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Methods for the spatial modeling of forest carbon in the Northern Forest

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METHODS FOR THE SPATIAL MODELING OF FOREST CARBON IN THE
NORTHERN FOREST

A Thesis Presented

by

Alison Adams

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The Faculty of the Graduate College

of

The University of Vermont

In Partial Fulfillment of the Requirements
for the Degree of Master of Science
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ABSTRACT

The ability to accurately measure and monitor changes in carbon stored in forests is critical to sustainably manage forested ecosystems. However, current land cover products covering the northeastern United States provide neither the spatial, informational, nor temporal resolution necessary to perform comprehensive longitudinal analyses of changes in carbon stored in the region. Most analyses of carbon storage consider only coarse forest types (e.g. “temperate continental, evergreen, mixed”) or employ expensive remotely-sensed products not available in all areas or across multiple time steps. In this study I employ new land cover products that categorize forests by species association to determine the influence on landscape-scale carbon storage estimates of including more specific delineations of forest type. I test three methods for calculating carbon stored at a landscape scale, using land cover inputs with forests delineated at varying specificities. The results of this research provide the basis for understanding past and future changes in the region’s forest carbon, and can inform forest management and planning at a regional scale.

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INTRODUCTION AND BACKGROUND

Forest change in the northeastern United States

Assessing changes in forest pattern, composition, and extent is a critical component of forest management, including managing forests for carbon storage. Due to widespread clearing of forested land for agriculture in the Northeast during the 18th and early 19th centuries, most stands in the northern forest have existed since only the mid-19th century or later. Nineteenth century industrialization and the opening of more productive lands in the West resulted in the mass abandonment of farmland in New England, allowing previously-cleared forests in the area to regrow (Mustard, Defries, Fisher, & Moran, 2012). In the eastern United States, less than 1% of the old-growth pre-colonial forest is thought to remain (Davis, 1996). As a result of this history as well as logging and additional disturbances, the vast majority of the forests in Vermont are relatively young: nearly all of Vermont's forests are younger than 150 years, with a mean age around 63 years (Pan et al., 2012). Mature forests with longer-lived shade-tolerant species such as sugar maple and balsam fir have become reestablished (Hall, Motzkin, Foster, Syfert, & Burk, 2002), but these stands tend to be more even-aged than the all-aged old growth stands that were more widespread in the Northeast prior to European colonization (Bormann & Likens, 1979a; Lorimer & Halpin, 2014).

Today, pressure from increasing development (V. Dale, Archer, Chang, & Ojima, 2005; Germain, Anderson, & Bevilacqua, 2007; Mockrin, Stewart, Radeloff, Hammer, & Johnson, 2012), decreasing large-scale forestland ownership (Bliss, Kelly, Abrams, Bailey, & Dyer, 2009), and the resulting parcelization of the landscape (Brighton, Fidel,

& Shupe, 2010) is causing a decline in forested land and creating an increasingly patchy, disconnected landscape. In the northern United States, the average size of a family-owned forest parcel decreased from 25 to 20 acres between 1993 and 2006 (Butler & Ma, 2011).

Climate change (Beckage et al., 2008; Galford et al., 2014), pests and pathogens (Schultz, Hanson, Wilmot, Decker, & Greaves, 2014), forest management practices (Ward, Worthley, Smallidge, & Bennett, 2013), and natural succession patterns are simultaneously affecting the composition of tree species found in forests in the region. A study of climate change in Vermont found that increasing temperatures are expected to increase suitable ranges for species such as oak, hickory, and red maple, while decreasing the ranges of spruce and fir species. Sugar maple and red spruce abundances are also expected to decline as precipitation patterns shift (Galford et al., 2014). Similar patterns are likely across the northern forest region, where climatic conditions and tree species abundances are similar. Additionally, unexplained red pine decline is decreasing the abundance of red pine across the region (Schultz et al., 2014). Finally, while most pests and pathogens have not reached outbreak levels in northern New England in recent years, localized future changes in tree species composition due to beech bark disease, forest tent caterpillars, hemlock woolly adelgid, and others are likely (Schultz et al., 2014).

Feedback and interactions between multiple stressors are also likely to affect the forest, though the specific outcomes are uncertain. For example, warmer temperatures may result in an increase of pests and pathogens, both in terms of number and range (Kliejunas et al., 2009). Meanwhile, an increase in carbon dioxide concentrations will lead to lowered nutrient level, more carbohydrates in leaves, and an increase in plant defenses, which could act as barriers against pathogens (Coakley, Scherm, &

Chakraborty, 1999). While ice storms (Ruiz-Benito et al., 2014) move northward and decrease in frequency in northern New England (V. H. Dale et al., 2001), other storms, including hurricanes and downbursts, may become more common (Schelhaas, Nabuurs, & Schuck, 2003).

Forests and ecosystem services

The composition, pattern, and extent of forests affect ecosystem processes and services beyond the provision of timber and other harvested wood products. These processes and services include but are not limited to biodiversity (Allen et al., 2013; Hansen et al., 2005), pollinator abundances (Blanche & Cunningham, 2005; Ricketts, 2004), water filtration and erosion control (Blanchard, Vira, & Briefer, 2015; Goetz, Wright, Smith, Zinecker, & Schaub, 2003; Vincent et al., 2015), and carbon storage (Ruiz-Benito et al., 2014). Additionally, forest composition and configuration can impact the nonmaterial benefits people receive from nature, including well-being and personal and community identity (O'Brien, 2006).

The effect of fragmentation on biodiversity is complex and non-linear. Allen et al. (2013) found that development-induced forest fragmentation in New England increases the richness of woody invasive plants, which in turn can alter the abundances of native flora and fauna. Furthermore, the spatial heterogeneity of landscapes is often used as a proxy for biodiversity (Rocchini et al., 2010). However, a recent study in the Atlantic Forest of Brazil found that fragmentation of forests decreased biodiversity in those forests

by creating an environment more favorable to generalist species (Lôbo, Leão, Melo, Santos, & Tabarelli, 2011).

Ricketts et al. (2004) found that the presence of forest fragments near coffee crops in Costa Rica enhanced pollinator activity: bee species richness was significantly higher in areas closer to forest patches than those farther away. Similarly, a study in Queensland, Australia found that rain forests are a source of beetle pollinators for nearby orchards (Blanche & Cunningham, 2005).

Forests can play a significant role in water quality and erosion control. When forests grow near waterways, they can help prevent runoff from nearby agricultural lands and/or development sites to maintain water quality (Goetz et al., 2003). Multiple watersheds in the United States, including the Catskill Watershed in New York and the Wasatch Watershed in Utah, have been protected using strategies that include conserving forests within their bounds (Blanchard et al., 2015; Sagoff, 2002).

Non-material benefits from forests are also an important—though under-studied—service that forested landscapes provide. Forests are a popular place for recreating, and can also improve mental health (Morita et al., 2007) and contribute to an individual's or community's sense of place or belonging (O'Brien, 2006). Changes in the extent, pattern, and composition of forests can in turn affect whether and how people receive these important benefits.

Most relevant to this study is the role forests play in regulating climate via the uptake and storage of atmospheric carbon. Forests store 80% of all aboveground biomass globally (Dixon et al., 1994). A study in Spain found that tree species diversity had a significant effect on carbon storage and tree productivity (Ruiz-Benito et al., 2014).

Lamlom and Savidge (2003) found variations in carbon stored between tree species beyond the differences captured in broad hardwood/softwood classifications, suggesting that the species composition of forests is an important factor in overall forest carbon storage. Accurately accounting for carbon stored in forests is critical to understanding the global carbon cycle, and can also influence the value of forested landscapes in carbon markets.

Estimating carbon storage

A number of methods other than direct measurement of carbon content are available to estimate carbon stored in trees. Coarse estimates of biomass, approximately double stored carbon, can be generated by multiplying total forest area by mean biomass density values (e.g. Olson, Watts, & Allison, 1983). Alternatively, direct measurement of a tree's diameter at breast height (DBH) and total height can be integrated into species-specific allometric equations (e.g. Jenkins, Chojnacky, Heath, & Birdsey, 2004) to calculate a tree's biomass. This same method can be used with forest inventory data, which typically includes DBH, total height, and species, to calculate biomass across a landscape. Forest inventory data is available only for discrete plots, so a wall-to-wall biomass map based on forest inventory data must be interpolated (Malhi et al., 2006; Wilson, Woodall, & Griffith, 2013).

Remote sensing technology provides a unique opportunity to estimate carbon storage on a landscape scale. Land cover maps generated from satellite imagery like the National Land Cover Database (NLCD) (Homer et al., 2015) can be used with carbon

estimates by land cover type such as those available from the IPCC (IPCC, 2006). The Natural Capital Project's InVEST carbon model uses this method, applying carbon storage values for each land cover type to a map of land cover (Tallis, Ricketts, & Guerry, 2011). Another popular approach employs remotely-sensed maps of canopy structure along with inventory data to estimate biomass (Cartus et al., 2014; Kellndorfer et al., 2013; Patenaude et al., 2004; Saatchi et al., 2011).

In general, all of these methods are limited by where and what data is available. Complete forest inventory data is not available in all locations. While general land cover data is available globally, land cover maps that include species classifications are not. High resolution LiDAR data is also not available in all locations, although lower-resolution MODIS and Landsat data can be used to generate estimates of canopy height and density. When consistent imagery is needed in particular conditions (e.g. cloud-free, dry, etc.) the lack of temporal resolution can also be a limitation. For example, Cartus et al. (2014) were limited by the lack of sufficient multi-temporal observations from ALOS-PALSAR to generate backscatter mosaics representing dry conditions.

When using allometric relationships to calculate biomass, species-specific equations are preferred because different tree species can differ markedly in architecture and wood density. However, in many areas, particularly tropical regions, there are so many different tree species that developing species-specific equations can be a challenge. As a result, in these areas species-specific equations may not be available for all trees (Ketterings, Coe, van Noordwijk, Ambagau', & Palm, 2001), and generalized equations may have to be used; this can be a source of significant uncertainty.

For simple applications of carbon storage values to a land cover map, misclassifications of cover type are a significant source of uncertainty. Additionally, simplifying variations in land cover by using broad categories can be a source of uncertainty. For example, some land cover maps, such as NLCD, use only coarse forest cover classifications (deciduous, evergreen, and mixed), despite the fact that different tree species within those categories store different amounts of carbon. Even when a map of tree species is used with average carbon storage or biomass values for those species, variations in biomass that may arise from environmental factors such as temperature, water availability, light availability, and nutrient availability may not be captured.

Ecological modeling

There are many important considerations when modeling ecological processes, as this research aims to do. Here I discuss 1) model selection bias and model validation, and 2) scale.

Model selection bias and model validation

Model selection bias is when the model selected is biased toward a particular output or pattern in the information it is modeling. This can occur as a result of the method that is employed for selecting the best model. For example, if a model is selected because it accurately predicts data points that it was modeled on—an error known as circular reasoning—that selection method is biased. In order to avoid this, it is best practice to use independent validation points (i.e. data that was not used to generate the model) in order to assess model accuracy, and/or to discuss the results from multiple

models. In this research, forest plots not used in model creation were employed to validate the carbon models.

However, even after an independent accuracy assessment has been performed, it still may be difficult to determine which model is the best model. More complex models may be more accurate, or they may be overfit. A more complex model may be generalizable to scenarios relatively similar to those in which the original dataset was collected (i.e. carbon storage data from a similar location, similar time period, etc.) but not generalizable to data from very different circumstances. On the other hand, a simpler model may not capture enough of the complexity in the process it is attempting to model (Myung & Pitt, 2003). Furthermore, even when a model is selected, it may still incorporate systemic errors or biases that will then propagate through its predictions. To address this, it is advisable to use and report the results from multiple models; greater agreement between model outputs often indicates greater accuracy. If the goal is to model the underlying regularity or processes that generated a given data set, the most useful model will be generalizable to other data sets generated by the same processes.

