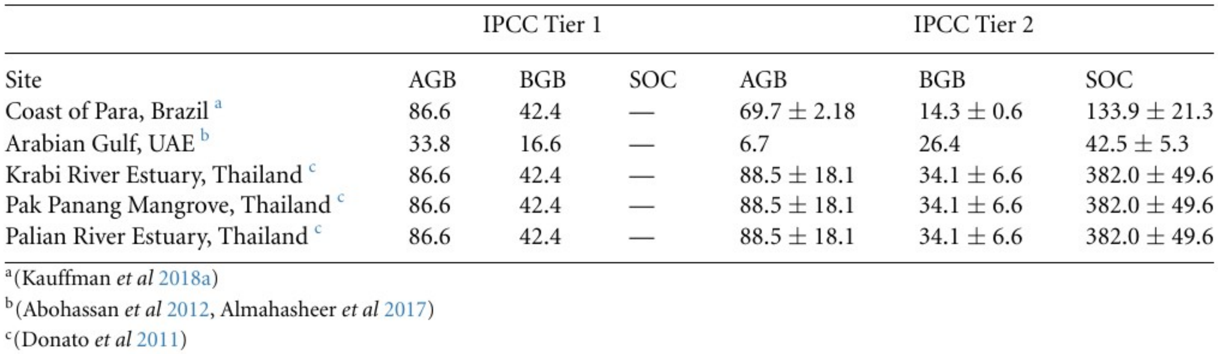
Tables and Figures

Table 1. Key climatic and geomorphological characteristics of the sites. The mean annual total suspended matter and tidal amplitude values are calculated by extracting and averaging TSM and tidal amplitude data within a 50 km buffer of all plots, and averaging across those values.



Site	Latitude	Longitude	Mangrove Type	Annual Precipitation (mm)	Mean Annual TSM (g m^{-3})	Mean Tidal Amplitude (cm)
Coast of Para, Brazil	−0.83	−46.56	Deltaic	2300	14.3 ± 0.4	144.6 ± 6.6
Arabian Gulf, UAE	24.17	53.61	Lagoon	<100	5.3 ± 0.2	28.0 ± 1.6
Krabi River Estuary, Thailand	8.02	98.94	Estuarine	2040	2.4 ± 0.2	69.7 ± 1.8
Pak Panang Mangrove, Thailand	8.44	100.18	Deltaic	2220	4.2 ± 0.3	17.8 ± 0.1
Palian River Estuary, Thailand	7.38	99.59	Estuarine	2350	3.0 ± 0.2	83.4 ± 1.8

Table 2. IPCC Tier 1 and Tier 2 estimates of baseline ecosystem carbon stocks for the mangroves of this study. The Tier 1 estimates use global default parameters provided in the Wetlands supplement to the IPCC Good Practice Guidelines for National Greenhouse Gas Inventories [66]. The Tier 2 estimates used published parameters from the countries and regions of our mangrove sites. All carbon stock estimates are provided in mean Mg C ha^{-1}, and standard errors of the mean are provided where available. Soil organic carbon stocks are constrained to 1 m depth.



	IPCC Tier 1			IPCC Tier 2		
Site	AGB	BGB	SOC	AGB	BGB	SOC
Coast of Para, Brazil [a]	86.6	42.4	—	69.7 ± 2.18	14.3 ± 0.6	133.9 ± 21.3
Arabian Gulf, UAE [b]	33.8	16.6	—	6.7	26.4	42.5 ± 5.3
Krabi River Estuary, Thailand [c]	86.6	42.4	—	88.5 ± 18.1	34.1 ± 6.6	382.0 ± 49.6
Pak Panang Mangrove, Thailand [c]	86.6	42.4	—	88.5 ± 18.1	34.1 ± 6.6	382.0 ± 49.6
Palian River Estuary, Thailand [c]	86.6	42.4	—	88.5 ± 18.1	34.1 ± 6.6	382.0 ± 49.6

[a] (Kauffman *et al* 2018a)

[b] (Abohassan *et al* 2012, Almahasheer *et al* 2017)

[c] (Donato *et al* 2011)

Table 3. Results of statistical tests for differences in site-level carbon pool estimates using predictive model vs. field inventory data. The tests are performed for aboveground biomass carbon (AGC) and soil organic carbon (SOC) constrained to a maximum of 1 m depth. All values are in Mg C ha^{-1}. All statistical tests are performed with the non-parametric Kruskal-Wallis analysis of variance given non-normality in the data.

	Field-based (Mg C ha^{-1})	Model-based (Mg C ha^{-1})	X^2	P-value	Significance
AGC					
Arabian Gulf, UAE	7.29 ± 2.2	10.5 ± 5.2	0.16	0.7	NS
Coast of Para, Brazil	147.4 ± 19.0	55.1 ± 11.8	6.63	0.01	**
Krabi River Estuary, Thailand	66.3 ± 5.3	58.3 ± 2.1	0.57	0.4	NS
Pak Panang Mangrove, Thailand	67.9 ± 7.9	73.5 ± 2.7	1.28	0.3	NS
Palian River Estuary, Thailand	100.5 ± 12.2	69.6 ± 3.2	1.86	0.2	NS
SOC					
Arabian Gulf, UAE	89.0 ± 11.6	270.0 ± 28.6	8.08	0.004	***
Coast of Para, Brazil	163.8 ± 10.0	365.5 ± 29.4	9.00	0.003	***
Krabi River Estuary, Thailand	315.5 ± 27.8	268.4 ± 59.0	0.32	0.6	NS
Pak Panang Mangrove, Thailand	113.1 ± 4.3	175.1 ± 4.4	14.29	<0.001	***
Palian River Estuary, Thailand	285.1 ± 9.1	357.7 ± 7.6	12.06	<0.001	***

Note: NS = not significant, * = significant at $\alpha = 0.1$, ** = significant at $\alpha = 0.05$, and *** = significant at $\alpha = 0.01$; degrees of freedom = 1 for all tests.

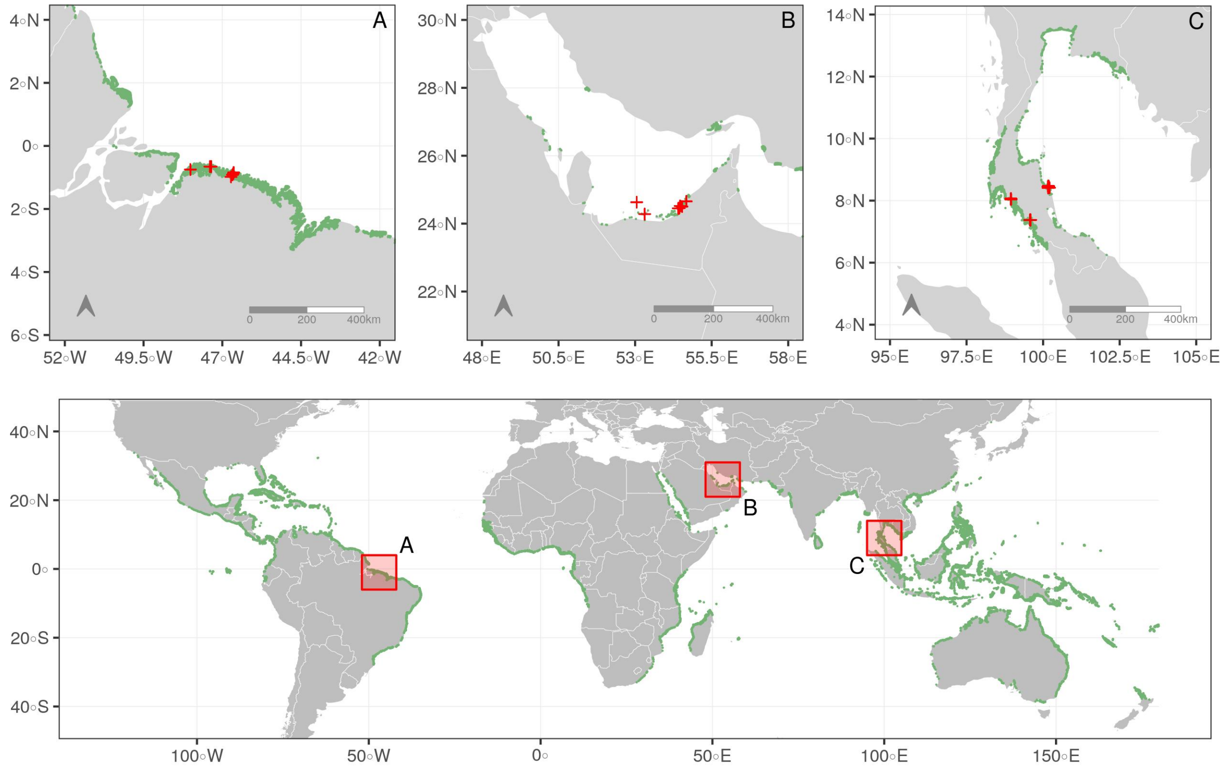


Figure 1. Location of the mangrove sites included in this study. The mangrove sites are located in Brazil, the United Arab Emirates, and Thailand. The three panels show: (A) the Brazilian plots located along the coast of Para, (B) the mangrove sites in the Arabian Gulf, and (C) the plots located in peninsular Thailand.

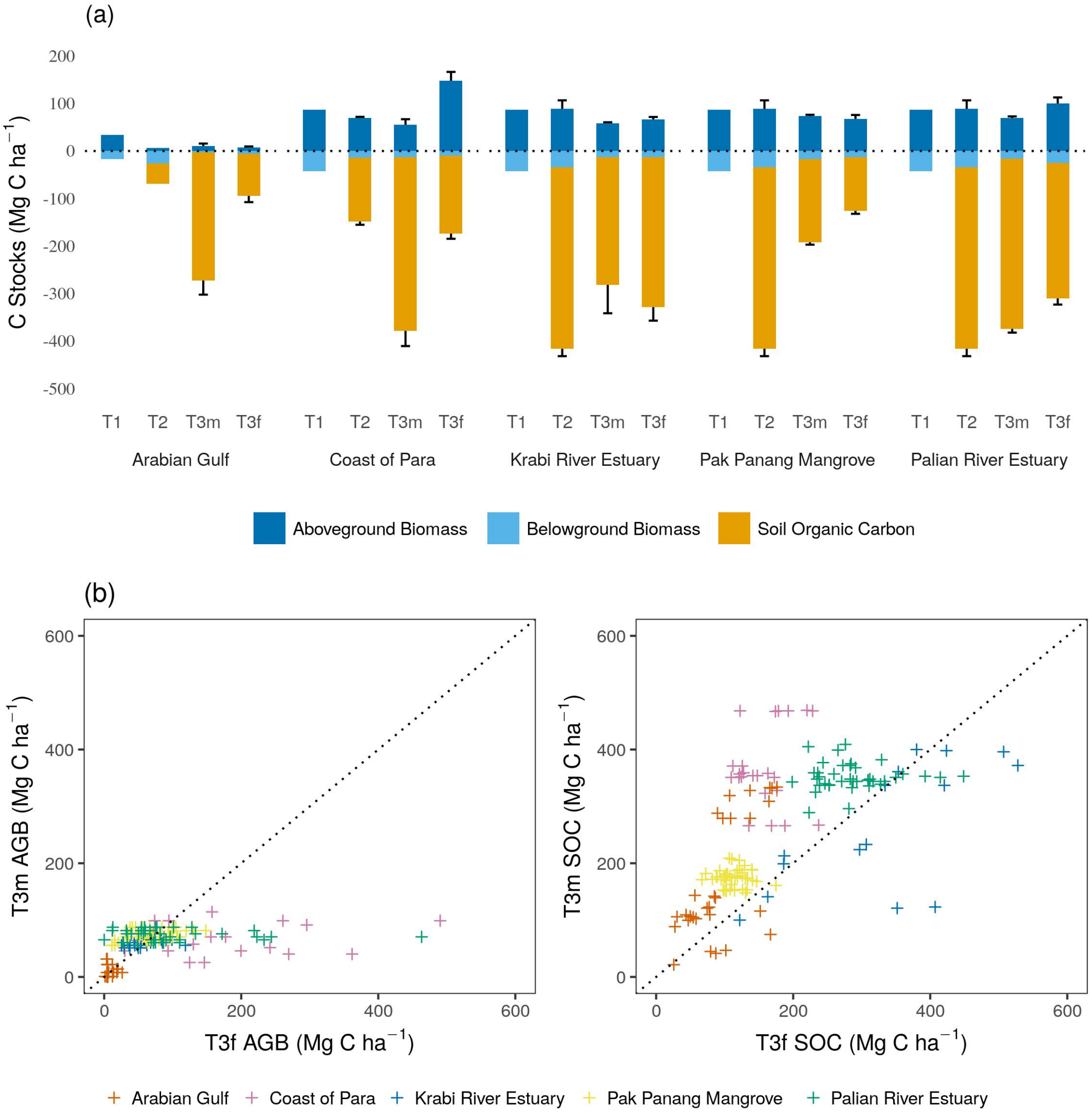


Figure 2. Two-panel plot summarizing the estimation of ecosystem carbon stocks for each of the five sites. Panel (a) compares the estimation approaches of Tier 1 (T1), Tier 2 (T2), Tier 3-model (T3m), and Tier 3-field (T3f) for the three key ecosystem carbon pools. Panel (b) shows Tier 3-model vs. Tier 3-field estimate of plot-level carbon stocks for the aboveground biomass and soil organic carbon pools. The SOC estimates in panel (a) are constrained to 1 m for the T2, T3m and T3f estimates. The Arabian Gulf plots are from the United Arab Emirates, the Coast of Para plots are from Brazil, and the Krabi River Estuary, Pak Panang Mangrove and Palian River Estuary plots are from Thailand.

2.6 Supplementary Information

1. Additional details of the study sites

Overview

The sites included in our analyses were selected for several key reasons. The first was that each of the inventories were designed with the primary objective of estimating site-level carbon stocks. The second was that they used a variation of the Kauffman and Donato protocols for sampling, which were designed to provide statistical estimates of forest structure and carbon stocks in mangroves. The protocols were designed specifically with the IPCC's Tier 3 estimation approach in mind and consequently provide a high quality estimate of ecosystem carbon stocks. Third, we selected sites that represented a range of different climatic and geomorphological settings in mangroves (estuarine, deltaic, and arid). The sites are not exhaustive of all mangrove typologies globally, but represent a range of environmental conditions in which mangroves are found. Finally, we selected sites with field inventory data that had not been included in the parameterization of the model. Both the predictive models used in this study were published within the last two years and thus there are limited field inventory datasets to test these models against given their exhaustive collection of inventory data. We personally collected the field inventory data for the sites in Thailand whereas we used published datasets for the sites from Brazil and the United Arab Emirates.

Coast of Para, Brazil

The mangroves in Brazil are found within a stretch of estuaries to the south of the Amazon River. While several of the mangroves sampled are located along different rivers, there is not sufficient data to treat them each as a separate site, and we therefore pool all plots into a single site for the coastline. For our purposes, the sites do not differ in terms of climatic conditions, tidal range (0.6 – 4.6 m), or total suspended matter, which are our key variables for defining geomorphological setting. Similarly, the salinity and pH levels across all sites are quite similar, indicating our pooling of sites across rivers is justified. The mangroves receive suspended sediment from the Amazon River, which is transported along the coast by wave action and subsequently transported into the mangrove forests by tidal flooding. Species composition across all sites consisted of *Rhizophora mangle*, *Avicennia germinans*, and *Laguncularia racemosa*. Examining the published estimates of biomass and soil organic carbon across the sites shows relative consistency, adding further justification for our pooling of all sites along the coastline [80].

Arabian Gulf, United Arab Emirates

The mangroves in the United Arab Emirates were located within the Arabian Gulf. Annual rainfall in the Arabian Gulf is <100 mm, whereas evaporation rates are 1000-2000 mm. The mangrove data from these sites are therefore representative of arid mangroves.

Salinity along the coastline is high and may reach >70 PSU during the summer due to restricted tidal flushing and low precipitation rates. The mangroves along the Arabian Gulf are monospecific stands of *Avicennia marina*, which are stunted in height due to climatic factors. The tidal regime is complex due to the development and interaction of waves within the Arabian Gulf. The spring tidal range is approximately 2.5 m, and tidal regimes are a mix of diurnal and semi-diurnal [126]. Similar to the sites from the Coast of Para, we pool the mangrove sites from the Arabian Gulf given data limitations and similarity in climatic and geomophological conditions across sites.

Krabi River Estuary, Thailand

The Krabi River Estuary is located in Krabi province along the Andaman coast of Thailand. The Krabi River Estuary was designated as a Wetland of International Importance under the Ramsar Convention in 2001. Although extensive aquaculture exists within the Krabi River Estuary, several groups (e.g., the Mangrove Action Project and the Raak Thai Foundation) are actively conducting mangrove restoration and afforestation through Community-Based Ecological Mangrove Restoration, particularly within abandoned shrimp ponds. The Krabi River Estuary is a relatively stable tidally-dominated mangrove. Transports of sediment occur along coastlines with heavy tidal flows shaping channels and islands parallel to tidal flows within the mangrove.

Pak Panang Mangrove, Thailand

The Pak Panang Mangrove is located in Nakorn Si Thammarat province on the east coast of peninsular Thailand. The Pak Panang Mangrove is publicly managed by the Department of Marine and Coastal Resources. Although publicly owned, local communities have resided in the mangrove since the 1960s and have used the forest to varying degrees. Despite a logging ban that exists in Thailand, dispersed cutting of trees and harvesting of non-timber forest resources such as crabs occurs throughout the mangrove forest. The Pak Panang Mangrove is a highly active depositional landscape primarily influenced by wave action. Large amounts of sediment are deposited at the mouth of the Pak Panang River, which is subsequently shaped by northward wave action along the coast to form the Talumphuk peninsula and spit. The Talumphuk peninsula shelters the Pak Panang Bay, which allows for low energy conditions necessary for mangrove trees to establish. In addition to natural regeneration, afforestation and restoration efforts have been undertaken within the Pak Panang Mangrove since the 1990s.

Palian River Estuary, Thailand

The Palian River Estuary is located in Trang province on the west coast of peninsular Thailand. Intact mangroves exist within the Palian River Estuary, as well as several stands of closed-canopy mangroves that were restored in abandoned aquaculture ponds. The mangrove forests are publicly managed by the Department of Marine and Coastal Resources and while no cutting is allowed, conversion of mangroves to aquaculture along the forest fringes has occurred. The mangroves of the Palian River Estuary are similar in geomorphological setting to the Krabi River Estuary but with a few key differences. Relative to the Krabi River Estuary, the main channel of the Palian River exists as a more prominent feature in the estuary, possibly providing a more significant riverine influence.

Calculation of Total Suspended Matter and Tidal Amplitude metrics

We characterized each site based on metrics of total suspended matter (TSM) and tidal amplitude. TSM is estimated from MERIS imagery produced by the Envisat satellite of the European Space Agency. The ocean colors bands of MERIS imagery provide spectral data optimized for conversion to estimates of total suspended matter, among other products. We extracted monthly TSM data for the near shore environment at each of our sites, and averaged all months from 2000-2012 to characterize mean annual sedimentary inputs to each site. The estimates are reported in Table 1 of the manuscript. We used the M2 tidal elevation amplitude product (FES2012) to characterize tidal amplitude. The FES2012 data is a hydrodynamic model that estimates tidal elevation (i.e., amplitude), tidal currents and tidal loading by assimilating altimeter data. We used the same total suspended matter and tidal elevation data that was input to the global map of soil organic carbon for examining variation in tidal influence across our sites [122].

2. Additional details of the methods

General approach

We compared baseline carbon stock estimates for five sites across four coastlines in Brazil, the United Arab Emirates, and Thailand. We used the IPCC's three tiers of methodological approaches for estimating extant carbon stocks as well as a pseudo-inventory that substitutes data from predictive models for field inventory data. The four different approaches were: i) global default parameters (IPCC Tier 1), ii) regional default parameters (IPCC Tier 2), iii) a statistically designed field inventory (IPCC Tier 3), and iv) a pseudo-inventory that substitutes predictive model data for field inventory data. The Tier 3 field inventory data were collected through intensive sampling campaigns of biomass and soil carbon stocks at each of the sites. We assumed that the Tier 3 field inventory data were of the highest accuracy as is commonly done within the literature. Using the modeled datasets of global mangrove carbon, we performed a pseudo-inventory by extracting carbon stock data from the modeled datasets using the geographic coordinates of each of our field plots. Finally, we estimated baseline carbon stocks for each site using the IPCC's Tier 1 and Tier 2 approaches. We then used statistical tests to identify significant differences in the baseline carbon stock estimates across sites. We compared both site-level and plot-level values given that both are important for carbon forest program design.

Additional details of the predictive models

Two spatially-contiguous maps of mangrove carbon stocks were used in this study. The first is a dataset of mangrove biomass stocks that was derived from remotely sensed measurements of mean canopy height and regional-level allometric equations [134]. The second is a dataset of soil organic carbon to 1 m depth that was modeled as a function of empirical estimates of soil organic carbon as well as environmental covariates [122]. Both datasets were produced at 30 x 30 m resolution and are publicly available for mangroves, globally. We recount key details of the models here whereas the full descriptions of their production can be found in the original publications.

The mangrove biomass dataset was produced by converting remotely sensed measurements of mean canopy height to biomass using allometric equations. The remotely sensed measurements of canopy height were extracted from the digital elevation model of the Shuttle Radar Topography Mission as well as lidar heights from the ICESat/GLAS Spaceborne Lidar mission. Field plots across three regions of the globe were then sampled to build regional scale allometric equations for both canopy height and basal-area weighted canopy height to biomass. Both allometric equations were assessed and the basal-area weighted canopy height equation was found to more accurately estimate biomass. Following the production of basal-area weighted canopy height maps, the data were converted to estimates of biomass using the regional allometric equations. The authors report notably high RMSEs of the biomass data, which range from 54.3 – 134.3 Mg ha^{-1} depending on the region-specific allometric equations (Supplementary Table 8 of the original study).

The soil organic carbon dataset was produced with a different approach. First, a global dataset of depth interval specific soil organic carbon measurements was collected using published and unpublished data. Second, a large list of environmental covariates that are known to influence soil organic carbon stocking and are globally available were collated as a raster stack. The geographic locations of the empirical soil carbon measurements were then used to extract estimates of the environmental covariates at those locations, and a random forest model was used to predict depth interval specific soil organic carbon as a function of the environmental covariates. Following its validation, the model was used to produce a globally coterminous map of mangrove soil organic carbon at 30 x 30 m resolution. Cross-validation of the model produced an R^2 value of 0.63 and a RMSE of 10.9 kg m^{-3} compared to a mean soil organic carbon density of 29.6 kg m^{-3}. Additional details are provided in the original publication [122].

Tier 3 field inventories of baseline carbon stocks Field inventories of the mangroves in Brazil and the United Arab Emirates

The mangrove sites in Thailand were sampled by the authors of this study, whereas the mangroves of Brazil and the United Arab Emirates were sampled by others. We refer the reader to the original publications for the Brazil and United Arab Emirates inventories for the full details of the sampling designs and methods [126, 80]. All field inventories used comparable sampling designs. Transects were randomly located within the forests and five to six plots of 7 m radius were established at 25 m intervals along each transect. All trees (DBH >5 cm) within the 7 m plot were identified to species and the stem diameter at breast height (DBH; 1.37 m height) was recorded. Soil cores were collected up to 2 m depth using standardized methods, which we describe in detail below. The data from the field inventories were collected from published datasets of the full field inventories (i.e., tree-level measurements of DBH). The data from the United Arab Emirates are available through the supplemental information of [126], whereas the data from the Brazil mangroves are available through the Sustainable Wetlands Adaptation and Mitigation (SWAMP) program database hosted by the Center for International Forestry (CIFOR).

Field inventories of the mangroves in Thailand

The mangrove forests of Krabi River Estuary and Pak Panang Mangrove were initially sampled in 2015, with additional soil cores collected from the forest plots in 2018 [18, 40]. All sampling in the Palian River Estuary was conducted in 2013. Sampling points for the establishment of transects were randomly located in the forest irrespective of distance from the shoreline. This design was taken given a primary concern for estimating site-level structure and carbon stocks rather than stratifying across ecological gradients (e.g., fringe vs. interior forests). Each transect consisted of four to six plots spaced at 25 meter intervals, totaling 75-125 m in length. The plots were 7 m in radius with a 2 m subplot nested at its center.

All trees greater than 5 cm DBH were identified to species and their DBH was subsequently recorded with a diameter tape. Within the subplot, the DBH of all saplings (height >1.37 m; DBH <5 cm) was recorded and trees were identified to species, whereas seedlings (height <1.37 m) were identified to species and counted. Soil cores were taken using a peat auger of one meter length, which minimizes compaction of soil cores in wet sediment. Upon extraction of a complete core, subsamples were taken from each of the 0-15, 15-30, 30-50, and 50-100 cm depth intervals. A second core from 100 – 200 cm depth was then taken from the same location and a fifth soil subsample was taken randomly from the 100 – 200 cm depth interval. Subsamples were 3 to 5 cm in length and were selected from the most "full" section of the depth interval. Soil depth was estimated by inserting a 3 m avalanche probe until the point of refusal (or its full length) at three separate points within each plot. The three depth estimates were averaged for a total plot-wise soil depth estimate.