Scale

Scale is an important aspect of spatial ecology. Different patterns and results can emerge depending on the scale of one's analysis. Wu et al. (2002) found that changing grain size and extent of a land cover map altered the values of all of the several landscape metrics they evaluated, with varying levels of predictability. This was an important consideration for the research in this thesis. For the carbon storage models, choosing the appropriate scale was critical because of the wide range of possible carbon storage values and the complexity of the processes that result in different carbon storage values. For

example, in an analysis of global carbon storage, the slight variations in carbon storage due to different tree species in the northeastern United States would not be significant compared to the difference in carbon stored between the Amazon and the northeastern United States; in a global context, all of the northeastern forest would have roughly the same value. On the other hand, for an analysis of carbon storage on the scale of a single hectare, variations due to slight differences in soil, hydrology, deer browse, and pathogens would be relevant. An even smaller scale study could examine how differences in microbial activity affect carbon content. Carbon storage varies with processes that happen on a wide range of scales, from microbial to continental; all models must obscure spatial variations in carbon storage to some extent, since there is always a smaller scale with even more variations that could be examined.

Choosing which scale to use depends on the organisms or processes in question and the intended applications of the study. For example, a study that examines the behavior of beetles that respond to habitat patches at a scale of a few square meters should define grain size in terms of square meters rather than hectares or square miles. Scale may also be dictated by the quality of data available.

For this research, it was important to consider carbon storage at a scale that could capture spatial patterns of tree species composition. Furthermore, considering spatial heterogeneity of tree species makes sense when studying a region the size of the Northeast, because the potential spatial variations in carbon storage resulting from this additional information may be visible and useful at this scale. Regional-level and state-level land use decisions rely on information at a finer resolution than “the entire

Northeast,” so considering differences in the forest within the Northeast is important for aiding these decisions.

MODELING CARBON STORAGE ACROSS A HETEROGENEOUS MIXED TEMPERATE FOREST

Abstract

Context The ability to accurately assess forest carbon storage is critical to understanding global carbon cycles and the effects of changes in land cover on ecological processes. However, existing methods for calculating carbon storage do not explicitly account for differences in carbon stored by different species of trees. Those methods that do reflect some of this variability, such as remotely-sensing canopy structure to estimate biomass, can be resource-intensive and difficult to reproduce over past or future time steps in order to assess change.

Objectives I examined the accuracy of several carbon mapping approaches to understand how specificity of forest type classification (for example, classifying forest as “sugar maple/birch” versus simply “deciduous”) affects landscape estimates of forest carbon storage in the northeastern United States.

Methods I constructed three distinct models to estimate aboveground and coarse roots forest carbon across the study region. These models varied primarily in the specificity of forest type classifications in the input maps and the corresponding carbon storage estimates used for each type. The forest classification schemes tested, from highest to lowest specificity, were: 1) relative basal area by species, 2) species association classes, and 3) coarse forest types (in accordance with IPCC (2006) guidelines).

Results The specificity of forest type classifications in the input maps did influence results, with higher carbon storage estimates generated by models using coarser forest classifications. Maps generated by models that included relative basal area or species

association classifications had similar means and standard deviations to the validation plots, as well as the highest correlations with 1000 random points from a remotely-sensed biomass map, suggesting that they better represent variability in carbon storage across the region; however, this variability was largely driven by the incorporation of stand age. Error increased at higher elevations, and decreased with higher total maple-beech-birch components. This likely reflects the dominance of low elevation hardwoods in the studies on which carbon storage estimate tables are based and demonstrates the importance of matching input estimates to region-specific studies.

Conclusions Current estimates of forest carbon storage from the US Forest Service predict 84-90 Mg/ha in this study area, a low value when compared with my modeled estimates of 104 Mg/ha, 108 Mg/ha, and 118 Mg/ha from the relative basal area, species association, and high IPCC models, respectively. If IPCC carbon estimates are to be applied in the northeastern US, the high end of these ranges should be used. Carbon storage estimates that consider different carbon storage capacities of different tree species are useful to explore temporal trends and relative spatial patterns in carbon storage across heterogeneous landscapes, but because of the coarse resolution and low accuracy of existing stand age maps, remotely-sensed biomass maps may be a better approach to quantify carbon stored at specific locations.

Keywords Landscape • C • Northeast • United States • Aboveground • Biomass

Introduction

Quantifying carbon stored in forested landscapes is critical to understanding how future changes in land cover may affect global carbon cycles, particularly since approximately 80% of the world's aboveground biomass is stored in forests (Dixon et al. 1994). Current US Forest Service estimates of forest carbon storage in aboveground and belowground live biomass, imputed from Forest Inventory and Analysis data, are about 150 million Mg C (84 Mg per hectare of forest in New York, and 90 Mg per hectare of forest in Vermont) for my study area (Wilson et al. 2013). At a regional scale, accurately assessing carbon stored in the landscape can inform decisions about land use by identifying valuable conservation areas and quantifying the potential impacts of land use conversion. Improved assessment of stored carbon also could alter estimates of the value of conserved forestland in carbon markets (Bishop and Pagiola 2012).

Carbon storage is an ecosystem service of particular importance in the northeastern United States. Recent studies have identified this area as a significant carbon sink (Myneni et al. 2001; Pan et al. 2011a), in part because the average age of forest stands is relatively low—around 60 years (Birdsey et al. 2006; Pan et al. 2011b). This is the result of the mass clearing of forests for agriculture by European settlers and subsequent 19th-century abandonment of these lands for jobs in cities and more productive farmland in the West in the 19th century (Mustard et al. 2012). The widely accepted model of forest development (Bormann and Likens 1979) describes low biomass immediately following disturbance, after which tree biomass accumulates over many decades. Field data from experimental forests indicate a leveling off into a shifting mosaic steady-state phase, to occur between 150 and 200 years post disturbance (van

Doorn et al. 2011; Pontius et al. 2016). Much of the current forests across the region are still aggrading from the legacy of clearing for agriculture or harvesting for timber (Cogbill et al. 2002), placing them within the range of biomass aggradation; these forests will likely continue to be an important and significant carbon sink in the coming decades. Furthermore, forests comprise approximately 90% of land cover in the Northern Forest (Gudex-Cross et al. in preparation) making them an even more important consideration in carbon cycles for this region than they are in other, less-forested areas.

Studies show that tree species contribute unevenly to landscape-scale carbon storage (Fearnside 1997; Bunker et al. 2005). Lamloom and Savidge (2003) found varying carbon content between tree species beyond the broad differences captured in typical hardwood/softwood classifications. These studies suggest that species distribution is likely to be an important consideration in determining how much carbon is stored at broad spatial scales. However, this empirical question remains largely untested.

Existing methods for calculating carbon stored in aboveground forest biomass at a landscape scale are often based on general carbon storage estimates assigned to broad categories of land use. Land cover maps generated from satellite imagery like the National Land Cover Database (NLCD) (Homer et al. 2015) can be combined with carbon estimates by land cover type or biome such as those available from the IPCC (2006) or Olson et al. (1983) to generate a spatially explicit estimate of carbon stored in a landscape. The Natural Capital Project's InVEST carbon model (Sharp et al. 2015) takes this approach, and a number of researchers have utilized this model or others like it (Naidoo et al. 2008; Nelson et al. 2008). However, due to the limited specificity of forest type classifications in broad-scale land cover datasets, this method fails to capture

differences in carbon stored by different tree species and forests of differing stand age and may falsely depict a landscape as homogeneous in its carbon storage capacity. Here and throughout this paper I use the word “specificity” to indicate the difference between forest classifications such as “deciduous,” “evergreen,” and “mixed” (not specific), and classifications such as “maple-beech-birch,” “aspen-birch,” “oak-pine,” and “spruce-fir” (more specific), or even classifications indicating an amount of each species present (most specific). Lack of forest type specificity in carbon estimates is a particular problem in regions like the northeastern US, where high spatial variability in forest cover and species composition is the norm.

Where it is available, forest inventory data that includes diameter at breast height (DBH) and total tree height can be used in allometric equations (Jenkins et al. 2004) to calculate carbon stored in individual inventory plots. Values between plots can then be interpolated to generate an estimate of carbon stored across a landscape (Brown et al. 1989; Malhi et al. 2006). Although this approach may account for some of the natural variability in carbon stored by different tree species—at least insofar as species variability is captured in forest inventory plots—interpolation between plots ignores the true spatial patterns of tree species distribution and stand age and may reflect inaccurate spatial estimates of the true abundances of different species across the landscape.

In recent years, researchers have harnessed remote sensing technology to estimate biomass by measuring canopy height and/or density and correlating these data with field measurements of biomass. Cartus et al. (2014) generated a map of aboveground biomass in Mexico’s forests using canopy density estimates from Landsat, L-Band SAR data from ALOS PALSAR, elevation information from the SRTM data set, and Mexico’s forest

inventory data (Inventario Nacional Forestal y de Suelos, or “INFyS”) as a model response. A similar approach was employed by Kelldorfer et al. (2013) to generate the National Biomass and Carbon Dataset for the United States. Other studies have modeled biomass across a landscape using LiDAR-derived canopy height data and on-ground or inventory-based estimates of biomass (Patenaude et al. 2004; Saatchi et al. 2011). These approaches can capture spatial variations in carbon storage due to species composition and stand age, but active remote sensing data such as LiDAR is not currently available across the landscape, is expensive to obtain where it is available, and is even more expensive to create where it is not. Furthermore, generating landscape scale carbon estimates for past time steps is only possible if this data has already been gathered for that time period; estimating future carbon storage using these methods is not possible. As a result, these methods can provide a good baseline to which to compare other estimates, but a different method for estimating biomass is needed in order to assess past changes and predict future changes in carbon stored across a landscape over time.

Freely-available land cover maps generated by remotely-sensed images such as those created by the Landsat satellites provide an opportunity to analyze carbon stored across a landscape at no cost. However, current land cover maps, such as NLCD, utilize only coarse forest delineations (deciduous, evergreen, and mixed). Here we use new maps of relative basal area by tree species (Gudex-Cross et al. in preparation), reclassified to various levels of species-specific forest type classifications to examine whether additional specificity in forest type classifications improves the accuracy of forest carbon estimates in the Northeastern US. We compare carbon assessments based

on several different model calibration configurations. From most- to least-specific forest type inputs, this includes the following models (also summarized in Table 1):

1. “Relative Basal Area” (1.RBA): percent basal area by forest type, matched with weighted, species specific carbon storage values (Smith et al. 2006)

2. “Species Associations” (2.SA): dominant species or forest type classes, matched with species specific carbon storage values (Smith et al. 2006)

3_t. “IPCC Style Traditional” (3_t.IS): coarse forest type classifications (temperate mountain, temperate continental, boreal coniferous), matched with carbon storage estimates from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (2006). Because IPCC Guidelines provide a range for each forest type, this approach is repeated three times based on the low, middle, and high carbon storage estimates provided by the IPCC

3_m. “Smith-based IPCC Style Match” (3_m.SIS): The same coarse IPCC forest type classifications are used as in 3_t.IS, but carbon storage values for each type are derived from (Smith et al. 2006). Values from the Smith et al. (2006) tables were averaged (as described in more detail in the methods section) to match the IPCC categories in order to control for inherent differences between the Smith et al. (2006) and IPCC (2006) carbon storage tables, and isolate the impact of species specificity on carbon storage estimates

#Table 1 approximately here#

Methods

Model data inputs

Carbon storage tables

Mapped forest types were converted to carbon storage values for 1.RBA, 2.SA, and 3_m.SIS models using the Smith et al. (2006) carbon storage tables for reforestation after clearcut harvest in the Northeast. These tables present regional averages of carbon stored by forest type (aspen-birch, maple-beech-birch, oak-hickory, oak-pine, spruce-balsam fir, and white-red-jack pine), stand age (5 - 125 years in 10 year increments), and carbon pool (e.g. live tree, soil, etc.). To best match my field validation data we used only the “live tree” carbon pool, which includes all aboveground biomass as well as coarse roots.