All DBH measurements for trees and seedlings were converted to biomass volume estimates using allometric equations. Species-specific allometric equations derived from the region were used when available [18]. In the absence of a species-specific equation, we substituted species-specific equations from the same genus (e.g., use of an *Avicennia marina* for *Avicennia alba*) given similar tree morphologies. A general allometric equation for mangrove trees with species-specific wood densities was used in all other cases [24, 84, 151]. All volume estimates were summed within plots and averaged across plots to obtain transect-wise estimates of dry-weight biomass volume. Conversion factors of 0.47 for aboveground biomass and 0.39 for belowground biomass were used to estimate biomass carbon as a function of dry-weight biomass.

All soil laboratory analyses were performed at the Faculty of Forestry at Kasetsart University in Bangkok, Thailand. Soil samples were analyzed for bulk density and percent organic carbon. The soil samples were dried at 60 °C until constant mass and bulk density was estimated as a function of dry-weight to volume. Total carbon was calculated using a TCN analyzer and the dry combustion method for carbon analysis. Soil organic carbon density (g/cm^3) was calculated as the product of bulk density and percent organic carbon. Total soil organic carbon estimates per ha were estimated by extrapolating depth-interval specific carbon densities to the volume of the depth interval and summing across depth intervals. Average values for each ecosystem carbon pool were calculated for all transects and used to estimate total ecosystem carbon stocks for all three sites. Additional details of the field sampling are provided in the supplementary information of [18].

Tier 1 & 2 carbon stock estimation overview

The IPCC provides guidance in estimating Tier 1 and Tier 2 carbon stocks and emissions. Tier 1 estimates are derived from default parameters and equations whereas Tier 2 estimates are derived from country- or region-specific parameters and equations. In calculating Tier 1 and Tier 2 estimates of carbon stocks for each of our sites, we followed the IPCC guidance from three key documents: i) the 2019 refinement to the 2006 Guidelines for National Greenhouse Gas Inventories, ii) the Good Practice Guidelines for Land Use, Land Use Change and Forestry, and iii) the 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands [39, 66, 67].

Tier 1 estimates of mangrove carbon stocks

The IPCC provides two methods for estimating changes in ecosystem carbon stocks: i) the gain-loss method, and ii) the stock-difference method [39]. The gain-loss method calculates the net change in biomass as a function of gross biomass gains and gross biomass losses. The stock-difference method, on the other hand, is time-resolved and spatially-explicit. The stock-difference method calculates changes in carbon stocks for distinct locations at given points in time. For the Tier 1 approach, only the gain-loss method is appropriate given data constraints [39]. Specifically, global default parameters do not allow for modeling gains or losses at distinct places or points in time but rather aggregate estimates of net change in stocks. The stock-difference approach is therefore only appropriate for Tier 2 or Tier 3 approaches.

For estimating baseline ecosystem stocks under a gain-loss method, the IPCC provides default global parameters for mangroves in the 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands [66]. Under the Tier 1 approach, losses from the soil organic carbon pool are assumed to be non-existent and we therefore omitted the soil organic carbon pool from our Tier 1 estimates of baseline carbon stocks. Similarly, while the IPCC recommends reporting the coarse woody debris pool, it is commonly omitted due to high levels of uncertainty and the relatively small contribution of coarse woody debris to ecosystem carbon stocks in mangroves. We consequently report only default parameters for aboveground biomass and belowground biomass carbon in mangroves.

The IPCC reports average values by land use and land use conversion type for estimation of biomass carbon. Given that we are concerned with baseline estimates of carbon stocks, we used values for "forest land remaining forest land." We used Tier 1 default parameters specific to "tropical wet" mangroves for the sites in Brazil and Thailand, which is the appropriate climatic zone for our sites. The IPCC reports an average dry-weight biomass value of 192 Mg C ha^{-1}, as well as a percent biomass carbon factor of 45.1%. Additionally, we estimated belowground biomass using the aboveground to belowground biomass ratio of 49% reported in the 2013 Wetlands Supplement. For the mangroves from the United Arab Emirates, we used values for "subtropical" mangroves. The IPCC reports limited default parameters for mangroves and the "subtropical" mangroves values best approximated the United Arab Emirates sites. The IPCC reports average dry-weight biomass of 75 Mg C ha^{-1} for subtropical mangroves, which we also adjusted by the percent biomass carbon factor of 45.1%. We estimated belowground biomass carbon as a function of aboveground biomass carbon similar to the tropical sites.

Tier 2 estimates of carbon stocks in mangroves

We derived Tier 2 estimates (country- or region-specific) using default parameters of ecosystem carbon stocks from published values of mangrove carbon stocks in the academic literature. We used values from individual studies for both Brazil and Thailand whereas we used a combination of two studies for the United Arab Emirates. To the best of our knowledge, no single inventory of both biomass and soil organic carbon stocks other than the inventory included in our analysis exists for the arid mangroves of the Middle East. Thus, we used the estimates of biomass and soil organic carbon from two separate studies.

For Brazil, we used published values of aboveground biomass carbon and soil organic carbon from a study that quantified mangrove ecosystem carbon stocks in the state of Ceará [78]. The state of Ceará is located along the same section of coastline as Para and also uses the Kauffman and Donato sampling protocols. The estimates of baseline carbon stocks are therefore expected to closely approximate the Brazil field inventory data used in our analysis and are justifiable values for a Tier 2 estimate. We used the estimates of biomass carbon stocks reported in the article directly whereas we constrained estimates of soil organic carbon to a maximum of 1 m depth to match the predictive model estimates of soil organic carbon.

We used two studies reporting biomass carbon and soil organic carbon stocks from mangroves of the Red Sea as Tier 2 estimates of baseline ecosystem carbon stocks for mangroves in the Arabian Gulf [1, 6]. Baseline carbon stock inventories in arid mangroves of the Middle East region are relatively rare. The studies we extracted values from did not use the Kauffman and Donato protocols but nonetheless provided robust estimates of site-level aboveground biomass carbon and soil organic carbon stocks in arid mangroves. The general approach of the biomass and soil organic carbon were sufficiently similar to the Kauffman and Donato protocols to justify their use. Specifically, aboveground and belowground biomass carbon were estimated by converting tree DBH measurements to dry-weight biomass estimates through allometric equations [1]. Sampling of soil carbon was performed through coring and subsampling the core along specified depth intervals, thus accounting for variation in soil organic carbon density with depth [6]. Both sites were monospecific stands of *Avicennia marina* and had similar climatic and geomorphological conditions to the Arabian Gulf.

For Thailand, we used values from one of the most well-cited studies for mangrove carbon stocks in Southeast Asia [35]. The study performed a regional inventory of mangrove carbon in Southeast Asia (25 sites across Borneo, the Ganges-Brahmaputra Delta, Java, Kosrae, Palau, Sulawesi, and Yap) and reports estimates of carbon stocks across all ecosystem carbon pools for mangroves. Mangrove carbon stocks are reported for all sites as well as disaggregated into estuarine and oceanic sites. We use the summary values for estuarine mangroves given that they are the most appropriate for our sites. The aboveground biomass, belowground biomass, and coarse woody debris are used directly from the table, whereas the soil organic carbon values require extrapolation to 1 m depth. No horizon specific data on soil bulk density, percent organic carbon, or carbon density is reported. We are consequently limited to using average bulk density and percent organic carbon values for the full core depth despite the fact that soil carbon density varies as a function of soil depth.

3. Additional points of discussion

The role of Geographic Information Systems (GIS) for mangrove carbon programs

Both of the modeled carbon stock datasets examined in this study are available as global rasters at 30 x 30 m resolution. Access, use, and analyses of these data therefore require the use of Geographic Information Systems (GIS) software, warranting a brief discussion of the role of GIS for mangrove carbon programs. Geospatial data analyses are common within the mangrove research community and may include studies of land cover and/or land use change, inventories, and predictive modeling as exemplified by the studies considered here [134, 122]. A large amount of sophisticated and well developed free and open source GIS software exists, including both graphical user interface (e.g., QGIS) and code-based (e.g., Program R, Python) platforms. Common within the research community, basic spatial analyses steps such as overlaying rasters and extracting values at points of interest or summarizing data for regions of interest are feasible for mangrove managers, policy-makers and practitioners. A large number of freely available resources exist to aid in these endeavors [14].

An extension of GIS is remote sensing, which typically consists of converting raw imagery of landscapes into processed data. Remote sensing can refer to a wide range of datasets but perhaps most commonly refers to the analysis of satellite imagery at local to global scales. Similar to GIS, remote sensing in mangroves is common but has unique challenges due to the mixing of water, soil, and vegetation within the same pixel [89, 47]. Ongoing satellite missions (e.g., the NASA Landsat program) provide publicly available data at repeat time intervals, which can allow for basic analyses and monitoring of landscapes. Although conversion of raw imagery to useful datasets is perhaps more complicated than analyzing pre-existing spatial datasets, there are also a large number of online tutorials to assist potential users in basic remote sensing procedures.

Additional discussion of predictive modeling in mangroves

Modern classification techniques, publicly available remotely sensed imagery, and large databases of ecological data have greatly enabled predictive modeling in the environmental sciences. Mangroves are simultaneously conservation hotspots and difficult to access, rendering predictive models particularly useful for filling important data gaps. As larger datasets and more powerful modeling techniques become available in the future, additional global datasets of key variables for mangroves will likely emerge. For example, moving beyond extant stocks to model net primary productivity, soil carbon accretion, or export of particulate and/or dissolved organic carbon would be highly valuable for the mangrove community. Predictive models are works in progress that are ultimately limited by the data available during their production. Approaches in which models are consistently maintained and updated via the incorporation of new training data are particularly valuable. Nevertheless, it is critical for model producers to provide clear guidance on the use of model outputs. Additionally, predictive modeling in mangroves would do well to align with existing and future efforts such that data are directly comparable across time and space. For example, the large number of remote sensing missions capable of measuring forest structure are likely to provide more consistent and regular estimates of biomass in forests, globally. Aligning future modeling efforts with these datasets will not only facilitate better understanding of their ecology and impacts from change, but also advance the forecasting of impacts from future pressures (including climate change) on mangroves in the future.

Other barriers to forest carbon programs

While we believe that accurate estimates of carbon stocks are important for designing and implementing valid carbon forestry programs, we recognize that there are other important barriers to the success of these programs [95, 146]. The quantification of carbon stocks in mangroves is a technical science, whereas the management of natural resources requires accounting for social, economic, and political factors. Considerations that relate to the human side of natural resource management – e.g., de-/centralization of governance, benefit sharing, assent of stakeholders, and/or leakage – can be stronger barriers or challenges for the success of carbon forestry programs than the quantification of carbon stocks [128, 70]. Our aim in this study was not to argue for more technical or complex inventories of carbon stocks in mangroves, which are often more expensive and add financial barriers to programs, but rather to situate publicly available data that is potentially more accurate and more representative of mangrove carbon stocks, globally. Uncertainty in carbon stocks can be dealt with by using conservative estimates, but may ultimately result in reduced benefits for local communities. Ultimately, carbon stock estimates should not constrain the development of carbon forestry programs, but should be robust enough that programs induce tangible draw-downs in atmospheric carbon. Although we only note a few of these barriers here, there is a large and robust literature on socio-economic and socio-political constraints to forest carbon programs. We strongly recommend the reader examine this literature for a more full and complete picture of forest carbon programs.

Chapter 3

Net loss statistics underestimate carbon emissions associated with mangrove land use and land cover change

Abstract

Converting mangroves to other land cover types can induce large emissions of carbon dioxide, depending on the type of land use and land cover change (LULCC). However, mangroves may also recover their ecosystem carbon stocks rapidly following restoration, potentially offsetting prior losses of carbon stocks. While a number of studies have quantified these tradeoffs at global scales using coarse metrics, fewer studies have quantified them at national scales at higher resolution. Here, we used high resolution datasets of land use and land cover in the mangrove-holding regions of Thailand to quantify emissions of carbon associated with gross versus net changes in mangrove extent from ∼1960-2014. We found emissions associated with metrics of gross gain and loss (7.18 ± 0.24 million Mg C) to be greater than those associated with net area change statistics (1.65 ± 0.26 million Mg C) by a factor of four. The difference in estimates arises from slower rates of carbon stock recovery following reforestation relative to carbon stock loss following LULCC. Overall, we found the greatest gains in mangrove carbon stocks to be from mangrove expansion in areas of accreting sediments, which were strongly correlated with district-level extent of undisturbed mangroves. Our results show that net loss statistics may greatly underestimate emissions associated with LULCC in mangroves. Additionally, our findings suggest that carbon sequestration associated with natural establishment by standing mangroves may offset substantial carbon stock losses at national scales.

Keywords

LULCC, climate change mitigation, natural climate solutions, soil organic carbon, wetlands, blue carbon

3.1 Introduction

Vegetated coastal ecosystems such as mangroves, seagrass beds, and salt marshes—commonly referred to as blue carbon ecosystems—are capable of stocking large quantities of organic carbon [35, 96, 98]. The vegetation structures of blue carbon ecosystems help promote the rapid burial of organic material in soils, both through direct contributions from belowground biomass production as well as the capturing of suspended mineral sediment in water columns [87]. Furthermore, the anaerobic conditions and abundant sulphate of intertidal soils help to suppress remineralization of soil organic carbon once it has been buried [19]. As a result of these processes, blue carbon ecosystems are estimated to account for half of the carbon burial in marine sediments despite occupying less than 2% of the coastal ocean floor [36]. Conserving and restoring blue carbon ecosystems have consequently been identified as promising natural climate solutions, potentially providing large carbon drawdowns at low costs [55, 71, 132].

Mangroves—the intertidal forests of tropical and subtropical coastlines—are a high-profile blue carbon ecosystem. Mangroves have historically had very high rates of deforestation [37] but have more recently seen reduced rates of loss [48, 116]. The ability of mangroves to rapidly sequester organic carbon while also providing abundant non-carbon ecosystem services has encouraged coastal managers and policymakers to reduce their deforestation [42]. At global scales, mangrove loss rates have been reduced from as much as 2% per year in the early 2000s to a mean annual rate of 0.26-0.66% from 2000-2012 [37, 57]. Given widespread historic losses of mangroves, there is interest in not only halting further deforestation of mangroves but also also in their restoration [54, 91].

Despite these successes, human-driven land use and land cover change (LULCC) continues to drive losses of mangroves [48]. LULCC in mangroves has both substantial and varied impacts on ecosystem carbon stocks, depending on the carbon pool and the type of LULCC that occurs [42, 81, 123]. For LULCC that disturbs organic soils—where the majority of carbon is found in mangrove ecosystems—the impacts on the climate over near- to mid-term time frames are uncertain. Some studies have shown rapid recovery of soil organic carbon stocks in mangroves following restoration [2, 117] whereas others have deemed the resulting emissions “irrecoverable,” or unable to be recovered on meaningful timescales for avoiding dangerous climate change [49, 79]. Others have suggested that substantial quantities of soil organic carbon may be preserved in aquaculture soils following LULCC [40].

Understanding of mangrove loss and gain has largely been driven by global or regional analyses of earth observation data [46, 116, 140]. While valuable in providing global snapshots of the state of mangroves, many of these studies use coarse aggregations of land use and land cover type (e.g., mangrove vs. non-mangrove) that make it difficult to disaggregate the effects of specific LULCC types on carbon emissions. While these methodologies are effective at quantifying mangrove deforestation in areas of rapid mangrove loss such as Myanmar [28], they may underestimate loss in regions where net loss is relatively static but conversion of mature mangroves to other land uses continues to occur. In recognizing this, recent studies have noted the importance of smaller-scale studies that are capable of modeling LULCC in mangroves across more-specific land cover classes and at finer spatial resolutions [42, 149].

Thailand is one country in which net mangrove loss is relatively low yet LULCC within its mangrove-holding regions continues to occur. Thailand has lost approximately half of its historical mangrove extent, largely through conversion to shrimp aquaculture [5]. Today, Thailand's coasts are a shifting mosaic of mangrove forest, active and abandoned aquaculture ponds, and other coastal land uses such as agriculture and salt farms. Within this landscape, it is unclear if mature mangrove forests are truly protected from further conversion, or whether continued losses are offset by gains in mangrove canopy cover from restoration projects and natural regeneration. Although widespread within Thailand, mangrove restoration projects are controversial due to low rates of establishment and seedling survival [141]. Under the case in which continued mangrove loss is offset by planted mangroves with low rates of survival, the greenhouse gas emissions associated with this shifting coastal landscape may be greatly underestimated by statistics of net area loss.

To examine the impacts of shifting LULCC on mangrove carbon stocks, we quantified gross versus net changes in Thailand's mangrove carbon stocks across nine different land cover classes from before their widespread conversion (ca. 1960) to the present (2014). Specifically, we asked how do changes in mangrove carbon stocks disaggregated by type of LULCC compare to carbon stock change estimates based on statistics of net loss of area? We answered this using multiple high-resolution datasets of land use and land cover data from mangrove-holding regions in Thailand. These datasets allowed us to model LULCC over multiple time periods and through distinct trajectories, as well as the associated gains and losses of pool-specific carbon stocks. Finally, we used scenario analysis to examine the potential of mangrove restoration to contribute to Thailand's Nationally Determined Contribution under the United Nations Framework Convention on Climate Change.

3.2 Methods

Description of datasets

Our analysis is based on datasets of mangrove carbon stocks and land use and land cover along Thailand's coasts. We used five datasets in this study: two published rasters of aboveground carbon and soil organic carbon stocks in mangroves, and three maps of land use and land cover in Thailand's mangrove holding regions. The aboveground carbon and soil organic carbon data are published rasters at approximately 30 x 30 m spatial resolution, which have been widely used for modeling of carbon stock changes in mangroves at broad geographic scales [122, 134]. Specifically, these maps have informed analyses at both national [88] and global scales [3, 117, 152]. Although in situ measurements of aboveground carbon and soil organic carbon data are preferable over global maps, these data are unavailable across wide geographic scales for Thailand, hence necessitating the use of these maps. Moreover, the maps of carbon stocks have been cross-validated and have associated uncertainty measurements, which we have incorporated into our analyses.

We obtained land use and land cover data from the Thai Department of Marine and Coastal Resources. The datasets map land use and land cover in mangrove holding regions of Thailand for the years 2000 and 2014. The extent of all land use and land cover categories in the 2000 dataset corresponds to the historical extent of mangroves in Thailand, giving us a third dataset before the widespread conversion of mangroves to aquaculture. Given that Thailand saw significant changes in its extent of mangroves beginning in the 1960s, we refer to this dataset as the "pre-1960" dataset [5]. All datasets were processed to align spatial properties (i.e., extent, resolution and projection) and data formats before being analyzed (see Section S1.1 of the supplementary information).

Characterization of district-level mangrove carbon stocks

To estimate potential changes in carbon stocks associated with mangrove loss and gain, we used the aboveground carbon and soil organic carbon rasters to derive average carbon stock values for each of Thailand's 97 coastal districts. The aboveground carbon and soil organic carbon datasets provided estimates of mangrove carbon stocks for the year 2000. Given no other means of estimating carbon stocks from pre-1960 or 2014, we consequently assumed that the district level averages are representative of carbon stocks in established mangroves across this time period. For districts that had mangroves fully extirpated from them by 2000, we obtained district-level averages by averaging across all districts within the province.

Mangrove carbon stocks vary spatially as a function of environmental constraints on their productivity and burial rates of carbon in sediments. Although the raster datasets account for spatial variability, the potential for geomorphology to vary within districts and potentially bias our estimates of carbon stocks exists. We tested for the spatial scale at which proxies for site geomorphology influenced mangrove carbon stocks using a k-means clustering algorithm and raster products of total suspended matter and tidal amplitude (Section S1.2). The clustering algorithm produced clusters at broader scales than districts, suggesting that district-level stock averages are sufficient for our purposes.

Modeling of land use and land cover change

We estimated LULCC for two time periods: from pre-1960 to 2000 and from 2000 to 2014. The total extent of the land use and land cover data from 2000 is the Thai Department of Marine and Coastal Resource's best estimate of the original extent of mangroves in Thailand (pers. comm. Srisawalak & Vincent), and we therefore used it as our estimate of pre-1960 mangrove extent. To obtain estimates of LULCC from 1960-2000, we summed the land use and land cover classes from the 2000 dataset. Although it is likely that individual pixels underwent multiple instances of LULCC from 1960 and 2000 (e.g., mangrove to aquaculture to mangrove), we did not have the independent estimates of losses and gains necessary to estimate gross changes in carbon stocks associated with these transitions. We consequently omitted the potential impacts on carbon stocks of these transitions from our analysis. Using the spatially-aligned rasters of land use and land cover from 2000 and 2014, we cross-tabulated the datasets to obtain LULCC from 2000 to 2014. We quantified transitions of a "no data" category in 2000 to other land use and land cover classes in 2014, which allowed us to identify new stands of mangroves that colonized areas not included in the 2000 dataset (e.g., prograding shorelines).

Modeling gains and losses of mangrove carbon stocks

Next, we modeled changes in carbon stocks as a function of the district-level average carbon stock densities and extents of LULCC. Our approach was similar to those of other recent studies [117]; however we believe it is a marked improvement for several reasons. First, we used data that identifies nine different land use and land cover types, which allows for examining LULCC specific effects on mangrove carbon stocks. Second, we used an improved approach for modeling changes in mangrove aboveground carbon and soil organic carbon stocks. Former approaches have relied on carbon stock recovery models that include all blue carbon ecosystems (i.e., both seagrasses & salt marshes) and may therefore use overly optimistic recovery rates of carbon stocks in mangroves [117, 103]. That is, aboveground carbon (and possibly soil organic carbon) pools in forests are expected to take substantially longer to develop relative to seagrass and salt marsh ecosystems and conflating their recovery times may produce biased results. Third, we modeled the recovery of aboveground carbon and soil organic carbon separately, which provides a refined description of carbon stock recovery in mangroves.

We parameterized five equations to model changes in carbon stocks as a function of time: loss of aboveground carbon, loss of soil organic carbon, gain of aboveground carbon, gain of soil organic carbon, and foregone carbon sequestration by standing forests. We excluded changes in carbon in the belowground biomass pool given that this pool is highly uncertain in mangroves. Moreover, default ratios for estimating belowground biomass as a function of aboveground biomass (e.g., a root:shoot ratio) are likely to vary spatially and we did not have a means to account for this variation [4].

Each of Eqs 1a, 1b, & 2 predicts the natural logarithm of the response ratio, where the response ratio is the ratio between carbon stocks in a disturbed versus undisturbed reference site. The losses in aboveground carbon and soil organic carbon are modeled as a linear function of time since LULCC, whereas gains in soil organic carbon are modeled as a log-linear function of time since LULCC.

Eqs. 1a & 1b:

$$ln(RR)_{AGC,\ SOC\ Loss} = a + b * t$$

Eq. 2:

$$ln(RR)_{SOC\ Gain} = a + b * ln(t)$$

Where:

- $ln(RR)$ is the natural logarithm of the response ratio for aboveground carbon loss (Eq. 1a), soil organic carbon loss (Eq. 1b), and soil organic carbon gain (Eq. 2),
- t is time since LULCC in years,
- and a and b are statistical parameters to be estimated from the data.

To parameterize the aboveground carbon loss (Eq. 1a), the soil organic carbon loss (Eq. 1b), and the soil organic carbon gain (Eq. 2) equations, we used data from two quantitative meta-analyses on impacts of land cover change on mangrove carbon stocks [103, 123]. Data from Sasmito et al was used to parameterize the aboveground carbon loss (Eq. 1a) and soil organic carbon loss (Eq. 1b) equations. For Eq.2, we used data on the recovery of carbon stocks in blue carbon ecosystems, which included all ecosystem pools and vegetated blue carbon ecosystems (e.g., seagrasses, salt marshes, and mangroves) [103]. However, we filtered their references to only those that report data on soil organic carbon recovery in restored mangroves and added data from one additional study that reports data on soil carbon recovery in Thai mangroves (S1.3) [40].

We then fit Eq. 1a using a linear regression model given that all data points came from independent sites, whereas we fit Eq. 1b and Eq. 2 using mixed effect models due to site-level correlations in the data. To account for this correlation, we included a random intercept by site. We fit Eq. 1 using the ”lm” function in the base package of Program R, whereas we fit the mixed effects models with the {nlme} package [112].

We modeled recovery of aboveground carbon in mangroves separately from soil organic carbon stocks using data reported by Sasmito and colleagues [123]. To model recovery of aboveground carbon, we used the Chapman-Richards growth curve, which is both a flexible and theoretically defensible descriptor of forest development across time (Eq. 3). The Chapman-Richards growth curve has four parameters, each of which describes theoretical components of growth: A, the maximum asymptotic growth limit, b a scaling parameter, k the rate of growth, and m an allometric constant. For our purposes, we were most concerned with A, the asymptotic growth limit, and k the rate of growth, which we discuss in detail below. The Chapman-Richards curve is specified as:

Eq. 3:

$$AGC = A * (1 - b * e^{(-k*t)})^{(1/(1-m))}$$

Where:

- AGC is aboveground carbon in Mg C ha^{-1},
- t is the age of the forest stand in years, and
- A, k, b, and m are parameters to be statistically estimated from the data.

Given that mangrove restoration has only begun to occur over the last 20-30 years, there are limited data on aboveground carbon stocks in older, restored forests. We consequently "anchor" our growth curve with data from established secondary mangrove forests in Thailand [18, 16, 40]. The data come from three sites, each of which have had continuous mangrove cover for over 20 years [16]. Given that the exact age of these stands are unknown (but are known to exceed 20 years), we randomly assigned stand ages from 30-60 years using a uniform distribution. Although an unconventional approach, we believe it to be reasonable for two reasons. First, this is functionally equivalent to setting the asymptotic growth limit parameter (A), a common practice to produce a modified form of the Chapman-Richards growth function. We do this using empirical data from three different sites spread across Thailand, which provide an empirically informed estimate of steady state aboveground carbon stocks in Thailand's mangroves. Second, for the purposes of our modeling, we are only concerned with estimating aboveground carbon stock recovery for mangroves up to 14 years of age. The asymptotic growth limit is therefore less important than accurate estimation of the aboveground carbon stocks in forests of no more than 14 years of age.

Nevertheless, we examined the effect of setting the asymptotic growth limit on our estimates of recovered aboveground carbon stocks with a sensitivity analysis. Specifically, we examined how varying our estimate of A by ± 50% effected our final results. Doing so varied our final estimate of net change in carbon stocks by 8%, which was within the 95% confidence interval of our best estimate. Further, varying the asymptotic growth limit by ± 50% adjusted the curve form to encompass the vast majority of our aboveground carbon stock data from 0 to 14 years of age, suggesting that these curves might represent minimum and maximum rates of aboveground carbon stock recovery (Figure S2 of the supplementary material). We therefore concluded that our approach for estimating the maximum potential growth was reasonable and had a minor impact on our results.

Finally, we used these data to estimate the model parameters for the Chapman-Richards function. To simplify statistical estimation of the parameters, it is common to fix both the scaling parameter b and the allometric constant m, allowing for the theoretical maximum stand-level biomass (A) and growth rate (k) to be statistically fit to the data [20]. Given relatively limited data, we followed this procedure and fixed both the scaling parameter ($b = 1$)

and allometric constant ($m = 0.5$). We then estimated the asymptotic maximum stand-level biomass and growth rate parameters (A and k) using non-linear mixed effects models, with site included as a random effect. All growth curves were parameterized using the {saemix} package in Program R (version 4.0.4), which employs the Stochastic Approximation Expectation Maximization algorithm to derive maximum likelihood estimates of the parameters [26].

Spatially-explicit values of carbon sequestration are absent for extant mangroves. To estimate the foregone carbon sequestration that is associated with loss of mangroves, we multiplied a global mean rate of carbon sequestration (1.5 Mg C ha^{-1} yr^{-1}) by the number of years since LULCC [7, 3].

Eq. 4:

$$Foregone\ Sequestration\ (Mg\ C\ ha^{-1}) = 1.5\ Mg\ C\ ha^{-1}\ yr^{-1} * years$$

Eqs. 1-4 describe the district-level losses and gains of aboveground carbon, soil organic carbon, and carbon sequestration potential associated with LULCC. Given that we did not have exact dates associated with when LULCC occurred, we followed the approach of Richards and colleagues and used a uniform distribution to randomly assign an "activity year" from 2000 – 2014 to each district [117]. This modeled all activity in an individual district as occurring in the same year, which is a strong simplification, but better approximates the time dependent nature of carbon stocks and gains relative to assuming all changes occurred in the year 2000. After assigning each district an activity year, we used Eqs. 1-4 to model the district-level carbon stock losses and gains and subsequently multiplied them by the district-level LULCC specific extents of mangrove loss and gain.

Quantifying gross vs. net change in mangrove carbon stocks

Using the LULCC data, we then modeled district level mangrove carbon losses (i.e., losses associated with loss of mangrove cover), recovery (reforestation of areas that were formerly mangrove), and gain (colonization of new areas that were not historically mangroves). The distinction between recovered mangrove carbon stocks and gains is important given that soil organic carbon is capable of being preserved following land cover change, even under systems of heavy disturbance such as conversion to aquaculture [40].

To estimate the recovery of carbon stocks that are associated with mangrove reforestation, we accounted for preserved carbon in our change in carbon stock estimates. We therefore subtracted estimates of preserved carbon stocks to obtain the net change in carbon stocks associated with mangrove loss, recovery and gain. Specifically, we multiplied the district-level extent of mangrove loss by the sum of the mean carbon stocks and foregone sequestration, less the preserved stocks in the soil organic carbon pool (Eq. 5). The estimate of preserved carbon is obtained from Eqs. 1a & 1b, which return the preserved carbon stocks as a function of time since LULCC.

Eq. 5:

$$C\ Stock_{loss} = Extent\ Loss * (C\ Stock + Sequestration - Preserved\ C)$$

For carbon stock gains in reforested or newly colonized areas, we multiplied the district-level extents of mangrove recovery and gain by the aboveground carbon and soil organic carbon gains in carbon stocks minus our modeled estimates of preserved carbon (Eq. 6). We subtracted estimates of preserved carbon from the carbon sequestration associated with establishment of new mangrove forests (i.e., gain estimates) to account for carbon stocks that may be present in the soil systems of mudflats, river banks, or other areas that mangroves may colonize. Although this is an approximate estimate, carbon stocks in the mud flats of Singapore have been estimated at 124-143 Mg C ha^{-1}, which is roughly equivalent to our estimates of preserved soil organic carbon stocks [110].

Eq. 6:

$$C\ Stock_{recovery,\ gain} = Extent_{recovery,\ gain} * (C\ Gain - Preserved\ C)$$

Finally, we summed the district-level estimates of carbon stock loss (Eq. 5) and carbon stock gain (Eq. 6) to obtain our estimates of carbon stock changes associated with gross changes in mangrove extent (Eq. 7). The key distinction of this approach is the recognition that carbon stocks in mangroves are lost and gained at different rates. The time-dependent modeling of carbon stock gains and losses consequently accounts for this under this approach.

Eq. 7:

$$C\ Stock_{gross\ area\ change} = C\ Stock_{loss} + C\ Stock_{recovery,\ gain)}$$

We then compared these estimates against those based on a net area loss statistic, which we estimated as a function of the net area change statistic (i.e., difference between 2000 and 2014 extents of mangroves) and our models for carbon lost with LULCC (Eq. 8). Notably, this approach focuses solely on loss and does not account for carbon stock gains on the landscape (however, our approach does account for preserved carbon stocks following LULCC). Estimating carbon emissions associated with net loss of area represents the most widely used approach within the literature.

Eq. 8:

$$C\ Stock_{net\ area\ loss} = Net\ Area\ loss * (C\ Stock + Sequestration - Preserved\ C)$$

Quantification of uncertainty

We quantified uncertainty in the district-level carbon stock values and the modeled estimates of carbon stock gains and losses, whereas we did not have a means of quantifying uncertainty in the land use and land cover data. The land use and land cover data were produced via a combination of remote sensing and ground-truthing. Officials from the Thai Department of Marine and Coastal Resources visited the individual land use and land cover polygons and confirmed the land use and land cover type, ensuring a high-quality dataset (pers. comm. Thai DMCR). Although we were not able to quantify uncertainty associated with these data, it is likely that their uncertainties do not exceed those of remote sensing products commonly used to estimate mangrove change at global scales [46].

We used a Monte Carlo simulation approach to quantify uncertainty in our estimates. First, we randomly generated district-level values for the aboveground carbon stocks, soil organic carbon stocks, and activity years using their statistical distributions. We used the first and second moments of the stocks' distributions (assumed to be Gaussian), whereas we generate values from a uniform distribution (ranging from 1 to 14) for the activity years. We then used the carbon stock values and our above models (Eqs. 1-5) to calculate district-level loss, recovery, and gain of mangrove carbon stocks. We saved the loss, recovery and gain values as the outputs of a single run and repeated the process for each district a total of 100 times, which we determined as an appropriate trade-off between simulation time and stabilization of standard errors of the means. Finally, we averaged the simulation run values and calculated their standard error as our final estimates of carbon stock changes and associated uncertainty.

We estimated uncertainty in the aboveground carbon and soil organic carbon raster data by simulating random spatial fields. To do this, we inputted district-level mean values (e.g., mean aboveground carbon for the district of Pak Phanang) into a spatial trend model and inputted raster-specific model errors (cross-validation root mean square error) into a covariance function. We used the models to simulate random spatial fields for each raster at the district-level, repeated this process a total of 40 times, and saved the mean carbon stock values from each run. We averaged these values and calculated their standard error as our final estimates of district level carbon stocks and associated uncertainty. Similar to above, we determined a total of 40 simulation runs to be an appropriate tradeoff between stabilization of uncertainty and computational time (Figure S1). All spatial simulations were performed using the {RandomFields} and {geostatsp} packages in R Version 4.0.4. [15, 127]. Additional details on the raster simulation are provided in the supplementary information (S1.4). Unless otherwise noted, we report all uncertainty in our results as mean values ± standard error of the mean.

Scenario analysis of potential for mangrove restoration to meet Thailand's Intended Nationally Determined Contribution

Finally, we examined the potential carbon sequestration that could be achieved via mangrove restoration through scenario analysis. Using the land use and land cover data from 2014, we identified land use and land cover classes that are likely to be available for mangrove restoration: aquaculture, agriculture, salt farms, and abandoned land. Other land use and land cover classes are either under extensive development (e.g., urban areas) or are inappropriate for restoration. Given that not all areas under aquaculture, agriculture, or salt farms are available for restoration, we examined the potential carbon sequestration associated with restoring set proportions of each land cover class. Specifically, we examined the climate change benefits associated with restoring 0.1%, 1%, 2%, 5%, and 10% of all land potentially available for restoration. The scenarios range from a feasible scenario (0.1%) to an ambitious target (10%) for restoring potentially available land. Given that we were more concerned with the technical potential for carbon sequestration through mangrove restoration than social, economic, or political constraints on restoration here, we distributed sites of restored agriculture and aquaculture evenly across all districts. In other words, we assumed that up to 10% of the district-level extents of agriculture, aquaculture and salt farms are potentially available for restoration. To quantify the associated carbon sequestration benefits, we multiplied the extents of potentially restorable land in each scenario using the district level averages of the aboveground carbon pool. Finally, we compared our estimates of the climate change mitigation potential from mangrove restoration against Thailand's Intended Nationally Determined Contribution under the United Nations Framework Convention on Climate Change.

3.3 Results

Characterization of land use and land cover change

In 2014, Thailand's mangrove cover was approximately 53% (245,300 ha) of its historical extent with substantial impacts from human-driven LULCC. The LULCC data confirm aquaculture as a major driver of mangrove loss, particularly during the period of extensification before 2000 (Tables 1 and S2). Aquaculture, agriculture and salt farms were the greatest drivers of mangrove loss in Thailand, occupying approximately 15.4%, 11.8% and 5.5% of the study region in the year 2014. Furthermore, extensive transitions in land use and land cover type across the aquaculture, agriculture, and salt farm classes occurred, suggesting that Thailand's mangrove holding regions are indeed a shifting landscape. For example, approximately 7,800 ha of aquaculture transitioned to agriculture and approximately 6,100 ha of aquaculture transitioned to salt farms between 2000 and 2014.

The data also show that net loss statistics greatly underestimate gross losses of mangroves in Thailand. Between 2000 and 2014, approximately 203,000 ha of mangrove extent did not undergo a land use or land cover transition. In other words, of the 252,000 ha of mangrove identified in 2000, approximately 49,500 ha of mangrove coverage was lost and 42,300 ha of mangrove coverage was gained by 2014, for a net loss of 7,200 ha. The largest changes in land use and land cover were seen for the aquaculture, agriculture, water, and the "no data" classes. The data show a loss of 8,300 ha of mangroves to aquaculture as well as a gain of 10,500 ha of mangroves in aquaculture areas for a net gain of 2,200 ha. Conversely, gains of approximately 7,900 ha of mangrove cover in agricultural areas were heavily offset by extensive losses of 19,000 ha of mangrove to agricultural lands.

We also found losses and gains that were not associated with direct anthropogenic land use or land cover conversion to be substantial. The largest gains in mangrove extent (17,200 ha) were identified as transitions from the "no data" class to mangroves, which we interpreted as mangrove colonization of regions that were not included in the 2000 land use and land cover data. Visual inspection of these regions suggest that they are largely mudflats, river banks, and prograding deltas. Additionally, the second largest loss transition (13,200 ha) was mangrove to the "water" class, which suggests the role of erosion and/or relative sea level rise and aligns with the findings of other studies [3, 48]. Although these transitions largely offset one another, the gains were higher than losses for a net gain of approximately 4,000 ha of mangrove (Table 1).

The spatial patterns of LULCC reveal that local mangrove loss (measured as a percent loss of mangrove extent within district) has been greatest along the Gulf of Thailand (Figure 1, Panel b). Massive losses of mangrove extent have occurred within the Chao Praya River delta (i.e., Bangkok), the eastern regions near Cambodia, and the southeastern coast of peninsular Thailand. Of the 97 districts examined, the top 10 in terms of areal extent of mangrove loss account for approximately 42% of total loss within the country (Table 2). Eight of these ten districts are found in either the Chao Praya River delta (i.e., Bangkok region) or the eastern region of the country. Furthermore, the top half of districts (by extent of loss) accounts for approximately 89% of national loss.

Parameterization of the carbon stock gain and loss models

The gain and loss models for aboveground carbon and soil organic carbon stocks in mangroves are shown in Figure 2, whereas the model coefficients are provided in Table 3. Although there are markedly few data points for the aboveground carbon loss model, deforestation of mangroves results in rapid loss of biomass by definition and thus the model is sufficient for our purposes. The relationships between time since LULCC and loss of aboveground carbon and soil organic carbon are linear, whereas the relationships between time since LULCC and aboveground carbon and soil organic carbon recovery are logistic and logarithmic, respectively (Figure 2).

Carbon emissions from mangrove LULCC

Net losses of mangrove carbon due to human-driven land use change (i.e., conversion of mangroves to aquaculture, agriculture, abandoned land, salt farms, or urban areas and ports) were approximately 32.26 ± 0.51 million Mg C from pre-1960 to 2000. For the more recent period of 2000 to 2014, gross total losses of land use change in mangroves were 9.79 ± 0.15 million Mg C. However, we also estimated gains in carbon stocks during the same time period of 2.60 ± 0.09 million Mg C, resulting in a net loss of 7.18 ± 0.24 million Mg C. Estimating carbon losses as a function of the net area of loss statistic (i.e., Eq. 8) estimates carbon emissions at approximately 1.65 ± 0.26 million Mg C for the same time period. Notably, the total emissions estimate from summing the gross losses and gains is greater than those based on net change in area by a factor of approximately four (Figure 3).

Carbon sequestration associated with recovery of areas that were formerly under mangrove was large, at approximately 2.08 ± 0.20 million Mg C. However, we also identified substantial carbon sequestration associated with the colonization of new areas of mangroves at 1.27 ± 0.12 million Mg C. Visual inspection of areas with high gains of mangrove extent suggests that these are driven by mangrove colonization of areas such as mud flats, river banks, or other areas of rapidly accreting sediment. Furthermore, gains in mangrove extent at the district-level were greatest for those districts that maintained large extents of undisturbed mangroves. Examining the relationship between district-level extent of new colonization and undisturbed extant mangroves revealed a strong positive correlation (Pearson's Correlation = 0.87) (Figure 4).

Carbon sequestration potential associated with mangrove restoration

The land use and land cover data show 1,500 ha of abandoned land potentially available for restoration in 2014. Similarly, approximately 70,700 ha of aquaculture, 54,500 ha of agriculture, and 25,300 ha of salt farms spanned Thailand's coastlines in 2014. Under our various scenarios of potential regeneration (all 1,500 ha of abandoned land and 0.1-10% of aquaculture, agriculture and salt farms), we estimate a range in potential associated carbon sequestration of 0.14 – 1.46 million Mg C over the next 10 years (Table 4). The low estimate corresponds to the restoration of 1,651 ha of deforested mangrove, whereas the high estimate corresponds to 16,550 ha of restored forest. Thailand committed to a 20% reduction in its business as usual emissions scenario of approximately 555 Mt CO2e by 2030 in its Intended Nationally Determined Contribution. As such, Thailand is responsible for reducing emissions by 111 Mt CO2e, or the equivalent of 30.3 million Mg C, by 2030. Our most optimistic estimate of carbon sequestration from mangrove restoration is approximately 1.46 million Mg C. This suggests that mangrove restoration, even under our best-case scenario, is likely to represent only 4.8% of Thailand's INDC from 2020-2030.

3.4 Discussion

Irrecoverable carbon and land use and land cover change in Thailand's mangroves

Our study provides three major insights for quantifying carbon emissions from land use and land cover change in mangroves. First, we demonstrated that quantifying greenhouse gas emissions associated with net loss of mangrove forests may underestimate emissions in regions with shifting land use and land cover patterns. We attribute this result to higher rates of carbon loss with mangrove conversion relative to carbon stock recovery with re-establishment of mangrove cover, despite high levels of carbon stock preservation and rapid rates of carbon stock recovery following forestation. For our specific case of Thailand, our estimates of carbon emissions from mangrove loss and gain were approximately 7.18 ± 0.24 million Mg C between 2000 and 2014, whereas calculating carbon emissions from net loss of mangrove extent numbers estimated emissions from the same time period to be 1.65 ± 0.26 million Mg C. The two estimates in emissions differ by a factor of almost 4. These results suggest that despite reduced rates of net mangrove deforestation in recent years [48, 116], emissions associated with patterns of mangrove clearing and re-establishment of new forests – either via natural colonization or active planting – may still be high over the decadal time frames crucial for mitigating climate change [49].

Our second key finding was the unexpected result that substantial expansion of mangrove extent was due to colonization of areas not included in the 2000 dataset (i.e., the "no data" to mangrove transition), accounting for approximately 41% of total gains. This transition was roughly equivalent to re-establishment of mangroves in both aquacultural and agricultural areas combined. Although some of this mangrove expansion may be due to planting programs, it is likely that much of these gains represent patterns of natural establishment. Visual inspection of these regions shows that many of these new gains are along the coastal fringes of mangroves, mudflats, river banks, and on rapidly prograding deltas (e.g., the Pak Phanang Mangrove forest). District-level extent of newly established mangrove forest and extent of undisturbed mangrove forest were highly positively correlated (Pearson Correlation = 0.87; Figure 4). This suggests that large undisturbed extents of mangroves contribute heavily to expansion of mangrove cover and the associated sequestration of carbon, offsetting anthropogenic (e.g., land use conversion) and natural (e.g., erosion) drivers of loss.

Finally, we estimated the potential carbon sequestration benefits associated with restoration of mangroves to be 1.46 ± 0.05 million Mg C by 2030 under our best-case scenario, which is approximately 5% of the emission reductions that Thailand has committed to by 2030. While 1.46 ± 0.05 million Mg C is a substantial drawdown of atmospheric carbon, mangrove restoration is unlikely to play a major role in Thailand's climate change mitigation goals. This finding aligns with the conclusions of others that sequestration of carbon in mangroves is likely to play a relatively small role in reducing greenhouse gas emissions at national scales [138]. Furthermore, mangrove reforestation is commonly plagued by low rates of establishment and survival coupled with ineffective metrics of success, such as extent planted rather than monitoring of forest establishment [91, 141]. Our estimate of potential carbon sequestration from restoration may therefore be optimistic, particularly given the assumption that 10% of aquaculture and agriculture are available for mangrove reforestation within a landscape of shifting land use, and the assumption that all restoration would be initiated in the year 2000. Examining the gross gains and losses of aquaculture, agriculture, and salt farm extent between 2000-2014, a net gain of only 2,200 ha of mangrove cover was found in aquaculture areas, which represents just 2.9% of aquacultural extent in the year 2000.

Our results show a greater climate change mitigation opportunity in halting continued loss of mangroves relative to mangrove reforestation activities. For example, under a business as usual scenario in which gross loss and gain rates from 2020-2030 match those from 2000-2014, an additional 4.4 million Mg C is expected to be emitted from land cover change in Thailand's mangrove holding regions. These emissions are more than double the potential carbon sequestration benefits from the base case restoration scenario, suggesting that greater climate change mitigation opportunities exist in halting continued turnover of mangrove forests relative to reforestation. The finding suggests that addressing the ephemerality of natural regeneration is a critical challenge for securing climate benefits from forests, which parallels the findings of others in terrestrial forest systems [114]. Furthermore, when coupled with our finding that most gains were found in districts with large extents of undisturbed mangrove forests, limiting loss may suggest conservation as an efficient mechanism for expanding mangrove cover. This finding parallels calls for further strengthening protection of existing forests in addition to afforestation and reforestation efforts in the land sector more broadly [131].

Potential limitations and sources of uncertainty

Our findings are dependent upon the models of carbon stock loss and gain, as well as the datasets that we used to parameterize them [103, 123]. Calculating mean gain and loss rates across all districts as a function of the national average carbon stocks helps put our gain and loss rates into perspective. Across all districts, the average carbon stock loss rate after approximately 7.5 years (the mean activity year from the simulation) was approximately 51% of average carbon stocks at the national level (i.e., losses of 198.4 Mg C ha^{-1} relative to mean stocks of 390.5 Mg C ha^{-1}). In other words, we estimated roughly half of mangrove carbon stocks to be preserved 7.5 years after LULCC, which is similar to what other studies have reported within Thailand [40]. Similarly, we estimated gains of carbon stocks to average 83.4 Mg C ha^{-1} (20.5 Mg C ha^{-1} of aboveground biomass carbon, 62.9 Mg C ha^{-1} soil organic carbon) across all districts for the same time period, or approximately 21% of mean national carbon stocks (i.e., an average of 72% of reference level carbon stocks in restored mangrove after 7.5 years).

Although filtering the carbon stock recovery data from O'Connor and colleagues to just soil organic carbon in mangroves presents a less optimistic picture relative to all total carobn stocks across blue carbon ecosystem combined, our mean numbers still represent rapid rates of carbon burial in mangrove soils. Annualized across the mean activity year period of 7.5

years, these gains would correspond to an average of 8.4 Mg C ha^{-1} yr^{-1} buried in soils. This value closely approximates some of the higher values (9.5 Mg C ha^{-1}) that have been reported in the literature and exceeds those reported for colonization of new areas by non-native mangroves (4.5 Mg C ha^{-1} yr^{-1}) [2, 135]. Similarly, estimating soil carbon gains using the upper and lower bounds of the soil organic carbon recovery model's 95% confidence interval estimates carbon stocks at 48-118% of a reference site after 7.5 years, which roughly corresponds to the time period of 10-25 years that others have estimated for carbon stock recovery in restored mangroves [2, 29, 86]. However, data on soil carbon stock recovery was notably limited and we feel that these estimates are uncertain and warrant further research.

A key assumption of our analysis was that the soil organic carbon stocks of mangroves in the year 2000 were well approximated by our district level averages. From our land use and land cover change statistics (Table 1), it is clear that mangrove-holding regions in Thailand are a shifting mosaic of aquaculture, agriculture, salt farms, and mangroves. Under the case in which a large extent of mangroves in 2000 are restored forests with pre-existing losses of their soil organic carbon stocks, the magnitude of soil organic carbon losses from these forest stands may be overestimated by a district-level average. However, we believe our results to be robust for several reasons. First, the mangrove soil organic carbon model we used incorporated soil carbon stocks in both undisturbed as well as restored and planted forests. While there may be biases due to over-sampling of primary forests, the dataset that the soil organic carbon model was parameterized on should mitigate these effects [122]. Second, research in Thailand has shown that aquaculture ponds are capable of preserving and recovering carbon stocks under re-establishment of mangrove cover, particularly within the top 15 cm of soil [40]. Under the scenario in which a mangrove stand is converted to aquaculture, the pond is abandoned, and mangroves re-establish in the pond, re-conversion of that pond to active aquaculture may involve re-disturbance of the soil as well as further mineralization of carbon that was preserved in the pond.

Another key uncertainty of our analyses was the inclusion of soil organic carbon losses from the transition of mangroves to the "water" class. Little data on the fate of soil organic carbon following the drowning of mangrove stands exists. However, with the death of drowned mangrove trees and rapid loss of biomass carbon, we would expect associated losses of soil organic carbon [42]. Research into methane production in mangroves suggests that aerenchyma in dead mangrove trees may act as conduits for gas exchange between belowground and aboveground systems, potentially oxidizing submerged soils and inducing mineralization of soil organic carbon stocks [73]. Others have found evidence that suggests particulate and dissolved organic carbon may be exported and sequestered in deep oceanic sinks, which would reduce losses from drowned mangrove soils [99]. It is unlikely, however, that losses of soil organic carbon in drowned mangrove stands are zero and thus our estimate that approximately half of soil organic carbon stocks are lost is a reasonable coarse estimate absent empirical data.