Similar aboveground and coarse root carbon storage values for the 3_t.IS model coarse forest type classes were derived from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2006: Table 4.7). This table provides a typical value for aboveground biomass, as well as a range of possible biomass values for each coarse forest type (e.g. temperate, boreal) and continent, for stands less than 20 years old and more than 20 years old. We used both the typical value and the high and low ends of the range to generate three carbon storage estimates. Biomass in the root carbon pool was added as a ratio of aboveground biomass, by domain, tree type (broadleaf vs. conifer), and size of tree defined by amount of aboveground biomass, in accordance with the IPCC guidelines (IPCC, 2006: Table 4.4). Biomass was converted to carbon stored in the 3_t.IS model using the IPCC values for carbon fraction of aboveground forest biomass for temperate forests (IPCC, 2006: Table 4.3).

Land cover data

Land cover data for these models comprised the United States portion of Landsat row 29 path 14 (Fig. 1) spanning the Adirondack Mountains in New York, Champlain Valley and Green Mountains of Vermont.

#Figure 1 approximately here#

From this Landsat imagery, Gudex-Cross et al. (in preparation) used a multi-temporal, object-based, spectral unmixing method to produce percent basal area maps at 30-meter resolution for the year 2014 for the ten most common species in the region (Fig. 2). This included: *Abies balsamea* (balsam fir), *Acer rubrum* (red maple), *Acer saccharinum* (sugar maple), *Betula* spp. (birches), *Fagus grandifolia* (American beech), *Picea rubens* (red spruce), *Pinus strobus* (Eastern white pine), *Populus* spp. (aspens), *Quercus* spp. (oaks), and *Tsuga canadensis* (Eastern hemlock). These percent basal area maps were converted to relative percent basal area. To do this I assumed that any non-mapped species were a negligible percentage of forest cover and thus that the ten represented species summed to 100% of basal area. These relative basal area maps were used as the land cover input for the 1.RBA model.

#Figure 2 approximately here#

Gudex-Cross et al. (in preparation) used the percent basal area data along with additional spatial variables to generate a classified map that identifies the single dominant species or species groups for each 30m pixel. The resulting classified map was used as the land cover input for the 2.SA and 3_m.SIS models. This map classifies the forest into 15 categories, which I matched with the forest categories in the Smith et al. (2006) carbon tables (Table 2 & Fig. 3).

#Table 2 approximately here#

#Figure 3 approximately here#

Stand age data

Stand age is a significant contributing factor in carbon storage and necessary descriptor to determine which carbon storage values to use in both the Smith et al. (2006) and IPCC (2006) tables. However, accurate landscape-level stand age maps are rare. For this region, I used the North American Carbon Program (NACP) Forest Age Maps data set and corresponding standard deviation map for the United States (Pan et al. 2012) to represent stand age in all of my models (Fig. 4). This map provides an estimate of stand age in the year 2006 at 1-kilometer resolution with a standard deviation of 10 years for most areas in the Northeast. Recent work on global and national carbon storage has incorporated this data set (Pan et al. 2011a; Zhang et al. 2012). To match the date of my land cover data, we assumed a consistent aging of all stands and added eight years to every pixel. The stand age map displays a distinct patchy pattern, which is a result of its heavy reliance on FIA plot data and interpolation between those plots. Stochastic small-gap dynamics and micro-disturbances are common across the region, so for each 30m pixel we selected a random number from a normal distribution with the Pan et al. (2012) stand age as the mean and the accompanying standard deviation map value as the standard deviation. This process was completed only once, but due to the large number of pixels in the study area, multiple repetitions (e.g. a Monte Carlo approach) would likely not have a significant effect on the total carbon storage value. While this randomization may introduce error at the site level, it serves to better represent landscape scale dynamics and heterogeneity.

Finally, stand age was rounded to the nearest age represented in the Smith et al. (2006) tables.

#Figure 4 approximately here#

Elevation data

Because the IPCC biomass tables distinguish between temperate mountain and temperate continental systems, elevation data (Fig. 5) were obtained from the US Geological Survey 3D Elevation Program website (U.S. Geological Survey 2015) to differentiate mountain and continental regions within the study area. Mountain systems were defined in accordance with the IPCC 2006 report as at or above 800 meters elevation (IPCC, 2006).

#Figure 5 approximately here#

The specifications for all data sources are summarized in Table 3.

#Table 3 approximately here#

Model design

The carbon storage models were built in Dinamica-EGO v3.0.4.0. Dinamica is a spatial modeling platform that is commonly used for land cover change models, but it is also well suited for simpler models where cell values are calculated based on a number of input tables and raster coverages. Inputs for each model included a land cover map and the stand age map, linked to a table of carbon storage values. Some models (3_t.IS and 3_m.SIS) also received an elevation map to link to the appropriate carbon storage value in the tables. When data were not available for at least one input, that pixel was given a null value. In the 3_t.IS and 3_m.SIS models, a conversion factor was applied to convert biomass to carbon stored based on forest type. This value was 0.51 for conifers and 0.48 for broadleaf species, in accordance with the IPCC (IPCC, 2006: Table 4.3). In all models, a

conversion factor was applied to convert the carbon storage value from Mg C per hectare to Mg C per 30m x 30m pixel (i.e. per 900m²).

The 1.RBA model used the maps of relative basal area derived from Gudex-Cross et al. (in preparation) as its forest type input. These data include a map for each tree species with values from 0 to 1. For each pixel, the model looked up the stand age and the relative basal area values, and then assigned a carbon storage value as a weighted average of the appropriate values in the Smith et al. (2006) carbon tables. The 2.SA model was similar, but used the reclassified Gudex-Cross et al. (in preparation) dominant forest type map (Table 2) and stand age value at each pixel to identify the appropriate values in the Smith et al. (2006) carbon tables.

The 3_t.IS model used a reclassified Gudex-Cross et al. (in preparation) map of coarse forest domain to match the categories typically included in the IPCC (2006) tables (Table 4). I assumed all spruce-fir forest to be boreal, and defined temperate continental systems as all other forest types below 800m, while temperate mountain systems were all other forest types above 800m. The model looked up the coarse forest domain, stand age and elevation at each pixel and assigned a carbon storage value based on IPCC biomass estimates. Because the IPCC (2006) tables provide a given biomass value for each class as well as a range around that value, I ran the model three times: once with the given values, and once each with the values at the high and low end of each range.

#Table 4 approximately here#

The 3_m.SIS model also used the Gudex-Cross et al. (in preparation) map of coarse forest domain to match the categories typically included in the IPCC (2006) tables.

However, to isolate the impact of forest type specificity without the confounding influence of a different carbon look up table, I repeated the 3_t.IS process by converting the Smith et al. (2006) tables to match the IPCC (2006) table categories. This included matching species types, ages, and elevations to the IPCC domains (Table 4). The 3_m.SIS model then used the reclassified domain and stand age value at each pixel to identify the appropriate values in the converted Smith et al. (2006) carbon tables. Elevation was not included in this model since the Smith et al. (2006) tables do not differentiate carbon storage based on elevation.

Validation

Independent field validation

Model estimates were validated using a network of long-term forest inventory plots maintained by the Vermont Monitoring Cooperative (Vermont Monitoring Cooperative 2015). This network includes 41 plots representing a range of species composition, elevation, and landscape position across Vermont. Plot inventories follow standard USFS Forest Inventory and Analysis methods, composed of four subplots with a 7.32-meter radius with species and DBH measurements for all stems greater than 5cm DBH. I used allometric equations (Jenkins et al. 2004) to estimate biomass for each tree in the plot. To generate data comparable to the Smith et al. (2006) live tree carbon data, which includes coarse roots, I used allometric equations for whole tree (component 1), which include aboveground and coarse root biomass. The Jenkins et al. (2004) paper includes a summary of all allometric equations in the literature, resulting in several for each species. I selected which allometric equations to use (Table 5) based on the following criteria:

- Minimum DBH of trees upon which the equation was based must be less than 6cm, to ensure small trees were included;
- Maximum DBH of trees upon which the equation was based must be greater than 5cm, to ensure that mature trees were included;
- The equation must be based on data from comparable New England, Midwest, or Quebec temperate mixed forests.
- If more than one equation met these criteria, the one with the largest sample size was selected.
- If no equations for a species met these criteria, generalized equations from Jenkins et al. (2003) were used for that species.

#Table 5 approximately here#

The stored carbon for all trees was summed by plot to determine a total carbon stored value per plot and then converted to C-per-m² to calculate a per-pixel value comparable to that generated by the spatial carbon models.

The center point of each validation plot was overlaid with the carbon storage maps. Because each plot is composed of four subplots, with a 43.92-meter radius from the center to the outer edge of the subplots, I created a 43.92-meter radius buffer around each validation point to extract the predicted carbon values. At each point, an average Mg C per pixel value for each model-generated map was calculated by averaging the values of any pixel that had at least half of its area within the validation point buffer zone (Fig. 6). Validation points located in areas with no data in my models—due to missing stand

age or forest type data—were excluded. Ultimately, 26 of the 41 plots were included in my validation analyses.

#Figure 6 approximately here#

Relative accuracy of each model was compared using the RMSE and percent error of actual vs. predicted carbon storage values across the 26 independent field validation points, using a reference line with an intercept of 0 and slope of 1 to represent perfect accuracy. I used Spearman's ρ correlations to examine relationships between the error in each model and various stand characteristics including: stand age, elevation, mean DBH, and total DBH for several species groups (all maple, beech, and birch species; "pioneer" species, including aspen, ash, oak, cottonwood, hickory, hornbeam, linden, cherry, and larch; all spruce and fir species; and all hemlock and pine species). This allowed me to examine how the models differ in accuracy across dominant species types and how stand age maps may be contributing to site specific error.

Spatial variability assessment

In addition to forest type estimates of carbon storage, recent remote sensing products have been developed based on direct modeling of vegetation structural characteristics. I used the NACP Aboveground Biomass and Carbon Baseline Data ("NBCD 2000") (Kellndorfer et al. 2013) (Fig. 7) to assess how my forest type models fared in terms of total carbon stored and the spatial pattern of carbon storage across a broader landscape. I used three zones (64, 65, and 66) of the FIA-derived "FIA ALD Biomass" map from this dataset. The NBCD 2000 dataset also includes a map derived using allometric equations—"NCE ALD Biomass"—but the authors recommend use of the FIA-derived map. Carbon was calculated as 47% of biomass, in accordance with the IPCC (IPCC,

2006: Table 4.3). To assess agreement between this NBCD 2000 biomass model and my model-generated maps, I calculated Spearman's ρ correlations between the NBCD 2000 map and my maps for 1000 random, spatially-distributed points across the study area. To my knowledge the NBCD 2000 dataset is the most accurate wall-to-wall assessment of carbon storage for this region, and therefore it provided the best means available to assess the spatial distribution of my carbon estimates region-wide. However, it should be noted that these analyses do not serve as a true accuracy assessment since the accuracies of this dataset for the sub-regions covering my study area range from $r^2 = .1225$ (zone 65) to $r^2 = .3364$ (zone 66), with RMSE values ranging from 4.2 to 5 kg C/m².

#Fig. 7 approximately here#

Results

Landscape scale carbon storage

Each of the carbon storage models generated a different carbon storage estimate for the entire study area (Table 6, "Total C across study region"). The highest forest carbon storage estimate—203.3 million Mg C—was produced using the coarse land cover maps with the modified Smith et al. (2006) tables (3_m.SIS). However, using the extreme high end of the standard IS table range (3_t.IS-high) produced similar values (201.9 million Mg C). The IS-middle (3_t.IS-middle) and IS-low (3_t.IS-low) values were far below all model estimates, at 130.0 million Mg C and 56.9 million Mg C, respectively. The remotely sensed NBCD 2000 biomass map falls in the middle of the range of total carbon across the various models if adjusted to include coarse root carbon pools. The NBCD 2000 dataset does not include coarse roots since that dataset maps aboveground biomass only;

adjusting for coarse roots using the IPCC (2006) aboveground to belowground biomass ratios increases the stored carbon value to 119.8-162.8 million Mg C, depending on the ratio of forest types used in that estimate.

#Table 6 approximately here#

Comparisons of carbon estimates across the range of IPCC provided values show an even stronger distinction in total carbon stored, varying by more than 300%. Only the extreme high of the IPCC range is comparable to results generated using the Smith et al. (2006) tables, regardless of forest type specificity.

A comparison of variability in carbon storage estimates showed a marked difference among the models, with two- to three times the variability in carbon estimates for the higher specificity 1.RBA and 2.SA models compared to the coarse resolution 3_t.IS and 3_m.SIS models (Table 6, Fig. 8). Without a map of actual carbon storage at every location, I was unable to determine if the variability captured in the species specific 1.RBA and 2.SA maps was also more accurate, but the means and standard deviations of the carbon storage values generated by these two models were most similar to those of the validation points ($\mu = 93.6$ Mg C/ha, $\sigma = 33.6$ Mg C/ha). The outputs from the 1.RBA and 2.SA show a distinct blocky pattern likely due to their heavy reliance on the similarly blocky stand age map (Fig. 4), but reflect higher spatial variability than the comparatively homogenous outputs from the 3_t.IS models.

#Figure 8 approximately here#

Comparing the outputs of these two species-specific models—with relatively detailed stand age inputs—to those of the 3_t.IS and 3_m.SIS models—with highly-

simplified stand age spatial maps (differentiating only between stands younger and older than 20 years)—shows a dramatic reduction in variability across the landscape.

Validation

Independent field validation

In order to estimate the accuracy of carbon storage models, I performed an accuracy assessment with 26 Vermont Monitoring Cooperative forest inventory plots across a wide range of forest types and landscape positions across the central section of my study area. If only the high end of the IPCC (2006) table range (3_t.IS-high) for carbon storage is considered, all four models were statistically similar in over-predicting mean carbon stored per hectare (Fig. 9). The 3_t.IS-middle and 3_t.IS-low models were significantly different—both providing estimates far below the validation plot actual carbon storage values.

#Figure 9 approximately here#

To explore factors that may be driving differences between the models, I ran Spearman's ρ correlations for the error vs. different stand characteristics (Table 7), as well for the actual error (including positive or negative signs) vs. different stand characteristics (Table 8) for each model. Both the 1.RBA and 2.SA models had significantly higher error at high elevations, while the 1.RBA model specifically over-predicted carbon storage at higher elevations. In contrast, there was no significant correlation between elevation and error for the other models. All models except the middle and low 3_t.IS models performed better in stands with high maple-beech-birch DBH, and all models except the high and low 3_t.IS model over-predicted carbon in stands with high spruce-fir DBH; the low 3_t.IS model had a positive correlation between error

and spruce-fir DBH, but under-predicted carbon at every validation point. All models under-predicted carbon storage in stands with high mean DBH. With few exceptions, stand age, hemlock-pine DBH, and pioneer DBH did not show significant relationships with error in the models.

#Table 7 approximately here#

#Table 8 approximately here#

While this assessment of total carbon storage accuracy for the broader landscape is compelling, comparing all actual vs. predicted carbon storage values across all validation points shows little agreement for any of the models. General fit (Table 9, r^2) was highest for coarse 3_m .SIS and 3_t .IS models that did not incorporate stand age, while accuracy (captured by RMSE and percent error in estimates) was worst for the low 3_t .IS coarse forest type model and best for the 3_m .SIS model. Increases in forest type specificity marginally increased the RMSE across the validation plots.

#Table 9 approximately here#

Spatial variability assessment

To further assess how my models captured spatial patterns of carbon storage, I computed Spearman's ρ correlations and fit lines between the NBCD 2000 biomass map and my models at 1000 random points across the study area (Table 10). My results showed that outputs from all models except 3_m .SIS were significantly correlated with the NBCD 2000 map, but only very weakly. By this measure, the higher species specificity models best match the inherent variability captured in remote sensing biomass products across the landscape. However, this relationship is still weak, likely resulting from

inaccurate stand age input maps. Using the coarse forest types, the 3m.SIS model showed no correlation with mapped biomass values across my validation sites.

#Table 10 approximately here#

Discussion

The difference in total carbon estimates generated by the models (Table 6) indicates that the level of specificity in forest composition used does impact results, with higher total carbon estimates generated as forest type specificity decreases (compare models 1-3 in Table 6). It is possible that these coarser forest type models overestimate the contribution of larger, dominant climax species. In this area the primary disturbance type consists of small scale gap dynamics (Seymour et al. 2002), creating a heterogeneous landscape of many mixed species assemblages. These include small fractions of pioneer and early successional species even in forests that would be classified based on the canopy dominant species. This indicates that carbon storage estimates based only on these coarse classifications could be interpreted as an estimate of carbon storage potential in undisturbed stands across the region.

The finding that the standard IPCC tables are only in agreement with other estimates of carbon storage—both at the per hectare and landscape level—at the high end of the IPCC ranges provided has important implications for use of these tables. The IPCC recommends using local or regional estimates instead of their carbon storage tables where these estimates are available, but estimates of average carbon stored by forest type are not available for most areas; the IPCC estimates are often the most viable—or only—option for land-cover-based, regional-scale estimates of carbon stored in forests. If other users of

the IPCC carbon storage tables employ the low and high end of their ranges to create confidence bounds on carbon storage, the resulting estimates (for forest types similar to the temperate mixed forests studied here) may be so broad as to be of little value. Similarly, if only the middle of the range is used, there is a potential to grossly underestimate what is predicted by other carbon models. The results of this study suggest that if IPCC values are to be used for larger scale assessments, it would be worthwhile to conduct some field validation or model comparison to narrow the range of IPCC values used by region.

The mid-range estimate from the NBCD 2000 biomass map was expected; this dataset tends to under-predict biomass in areas with high biomass while over-predicting in areas with low biomass. While true biomass values for this region according to the NBCD 2000 validation points range from 0 to approximately 40 kg/m^2 , almost all of the predicted values in the map range from 0 to only 20 kg/m^2 . The NBCD 2000 map also has considerable error (Table 11), so the true total carbon value may be well above or below the dataset's predicted value.

#Table 11 approximately here#

In addition to estimating total carbon storage, landscape models are useful for assessing the variability and distribution of carbon storage across a landscape. Although I was unable to assess the accuracy of the spatial distribution of the 1.RBA and 2.SA outputs, the heterogeneity of species distribution, stand age, and growing conditions across the northern forest region suggests that these high specificity models generate maps that are likely more representative of the variability in stand characteristics witnessed across the landscape than what is provided by the coarser resolution models.

The finding that the 1.RBA and 2.SA outputs are best correlated with the remotely-sensed NBCD 2000 map further supports this conclusion.

Higher variability in the 1.RBA and 2.SA model outputs results partially from the increased species specificity over the coarse forest type models, based on unique, species specific carbon estimates and their pattern of distribution across the landscape. However, a comparison of the 1.RBA and 2.SA model outputs, both of which were based on the same stand age map, found that they did not differ significantly in spite of their differences in species specificity. This indicates that variability in the carbon storage map is primarily driven by stand age (Figs. 3 & 4). A Spearman's ρ correlation at 1000 random points confirmed that the 1.RBA- and 2.SA-generated maps are strongly correlated ($\rho = 0.9400$, $p < 0.0001$), while neither map was more than weakly correlated with any of the maps from the other models, which did not rely as heavily stand age. The similar blocky patterns between the stand age input map and the 1.RBA and 2.SA output maps further suggests that it is stand age, and not the specificity of species classifications, that is primarily driving the spatial patterns in carbon storage estimates for the 1.RBA and 2.SA models.

The reduction in variability in the 3_t.IS and 3_m.SIS model outputs is driven largely by the fact that these models incorporate only coarse delineations in domain type (“boreal” or “temperate”), stand age (above or below 20 years), and, in the case of the 3_t.IS models, elevation (above or below 800 meters). Most of the forest in the study area is temperate, older than 20 years, and at elevations below 800 meters, so these models generate relatively uniform spatial outputs.

There are many potential sources of error contributing to the 31.6 to 40.4 percent error for the best-performing models (Table 9). The stand age map is likely a primary driver of error, particularly in the 1.RBA and 2.SA models, and will be discussed in more depth later in this section. Calculation of carbon stored in the validation plots assumed that forest between subplots (see Fig. 6) was the same as inside the subplots. Differences in tree species composition or the range of sizes of tree species within the plots would affect my validation calculations. Generalizations that were likely made to generate the allometric equations and carbon storage tables that I used are another source of error, as are potential mistakes made during field measurement of these plots. Misregistration of pixels in the various spatial data layers used in this study is another potential source of error, as that may have resulted in the wrong stand age or forest type being selected from the carbon storage tables, or a misalignment of the validation plots with the mapped carbon storage pixels. Finally, the validation plots were not randomly distributed across the landscape, and many of them are on mountaintops. This likely biased the validation calculations toward lower per hectare carbon storage values than would be representative of the entire region, as well as toward species associations—such as spruce-fir—that are more represented in these high elevation stands.

The influence of stand age on carbon storage is logical based on previously-discussed carbon aggradation models for temperate forests. Most forests in the northeastern US have not yet reached stand ages where biomass accumulation is expected to begin leveling off; appropriately, the Smith et al. (2006) carbon tables for this region, which only go up to stand ages of 125 years, do not reflect a leveling off of biomass accumulation even at their highest values. The young average age of forests may explain

why stand age is such a critical factor in assessing carbon storage in this region, and highlights the importance of including accurate stand age maps in estimates of spatial patterns of carbon storage across the landscape. Unfortunately, the stand age map available does not have reported accuracies, is intended to be applied at a broad scale rather than at the pixel level, and displays a blocky pattern that does not reflect the actual historical land use or more recent disturbance patterns in this region. Furthermore, when I compared mean DBH in the validation plots to stand age according to the stand age map using Spearman's ρ , I found no significant correlation between the two variables. If the stand age map were accurate, I would expect to find a significant positive correlation between the two. These inaccuracies appear to be driving much of the error in the species-specific models.

These results provide useful information in the interpretation of carbon estimates. While it is critical to include stand age in regions like the one studied here, where forest structure and composition is highly variable and tied to time since disturbance, the inaccuracy of spatial products to estimate stand age may limit sub-regional interpretation. Because the stand age map utilized in this study is designed to capture the typical stand age for this region and forest type, and also matches estimates of the variability in stand age across the landscape, use of this highly influential stand age map may be appropriate for total carbon storage estimates across landscapes. If patterns across the landscape and not overall storage are of interest, more accurate stand age information is necessary.

The dramatic under-prediction of carbon storage at the per-hectare level by the middle and low 3tIS models in my independent field validation further suggests that

current IPCC tables underestimate carbon storage in forests across the region unless the extreme high end of the table ranges is used.

Additionally, my analysis of stand characteristics vs. error (Tables 6 & 7) suggests that apparent over-prediction of carbon storage by the 1.RBA and 2.SA models may result from the disproportional number of validation plots at higher elevations on the VMC intensive study areas on Mt. Mansfield and Lye Brook. While maintaining a similar species composition, higher elevation forests at these sites consist of relatively stunted, smaller trees due to harsh climate conditions (Speed et al. 2015). Such conditions exist across the study area, particularly in areas of the Adirondacks in the West and White Mountains in the east, but the majority of the study area, and the northern forest in general, occurs at lower elevations. However, the Smith et al. (2006) tables used in these models do not differentiate between carbon stored by the same forest types at different elevations; rather, they represent an average of carbon stored in forest types across a range of elevations. Therefore, I do not consider these over-predictions on VMC validation plots to correspond to an over-prediction across the larger landscape. The IPCC-based 3_t.IS models recognize and account for differences in carbon storage for similar forest types at different elevations, with lower estimates of carbon for young forests at high elevations as compared to low elevations, and higher estimates for older forests at high elevations. This indicates that in regions dominated by mature, higher elevation forests, the IPCC-based estimates may over-predict carbon storage with their generalized values that do not accurately account for elevation-related differences in the region.