Implications for mangrove conservation and restoration

While our study was specific to Thailand, the results have implications for mangrove restoration as a climate change mitigation action at global scales. Specifically, Thailand has key characteristics that would suggest it may benefit greatly from mangrove reforestation as a climate change mitigation action: it historically had large extents of mangroves, approximately 50% of its mangroves have been lost to land use change, and expansion of mangrove cover is specifically listed in its INDC. Thailand is also consistently ranked in the top 10-20 nations in terms of mangrove extent, standing carbon stocks, and potential carbon emissions [8, 58]. These characteristics suggest that Thailand stands to benefit heavily from mangrove restoration. However, as our results show, the climate benefits from mangrove restoration are modest relative to halting potential emissions from gross losses.

For countries with fewer opportunities for mangrove reforestation, it is perhaps unlikely that mangrove afforestation and reforestation will provide major climate change mitigation benefits in the short and medium-term. Furthermore, our findings suggest that large extents of undisturbed mangroves are associated with extensive gains in mangrove cover, which offset anthropogenic and natural drivers of loss. The findings ultimately suggest a multi-pronged approach that focuses on not only protecting established mangroves, but also strengthening protection of naturally regenerating areas, investing in restoration of deforested and degraded areas, and in research to increase planting survival.

Lastly, it is important to unambiguously state that our findings are not arguments against mangrove restoration. Mangroves provide myriad environmental goods and benefits to humans across local and global scales and expanding mangrove coverage will ensure these benefits continue to accrue. Sequestration of atmospheric carbon is included in these ecosystem services and we should therefore expect climate change mitigation benefits with successful restoration of mangroves. Rather, out study tempers expectations concerning the magnitude at which restoring mangroves might mitigate carbon emissions at national scales over relevant timeframes for mitigating dangerous climate change and adds further credence to protecting extant mangroves. To realize these benefits, heightened monitoring and enforcement of avoided mangrove conversion must occur simultaneously. Further, our findings suggest that net loss of area statistics may mask adverse changes to our environment. These same dynamics have recently been shown for wetlands in China, finding that extensive losses of natural wetlands are being replaced by artificial wetlands, which in turn drives the loss and degradation of ecosystem services [150]. It is apparent that monitoring conservation and restoration goals should focus on gross loss and gain statistics rather than net loss, as these statistics will uncover trade-offs in the values that we attribute to ecosystems.

3.5 Conclusion

Mangroves are carbon-rich ecosystems whose conversion and restoration have substantial impacts on the climate. Our results demonstrate that net loss of area statistics in mangroves may greatly underestimate emissions from mangrove loss. Areas in which mangroves are lost and subsequently recovered may consequently hide emissions from the soil organic carbon pool, which can be large. For our particular case of Thailand, we estimated emissions to be almost four times greater than those of a net loss approach when accounting for gross changes in area. In addition to better estimates of mangrove carbon stocks, improved data on specific LULCC transitions in mangrove holding regions is critical for better management of blue carbon in mangroves. Accounting for hidden emissions from shifting land use in mangrove holding regions is key to designing mangrove conservation policy, particularly given the current prevalence of ecosystem restoration globally.

Acknowledgements

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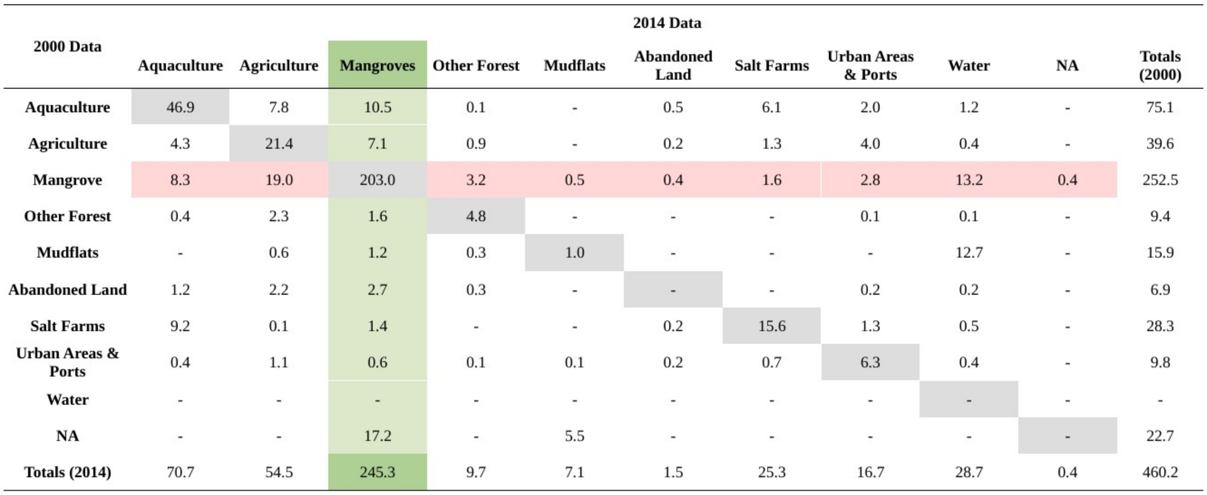
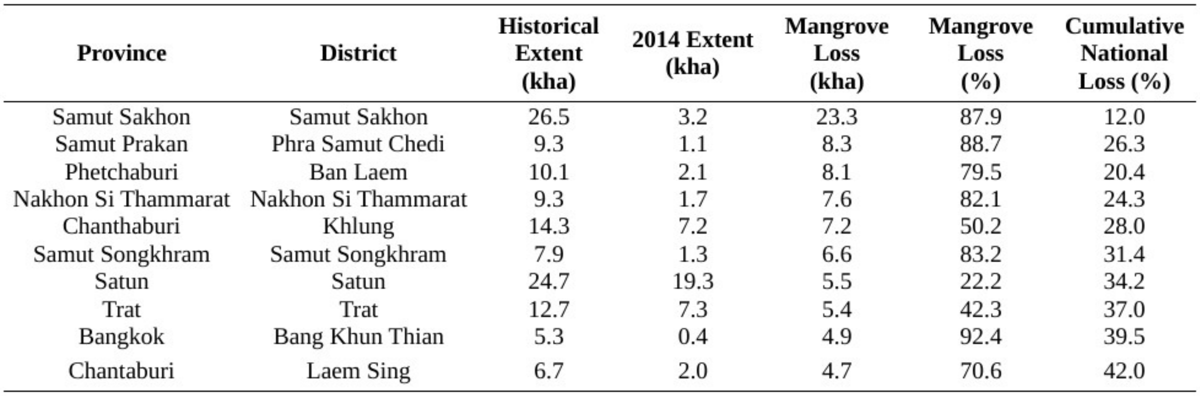
Tables and Figures

Table 1. Land use and land cover transitions in areas of Thailand historically under mangrove cover from 2000 to 2014. All values are in thousands of hectares. The red row represents loss of mangroves to other land use and land cover categories in 2014, whereas the green column represents transition of other land use and land cover classes to mangroves.



2000 Data	2014 Data										
	Aquaculture	Agriculture	Mangroves	Other Forest	Mudflats	Abandoned Land	Salt Farms	Urban Areas & Ports	Water	NA	Totals (2000)
Aquaculture	46.9	7.8	10.5	0.1	-	0.5	6.1	2.0	1.2	-	75.1
Agriculture	4.3	21.4	7.1	0.9	-	0.2	1.3	4.0	0.4	-	39.6
Mangrove	8.3	19.0	203.0	3.2	0.5	0.4	1.6	2.8	13.2	0.4	252.5
Other Forest	0.4	2.3	1.6	4.8	-	-	-	0.1	0.1	-	9.4
Mudflats	-	0.6	1.2	0.3	1.0	-	-	-	12.7	-	15.9
Abandoned Land	1.2	2.2	2.7	0.3	-	-	-	0.2	0.2	-	6.9
Salt Farms	9.2	0.1	1.4	-	-	0.2	15.6	1.3	0.5	-	28.3
Urban Areas & Ports	0.4	1.1	0.6	0.1	0.1	0.2	0.7	6.3	0.4	-	9.8
Water	-	-	-	-	-	-	-	-	-	-	-
NA	-	-	17.2	-	5.5	-	-	-	-	-	22.7
Totals (2014)	70.7	54.5	245.3	9.7	7.1	1.5	25.3	16.7	28.7	0.4	460.2

Table 2. Top ten districts as ranked by absolute area of mangrove loss. The ten districts account for approximately 42% of historical mangrove loss in Thailand.



Province	District	Historical Extent (kha)	2014 Extent (kha)	Mangrove Loss (kha)	Mangrove Loss (%)	Cumulative National Loss (%)
Samut Sakhon	Samut Sakhon	26.5	3.2	23.3	87.9	12.0
Samut Prakan	Phra Samut Chedi	9.3	1.1	8.3	88.7	26.3
Phetchaburi	Ban Laem	10.1	2.1	8.1	79.5	20.4
Nakhon Si Thammarat	Nakhon Si Thammarat	9.3	1.7	7.6	82.1	24.3
Chanthaburi	Khlung	14.3	7.2	7.2	50.2	28.0
Samut Songkhram	Samut Songkhram	7.9	1.3	6.6	83.2	31.4
Satun	Satun	24.7	19.3	5.5	22.2	34.2
Trat	Trat	12.7	7.3	5.4	42.3	37.0
Bangkok	Bang Khun Thian	5.3	0.4	4.9	92.4	39.5
Chantaburi	Laem Sing	6.7	2.0	4.7	70.6	42.0

Table 3. Model coefficients and statistics for the aboveground carbon and soil organic carbon loss and recovery models.

Model Coefficients and Statistics								
	a	*b*	*k*	*DF* [a]	R^2	*F-Stat.*	*P-val.*	*LL* [b]
Eq. 1a: AGB Loss	-0.49 ± 0.49	-0.22 ± 0.08 ·		4	0.65	7.45	0.05	-
Eq. 1b: SOC Loss	-0.26 ± 0.29	-0.04 ± 0.02 *	-	32	-	-	-	45.00
Eq. 2: SOC Recovery	-0.45 ± 0.16 **	0.07 ± 0.06	-	20	-	-	-	-1.72
Eq. 3: AGC Recovery	90.56 ± 13.70 ***	-	0.11 ± 0.04 ***	59	-	-	-	39.98

*Significance levels: <0.001 ***; 0.001 **; 0.01 *; 0.05 ·*

[a] *Degrees of freedom*

[b] *Log-restricted likelihood*

Table 4. Scenario analysis of potential carbon sequestration from mangrove restoration in abandoned land and various proportions of aquaculture, agriculture, and salt farm extent. The time frame of consideration is the same as Thailand's Nationally Determined Contribution, or from 2020-2030. All potential carbon sequestration values are reported as the mean ± the standard error.

Restoration Scenario	Potential Sequestration, 2020-2030 (Million Mg C)
1,500 ha of abandoned land & 0.1% of aquaculture, agriculture and salt farm extent	0.14 ± 0.01
1,500 ha of abandoned land & 1% of aquaculture, agriculture and salt farm extent	0.26 ± 0.01
1,500 ha of abandoned land & 2% of aquaculture, agriculture and salt farm extent	0.40 ± 0.01
1,500 ha of abandoned land & 5% of aquaculture, agriculture and salt farm extent	0.79 ± 0.03
1,500 ha of abandoned land & 10% of aquaculture, agriculture and salt farm extent	1.46 ± 0.05

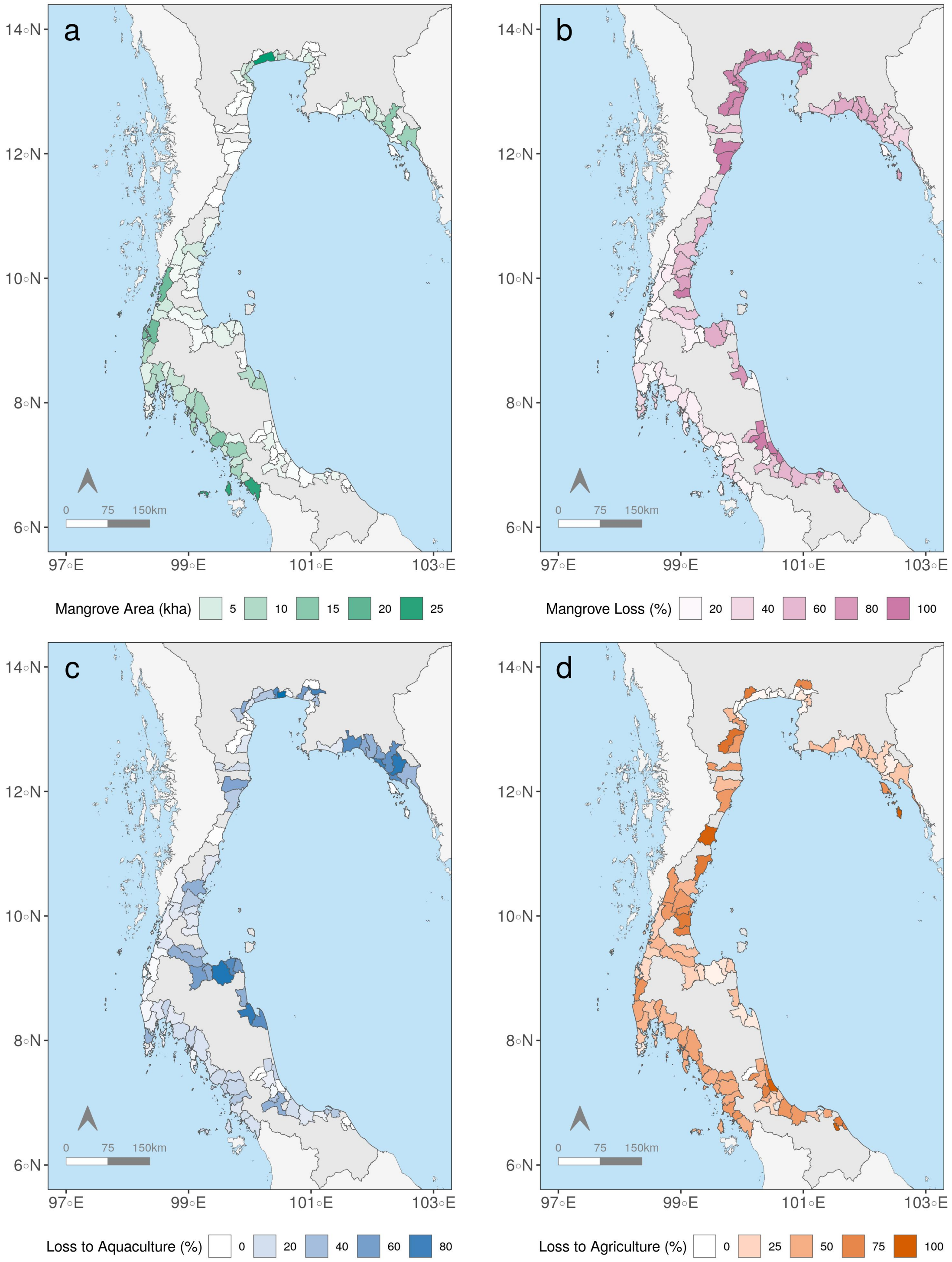


Figure 1. District level summaries of a) historical mangrove extent (in thousands of hectares), b) percent loss of historical mangrove extent, c) percent of mangrove loss attributed to aquaculture, and d) percent of mangrove loss attributed to agriculture.

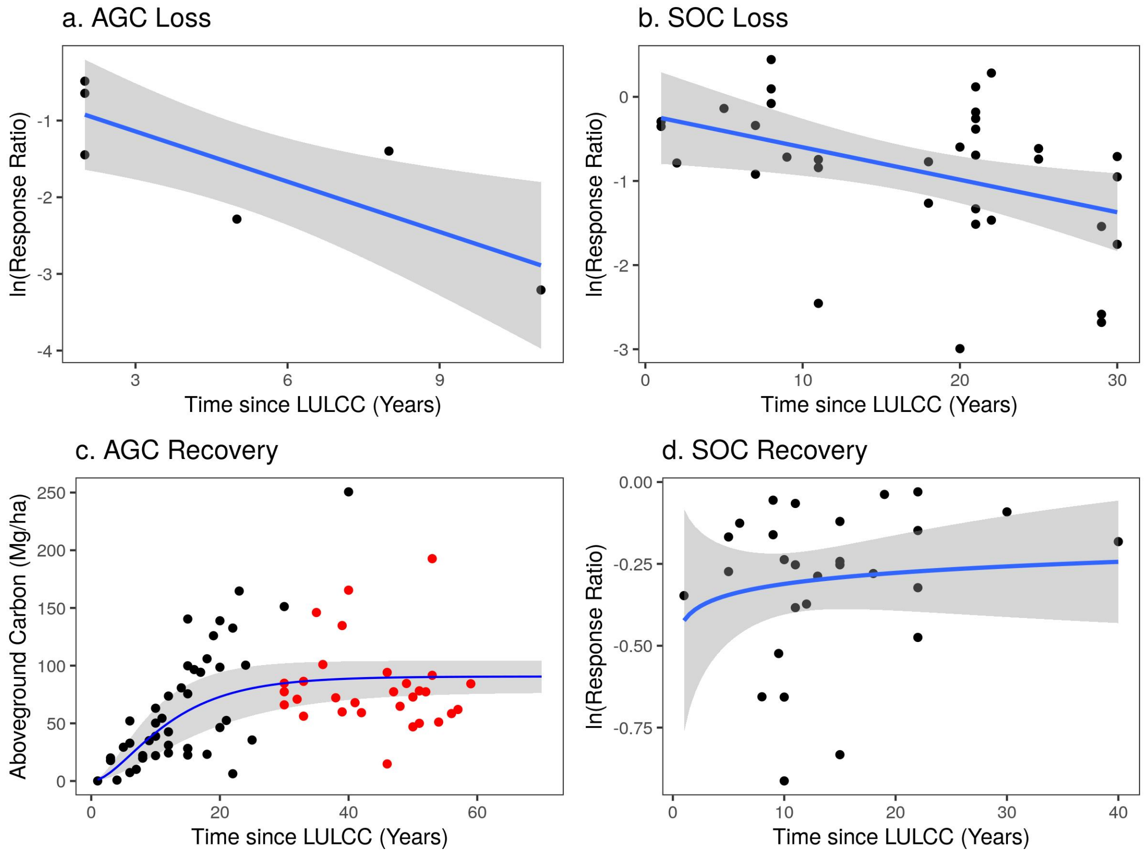


Figure 2. Relationships between time since LULCC and gains and losses of aboveground carbon and soil organic carbon. Losses of aboveground carbon (a) and soil organic carbon (b) and gains of soil organic carbon (d) are modeled as the natural log of the response ratio, which are the carbon stocks present following LULCC relative to an undisturbed reference site. The recovery of aboveground carbon relationship (c) is modeled using the Chapman-Richards growth curve. The red points in (c) are from established secondary mangrove forests in Thailand to "anchor" the growth curve at older ages.

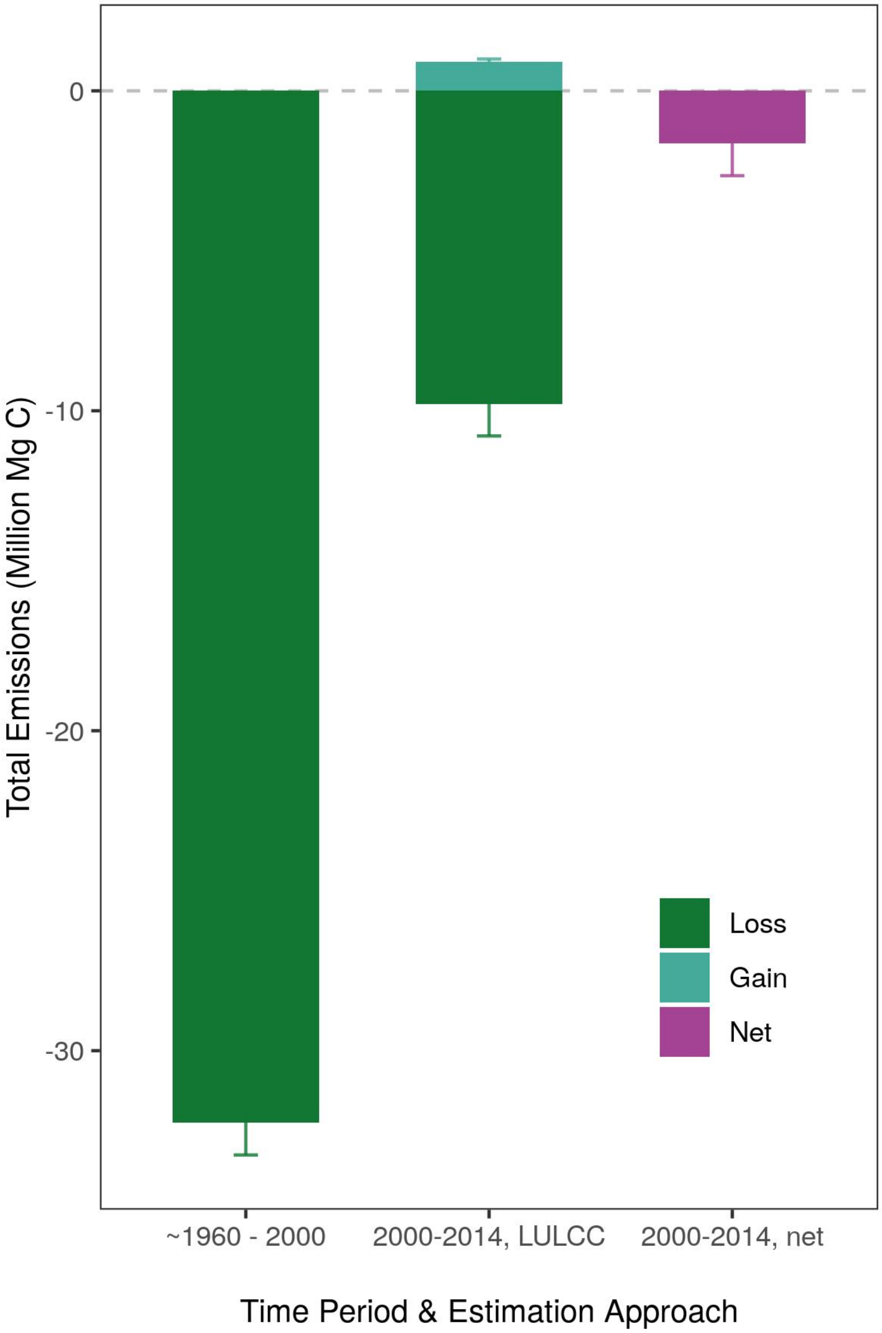


Figure 3. Summary of carbon stock changes in mangrove holding regions of Thailand for the periods from ca. 1960 to 2000, and 2000 to 2014. For the period of 2000-2014, both the gross loss and gain approach used in this study ("2000-2014, LULCC") and an emissions estimate based on a mangrove net loss statistic ("2000-2014, net") are shown. Gains in mangrove carbon stocks were not able to be estimated from 1960 to 2000 are consequently not shown. The error bars show the 95% confidence intervals of each estimate.