Higher composition of the common northern hardwood components (maple, beech, birch) resulted in less error in all but the 3_t.IS-low and 3_t.IS-middle models. Error in these low ends of the IPCC range models results from their gross under-estimation of carbon storage for this region. The relationship between species composition and error in the 1.RBA, 2.SA, 3_t.IS-high, and 3_m.SIS models is likely because carbon table estimates used to model carbon across the landscape are most reliable for these highly studied species.

The fact that this northern hardwood component is also common across the landscape results in lower error for the coarse resolution 3_t.IS-high and 3_m.SIS model because these species are very common components of the general temperate continental forest type included in the IPCC carbon storage table: higher proportions of these common species are more representative of the general forest type their table is meant to capture. It is when other less common species are mixed in these broad forest types that the accuracy of the coarse resolution 3_t.IS and 3_m.SIS models are compromised. This indicates that species specificity may be most useful in mixed stands with a significant proportion of less common species.

The under-prediction of carbon storage in sites with high spruce-fir DBH in most models is likely due to the fact that most of these forests are found at high elevations in this region. As previously discussed, higher elevation forests store less carbon than lower elevation forests due to harsh conditions (Speed et al. 2015). The Smith et al. (2006) and IPCC (2006) tables, since they represent averages over larger areas, may not be sufficiently weighted to account for the disproportionate representation of high elevation spruce-fir forests in this region.

Particularly interesting is the under-prediction of carbon storage by all models for stands with higher mean DBH. Recent evidence suggests that older forests may capture and store more carbon than current models suggest (Gunn et al. 2014). Most carbon storage tables, allometric equations, and carbon modeling scripts are disproportionately based on early to mid-successional forests and lack data from late-successional and old-growth (LSOG) stands. Gunn et al. (2014) found that LSOG carbon stocks were high relative to regional means that are often used for carbon modeling. This explains why all of my models under-predicted carbon on larger, more mature forests and indicates that forest carbon models may be improved with calibration to include consideration of more mature forests in their carbon storage estimates.

The comparison of actual vs. predicted carbon storage values across all validation points (Table 9) indicates that estimates of carbon storage provided in the Smith et al. (2006) tables may be a better fit for the region than the IPCC estimates. Increases in RMSE as forest type specificity increased likely results from heavy reliance on the stand age map in both the 1.RBA and 2.SA models, as discussed previously. This again highlights the importance of accurate stand age maps if spatial patterns and locational assessments are desired, particularly when the significant resources needed to perform a remotely-sensed analysis like the NBCD 2000 biomass map are not available.

My assessment of my results vs the NBCD 2000 biomass at 1000 random points indicates that while overall estimates of total carbon storage across broad spatial scales or multiple time steps are possible with these models, accurately quantifying carbon stored at a specific location using this approach is not recommended. When available for the location and time period in question, remotely-sensed maps like the NBCD 2000 dataset

may be a better approach for quantifying carbon stored at a specific location.

Additionally, these models are appropriate for assessment of carbon in aboveground biomass and coarse roots only; other carbon pools were not considered in this study and may vary nonlinearly with the pools assessed.

Conclusion

Current US Forest Service estimates of forest carbon storage in aboveground and belowground live biomass for this study area are 84-90 Mg C per hectare (or 7.6-8.1 Mg per 30x30m pixel), or about 150 million Mg total C (Wilson et al. 2013). A comparison with the values generated by my models (103.8 – 117.7 Mg/ha, and 178.1-203.3 million Mg total C for the 1.RBA, 2.SA, 3m.SIS, and 3t.IS-high model outputs) suggests that these may be underestimates.

Although remotely-sensed biomass maps such as the NBCD 2000 dataset appear to provide a more accurate approach to quantifying carbon stored at specific locations, they are not always available or appropriate for carbon storage analyses (e.g. when estimates of changes over time are desired). In these cases, land cover data and carbon storage tables such as those used in the models in this study may be the best approach. In these cases, when IPCC guidelines are used in the northeastern US, the high end of the IPCC range is most accurate. Estimating carbon for the Northeast using mid-range values from the IPCC tables may generate gross underestimates.

My results indicate that the level of specificity in forest composition inputs in carbon models does impact results, with higher total carbon estimates as specificity decreases. High specificity models are also likely more representative of the variability in

stand characteristics witnessed across forests in the northeastern United States. However, the broader pattern across the landscape is primarily driven by stand age estimates, highlighting the importance of more accurate spatial stand age layers. Carbon storage estimates could also be improved via modification of the Smith et al. (2006) tables to capture variability across coarse stand age and elevation classes (similar to IPCC tables).

Future investigation of the importance of species specificity in landscape-scale assessments of carbon storage should attempt to better isolate the effect of tree species. In order to accomplish this, carbon storage tables like the Smith et al. (2006) tables must provide values for each species that do not depend on stand age.

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Tables

Table 1 Model descriptions

Model abbreviation	Model description
1.RBA	Calculates carbon stored using forest cover maps of relative basal area for the 10 major tree species in the Northern Forest, as well as Smith et al. (2006) carbon storage tables, which are weighted according to the relative percent basal area values for each species.
2.SA	Calculates carbon stored using a classified forest cover map of dominant species association, derived from Gudex-Cross et al. (in preparation) and reclassified to match the Smith et al. (2006) species association categories. Uses the Smith et al. (2006) carbon storage tables for carbon storage values.
3m.SIS	Calculates carbon stored using a classified forest cover map of categories from the IPCC (2006) for this region--temperate continental, temperate mountain, and boreal coniferous, above and below 20 year stand age. This map was reclassified from the Gudex-Cross et al. (in preparation) classified species association map. Carbon storage values are derived from Smith et al. (2006) carbon storage tables, which were averaged to create carbon storage values comparable to those provided by the IPCC (2006).
3t.IS-high	Calculates carbon stored using a classified forest cover map of categories from the IPCC (2006) for this region--temperate continental, temperate mountain, and boreal coniferous, above and below 20 year stand age. This map was reclassified from the Gudex-Cross et al. (in preparation) classified species association map. Carbon storage values are from the IPCC (2006); this model uses the high end of the range provided.
3t.IS-middle	Calculates carbon stored using a classified forest cover map of categories from the IPCC (2006) for this region--temperate continental, temperate mountain, and boreal coniferous, above and below 20 year stand age. This map was reclassified from the Gudex-Cross et al. (in preparation) classified species association map. Carbon storage values are from the IPCC (2006); this model uses the middle number provided.
3t.IS-low	Calculates carbon stored using a classified forest cover map of categories from the IPCC (2006) for this region--temperate continental, temperate mountain, and boreal coniferous, above and below 20 year stand age. This map was reclassified from the Gudex-Cross et al. (in preparation) classified species association map. Carbon storage values are from the IPCC (2006); this model uses the low end of the range provided.

Table 2 Gudex-Cross et al. (in preparation) land cover classifications for species and forest type map (left) and my reclassifications to match the Smith et al. (2006) carbon table classifications for the Northeastern US (right)

Gudex-Cross et al. classification	Smith et al. (2006) reclassification
Eastern hemlock	white-red-jack pine
red spruce	spruce-fir
Eastern white pine	white-red-jack pine
birches	aspen-birch
American beech	maple-beech-birch
red maple	maple-beech-birch
balsam fir	spruce-fir
sugar maple	maple-beech-birch
oaks	oak-hickory
spruce-fir	spruce-fir
spruce-fir-birch	spruce-fir
northern hardwoods	maple-beech-birch
mixed conifers	combination of spruce-fir and white-red-jack pine
mixed hardwoods	combination of aspen-birch, maple-beech-birch, and oak-hickory
mixed	combination of all Smith et al. (2006) categories for the Northeast

Table 3 Data with sources and original resolution for all carbon models

Data	Source	Original resolution	Models used
Carbon storage by specific forest type	Smith et al. 2006	N/A	1.RBA, 2.SA, 3m.SIS
Biomass by coarse forest type	IPCC 2006	N/A	3t.IS
Carbon fraction in aboveground biomass	IPCC 2006	N/A	3t.IS, 4.NBCD
Relative basal area maps by species	Gudex-Cross et al. <i>in preparation</i>	30 meters	1.RBA
Classified species and forest types map	Gudex-Cross et al. <i>in preparation</i>	30 meters	2.SA, 3m.SIS
Stand age map	Pan et al. 2012	1 kilometer	1.RBA, 2.SA, 3m.SIS
Elevation map	USGS 2015	1 meter	3t.IS

Table 4 Parameters for assigning carbon storage values from the IPCC 2006 report (IPCC, 2006), and for generating similarly coarse values from the Smith et al. (2006) tables for the 3m.SIS model. The values given are per hectare—they were converted to per pixel values in all models.

Parameters		Biomass values applied to each pixel (Mg/ha)					
Land cover as reclassified to match Smith et al. (2006) tables	Elevation (m)	IPCC 2006 Table 4.7 categorization	Stand age (years)	3t.IS-high	3t.IS-mid	3t.IS-low	3m.SIS
spruce-fir	N/A	boreal coniferous	< 20	90	50	10	11.5*
			>= 20	90	50	10	87.9**
all other classes	< 800	temperate continental	< 20	130	60	10	30.3***
		temperate continental	>= 20	200	130	50	122.46****
	>= 800	temperate mountain	< 20	110	50	20	30.3***
		temperate mountain	>= 20	280	130	40	122.46****

*Carbon storage value from the spruce-fir Smith et al. (2006) table at stand age 15.

**Carbon storage value from the spruce-fir Smith et al. (2006) table at actual mean stand age for all spruce-fir pixels (74.67, which I rounded to 75).

***Mean of carbon storage values in all other Smith et al. (2006) tables at stand age 15.

****Mean of carbon storage values in all other Smith et al. (2006) tables at actual mean stand age for all non spruce-fir pixels (74.57, which I rounded to 75).

Table 5 Equations used to calculate biomass of species in validation plots. For complete source data on equations, see corresponding equation numbers in Appendix A

Species	Equation Form ID	a	b	c	d	Diameter units	Biomass units	Reference	Equation number (see Appendix A)
<i>Abies balsamea</i> (Balsam fir)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	0.8162	0.0000	2.4140	1.0000	in	lb	Young et al. 1980	19
<i>Acer pensylvanicum</i> (Striped maple)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-1.9123	0.0000	2.3651	1.0000	cm	kg	Jenkins et al. 2003	2643
<i>Acer rubrum</i> (Red maple)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	1.1876	0.0000	2.3703	1.0000	in	lb	Young et al. 1980	37
<i>Acer saccharum</i> (Sugar maple)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	1.4778	0.0000	2.3216	1.0000	in	lb	Young et al. 1980	40
<i>Acer</i> sp. (Maple)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.0127	0.0000	2.4342	1.0000	cm	kg	Jenkins et al. 2003	2645
<i>Alnus rubra</i> (red alder)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	1.0103	0.0000	2.1878	1.0000	in	lb	Young et al. 1980	43
<i>Betula alleghaniensis</i> (Yellow birch)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	1.3451	0.0000	2.3355	1.0000	in	lb	Young et al. 1980	46
<i>Betula lenta</i> (Black birch; Sweet birch)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-1.9123	0.0000	2.3651	1.0000	cm	kg	Jenkins et al. 2003	2643
<i>Betula papyrifera</i> (Paper or White birch)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-1.9123	0.0000	2.3651	1.0000	cm	kg	Jenkins et al. 2003	2643
<i>Betula papyrifera</i> va (Mountain Paper birch)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	0.7434	0.0000	2.6398	1.0000	in	lb	Young et al. 1980	48
<i>Betula populifolia</i> (Gray birch)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	1.3649	0.0000	2.2951	1.0000	in	lb	Young et al. 1980	50
<i>Carya cordiformis</i> (Bitternut hickory)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.0127	0.0000	2.4342	1.0000	cm	kg	Jenkins et al. 2003	2645
<i>Carya ovata</i> (Shagbark hickory)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.0127	0.0000	2.4342	1.0000	cm	kg	Jenkins et al. 2003	2645
<i>Fagus grandifolia</i> (American Beech)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	1.5546	0.0000	2.2911	1.0000	in	lb	Young et al. 1980	54
<i>Fraxinus americana</i> (White ash)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.4800	0.0000	2.4835	1.0000	cm	kg	Jenkins et al. 2003	2644
<i>Fraxinus nigra</i> (Black ash)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.4800	0.0000	2.4835	1.0000	cm	kg	Jenkins et al. 2003	2644
<i>Fraxinus pennsylvani</i> (Green ash)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.4800	0.0000	2.4835	1.0000	cm	kg	Jenkins et al. 2003	2644
<i>Larix laricina</i> (Tamarack)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.0336	0.0000	2.2592	1.0000	cm	kg	Jenkins et al. 2003	2646
<i>Ostrya virginiana</i> (Hop hornbeam; Ironwood)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.4800	0.0000	2.4835	1.0000	cm	kg	Jenkins et al. 2003	2644
<i>Picea mariana</i> (Black spruce)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	6.6600	0.0000	1.9470	1.0000	cm	g	Renz and Auclair 1980	25
<i>Picea rubens</i> (Red spruce)	$\log_{10} \text{biomass} = a + b \cdot (\log_{10}(\text{dia}^c))$	2.3151	2.1830	1.0000	1.0000	cm	g	Whittaker et al. 1974	26
<i>Pinus strobus</i> (Eastern white pine)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	0.5725	0.0000	2.4678	1.0000	in	lb	Young et al. 1980	29
<i>Populus deltoides</i> (Eastern cottonwood)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.2094	0.0000	2.3867	1.0000	cm	kg	Jenkins et al. 2003	2642
<i>Populus grandidentat</i> (Bigtooth aspen)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.2094	0.0000	2.3867	1.0000	cm	kg	Jenkins et al. 2003	2642
<i>Populus tremuloides</i> (Quaking aspen)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.2094	0.0000	2.3867	1.0000	cm	kg	Jenkins et al. 2003	2642
<i>Prunus pennsylvanica</i> (Pin cherry)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	1.2667	0.0000	2.1657	1.0000	in	lb	Young et al. 1980	62
<i>Prunus serotina</i> (Wild black cherry)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.4800	0.0000	2.4835	1.0000	cm	kg	Jenkins et al. 2003	2644
<i>Quercus alba</i> (White oak)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.0127	0.0000	2.4342	1.0000	cm	kg	Jenkins et al. 2003	2645
<i>Quercus prinus</i> (Chestnut oak)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.0127	0.0000	2.4342	1.0000	cm	kg	Jenkins et al. 2003	2645
<i>Quercus rubra</i> (Northern red oak)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.0127	0.0000	2.4342	1.0000	cm	kg	Jenkins et al. 2003	2645
<i>Quercus velutina</i> (Black oak)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.0127	0.0000	2.4342	1.0000	cm	kg	Jenkins et al. 2003	2645
<i>Sorbus americana</i> (American mountain-ash)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.4800	0.0000	2.4835	1.0000	cm	kg	Jenkins et al. 2003	2644
<i>Tilia americana</i> (Basswood; American linden)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.4800	0.0000	2.4835	1.0000	cm	kg	Jenkins et al. 2003	2644
<i>Tsuga canadensis</i> (Eastern hemlock)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	0.8645	0.0000	2.3859	1.0000	in	lb	Young et al. 1980	34
<i>Ulmus americana</i> (American elm)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.4800	0.0000	2.4835	1.0000	cm	kg	Jenkins et al. 2003	2644
<i>Ulmus rubra</i> (Slippery elm)	$\ln \text{biomass} = a + b \cdot \text{dia} + c \cdot (\ln(\text{dia}^d))$	-2.4800	0.0000	2.4835	1.0000	cm	kg	Jenkins et al. 2003	2644

Table 6 Summary of model outputs and equivalent values from NBCD 2000 map; models are listed by decreasing specificity. The NBCD 2000 value does not include coarse roots since that dataset maps aboveground biomass only

	Total C across study region (million Mg)		Standard deviation (Mg/ha)		
	Mean C (Mg/ha)	Max (Mg/ha)	Min (Mg/ha)	Max (Mg/ha)	Min (Mg/ha)
1.RBA	178.1	103.78	29.89	0.00	206.53
2.SA	185.3	108.00	32.89	0.00	238.11
3m.SIS	203.3	118.44	17.78	11.50	122.46
3t.IS-high	201.9	117.67	14.22	56.92	171.36
3t.IS-middle	130.0	75.78	9.44	34.31	85.53
3t.IS-low	56.9	33.22	6.33	6.86	35.70
NBCD2000	119.8-162.8	58.22	20.00	0.00	111.11

Table 7 Correlation coefficients and p-values for the magnitude of error vs. different potential explanatory variables, by model.

	Stand age	Elevation	Mean DBH	Maple-		Pioneer		Spruce-fir		Hemlock-	
				beech-birch total DBH	total DBH	total DBH	total DBH	total DBH	total DBH	total DBH	total DBH
1.RBA	0.1967	**0.5241	*-0.4017	**0.5669	-0.1969	0.3551	-0.4079				
2.SA	0.2313	*0.4250	-0.2786	*-0.4083	-0.2262	0.2147	*-0.4516				
3m.SIS	0.0900	-0.0058	-0.3251	**0.6774	0.0340	0.3111	0.0770				
3t.IS-high	-0.2710	-0.2007	0.0332	**0.5669	0.1195	-0.1151	0.1525				
3t.IS-middle	-0.0462	-0.0304	*0.4250	*0.3895	0.0340	-0.3400	0.1078				
3t.IS-low	0.0335	-0.1891	**0.6062	**0.5529	0.1041	**0.5483	0.2380				

* indicates significance at the $p < 0.05$ level

** indicates significance at the $p < 0.01$ level

Table 8 Correlation coefficients and p-values for the signed error vs. different potential explanatory variables, by model

	Stand age	Elevation	Mean DBH	Maple-		Pioneer		Spruce-fir		Hemlock-	
				beech-birch total DBH	total DBH	total DBH	total DBH	total DBH	total DBH	total DBH	total DBH
1.RBA	*0.4646	*0.4557	** -0.5740	** -0.5321	-0.1407	**0.5065	-0.3443				
2.SA	**0.5214	0.3627	* -0.4462	* -0.4459	-0.0603	*.4037	-0.3473				
3m.SIS	-0.0021	0.1781	** -0.5644	* -0.4900	-0.1027	**0.5167	-0.2290				
3t.IS-high	-0.2296	-0.0530	* -0.4126	-0.2496	0.0142	0.3771	-0.1406				
3t.IS-middle	-0.0537	0.0598	** -0.5323	** -0.5105	-0.0625	*0.4540	-0.1019				
3t.IS-low	-0.0335	0.1891	** -0.6062	** -0.5529	-0.1041	**0.5483	-0.2380				

* indicates significance at the $p < 0.05$ level

** indicates significance at the $p < 0.01$ level

Table 9 Accuracy assessment, r^2 (based on best fit line), RMSE (based on line with intercept 0 and slope 1), and percent error for all six models at validation points

	r^2	RMSE (Mg C)	Percent error (%)
1.RBA	0.003	4.18	40.4
2.SA	0.061	3.75	35.7
3m.SIS	0.178	3.23	31.6
3t.IS-high	0.083	3.59	36.6
3t.IS-middle	0.181	3.56	58.3
3t.IS-low	0.267	6.47	258.6

Table 10 Model assessment vs. NBCD 2000 biomass map. Spearman's rho coefficients (first column) were computed vs. the NBCD 2000 map at 1000 random points

	Spearman's rho coefficient	r ²	RMSE
1.RBA	**0.1631	0.026	4.94
2.SA	**0.1515	0.023	5.44
3m.SIS	0.0525	0.009	5.77
3t.IS-high	**0.1064	0.009	5.66
3t.IS-middle	**0.0980	0.006	2.32
3t.IS-low	**0.0908	0.006	2.92

** indicates significance at $p < 0.01$. R² (for best fit line) and RMSE (compared to a reference line with an intercept of 0 and slope of 1 to represent perfect accuracy) computed for each model vs the NBCD 2000 map at 1000 random points

Table 11 NBCD 2000 accuracies for the zones that overlap my study region. Note that two accuracies are reported for Zone 65, because the elevation data upon which the NBCD map is based was not acquired within a ~8000 km² region in that zone; the authors refer to this region as “the diamond.” As a result, two accuracies were calculated for Zone 65

	r ²	RMSE (kg C/m ²)
Zone 64	0.1369	5.0
Zone 65 - in "diamond"	0.1225	5.0
Zone 65 - outside "diamond"	0.1764	4.8
Zone 66	0.3364	4.2

Figures

Fig. 1 The study area and validation plot locations

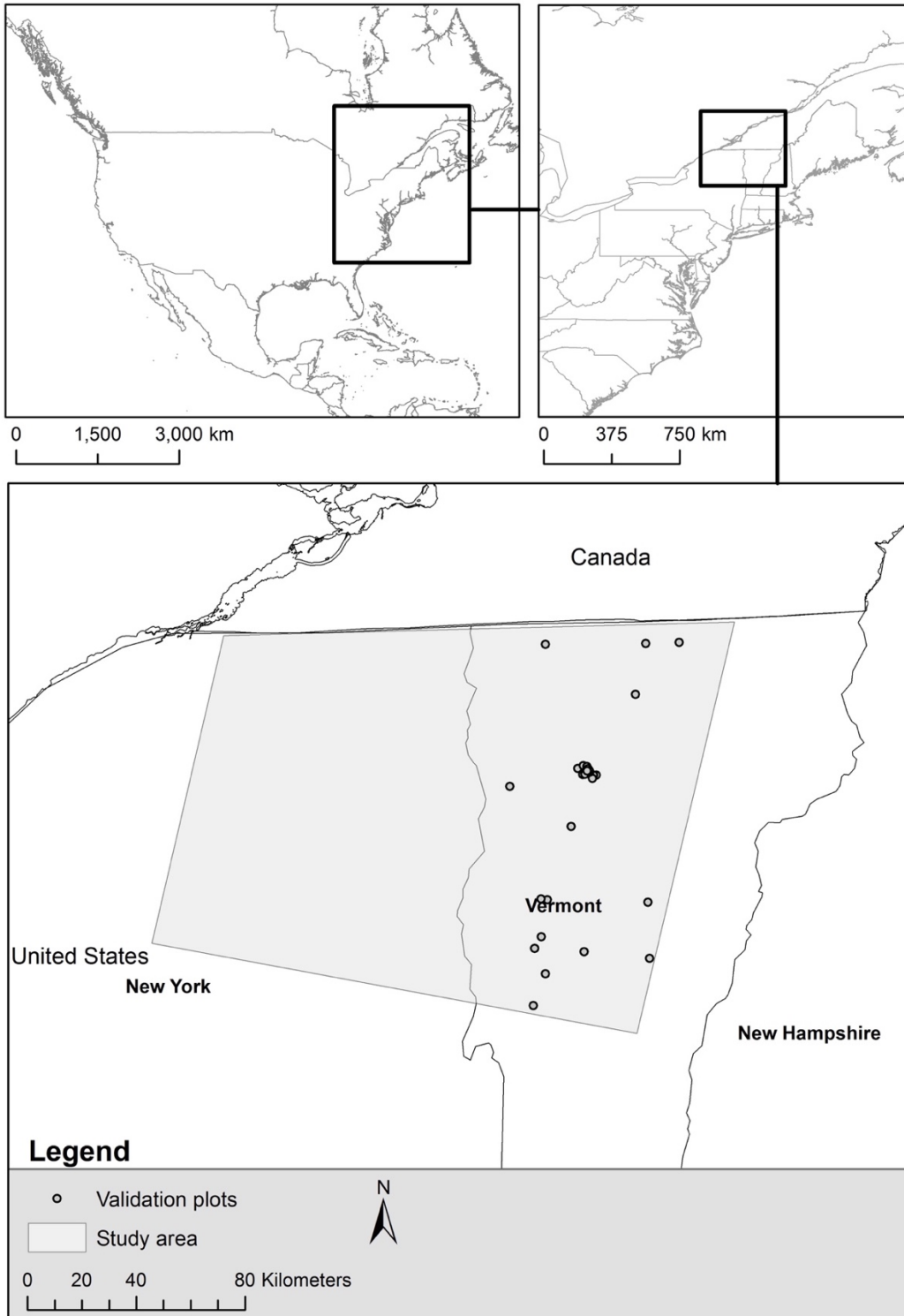


Fig. 2 Three of the relative percent basal area maps: *Abies balsamea* (top left), *Acer saccharum* (top right), and *Betula* spp. (bottom). Similar maps for *Acer rubrum*, *Fagus grandifolia*, *Picea rubens*, *Pinus strobus*, *Populus* spp., and *Quercus* spp. were also used in the 1.RBA model