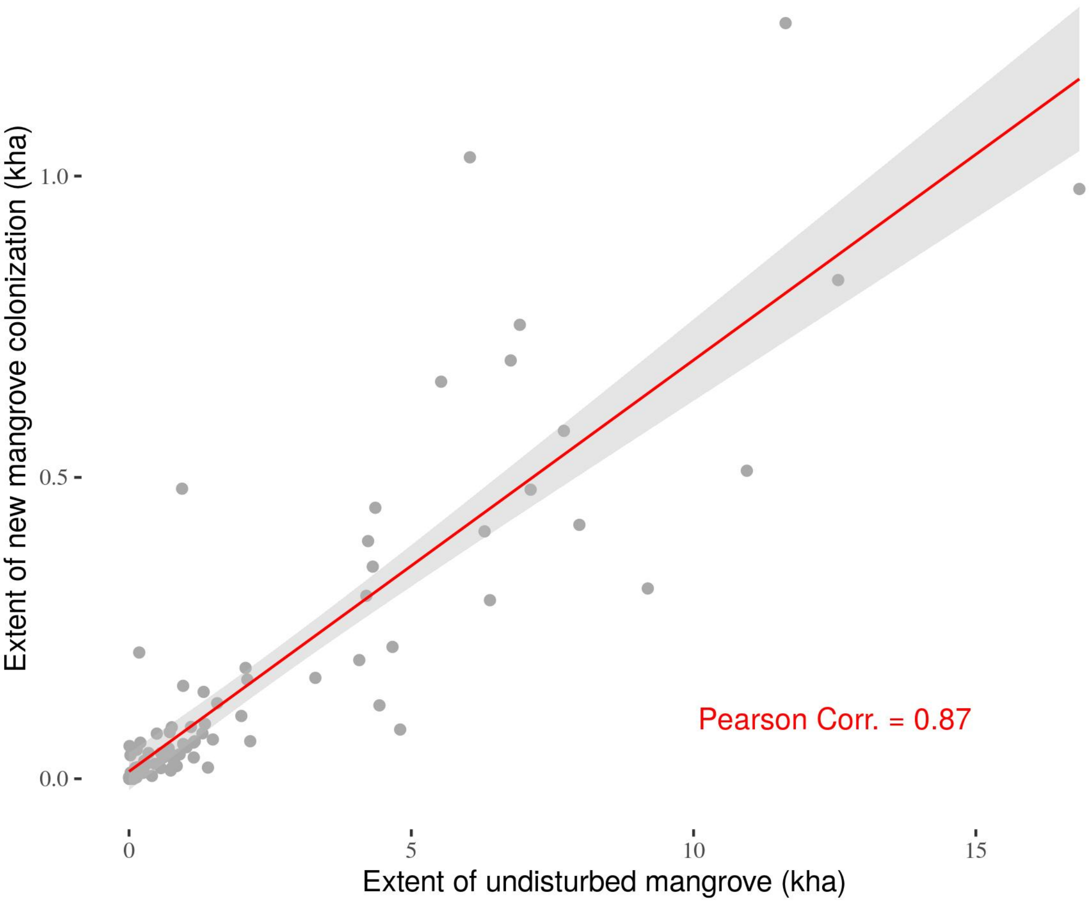


Figure 4. Relationship between district-level extent of mangrove establishment in new areas versus extent of undisturbed mangrove forest. The gray points are values from individual districts whereas the trend line is a linear fit between the two variables. A positive and highly correlated relationship is found between the two variables, suggesting much of the gains in mangrove cover between 2000-2014 were associated with large undisturbed extents of mangroves.

3.6 Supplementary Information

Additional details of methods

Pre-processing of spatial datasets

The data were prepared by first resolving differences in the spatial properties of the datasets. We processed all spatial data with Geospatial Data Abstraction Library (GDAL) functions. We elected to use the aboveground biomass dataset as a reference for matching the spatial properties of the other datasets given that the aboveground biomass dataset is provided as a raster that fully encompasses Thailand's coastlines. We aligned the soil organic carbon data to the aboveground biomass data by reprojecting and resampling the soil organic carbon data. Specifically, we downloaded and merged tiles from the soil organic carbon dataset that correspond to the extent of Thailand, reprojected the data, and resampled the data to precisely match the pixel-level locations of the aboveground biomass data (provided as a raster for all of Thailand). Both rasters were then reprojected to an equal-area projection (Asia South Albers Equal Area Conic, EPSG:102028).

The land use and land cover data were collected under an extensive campaign of remote sensing and ground-truthing by the Thai DMCR and are among the best available data of coastal land use in Thailand (pers. comm. DMCR 2020). The data demarcate land use and land cover in 2000 and 2014 for regions of Thailand that were historically under mangrove forest cover. Consequently, combining all land use and land cover categories in the 2000 dataset provided us with a dataset of historical mangrove extent (pre-1960), which we considered a largely undisturbed state. The three datasets thereby provide us with high quality information on historical mangrove extent from pre-1960 as well as land use and land cover type from 2000 and 2014.

The land use and land cover datasets contained cover types that were overly detailed for the purposes of our study and would complicate the interpretation of our results. Before converting the three datasets to rasters, we collapsed land use and land cover categories that were both i) functionally similar in terms of carbon fluxes from LULCC, and ii) relatively minor in extent (e.g., 138 ha for the "ports" land use). Specifically, we combined classes for "terrestrial forest," "peat forest," and "beach forest" into a single "other forest" class, combined classes for "urban areas," "ports," and "mines" into a single "developed areas" class, and combined a "sand" class with a "mudflats" class (Table S1). Any transitions from mangroves to these combined types would impact similar ecosystem carbon pools, which was our primary concern for the LULCC data. After resolving differences in land use and land cover categories, we produced the historical mangrove cover dataset by merging the features across all land use and land cover classes in the 2000 dataset. Finally, we converted the three datasets (1960, 2000, and 2014) to rasters, providing us with spatially-identical rasters of aboveground biomass carbon, soil organic carbon, and land use and land cover from pre-1960, 2000, and 2014.

K-means clustering algorithm to test for effects of site geomorphology

To examine the potential for site geomorphology to vary within districts, we used a k-means clustering algorithm and raster datasets of total suspended matter and tidal amplitude to assess variation in proxies of site geomorphology [75]. Both the total suspended matter and tidal amplitude data were obtained as published products. The total suspended matter data were calculated using the ocean colors band of Envisat's MERIS imagery whereas the tidal amplitude data were produced using the FES 2012 hydrodynamic model [23]. Using these datasets, we extracted total suspended matter and tidal amplitude data along the coasts of Thailand and subsequently input these values into a k-means clustering algorithm. The algorithm identified regions of similar geomorphology at broader scales than the district level (i.e., a single cluster for the whole eastern coast of Thailand and two clusters for the western coast), suggesting that the district-level averages produced stock averages at finer-scale spatial resolutions than a modeling exercise based on proxies of geomorphology otherwise would.

Compiling of data on soil organic carbon stock recovery in mangroves

To better approximate soil organic carbon stock recovery in mangroves, we filtered the data from Figure 4 of O'Connor and colleagues to just those studies that report data on soil organic carbon stock recovery in mangroves [103]. We filtered the references of their study using titles and abstracts to those that report soil organic carbon stocks to at least 50 cm depth in both restored mangroves as well as an undisturbed reference site. Namely, we filtered their studies to six studies [2, 11, 22, 38, 111, 153], as well as a relevant study from Thailand that they had omitted [40]. We then extracted carbon stock data for both the restored sites and undisturbed reference sites, as well as the time since the sites were restored. We then calculated the natural logarithm of the response ratio for these data, which we then used to parameterize our soil organic carbon recovery model.

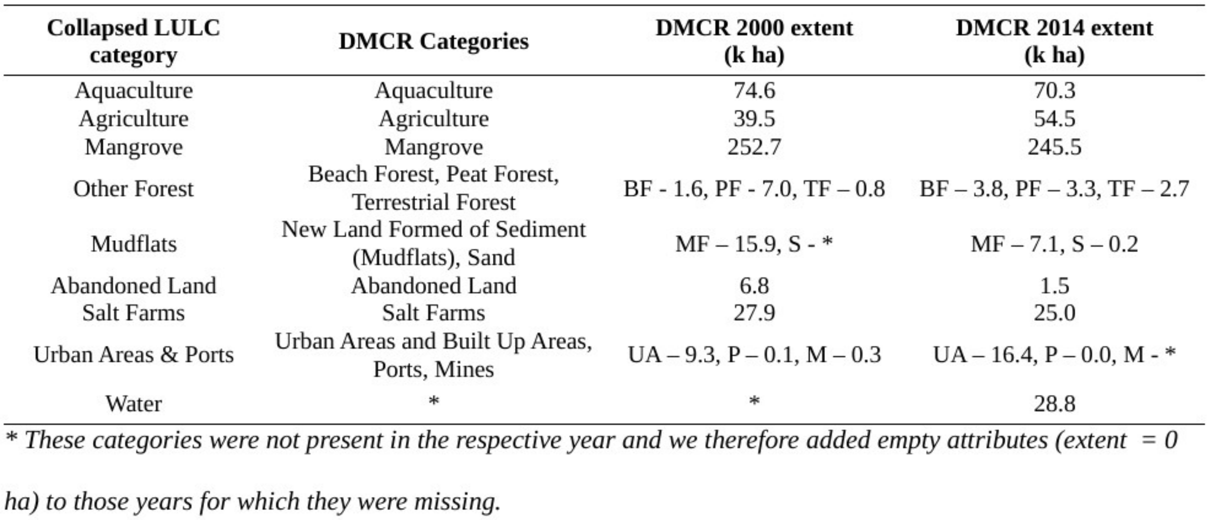
Additional details of estimating uncertainty in the carbon rasters

For the two carbon rasters, we estimated uncertainty using a Monte Carlo approach that accounted for raster-specific model error. To estimate uncertainty in the raster data, we combined the reported model error with district-level mean carbon stock values and simulated spatial random fields for each raster layer within each district [15, 64]. Specifically, we modeled the spatial random field as a non-zero mean stationary Gaussian process with an isotropic covariance function [15, 32]. The covariance function depends solely on the distance between two points and is appropriate for our purposes given that we have no additional information on spatial dependence in the data. We input the district-level mean values (e.g., mean aboveground biomass for the district of Pak Phanang) into a spatial trend model, whereas we input the raster-specific model errors (cross-validation root mean square error) into the covariance function. We then used this model to simulate random spatial fields for both rasters, clipped to each district. Each random spatial field can be interpreted as a plausible realization of the data, incorporating both model uncertainty and spatial covariance.

To determine an appropriate number of simulations to run, we repeated the process for a subset of districts up to 50 times and plotted the improvement in standard errors resulting from increased numbers of runs. We identified forty runs as an appropriate balance between a stable standard error value and computational time. Consequently, we simulated spatial random fields forty times for each raster within each district, calculating and saving the district-level means of the simulated data in each run. We then calculated the average of these means and the standard error of the means as our final estimates of mean carbon stock value and associated uncertainty. All spatial modeling was performed with the {RandomFields} and {geostatsp} packages in R Version 3.6.3 [15, 127].

Supplementary Tables & Figures

Table S1. Land use and land cover classes of the original datasets as well as the collapsed land cover types that we designated. Land use and land cover classes that were functionally similar in terms of the climate change impacts from their transitions and that were relatively minor in extent were combined. Numbers in parentheses are approximate areal extents in thousands of hectares.



Collapsed LULC category	DMCR Categories	DMCR 2000 extent (k ha)	DMCR 2014 extent (k ha)
Aquaculture	Aquaculture	74.6	70.3
Agriculture	Agriculture	39.5	54.5
Mangrove	Mangrove	252.7	245.5
Other Forest	Beach Forest, Peat Forest, Terrestrial Forest	BF - 1.6, PF - 7.0, TF – 0.8	BF – 3.8, PF – 3.3, TF – 2.7
Mudflats	New Land Formed of Sediment (Mudflats), Sand	MF – 15.9, S - *	MF – 7.1, S – 0.2
Abandoned Land	Abandoned Land	6.8	1.5
Salt Farms	Salt Farms	27.9	25.0
Urban Areas & Ports	Urban Areas and Built Up Areas, Ports, Mines	UA – 9.3, P – 0.1, M – 0.3	UA – 16.4, P – 0.0, M - *
Water	*	*	28.8

** These categories were not present in the respective year and we therefore added empty attributes (extent = 0 ha) to those years for which they were missing.*

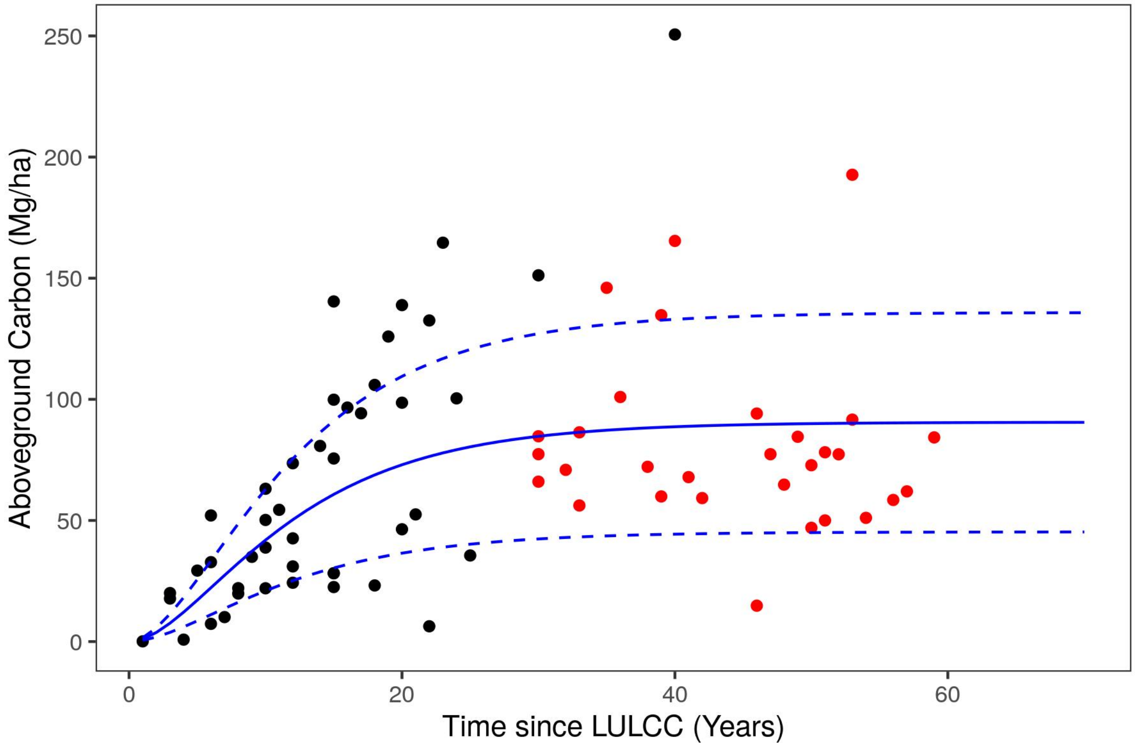


Figure S1. Sensitivity of the aboveground carbon growth curve to setting the theoretical asymptotic growth limit parameter (A). The solid blue line represents our best estimate of the growth curve, whereas the dashed blue lines represent varying the asymptotic growth limit parameter by ± 50%. Varying the asymptotic growth limit by ± 50% produced minor changes in our final results of approximately 8%, which was within the 95% confidence interval of our best estimate.

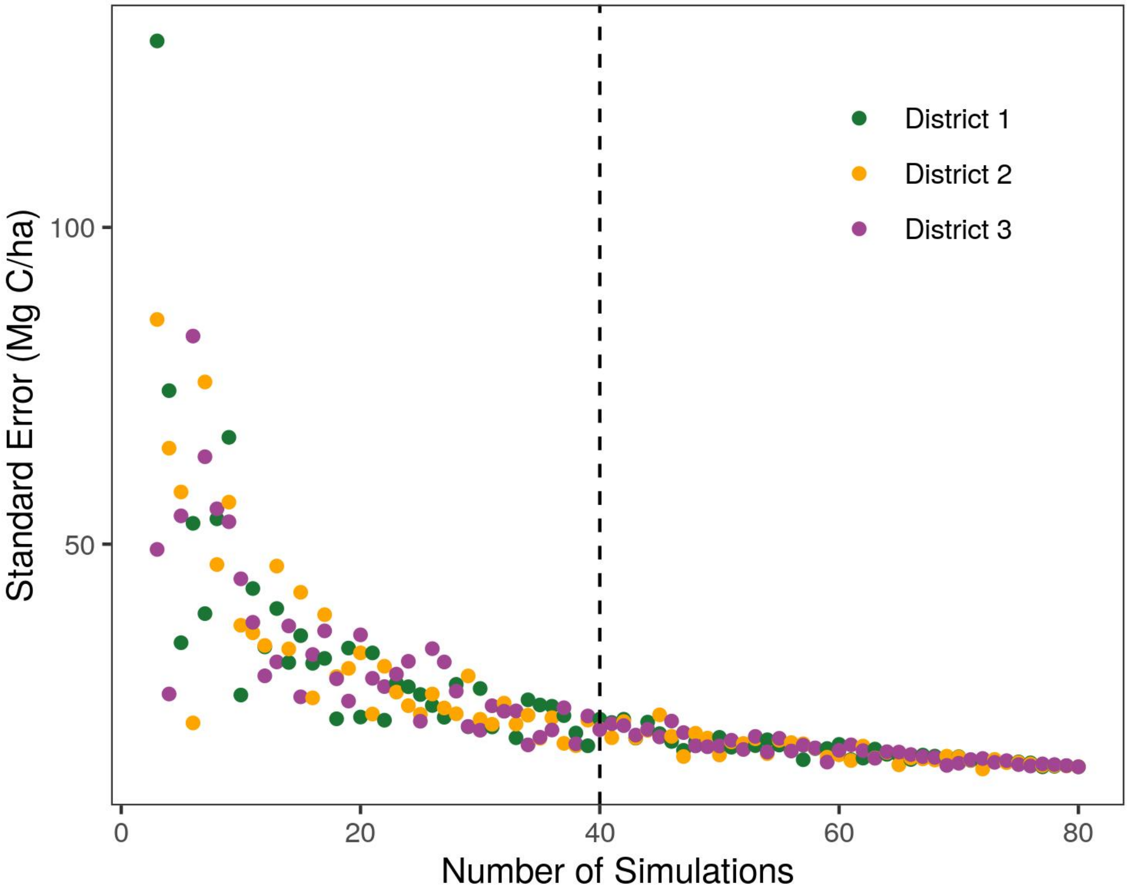


Figure S2. Relationship between standard error of the mean and the number of simulations for simulating random spatial fields of the aboveground carbon and soil organic carbon data.

Chapter 4

Rates and drivers of aboveground carbon accumulation in global monoculture plantations

Abstract

Restoration of forest cover has been highlighted as a key action for mitigating climate change. While there are myriad ways to restore forest cover, planting of monoculture plantations is a globally dominant strategy. Despite the prevalence of monoculture plantations, we lack robust understanding of the degree to which they can meet international goals to mitigate climate change. To improve this understanding, we assembled a comprehensive database of 3,436 field-plot measurements from monoculture plantations across all forested continents of the globe. We then used these data to model carbon accumulation in aboveground biomass and examined the biological, environmental and human factors that mediate this growth. We identified carbon accumulation rates as high as 8.1 Mg C ha^{-1} yr^{-1} for select genera (e.g., *Eucalyptus*); however, these rates varied by a factor of approximately four across genera, plant functional types, and biomes. We further found that broadleaved species (both temperate and tropical) had growth rates that were roughly three to five times those of temperate and tropical needleleaved species. Variation in aboveground carbon accumulation rates was strongly mediated by genera, endemism, prior land use, and plant traits across global scales, whereas factors such as biome were found to have little effect. Although planting of exotic species had a strong positive effect on rates of carbon accumulation, this effect was only marginally significant after accounting for fertilizer use. By fitting globally-applicable nonlinear growth curves, we anticipate that our results will facilitate more sophisticated understanding of the climate impacts of monoculture plantations relative to the more commonly used mean annual rates.

Keywords

natural climate solutions, climate change mitigation, IPCC, silviculture, nature-based climate solutions, nonlinear growth models

4.1 Introduction

Restoring forest cover is a high-profile option for using nature to mitigate climate change [55, 130]. Although a range of options exist for successfully restoring forest cover to landscapes, actors across the public, private, and non-profit sectors have interpreted this as a need for planting trees [62, 131]. For example, two thirds (66%) of high-level commitments for tropical forest restoration involve planting and almost half (45%) involve the establishment of monoculture plantations [92]. Despite their dominance within the forestry space, we lack a sophisticated understanding of the degree to which monoculture plantations can meet goals for mitigating climate change.

Tree planting—and monoculture plantations specifically—are controversial because they can negatively impact ecosystems when poorly implemented [109]. Tree planting in native grasslands, for example, can have perverse impacts on biodiversity and grassland ecosystem functioning [145]. Elsewhere, plantations may have limited or adverse biodiversity impacts depending on the species planted and the prior land cover type [63]. On the other hand, tree planting can be an effective action to mitigate climate change when done appropriately [34], and monoculture plantations may also be the most viable option to restore forest cover in areas where economic returns are paramount. Further, we need rapid removals of atmospheric carbon to constrain the climate crisis and plantation forests may sequester carbon slightly more rapidly than naturally regenerating forests, particularly during early phases of establishment [13, 69].

Plantation forestry is a well-established practice for growing trees that has existed for centuries [109]. Plantation forest managers have adopted practices from the agricultural sector as well as developed silvicultural practices to improve the growth, form, and yields of trees [21, 82, 100]. As such, plantation managers face myriad decisions in the establishment and management of plantations [31]. For example, not only are managers tasked with locating plantation forests, but they must also make decisions on what species to plant as well as how to manage the trees over short and long time frames. At local scales with relatively constrained conditions (e.g., loblolly pine plantations in the southern United States), these decisions are well-understood. However, there is widespread desire to invest internationally in forests for their climate benefits, and the consequences of management decisions on climate outcomes at global scales are poorly understood [12]. Specifically, we lack even a systematic understanding of how much carbon monoculture plantations can capture and how that mitigation potential varies by factors such as species, location, or management type.

To improve this understanding, we systematically reviewed the literature and extracted, from over 600 publications, empirical measurements of carbon held in the aboveground biomass of monoculture plantations. Using this dataset, we then analyzed potential drivers of variation in rates of aboveground carbon accumulation in monoculture plantations, parameterized curves to predict carbon stocks as a function of time, and derived default accumulation rates. In assessing the potential drivers of carbon accumulation, we sought to account for the major biological, environmental, and human factors that affect growth rates in plantation forests. Our objective was to close key knowledge gaps on the important yet under-studied role that monoculture plantation establishment, a dominant global reforestation strategy, may play in mitigating climate change.

4.2 Methods

Dataset compilation and standardization

We systematically reviewed the literature to identify studies reporting data on biomass and carbon stocks in monoculture plantations. The search was part of a larger effort to quantify biomass accumulation associated with re-establishing tree cover more generally [27]. We provide an abbreviated description of the dataset compilation and standardization process here whereas the full details are provided in both the Supplementary Information and other studies that used the same literature search [27].

The literature search considered over 11,000 articles, which we filtered to 640 studies quantifying biomass (or carbon) stocks in forest plantations. We then further winnowed these to include studies that reported i) empirical measurements of biomass or carbon in the aboveground pool; ii) age of the plantation at the time of field measurements; and iii) a latitude and longitude pair or sufficient geographic detail from which geographic coordinates could be obtained. We only collected data on aboveground stocks given that belowground biomass and soil organic carbon stock data were sparse, and variation in field sampling methods make synthesizing belowground biomass and soil organic carbon stocks across studies difficult [27, 101, 102]. We omitted understory biomass given that understory vegetation in monocultures is a small proportion of total biomass [13].

For each included study (n = 236), we collected information on biomass (or carbon) stocks, age, geolocation, tree crop species, prior land use/disturbance, and management practices such as planting density, rotation length, site preparation, fertilization, irrigation, vegetation control, and thinning. To account for spatial structures in the data, we grouped measurements by site. When studies empirically determined the percent biomass that was carbon, we retained their values; however, when studies used a default factor (e.g., 0.5) to convert biomass to carbon within biomass, we adjusted these values using the Intergovernmental Panel on Climate Change's recommended factor of 0.47 [39].

Potential drivers of variation in aboveground carbon accumulation

To explain variation in biomass accumulation across global plantations, we sought to account for the major biological (genus, endemism, and plant traits), human (prior land use and management practices), and environmental (biome) factors that may control growth. We describe the collection of these data below and summarize key characteristics of each of the potential drivers in Table 1.

Tree crops are commonly selected from a limited number of genera for characteristics such as growth rate and suitability for wood products. Furthermore, exotic species are commonly planted within monoculture plantations for the same reasons, but may also have adverse impacts on local environments. We collected data on the planted tree species from all studies; however, we collapsed the species data to genus (including both hybrids and clones) to reduce the feature space of the data. Additionally, to test for the effect of planting exotic species on growth, we coded all species as being either endemic or exotic to the locale in which they were planted.

Although genus can serve as a proxy for suites of plant traits, we further examined the effect of species-level plant traits given that trait data may vary within genera. Analyzing trait data could be informative for selecting additional candidate species not commonly used within plantation forestry (e.g., endemic species). To create an initial list of candidate traits, we used the TRY Plant Trait Database to identify plant traits with data for as many of the planted species in our database as possible [76]. Doing so identified 12 candidate traits; however, we ultimately excluded eight of these due to insufficient variation in the trait to explain variation in aboveground carbon. For example, all species were classified as "woody" for the "plant woodiness" trait. For the traits we included (leaf compoundness, leaf phenology, leaf type, and nitrogen fixation capacity), we then manually filled data gaps for species that were not found in the TRY database. Additionally, we extracted species-specific wood density data from the Global Wood Density Database [151]. We averaged wood density values for species with more than one wood density observation in the database, whereas we used genus level averages for species not found in the database.

Prior land use can have a strong control on subsequent vegetation growth depending on both the type and intensity of land use [129]. Studies commonly reported prior land use type, which we coded into our database. However, we were unable to include intensity of land use as it was rarely reported. We generally found four types of land use/disturbance to be well-represented within the literature: clear-cut harvest, croplands (inclusive of shifting cultivation), pasture, and fire. When studies reported multiple prior land use types, we coded the most recent land use into our database.