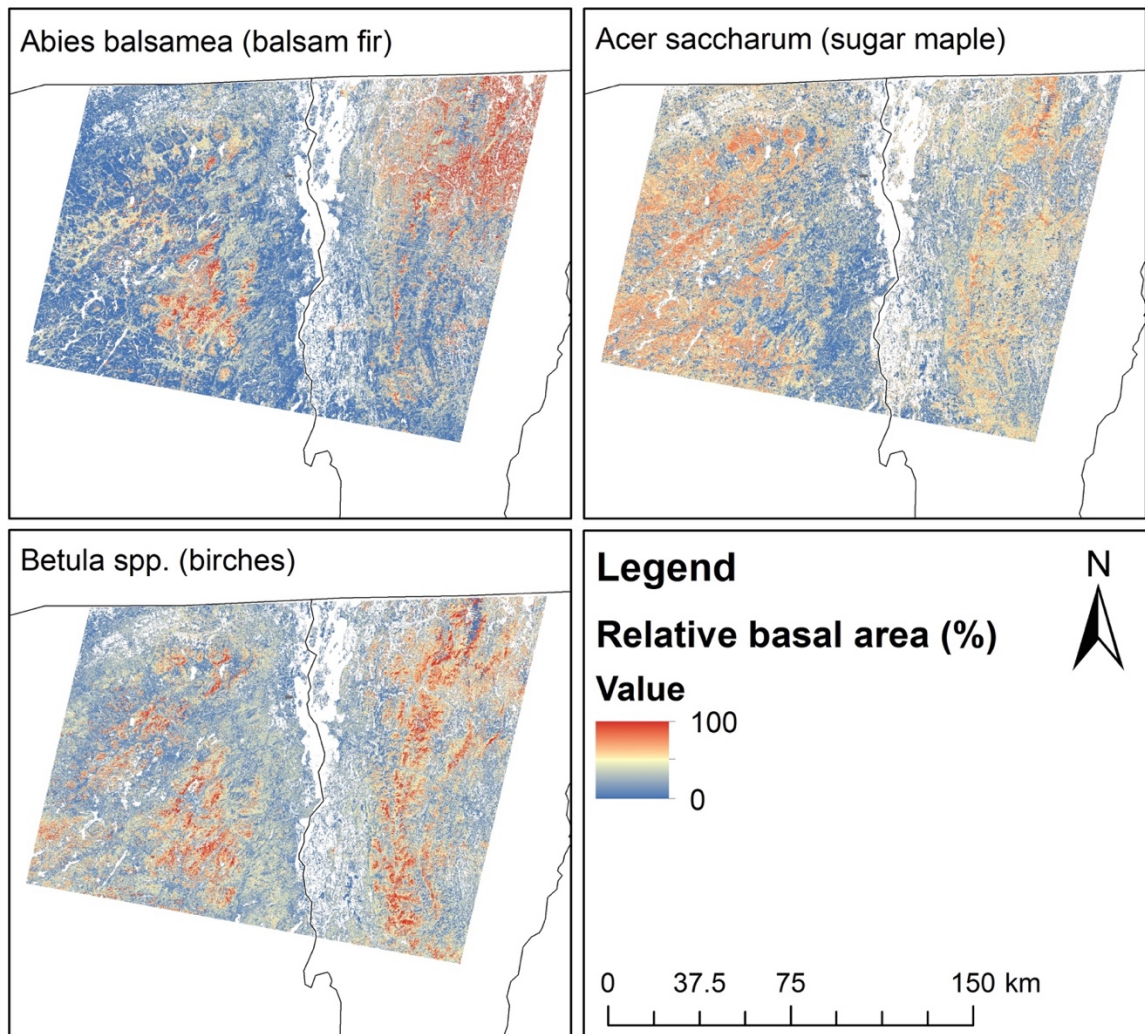


Fig. 3 Original classified forest type map by Gudex-Cross et al. (in preparation) (top), and my reclassified version to match the classes in the Smith et al. (2006) tables (bottom)

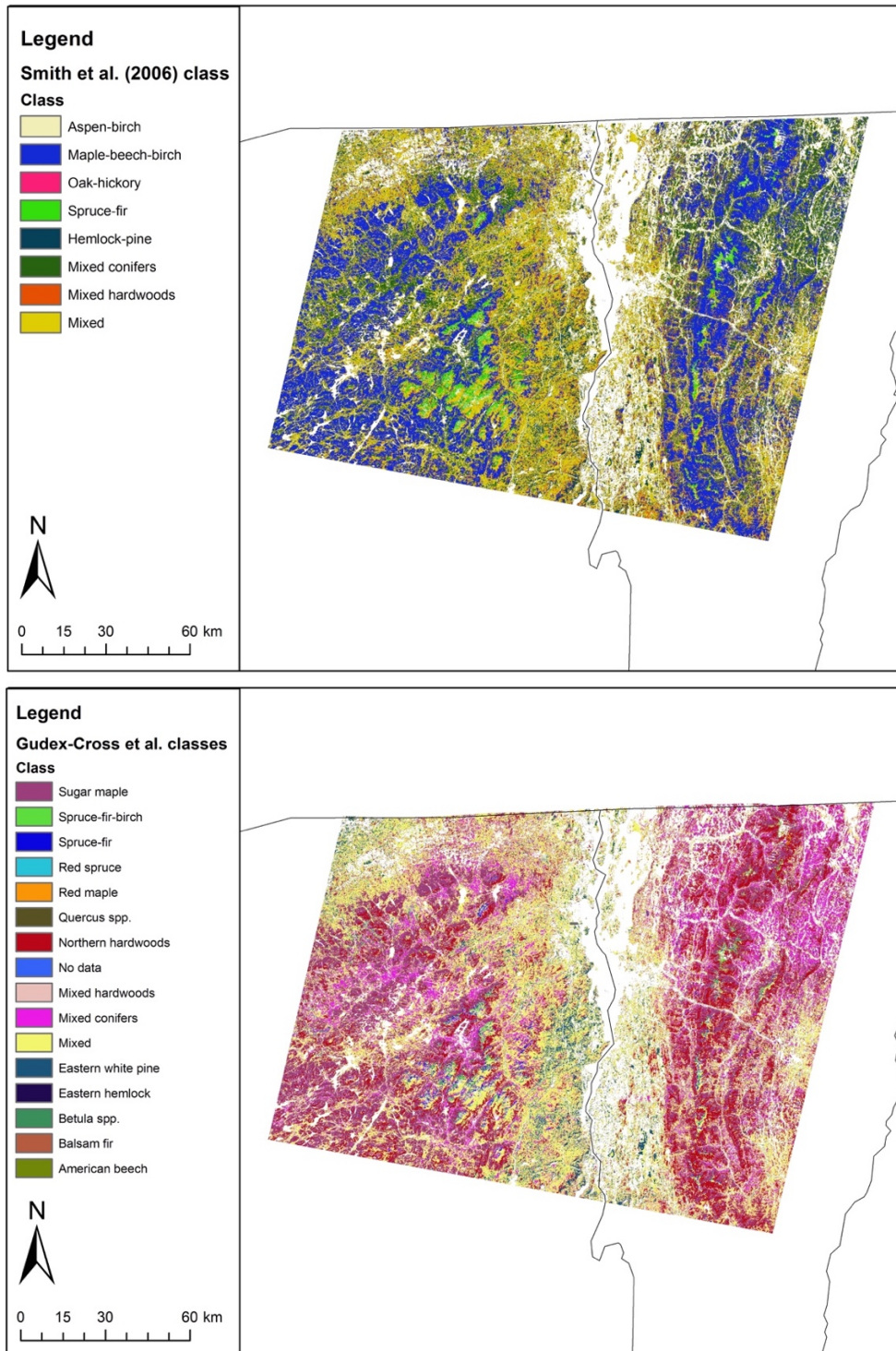


Fig. 4 Pan et al. (2012) stand age map used in all of the models, prior to randomization

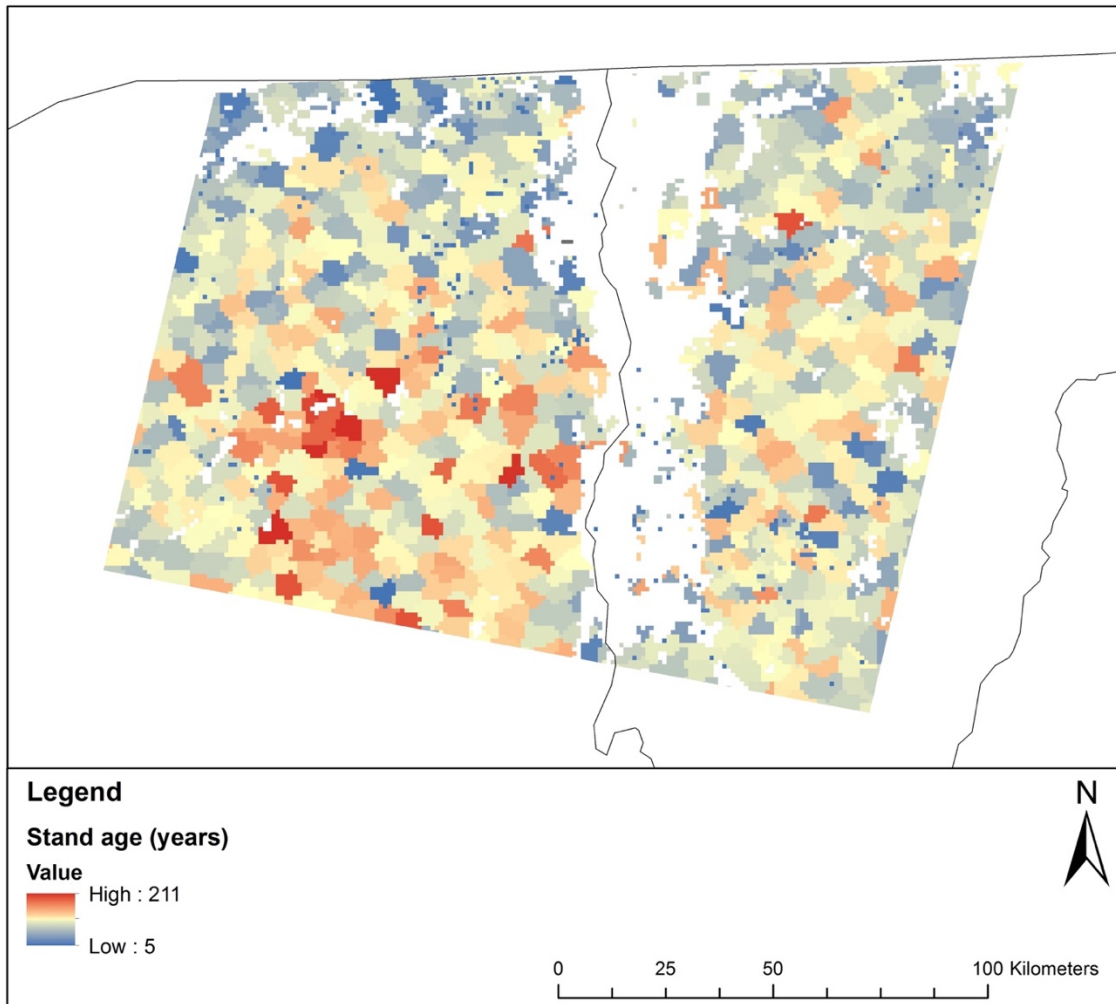


Fig. 5 US Geological Survey (2015) elevation data used in the 3_t .IS and 3_m .SIS models