We examined the effect of management practices on carbon accumulation in plantations to the degree that studies allowed. Studies did not consistently report management practices at the same level of detail, but many provided information on planting density, site preparation, fertilization, irrigation, management of competing vegetation, or thinning. We qualitatively recorded all management practices that were reported in the studies, which we then coded into a presence versus absence variable for statistical analyses. Although substantial variation in the use of a given management practice may exist (e.g., different types or quantities of fertilizer), a presence/absence variable for each type of management practice was an optimal compromise between accounting for the use of management practices and obtaining management data for as many studies as possible.

Finally, biomass accumulation in plantations is expected to vary across climates, which can be proxied by biome type. To examine the effect of climate on plantation biomass, we spatially intersected the locations of all sites with a map of major ecological zones. Namely, we used both a map of global biomes as well as the United Nations Food and Agriculture Organizations classification of ecozones [33, 106]. We refer to the first as "biomes" whereas we refer to the second dataset as "FAO Ecozones." Plantations are not common across all global biomes and we therefore omitted biomes for which data were sparse (e.g., flooded grasslands and savannas, mangroves, and montane grasslands and shrublands). Further, plantations in non-forest biomes are often not successful and can cause severely negative biodiversity impacts [145].

Statistical analyses of variation in plantation biomass

For each of the potential drivers of aboveground carbon accumulation in plantations, we tested for their effect in explaining variation in plantation carbon using linear mixed effects models [59]. We square root transformed both aboveground carbon and stand age prior to fitting the models to improve the linear relationship between the two variables (Figure S1 of the Supplementary Information). Random intercepts for site were included in all models to account for spatial autocorrelation [13, 125]. We then modeled aboveground carbon as a function of stand age, the driver under consideration, and the interaction of stand age and the driver (all fixed effects). Since data on drivers were missing for some observations, we subsetted the data to each driver of interest before fitting the models. Further, for genus of tree crop, we filtered the subsetted dataset to only genera with 20 or more observations to reduce the levels of the driver and potential effects of sparse data. We examined each of the 14 individual drivers (i.e., a separate analysis per trait and management practice; see Table 1), testing for the significance of including the driver of interest via Analysis of Variance (ANOVA). When assessing the significance of variables, we fit each model using maximum log-likelihood to allow comparison of models with different fixed effects.

To examine the relative effects of the drivers, we ran three full models using the observations that had complete data across three subsets of drivers. First, we ran a model including all drivers except those relating to management practices (i.e., genus, endemism, plant traits, prior land use, and biome). We ordinated the plant trait data prior to including it in the model given that the majority of the trait data were categorical in nature, repeated across species, and likely exhibited correlation across traits. To do so, we used Factor Analysis of Mixed Data (FAMD), a principal component method appropriate for datasets of both continuous and categorical variables. Data on management practices were highly limiting and we were therefore only able to consider two management practices—planting density and the use of fertilizer—each of which was considered in a separate model in combination with all other drivers. Again, we included the ordinated plant trait data in these models. Similar to our models of individual drivers, we filtered the datasets to only those genera with 20 or more observations to reduce the levels of this driver and reduce potential effects of sparse data. Given data limitations, we did not include interactions in the model but specified each driver as an additive effect. We accounted for spatial autocorrelation by including random intercepts by site, similar to our models of individual drivers. All models were fit using the {nlme} package in Program R [112].

Development and validation of growth curves

We produced predictive growth curves of aboveground carbon stocks for all genera and plant functional types with greater than 100 observations in the database. Plant functional types are a means of representing broad classes of plants that share similar growth forms and life histories across biomes. For our purposes, plant functional types are a convenient way of incorporating data from relatively less-represented genera into growth curves, as well as producing curves that are generalizable across plantation species not included in our database. Here, we combined climatic information from our biome dataset with leaf type to produce plant functional types for all species within our database (e.g., tropical broadleaf species).

We considered four different growth curve forms to be fit to the data: logarithmic, linearized logistic, logistic, and the Chapman-Richards growth function. After assessing each curve form (see Supplementary Information), we elected to fit the Chapman-Richards function (Eq 1), which is i) based in theoretical growth of forest stands over time, ii) more flexible than other logistic curves, and iii) widely employed within the forest modeling literature [20, 111, 118]. The Chapman-Richards curve is specified as:

$$AGC = A * (1 - b * e^{(-k*t)})^{(1/(1-m))}$$

Where:

- AGC is aboveground carbon in Mg C ha^{-1},
- t is the age of the forest stand in years, and
- A, k, b, and m are parameters to be statistically estimated from the data.

Given that the Chapman-Richards function is a theoretical growth curve, the parameters are biologically meaningful. Specifically, A represents the asymptotic maximum stand-level biomass, b is a scaling parameter, k is the rate of growth, and m is an allometric constant that determines the shape of the curve. To simplify statistical estimation of the parameters, it is common to fix both the scaling parameter b and the allometric constant m, allowing for the theoretical maximum stand-level biomass (A) and growth rate (k) to be statistically fit to the data [20]. Given that our database is unbalanced and holds data across a host of species found under varying environmental conditions, we followed this procedure and fixed both the scaling parameter ($b = 1$) and allometric constant ($m = 0.5$). We then estimated the asymptotic maximum stand-level biomass and growth rate parameters (A and k) for each plant functional type and genus using non-linear mixed effects models, with site included as a random effect. To reduce the effects of sparse data at older ages, we truncated each data subset to the 95^{th} percentile by age before fitting the models. All growth curves were parameterized using the {saemix} package in Program R (version 4.0.4), which employs the Stochastic Approximation Expectation Maximization algorithm to derive maximum likelihood estimates of the parameters [26].

We assessed the predictive capability of the models using root-mean-square error (RMSE), calculated via a cross-validation procedure with a 15% to 85% validation data to training data split. Given that we used mixed effects models, we set aside data for validation by randomly selecting all data from 15% of the sites rather than 15% of observations across all sites. Although doing so ensures a true out-of-sample validation, the unbalanced nature of our database will cause the number of observations included in the training versus validation datasets to vary. We then calculated the RMSE across the predicted and observed values retained in the validation dataset. We repeated this procedure a total of 25 times for each growth curve, retaining the RMSE values from each run and averaging across them to obtain our final RMSE estimates. We report both the averaged RMSE values as well as RMSEs that are normalized by mean aboveground carbon, which facilitates comparison across models.

Calculation of annualized biomass accumulation rates

To improve the utility of our analyses for broader policy and practitioner audiences, we also generated annualized rates to use as default values of aboveground carbon accumulation in monoculture plantations. We calculated plot-level carbon accumulation rates by dividing stand-level aboveground carbon by stand age. To reduce the effects of different species tending to be managed on different rotation lengths, we first filtered all data to stands younger than 30 years in age. After calculating the rates at the plot level, we subsequently summarized these values for the major i) genera, ii) plant functional types, and iii) biomes in our database. Unless otherwise stated, all values presented in the text are mean values ± the standard error of the mean.

4.3 Results

Data availability

Our final database includes 3,436 measurements of aboveground carbon in monoculture plantations, collected from 2,339 plots across 579 distinct sites. The geographic location of the sites were primarily in Asia (56%), North America (20%), Europe (10%), and South America (9%), with the remainder located in Oceania and Africa (5%; see Figure 1). Data from China drove the geographic distribution of the dataset, accounting for over 40% of all observations. The plantation data included 90 distinct genera of tree; however, 34 of these genera had fewer than three observations and were therefore poorly represented in the database. The three most well represented genera of tree crop were *Pinus*, *Eucalyptus*, and *Cunninghamia*, accounting for 63% of observations in the database. Across all observations, the mean stand age was 16.9 years (range of 1 – 98 years) and the mean aboveground biomass carbon was 47.5 Mg C ha^{-1} (range of 1.0 – 516.5 Mg C ha^{-1}).

Drivers of aboveground carbon accumulation

Our results for the significance of each driver in explaining aboveground carbon accumulation are summarized in Table 2, whereas we report the t-test results for individual levels of the drivers in the text below. Due to the large number of levels of driver that have been tested (>100), we do not summarize these results in a table but rather give an overview of the direction and magnitude of the effects. Similarly, we only provide a summary table of the significance of including drivers in our full models (Table 3), but discuss the key driver effects of our full models in the text below.

As hypothesized, all driver types explained significant variation in aboveground carbon in plantations, with the exception of planting density (Table 2). The effects of individual genera were variable in both magnitude and direction. For example, the interaction of genus and square root of stand age varied between 54% (*Robinia*, t = -3.68, P = 0.0002) to 148% (*Eucalyptus*, t = 4.69, P = <0.0001) of the base level effect for aboveground carbon accumulation (*Acacia*, t = 10.76, P = <0.0001). Aboveground carbon accumulation rates were 133% higher in plantations with exotic rather than endemic species (t = 7.82, P = <0.0001). Prior land use of croplands, harvest, and pasture all had significant effects on the rate of aboveground carbon accumulation. Specifically, the rate of carbon accumulation on formerly harvested land (t = -4.99, P = <0.0001) and pasture (t = -4.57, P = <0.0001) was roughly 70% and 65% of former croplands, respectively. Fertilizer use resulted in a relatively minor increase (8%) in the rate of aboveground carbon accumulation (t = 2.2, P = 0.03) relative to unfertilized stands, whereas thinning decreased the rate of carbon accumulation by 26% (t = -7.88, P = <0.0001). Relative to Mediterranean Forests, Woodlands & Scrub, only Temperate Broadleaf & Mixed Forests (t = -2.47, P = 0.01) and Tropical & Subtropical Moist Broadleaf Forests (t = -2.56, P = 0.01) had significant effects on carbon accumulation rates, both of which decreased rates by roughly 25%.

Our full models identified stand age, genus, prior land use, and the ordinated plant trait data as statistically significant effects across all three models (Table 3). Ordinating the plant trait data produced two axes that explained approximately 54% of the trait data variance. The first axis primarily accounted for the leaf type, leaf phenology, and nitrogen fixation data, whereas the second axis primarily represented the wood density data (Table 3 & the Supplementary Information). For Full Model 1 (no management practices), we identified the largest positive effects on rate of carbon accumulation for planting of exotic tree species and the genus *Eucalyptus*. Conversely, we found strong negative effects on rate of carbon accumulation for the coniferous genera (e.g., *Picea* and *Cryptomeria* relative to *Acacia*) as well as prior land uses of fire, harvest and pasture (relative to cropland). For the management data, the effect of planting density was non-significant, whereas we found a significant positive effect on growth for the use of fertilizer ($t = 3.2$, $P = 0.001$). For the model including the use of fertilizer, the effect of endemism was non-significant ($t = 0.5$, $P = 0.6$), whereas it was highly significant with a strong positive effect on rate of carbon accumulation in the other full models.

Growth curves

Relationships between aboveground carbon and stand age varied across plant functional types (Figure 2) and genera (Figure 3). Of the four plant functional types considered, tropical broadleaf forests had the fastest growth rate ($k = 0.2$) by a factor of roughly 1.7 (temperate broadleaf) to 5 (temperate needleleaf) times those of the other plant functional types. Despite the slowest growth rate, temperate needleleaf forests had asymptotic growth limits that were almost double those of the other plant functional types (1.7 to 1.9-fold). The genera growth curves suggest that within temperate needleleaf forests, *Pseudotsuga* had the highest asymptotic growth limits (199.7 Mg C ha^{-1}). Growth rates across the six genera of tree differed greatly, with the broadleaf genera again exhibiting growth rates that were roughly 2-4 times greater than those of the needleleaf genera. Within broadleaf genera, the two tropical genera (*Eucalyptus* and *Acacia*) had roughly double the growth rate of the sole temperate broadleaf genus (*Populus*).

The results of the model validation procedure suggests that variation in the data is not fully captured by a growth curve that predicts yield solely as a function of age. Our normalized RMSE values ranged from 0.71 (*Cunninghamia*) to 1.36 (*Populus*), suggesting that the model error ranged from roughly 75% of mean aboveground carbon in the best case to 133% of mean aboveground carbon in the worst case. Despite the large error, the nonlinear growth curves are theoretically defensible and are an improvement over the annualized (linear) growth rates and logarithmic growth curves that are commonly used to describe forest growth. Linear growth rates do not reflect how forest stands develop over time and logarithmic growth curves commonly start with negative intercepts, which are biologically impossible.

Calculation of aboveground carbon accumulation rates

Although Chapman-Richards growth curves best capture stand development through time, practitioner and policy audiences frequently need robust linear rates to use in reforestation strategy development. We therefore estimated annualized aboveground carbon accumulation rates. These varied by genus of tree, plant functional type, and biome (Figure 4). Across genera, *Eucalyptus* plantations had the highest annualized carbon accumulation rates (8.15 ± 0.18 Mg C ha^{-1} yr^{-1}). Generally, broadleaved tropical genera (*Eucalyptus* & *Acacia*) had the highest accumulation rates and drove the high mean growth rates for tropical evergreen broadleaf species and tropical & subtropical grasslands, savannas, and shrublands. *Populus*, the primary temperate broadleaved genus in our database, exhibited a slightly higher carbon accumulation rate (3.78 ± 0.23 Mg C ha^{-1} yr^{-1}) relative to the coniferous genera; however, some *Populus* monocultures in our database were from tropical biomes. All four coniferous genera had roughly similar carbon accumulation rates, with the highest mean rate seen for *Pseudotsuga* (3.16 ± 0.16 Mg C ha^{-1} yr^{-1}).

Across plant functional types, differences in aboveground carbon accumulation rates were less pronounced with the exception of tropical broadleaf plantations having the highest rate (6.68 ± 0.15 Mg C ha^{-1} yr^{-1}; Figure 4b). Across biomes, tropical & subtropical grasslands, savannas, & shrublands (8.08 ± 0.36 Mg C ha^{-1} yr^{-1}) and tropical & subtropical moist broadleaf forests (4.39 ± 0.11 Mg C ha^{-1} yr^{-1}) had the highest accumulation rates (Figure 4c). The four other major biomes (temperate grasslands, savannas, and shrublands; temperate broadleaf mixed forests; temperate coniferous forests; and Mediterranean forests, woodlands, and shrublands) all had relatively similar rates of less than 3 Mg C ha^{-1} yr^{-1}.

4.4 Discussion

Our results provide insight into the key drivers of variation in aboveground carbon accumulation in monoculture plantations across global scales, as well as quantify differences in accumulation patterns across major plant functional types and genera of tree. By using a growth function with biologically meaningful parameters, we identified theoretical maximums of stand-level carbon as well as growth rates across the major genera of tree crops planted globally. To facilitate better utility of our results and analyses, we provide additional discussion of i) how well our database represents global plantation forests, ii) drivers of variation in aboveground carbon accumulation, and iii) the utility of our parameterized growth curves and mean aboveground carbon accumulation rates in the following sections.

Database representativeness of global plantation forestry

Understanding of the typology and spatial distribution of global plantation forests is relatively lacking due to a) proprietary holdings of plantation forest data, and b) difficulties in differentiating between planted versus natural forests via remote sensing. The 2020 Forest Resources Assessment of the United Nations Food and Agriculture Organization provides arguably the best snapshot view of plantation forests across the globe [41]. Relative to statistics from the 2020 Forest Resources Assessment, our database represents some geographic regions of plantation forests well, whereas it fully misses others. In 2020, China (84.7 Mha; 29%), the USA (27.5 Mha; 9%), Russia (18.8 Mha; 6%), Canada (18.2 Mha; 6%), Sweden (13.9 Mha; 5%) and India (13.2 Mha; 5%) held the largest extents of global planted forests (60% of plantation forests in total). Using the percent of database observations by country as a proxy for representativeness, data from these countries were represented to varying degrees within our database. China (43%) and the USA (16%) were overrepresented, Canada (2%) and India (3%) were underrepresented, and Russia (0%) and Sweden (0%) were wholly absent from our database, a surprising result given their large expanses of plantation forests.

China was overrepresented in our database, primarily due to including approximately 1,700 observations summarized in one study [56]. We elected to include these observations given the importance of China for plantation forests at global scales and the fact that the data are a conglomeration of China's National Forest Inventory. However, we tested the sensitivity of our results to this decision by re-running our analyses without observations from this study. Our key results, for example the ranking of genus-level accumulation rates and their raw values, did not change when excluding these data. Rather, including the data filled out our growth curves substantially for key species such as Chinese fir (*Cunninghamia lanceolata*), which is estimated to account for over a quarter of all forested land and timber production in China [154].

Despite differences at the country level, our database accounts for the genera of tree crop species that dominate plantations globally. Comprehensive data on plantation species by location and percent of global plantation forests is difficult to obtain, but 2006 data from the FAO suggests that *Pinus*, *Cunninghamia*, *Eucalyptus*, *Populus*, *Acacia*, *Larix*, *Picea*, *Tectona*, *Castanea* and *Quercus* plantations dominate global plantation forestry, representing approximately 70% of global planted area [74]. Our database represented these genera well, with these same ten genera accounting for 80% of our observations. Although data from plantation forests in Russia and Sweden are absent from our database, we collected extensive data on *Pinus*, *Picea* & *Larix* monocultures in northern latitudes from other countries (i.e., USA & Canada). Furthermore, while country level summaries provide a convenient lens for assessing how well our database represents global plantation forests, our analyses were not country specific. Rather, they were conducted by plant functional types, genera, and biomes. It is unlikely that the absence of data from Russia or Sweden biases our results. Nevertheless, future work on plantation biomass in Russia and Sweden would benefit understanding of biomass growth in boreal planted forests.

Variation in drivers of aboveground carbon accumulation

With the exception of planting density, all of our hypothesized drivers of carbon accumulation rates in plantations were found to have statistically significant effects when examined individually (Table 2). Our full models are consequently most informative in understanding the relative effects of drivers on aboveground carbon accumulation in plantations (Table

3). Genus, prior land use, and plant traits were identified as key variables for explaining variation in aboveground carbon accumulation. Genus and plant traits would suggest that biological factors (i.e., growth traits inherent to species) are the major driver of variation in growth rates at global scales. However, selection of species for planting can also be thought of as a key management decision (i.e., a human factor). Endemism of tree species, another factor in species selection, was also found to be highly significant in two of our models, but was only marginally significant ($F = 3.1$, $P = 0.08$) in the full model that accounted for the use of fertilizer. This finding suggests that should nutrient limitations on growth be lifted within plantations, endemic species may perform as well as exotic species that are selected for high growth limits. Further research to better understand the trade-off between use of fertilizer versus exotic species would be of value given that both practices are believed to typically have adverse impacts on local environments [109].

For the third highly significant driver, prior land use, we found carbon accumulation rates to be higher for plantations established on former croplands relative to former pastures, clear-cuts (of both prior rotations and native vegetation), or areas that have formerly burned. This finding parallels the results of others, which show secondary forest growth to be higher on former croplands than pasture, with negative growth effects associated with frequency of fire [147]. Our findings further indicate that monoculture plantations established on former crop or pasture lands may accumulate carbon faster than areas that were formerly forested but clear-cut. This finding has key implications for siting of future monoculture plantations, suggesting that clear-cutting of intact forests may not only have severe and adverse impacts on biodiversity, but may generally have lower growth rates than establishing plantations on former cropland or pastures.

Unexpectedly, biome was found to be non-significant in our full models. Synthetic analyses of carbon accumulation in natural forests suggest that while biome is important, decomposed metrics of climate variables (e.g., seasonality of precipitation) may be important for parsing out variation in aboveground carbon accumulation [102]. The non-significance of biome could also be due to the fact that plantations are actively managed, and constraints on growth are less likely to be tied to climatic factors as much as species growth rates or management practices that remove constraints on growth (i.e., fertilizer or irrigation) [133].

Our analyses of the relative effect of management practices were constrained by data limitations. We were only able to examine two management practices within our full models given that including others would have required omission of key drivers that we sought to control for (e.g., genus). Additionally, our categorical coding of management practices greatly simplified the diversity of actions that may occur within each type of management practice. Nevertheless, our results suggest that some management practices are likely to be important for explaining variation in carbon accumulation in monoculture plantations. Although we found planting density to have a non-significant effect on plantation biomass, the use of fertilizer was statistically significant. This result agrees with expectations, given that fertilizer use directly supports growth and would be expected to associate with higher plantation biomass [133]. Our interpretation is that while management practices are important for plantation biomass growth, they are difficult to generalize and may therefore have limited utility in predicting carbon accumulation across broad scales.

Nonlinear accumulation of aboveground carbon in plantation forests

Although variation in our data was high, we identified distinct patterns of growth across plant functional types and genera. Furthermore, our use of nonlinear growth functions provided theoretically-informed understanding of aboveground carbon accumulation in monoculture plantations (Table 4). For example, we were able to distinguish rapid growth rates for genera commonly grown on short rotations for pulpwood (e.g., *Eucalyptus*, *Acacia*, or *Populus*) versus slower growing coniferous species that are commonly grown for timber (e.g., *Cunninghamia*, or *Pseudotsuga*).

Although it is well known that species from genera such as *Eucalyptus*, *Acacia* or *Populus* accumulate biomass quickly (indeed, it is why they are grown on short rotation lengths), our parameterization of growth curves are valuable for multiple reasons. First, they are significant improvements over annualized mean aboveground carbon accumulation rates, which do not account for periods of slow growth during early stand development, the rapid increase of biomass accumulation at intermediate growth rates, nor the slowing of growth as stands age. These distinctions are critical for accurate assessments of time-dependent actions to mitigate climate change within the forest sector. For example, initial delays in carbon accumulation rates during the first five years of growth represent half of the time window under which many public and private-sector programs have committed to reduce emissions (e.g., by 2030). Assuming immediate and sustained rates of biomass accumulation within forestry projects may have large consequences for carbon budgets at decadal scales.

Second, plantation forestry may be an attractive natural solution to climate change under select circumstances given the economic benefits that can accrue to landowners, which may help incentivize restoration of forest cover. The use of a nonlinear growth function is key to modeling economic returns from productive plantation forestry. For example, key forest management decision-making such as identifying optimal rotation lengths (including for joint management of timber and carbon) is dependent on nonlinear stand growth [105]. Although these curves are widespread within the commercial forestry sector, they are commonly proprietary in nature and are therefore largely unavailable to the academic, governmental, and non-governmental communities. Our growth curves may consequently prove useful in examination of the climate benefits that could be achieved by incentivizing improved plantation forest management, particularly at broad geographic scales.

Annualized rates of aboveground carbon accumulation

Comparing our mean annualized carbon accumulation rates against those of naturally regenerating forests helps situate our findings. However, the comparison should be made with the understanding that planted and naturally regenerating forests are functionally different systems and carbon accumulation rates are only one metric of comparison [13]. Converting aboveground biomass change rates (Mg ha^{-1} yr^{-1}) derived by Requena-Suarez and colleagues to accumulation of carbon in aboveground biomass yields accumulation rates in younger (<20 years) naturally regenerating secondary forests of approximately 1.1 – 3.6 Mg C ha^{-1} yr^{-1} [115]. Similarly, Cook-Patton and colleagues found annualized aboveground carbon accumulation rates to range from 0.1 – 6.0 Mg C ha^{-1} yr^{-1} for naturally regenerating forests [27]. For monoculture plantations, we determined a range of 0.9 – 8.2 Mg C ha^{-1} yr^{-1} for aboveground carbon accumulation in young stands. While the lower rates are roughly similar, the high end of biomass carbon accumulation in plantation forests is roughly 1.4 - 2.3 times greater than that of naturally regenerating forests. Other studies have found that biomass accumulation rates averaged across all plantation types are significantly, but only slightly, higher than biomass accumulation from natural regeneration [13]. In disaggregating by plantation type, our results suggest that select monoculture plantations may have rapid rates of biomass accumulation. However, we reiterate that rate of aboveground carbon accumulation is only one point of comparison and we discuss other important considerations between monoculture plantations and other reforestation approaches in the following section.

Contextualizing our findings

It is important to situate our findings within the broader natural climate solutions arena, which we attempt to do here. Monoculture plantations are only one pathway of many (e.g., natural regeneration, assisted natural regeneration, agroforestry, diverse plantations) for restoring forest cover [30, 62]. Currently, only 7% of global forest cover has been planted, with the remainder having established through natural regeneration. As such, although it is currently the dominant approach for commitments and investments in reforestation, planting of monocultures accounts for a relatively small proportion of reforestation across the globe.

Our analysis combined both productive and non-productive monoculture plantations, which have very different values for society. It is currently unclear how commitments to reforest by planting breakdown across productive versus non-productive plantations. Although our growth curves describe accumulation of aboveground carbon across both system types, there are additional considerations that are important for distinguishing between them. For example, productive plantations provide key needs for society, including timber, paper, or other fiber based-products. When managed sustainably and integrated into a broader landscape, plantation forestry can help reduce impacts on productive natural forests (e.g., concessions) and meet demand for harvested wood products efficiently [109]. Further, substitution of sustainably produced timber for carbon intensive products such as concrete or steel can have large reductions in carbon intensity and expand carbon stocks beyond what would otherwise be achieved on the landscape [93, 104]. Accurately assessing the climate benefits of productive plantations therefore requires accounting for the carbon impacts of harvested wood products from these systems.

For non-productive monoculture plantations, there are other critical factors to consider in assessing their potential climate benefits. For example, although we identified rapid rates of aboveground carbon accumulation, our dataset included productive systems and our curves may therefore poorly predict aboveground carbon accumulation over time-frames that exceed typical rotation lengths. Studies have shown that biodiverse forests stock more carbon than monoculture plantations over long-term timeframes, as these forests tend to have more complex forest structures and greater niche partitioning of resources [94, 108]. Moreover, biodiverse forests are likely to be more resilient to disturbances such as pests or natural disasters, which is key for the permanence and durability of carbon sequestered on the landscape over long time-frames [107]. Additional work is urgently needed to better understand the nature of commitments to reforest by planting such that we may better-account for nuance and differences across these varying systems.

4.5 Conclusion

Monoculture plantations are a globally dominant strategy for mitigating climate change in the land-use sector. Here, we provided improved understanding of aboveground carbon accumulation rates across a variety of monoculture plantations, as well as the key drivers that mediate their growth. Our results provide a foundation for improved modeling of in situ carbon dynamics in monoculture plantations, as well as the climate benefits of improved plantation management practices, such as optimizing rotation lengths for joint production of wood products and carbon. We anticipate that our growth curves will provide a key building block in more systematic understanding of the climate impacts that global monoculture plantations will have.

While sequestration of atmospheric carbon is a key motivation for environmental planners and land use decision-makers, the selection of monoculture plantation forestry versus other approaches for restoring forest cover should be made across myriad considerations: biodiversity, economics, social factors, and feasibility, among others. Furthermore, although we focused on monoculture plantations here, there are a wide variety of plantation systems that are implemented across the globe (including biologically diverse ones), each of which has varying benefits and drawbacks. In giving fair consideration to the numerous forestry systems that exist today—one of which we explore here—we will better operationalize the diverse array of tools that we have for avoiding the most severe impacts of climate change.

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Tables and Figures

Table 1. Potential drivers of variation in aboveground carbon accumulation rates across global monoculture plantations.

Potential Driver	Description	Levels of Variable
Genus of Tree Crop [a]	Reported genus of tree crop obtained from literature review	genus
Endemism [a]	Planting of exotic vs. endemic species	exotic, endemic
Plant Traits		
Leaf type [c]	Species-level leaf type (TRY ID 17)	broadleaf, needleleaf, scaled
Leaf compoundness [c]	Species-level leaf compoundness (TRY ID 37)	simple, compound
Leaf phenology [c]	Species-level leaf phenology (TRY ID 43)	deciduous, evergreen
Nitrogen fixation [c]	Species-level nitrogen fixation capacity (TRY ID 8)	fixing, non-fixing
Wood density [d]	Species-level wood density	continuous variable
Prior Land Use [a]	Reported prior land use obtained from literature review [a]	harvest, cropland, pasture, and fire
Management Practices [a]		
Planting density	Planting density (stems/ha)	continuous variable
Use of fertilizer	Fertilizer used in plantation	yes / no
Use of irrigation	Irrigation used in plantation	yes / no
Use of weeding	Competing vegetation controlled	yes / no
Use of thinning	Plantation thinned	yes / no
Biome [b]	Terrestrial Ecoregions of the World Map	biome type

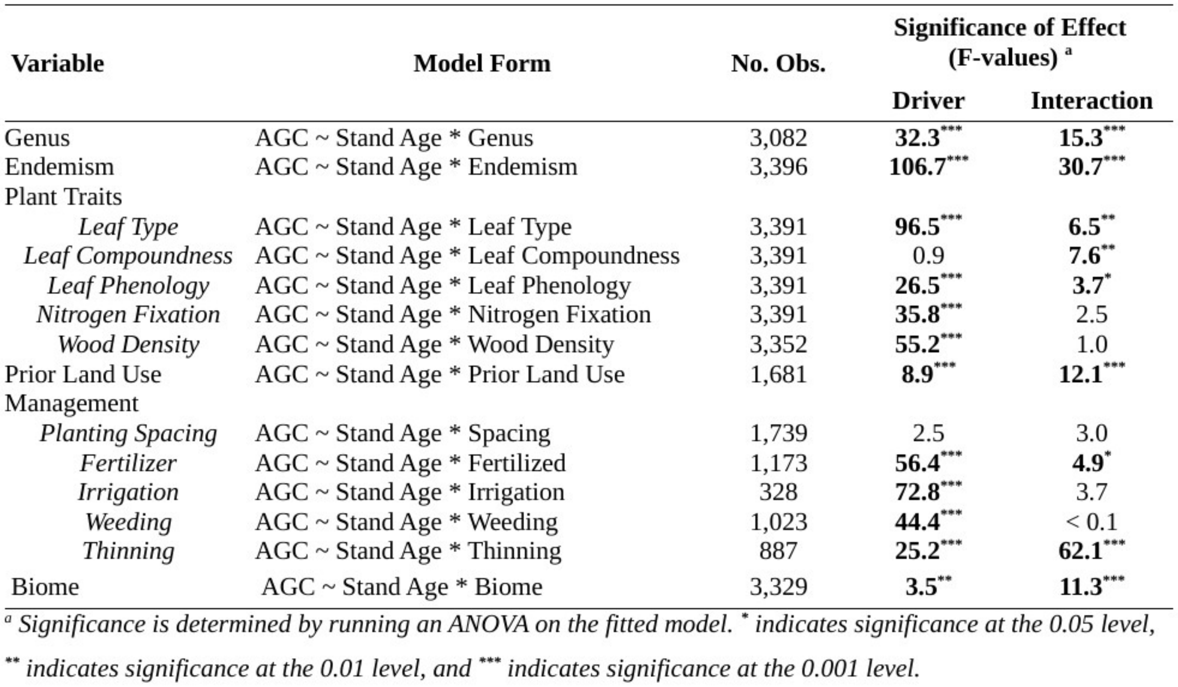
[a] *Reported in the database compiled for this study.*

[b] *Olson et al., 2001; Dinerstein et al., 2017*

[c] *TRY Plant Trait Database*

[d] *Global Wood Density Database*

Table 2. Results of linear mixed effects regression analysis of potential drivers on aboveground carbon accumulation in monoculture plantations. Aboveground carbon (AGC) and stand age are square root transformed in all models.



Variable	**Model Form**	**No. Obs.**	**Significance of Effect (F-values)** [a]	
			Driver	**Interaction**
Genus	AGC ~ Stand Age * Genus	3,082	**32.3*****	**15.3*****
Endemism	AGC ~ Stand Age * Endemism	3,396	**106.7*****	**30.7*****
Plant Traits				
Leaf Type	AGC ~ Stand Age * Leaf Type	3,391	**96.5*****	**6.5****
Leaf Compoundness	AGC ~ Stand Age * Leaf Compoundness	3,391	0.9	**7.6****
Leaf Phenology	AGC ~ Stand Age * Leaf Phenology	3,391	**26.5*****	**3.7***
Nitrogen Fixation	AGC ~ Stand Age * Nitrogen Fixation	3,391	**35.8*****	2.5
Wood Density	AGC ~ Stand Age * Wood Density	3,352	**55.2*****	1.0
Prior Land Use	AGC ~ Stand Age * Prior Land Use	1,681	**8.9*****	**12.1*****
Management				
Planting Spacing	AGC ~ Stand Age * Spacing	1,739	2.5	3.0
Fertilizer	AGC ~ Stand Age * Fertilized	1,173	**56.4*****	**4.9***
Irrigation	AGC ~ Stand Age * Irrigation	328	**72.8*****	3.7
Weeding	AGC ~ Stand Age * Weeding	1,023	**44.4*****	< 0.1
Thinning	AGC ~ Stand Age * Thinning	887	**25.2*****	**62.1*****
Biome	AGC ~ Stand Age * Biome	3,329	**3.5****	**11.3*****

[a] *Significance is determined by running an ANOVA on the fitted model.* * *indicates significance at the 0.05 level,* ** *indicates significance at the 0.01 level, and* *** *indicates significance at the 0.001 level.*

Table 3. Results of comparative models across drivers. F-Values and their significance are produced by running an Analysis of Variance (ANOVA) on each model. For each model, square root transformed aboveground carbon is modeled as a linear combination of the listed drivers with site ID included as a random intercept. Stand age was square root transformed to linearize its relationship with aboveground carbon.

Driver	**Full Model 1 (n = 1,433)**		**Full Model 2 (n = 1,137)**		**Full Model 3 (n = 705)**	
	Num. DF	**F-Value [a]**	**Num. DF**	**F-Value [a]**	**Num. DF**	**F-Value**
Stand Age	1	**1710.6*****	1	**1480.2*****	1	**773.6*****
Genus	9	**14.9*****	9	**15.5*****	9	**14.7*****
Endemism	2	**9.0*****	2	**6.7****	1	3.1
Prior land use	3	**11.5*****	3	**28.5*****	3	**25.8*****
Biome	10	0.8	9	0.7	9	1.2
Leaf Type, Phenology, & N Fixation	1	**9.9****	1	**12.2*****	1	**8.4****
Wood Density	1	**4.9***	1	**8.1****	1	**14.4*****
Planting Spacing	-	-	1	0.8	-	-
Use of Fertilizer	-	-	-	-	1	**10.3*****

[a] Significance is determined by running an ANOVA on the fitted model. * indicates significance at the 0.05 level, ** indicates significance at the 0.01 level, and *** indicates significance at the 0.001 level.

Table 4. Parameter estimates of the Chapman-Richards growth curves. All subsets of the data are constrained to the 95th percentile by age to reduce the effects of sparse data at older ages.

Model	**N**	**Max. Age (95%)**	**Parameter Estimates**		**RMSE**	**Normalized RMSE [a]**
			***A* (S.E.)**	***k* (S.E.)**		
Plant Functional Types						
Temperate Needleleaf	1,207	50	149.8 (13.8)	0.04 (0.003)	85.3	1.77
Temperate Broadleaf	364	40	77.0 (7.0)	0.12 (0.014)	46.2	1.02
Tropical Needleleaf	608	41	78.2 (7.7)	0.07 (0.007)	44.6	0.92
Tropical Broadleaf	818	26	88.6 (6.6)	0.20 (0.020)	52.1	1.01
Genera						
Pinus	1,153	46	96.4 (7.6)	0.05 (0.004)	54.5	1.34
Eucalyptus	515	15	95.8 (8.3)	0.22 (0.018)	54.0	1.15
Cunninghamia	454	40	55.7 (5.4)	0.09 (0.012)	30.5	0.71
Populus	176	29	78.9 (13.0)	0.11 (0.020)	56.8	1.36
Pseudotsuga	137	48	199.7 (19.7)	0.05 (0.006)	90.7	1.04
Acacia	108	19	92.1 (12.9)	0.23 (0.052)	48.1	0.83

[a] We normalized RMSE values using mean within-group AGC (e.g., mean Pinus AGC). RMSE was calculated for each model using a 15:85% validation to training data split, bootstrapped a total of 25 times. The reported normalized RMSE values are the averages across all 25 runs.

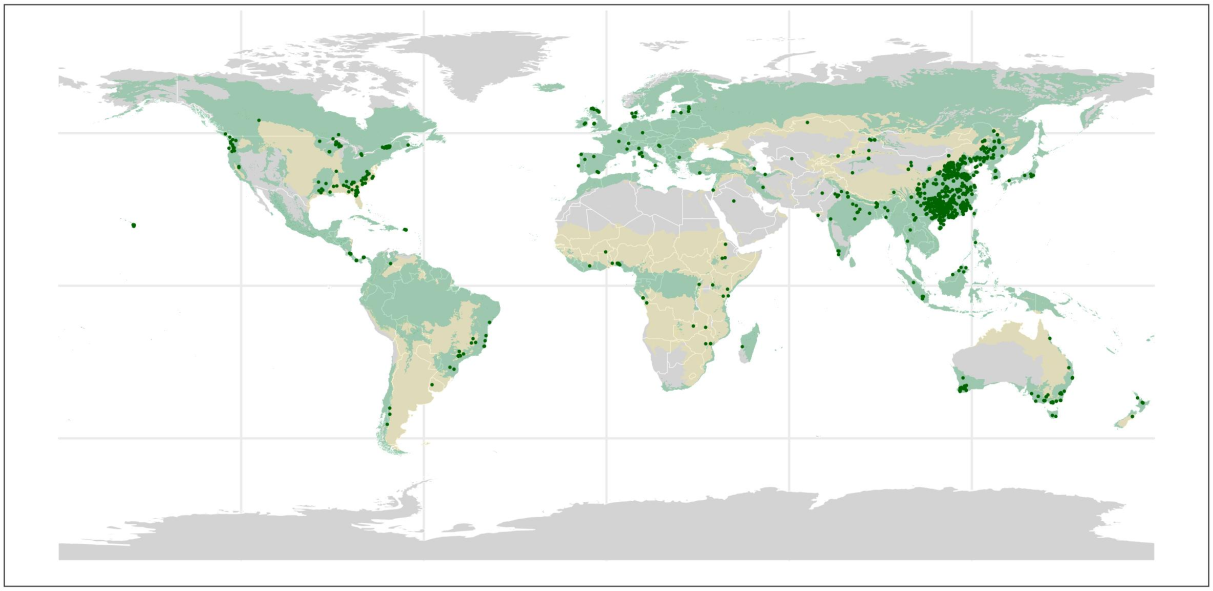


Figure 1. Global distribution of sites collected within the literature database. We identified a total of 3,436 observations of aboveground carbon in plantations, spread across 2,339 plots from 579 sites. Forested biomes are displayed in light green whereas grassland, savannas, and shrubland biomes are displayed in pale yellow.

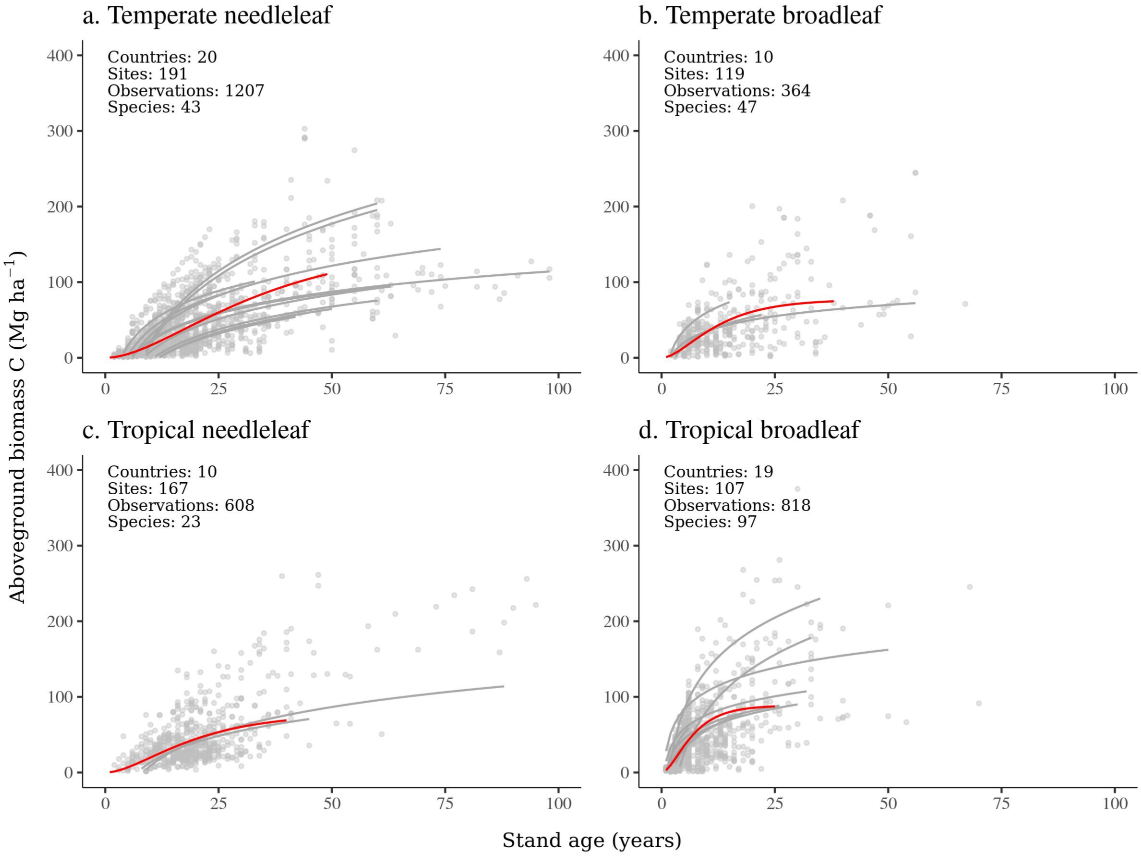


Figure 2. Growth curves by plant functional type. Chapman-Richards growth functions are displayed in red, with the top 5% of observations by age truncated to avoid the effects of sparse data at older stand ages. The grey curves are for visual comparison of species level trends only, and are logarithmic relationships between stand age and aboveground carbon for individual species with greater than 20 observations in the database.

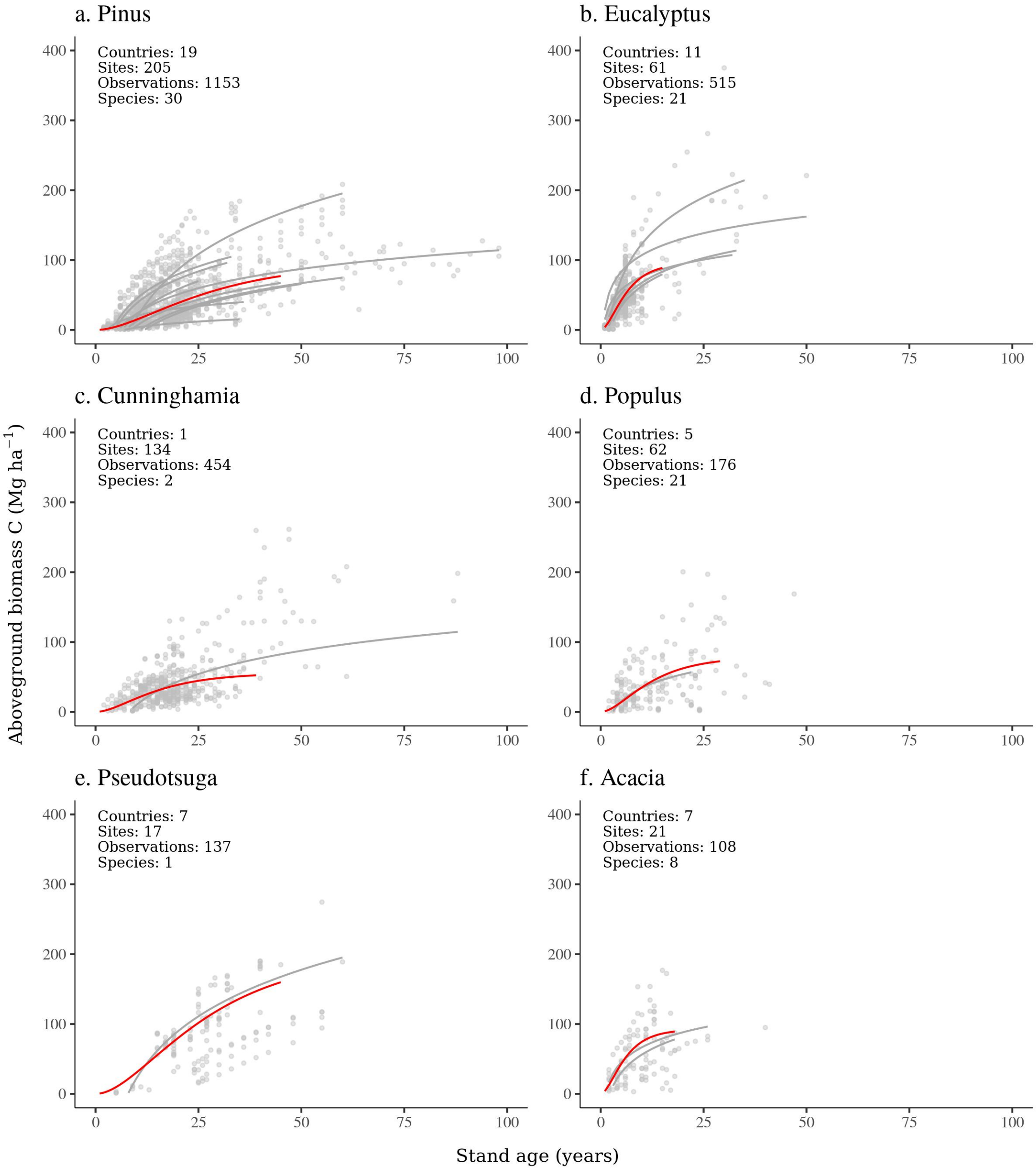


Figure 3. Growth curves by genus. Chapman-Richards growth functions are displayed in red, with the top 5% of observations by age truncated to avoid the effects of sparse data at older stand ages. The grey curves are for visual comparison of species level trends only, and are logarithmic relationships between stand age and aboveground carbon for individual species with greater than 20 observations in the database.

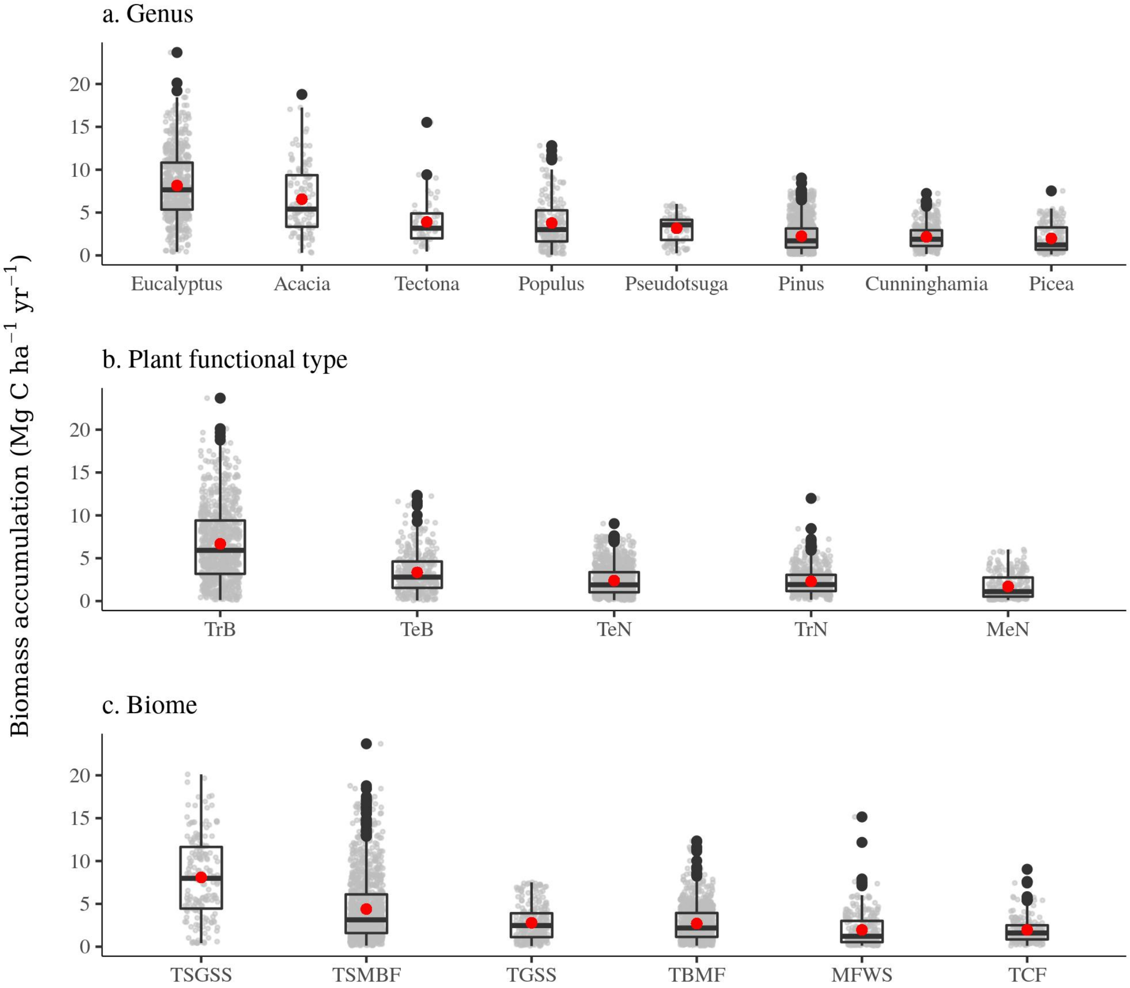


Figure 4. Aboveground carbon accumulation rates for the major genera (a), plant functional types (b), and biomes (c). Red points represent mean values. Plant functional type codes: TrB – tropical broadleaf; TeB – temperate broadleaf; TeN – temperate needleleaf; TrN – tropical needleleaf; MeN – Mediterranean needleleaf. Biome codes: TSGSS – tropical & subtropical grasslands, savannas, and shrublands; TSMBF – tropical & subtropical moist broadleaf forests; TGSS – temperate grasslands, savannas & shrublands; TBMF – temperate broadleaf & mixed forests; MFWS – Mediterranean forests, woodlands & scrub; TCF – temperate conifer forests.

4.6 Supplementary Information

Dataset Compilation

We systematically reviewed the literature to identify studies reporting data on biomass and carbon stocks in monoculture plantations. The literature search was performed on 19 April 2017 and was part of a larger effort to collect data on biomass accumulation associated with expanding forest cover more generally [27]. Studies published since 1975 were identified on Web of Science using the keyword search terms: TOPIC: (biomass OR carbon OR agb OR recover* OR accumulat*) AND (forest) AND (restorat* OR reforest* OR afforest* OR plantation* OR agroforest* OR secondary*). We reviewed the abstracts and titles of the 10,937 peer-reviewed studies that the search initially returned to identify studies focused on re-establishing tree cover (N ∼5,500), which we further constrained to those that quantified biomass or carbon stocks (N ∼1,400). Finally, of these ∼1,400 studies, we identified 640 studies that quantified biomass stocks in forest plantations, comprising our final list of candidate studies.

We then reviewed each of these 640 studies to determine whether the study was to be included in our database. To be included, the study had to report i) empirical measures of biomass or carbon in the aboveground pool; ii) age of the plantation at the time of field measurements; and iii) a latitude and longitude pair or sufficient geographic detail from which geographic coordinates could be obtained. We focused exclusively on aboveground biomass, because accurate estimates of changes in soil organic carbon stocks require pre-post measurements that are not readily available in the literature. Similarly, belowground biomass data were sparsely reported, may be unreliable due to inconsistent field sampling, and are believed to account for a small proportion of total biomass in plantation systems [13]. Prior reviews have found that up to 62% of root biomass data is unreliable due to unverifiable sampling methods [101]. We consequently did not collect information on belowground biomass stocks. Additionally, we did not collect data on understory vegetation biomass, as it is a minor component of total biomass in monoculture plantation systems. Given the importance of management practices on plantation tree growth, we collected information on planting density, rotation length, site preparation, fertilization, irrigation, and vegetation control (e.g., thinning), in addition to biomass (carbon) stocks, age, geolocation, tree crop species, and prior land use/disturbance. We collected quantitative measures where possible and later coded the qualitative data on management practices to facilitate statistical analyses (described in the main text).

Preprocessing and Standardization of Data

We considered grouping measurements by both site and plot to account for spatial autocorrelation. The precision of site geolocation was highly variable across studies. Some studies reported specific geolocations for each plot within a site. We harmonized the site codes to better account for autocorrelation in environmental and climatic conditions across global scales. For example, a large number of studies used chronosequences as their experimental design, which attempt to control for environmental and climatic conditions by definition. We therefore coded chronosequences as coming from a single site. Conversely, sites that had repeat measurements across time (e.g., measurements of biomass across multiple years) were grouped by plot but considered as distinct sites. Our handling of spatial structure in the database consequently attempts to accounts for correlation across observations at global scales.

When studies empirically measured carbon concentrations in biomass and reported values of biomass carbon, we retained those values. Many studies used a default factor of 0.5 to convert aboveground biomass to carbon in aboveground biomass, which we adjusted to the IPCC's default conversion factor of 0.47 [39]. The majority of studies reported only biomass (carbon) in the tree crop without any reporting of understory vegetation. Further, plantations commonly remove understory biomass and the relative contribution of understory vegetation to total biomass is consequently small [27]. We therefore only collected tree crop biomass data. Most studies used allometric equations that estimated biomass across the stem, branch, twig, and foliage pools. We omitted those that reported only stem biomass given that substantial biomass may be found in the branch and twig pools, but retained studies that reported only woody biomass (stem, branch and twig) given the relatively small contribution of foliage to total biomass.

One study reported biomass data across 1,716 plots from 323 planted forest sites across China, accounting for a substantial portion of our final dataset [56]. Although others have elected to exclude the portion of this dataset that corresponds to naturally regenerated forests from their analyses, we elected to retain the data for three reasons: i) China represents a very large proportion of the globe's planted forests, ii) plotting of biomass data in Chinese planted forests from this study versus those of others did not suggest the potential introduction of bias, and iii) inclusion of the data substantially increased the number of observations in our database. To avoid duplicates in data, we ensured that observations were not already included in our database, matched site codes where appropriate, and filtered the dataset to only monospecific plantations. Unfortunately, management information was not available for these data and we were unable to include them in our analyses of drivers of variation in aboveground carbon accumulation.

Additionally, a second study reported approximately 600 observations of biomass for *Eucalyptus* plantations from eight sites in Brazil [136]. The study was focused directly on the influence of water, nutrients and stand uniformity on biomass production and was consequently highly relevant for our study. *Eucalyptus* plantations are managed on short rotation lengths in Brazil and inclusion of observation level data from this study heavily biased our data on tropical broadleaf forests towards younger ages. To reduce the influence of these data on our growth curves, we averaged observations that were i) from the same site, ii) were the same age, and iii) were managed via the same practices. Doing so reduced the total number of observations from this study from 649 observations to 199 and alleviated concerns that this study was overly influencing our *Eucalyptus* and tropical broadleaf growth curves.

Finally, we identified one measurement with an anomalously high carbon accumulation rate that we could not explain (~40 Mg C ha^{-1} yr^{-1}). The value was greater than eight standard deviations from the mean carbon accumulation rate for that genus (*Acacia*) and we decided to exclude it. We also identified several other observations with carbon accumulation rates greater than three standard deviations from their genus-level mean. Although this is a strong deviation, we retained them in the final dataset. Finally, our measurements for stand ages greater than 100 years were largely dominated by one study, and the degree to which the study is representative of plantation forests is unclear. Given that time frames of less than 100 years are more representative of plantation forests and are adequate for assessing climate change mitigation actions, we filtered our database to those observations that were less than 100 years of age.

Transformation of data for driver analysis

To help linearize the relationship between aboveground carbon and stand age, we square root transformed both variables. The linear relationship facilitates the driver analysis, which was examined through linear mixed effects models. The linearized data is shown in Figure S1.

Selection of growth curve forms

We considered four growth curve forms for modeling the accumulation of aboveground carbon in monoculture plantations: logarithmic, linearized logistic, logistic, and the Chapman-Richards curve. Logarithmic curves are commonly used to approximate biomass (or carbon) accumulation in forests over time and, of the four curves considered, are the easiest to fit [113]. However, they do not account for the logistical growth pattern known to describe carbon accumulation in forests. The three remaining curves all describe logistic growth patterns. The first (Linearized Logistic, Eq. S2) is common within the forest economics literature and is commonly used due to its ease of fitting (taking the log of aboveground carbon linearizes the equation). The logistic (Eq. S3) and Chapman-Richards (Eq. S4) curves are nonlinear in form. Although more sensitive to nonlinear variations in data, they are more complicated to fit.

The forms of each growth curve are:

Eq. S1. Logarithmic.

$$q(t) = log_e(t)$$

Eq. S2. Linearized logistic.

$$q(t) = e^{(1-b/t)}$$

Eq. S3. Logistic.

$$q(t) = A/1 - b * e^{(-k*t)}$$

Eq. S4. Chapman-Richards.

$$q(t) = A * (1 - b * e^{(-k*t)})^{1/(1-m)}$$

Where:

- $q(t)$ is aboveground carbon in Mg C ha^{-1},
- t is stand age in years, and
- A, b, k, and m are parameters to be estimated from the data.

We considered several criteria in selecting which growth curve to fit: ease of parameterization, accurate description of theoretical biomass accumulation patterns (i.e., logarithmic vs. logistic), and visual fit to the data. After plotting all four curves against several subsets of the data (e.g., see Figure S2, data for temperate pines; other subsets not shown), it was clear that the Chapman-Richards curve outperformed the other three logistic curves. Given that the Chapman-Richards curve is commonly employed, is theoretically defensible, and not overly complicated to fit, we elected to use it to model the accumulation of aboveground carbon.

Factor Analysis of Mixed Data for plant trait data

Our plant trait Factor Analysis of Mixed Data (FAMD) reduced the trait data to two axes, which accounted for 53.9% of the variance in the trait data. The first axis (33.2% of variation) primarily represented the leaf type, nitrogen fixing capacity, and leaf phenology data, whereas the second axis (20.7% of variation) overwhelmingly represented the wood density data (Figure S3a). Leaf compoundness did not contribute substantially to either axis. As expected, we identified strong separation of species across the broadleaved versus needleleaved categories of leaf type, deciduous and evergreen categories of leaf phenology, and N-fixing versus non N-fixing categories (Figure S3b). Distinct clustering is seen across the four categorical traits (leaf type, leaf phenology, leaf compoundness and nitrogen fixation capacity), whereas the spread of species within these groupings (i.e., the diagonal spread of grey points) is primarily driven by differences in wood density (Figure S3b).

Supplementary Figures

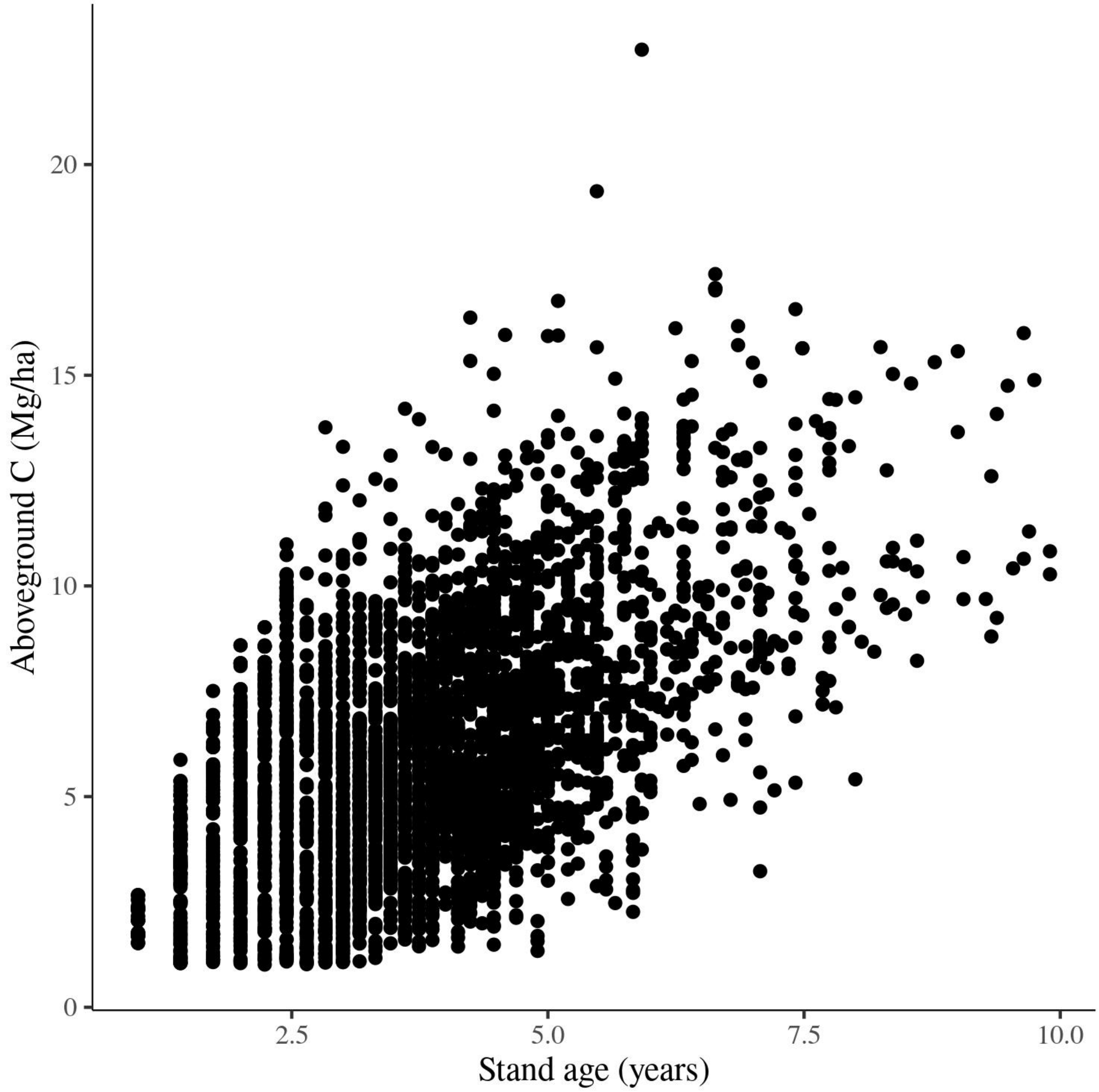


Figure S1. Linearization of the aboveground carbon and stand age data via square root transformation.

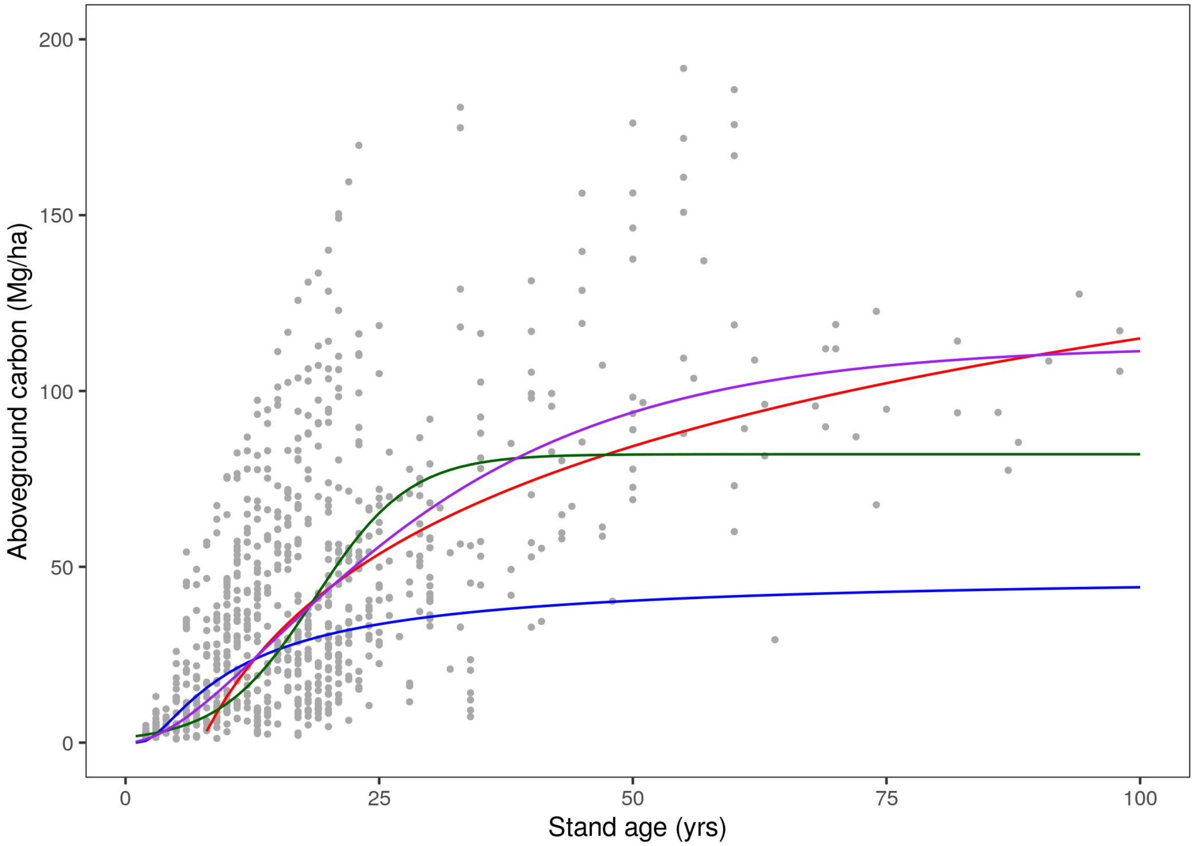


Figure S2. Comparison of growth curve forms. Four growth curve forms fit to all temperate pine data in our database. The curves are logarithmic (red), linearized logistic (blue), logistic (green), and the Chapman-Richards curve (purple).

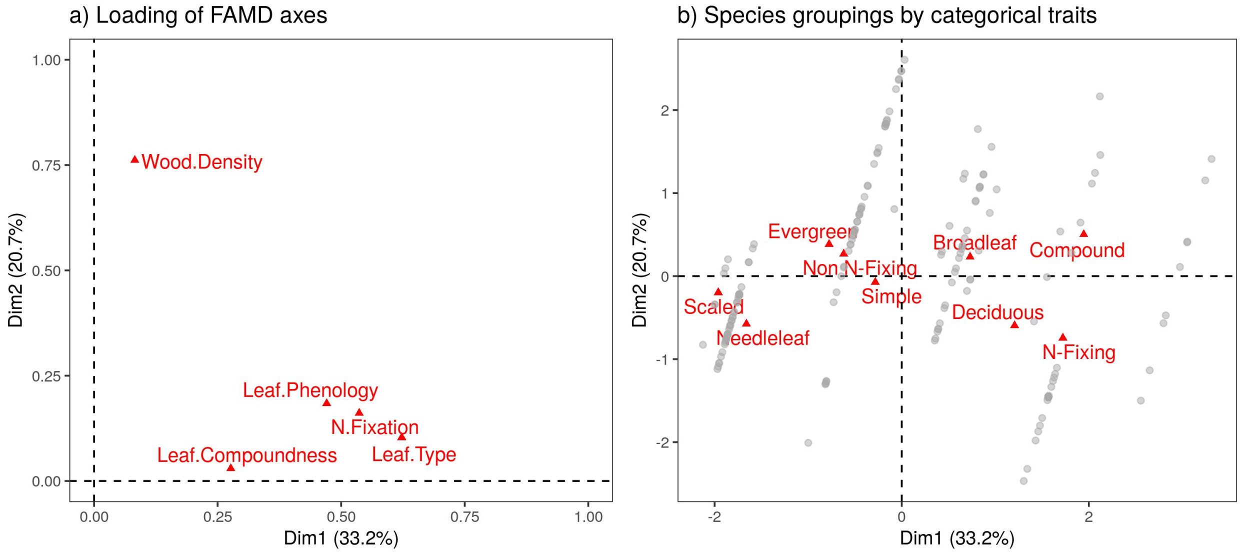


Figure S3. Exploratory analysis of trait data using factor analysis of mixed data. Panel a) shows loading of the traits on the two FAMD axes, whereas panel b) shows the species-level groupings across the levels of the categorical trait data. Diagonal distribution of grey points in panel b) is driven by differences in wood density data.

Chapter 5

Conclusion

5.1 Overview

Better forest stewardship has large potential for helping to mitigate climate change due to the scale at which forest conservation and expansion could occur. Although a range of pathways for conserving and expanding forests exist, this dissertation examined two prominent ones: i) the conservation and reforestation of mangrove forests, and ii) the expanded planting of monoculture plantations. I have examined these actions by undertaking three studies with highly applied results. Further, the lenses and geographic scopes through which I have examined these topics were designed to directly improve the management and policy that impacts these forest ecosystems.

First, I critically assessed the role that predictive model data can play in mangrove forest carbon design. Field-based measurements of carbon stocks in mangroves are expensive to obtain due to access issues and the necessity of accounting for the soil organic carbon pool. As such, the availability of accurate predictive model data is of great benefit to resource-constrained actors. The results of my second chapter suggest that, at the site level, estimates of carbon stocks in mangroves may vary depending on whether field data or predictive model data is used. Although it is nearly impossible to determine a "true" estimate of carbon stocks, conventional belief is that for a given site, field based measurements are more accurate than global maps. This does not mean that predictive modeling holds no value for carbon forest programs in mangroves; rather, it means that further work to iterate on these models (as well as additional collection of field-based assessments) would improve their utility. The implications of the results speak to a broader concern within the forest carbon world; should baseline estimates of forest carbon stocks be inaccurate, programs employing these baselines may be subject to criticism that they are producing false climate benefits. For mangroves, these global maps remain highly valuable (particularly at broader scales) but should be used with caution.

Second, I used a modeling and scenario analysis framework to examine the degree to which mangrove reforestation can contribute to Thailand's climate change mitigation goals.

Mangroves are among the most carbon rich ecosystems globally and their deforestation induces large emissions of carbon to the atmosphere. However, recent evidence also suggests that reforestation of mangroves may result in the rapid accumulation of carbon in the vegetation and soil pools. I iterated on recent studies to improve the modeling of carbon stock recovery in mangroves, used high resolution land use and land cover change data, and situated my results at a national scale - the scale most relevant for mangrove conservation and reforestation policy. The results of my third chapter suggest that the climate benefits from widespread mangrove reforestation in Thailand would meet a significant but small proportion of their Nationally Determined Contribution to the 2015 Paris Agreement. Further, my results suggest that much of mangrove forest regrowth might be associated with natural expansion of undisturbed patches of mangroves; however, future research is needed to confirm this. Importantly, the results of this chapter are constrained by key uncertainties. While the mangrove community has done well to quantify carbon stocks in standing forests, data on the time-dependent recovery of carbon stocks in mangroves is lacking. Additional research that improves understanding of carbon accumulation in reforested mangroves would greatly benefit the mangrove conservation and climate change mitigation communities.

Third, I produced a synthetic view of the rates and variations in rates at which carbon is accumulated in the aboveground biomass of monoculture plantations globally. Although growth of biomass in monoculture plantations is well understand in localized contexts, there is currently no synthetic understanding of how this growth varies by key factors such as genus of tree crop, geographic region, or management practice across the globe. This is a key knowledge gap for the forests and climate arena, as the majority of commitments for reforestation are for planting monoculture plantations and many of these are motivated by a need to mitigate climate change. Taking a meta-analysis approach, I built a database of approximately 3,500 observations of aboveground carbon in monoculture plantations across the globe and produced a refined understanding of how carbon accumulates in these systems. The results of my fourth chapter suggest that carbon accumulation rates vary substantially across genus of tree and geographic region. Further, I found a range of biological, environmental, and human factors to mediate these rates of growth. I used nonlinear growth curves to model the accumulation of carbon across time, which is a more theoretically defensible approach relative to mean accumulation rates or logarithmic growth curves. My findings greatly improve our understanding of how carbon accumulates in monoculture plantations, which will be of high utility for assessing various options to expand forest cover across broad geographic scales.

5.2 Future research needs

Although my dissertation has improved understanding of forest carbon management in mangroves and monoculture plantations, future research remains critical to further improve management and policy in the forests and climate arena. Below, I provide additional thoughts and details on two key research avenues that would greatly benefit communities concerned with forest carbon management and policy-making.

The first avenue to consider is whether carbon stocks in deforested mangroves are recoverable over meaningful time-frames to mitigate climate change. Although my third chapter sought to improve understanding of this question, an honest evaluation of the results would suggest that the data necessary to answer this question are lacking. While the scientific community has done well to quantify carbon stocks in extant mangroves, key uncertainties on how quickly carbon accumulates in reforested mangroves remain. Furthermore, other work that I have collaborated on during my doctoral studies suggests that shrimp aquaculture ponds, the dominant driver of mangrove deforestation, are capable of preserving large quantities of organic carbon in their soils. Mechanistic explanations of this are lacking. On the one hand, flooding of aquaculture ponds may recreate anaerobic conditions shortly after their construction, suppressing oxidation rates of mangrove-derived organic carbon and therefore preserving it in the soil. Conversely, aquaculture ponds are intensive systems that receive large amounts of feed, nutrients, and other organic matter. As such, the soil organic carbon found to be preserved in these ponds may be a result of the productive aquaculture system rather than derived from preserved mangrove biomass. Further research on the dynamics of carbon in aquaculture ponds would greatly improve our understanding of the climate impacts of mangrove loss and gain, in addition to studies that quantify carbon gain in these systems.

The second research need is a more holistic view of carbon dynamics in monoculture plantations. Specifically, monoculture plantations are commonly established for productive purposes, with the tree crops harvested at set ages for the production of timber, pulp and paper, or other fiber-derived products. In these systems, substantial portions of carbon may be removed from the landscape and integrated into the built environment through the use of long-lived wood products (e.g., the use of timber in housing), which would produce additional stocks of carbon following regrowth of the plantation. Currently, comparisons of the climate benefits of monoculture plantations versus other pathways for forest expansion rarely consider the additional stocks of carbon that may be produced through productive plantation systems. Comprehensive understanding of carbon dynamics in monoculture plantations and their associated harvested wood products is highly uncertain. On the one hand, the climate impacts of forest management in plantations are poorly constrained, which my fourth chapter sought to improve. On the other hand, life cycle assessments of the climate impacts of forest products are uncertain and rarely account for the climate impacts of forest management decisions. Accurate understanding of the climate impacts of productive plantations will ultimately require the life cycle assessment and forest management scientific communities to align their respective fields. Only then will we have a comprehensive understanding of the climate impacts of productive plantation forestry.

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