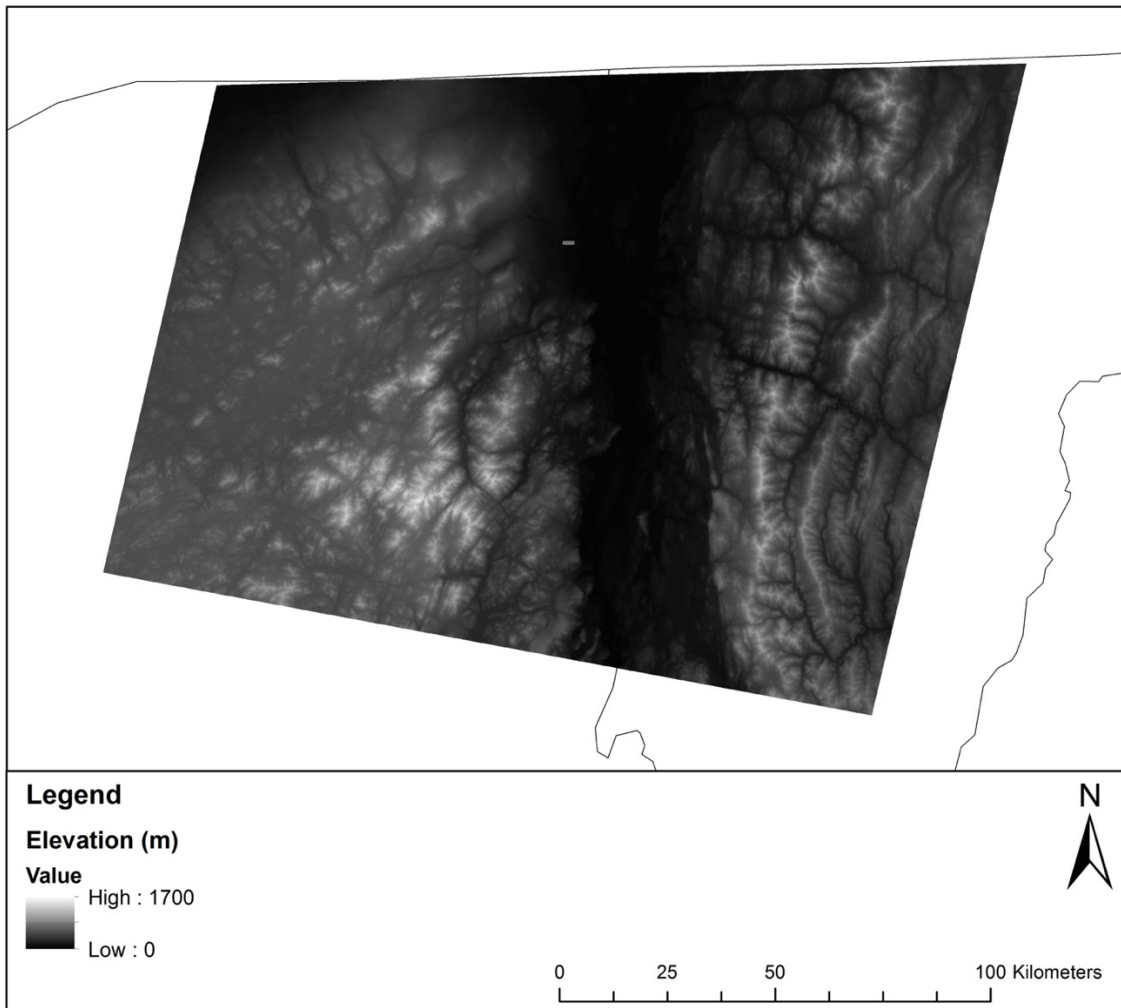
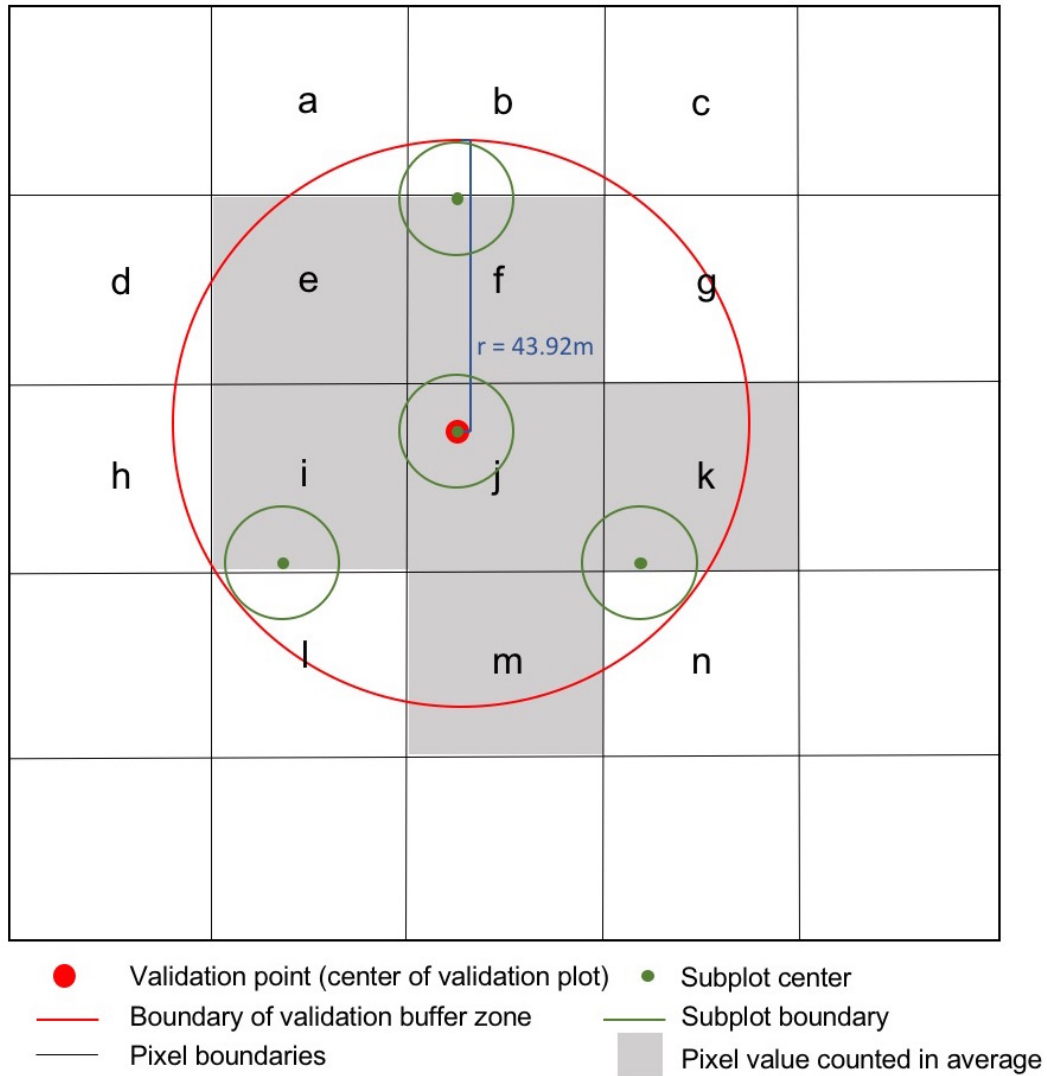


Fig. 6 Diagram of validation process for each model. Letters represent pixel values in a model-generated carbon storage map. Only pixels with at least 50% of their area within the buffer were counted in the average



Average value to compare to validation point value for this model = $(e + f + i + j + k + m)/6$

Fig. 7 NBCD Biomass data set (Kellndorfer et al. 2013) clipped to the study area

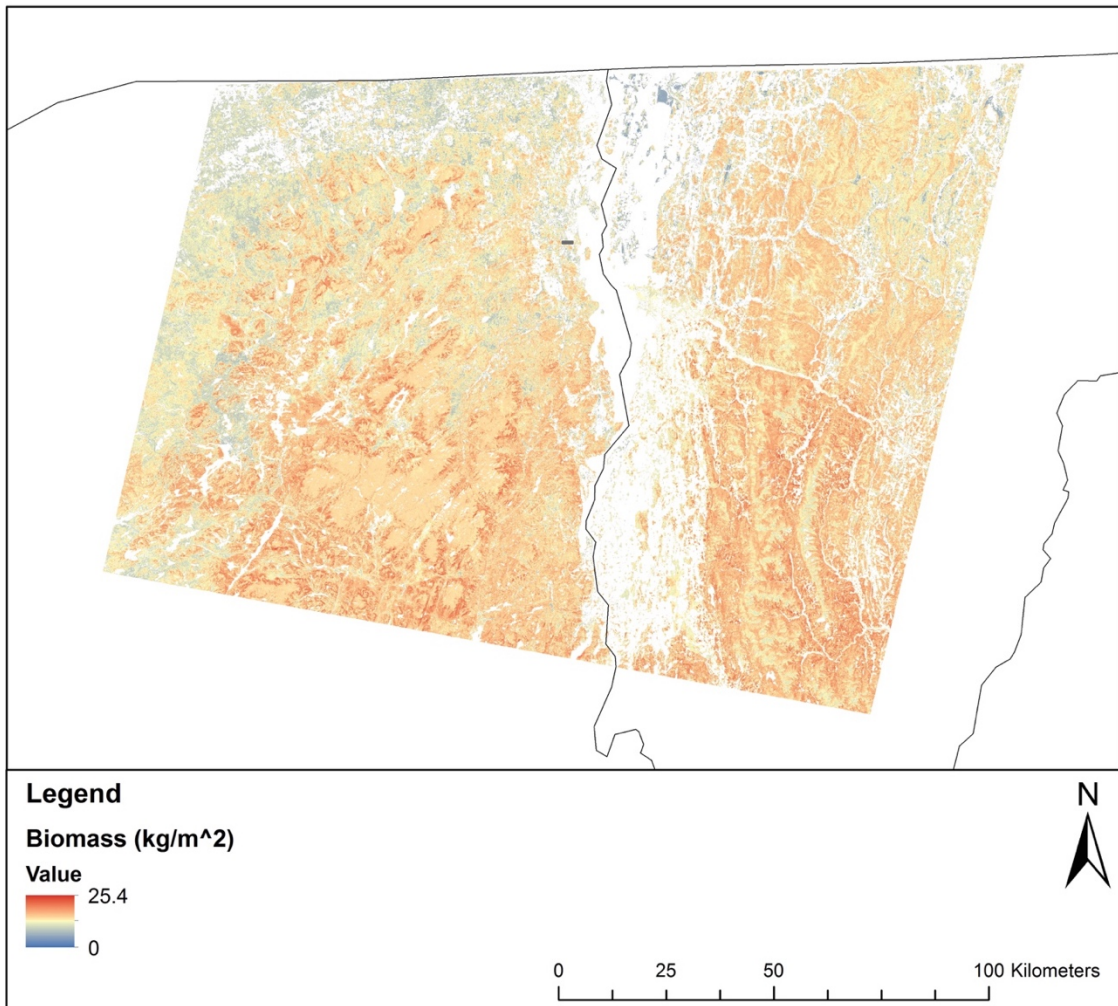


Fig. 8 Map outputs of all six carbon models. Note the blocky pattern in both 1.RBA and 2.SA maps resulting from the influence of stand age maps, and the lack of landscape heterogeneity in the 3.IS models

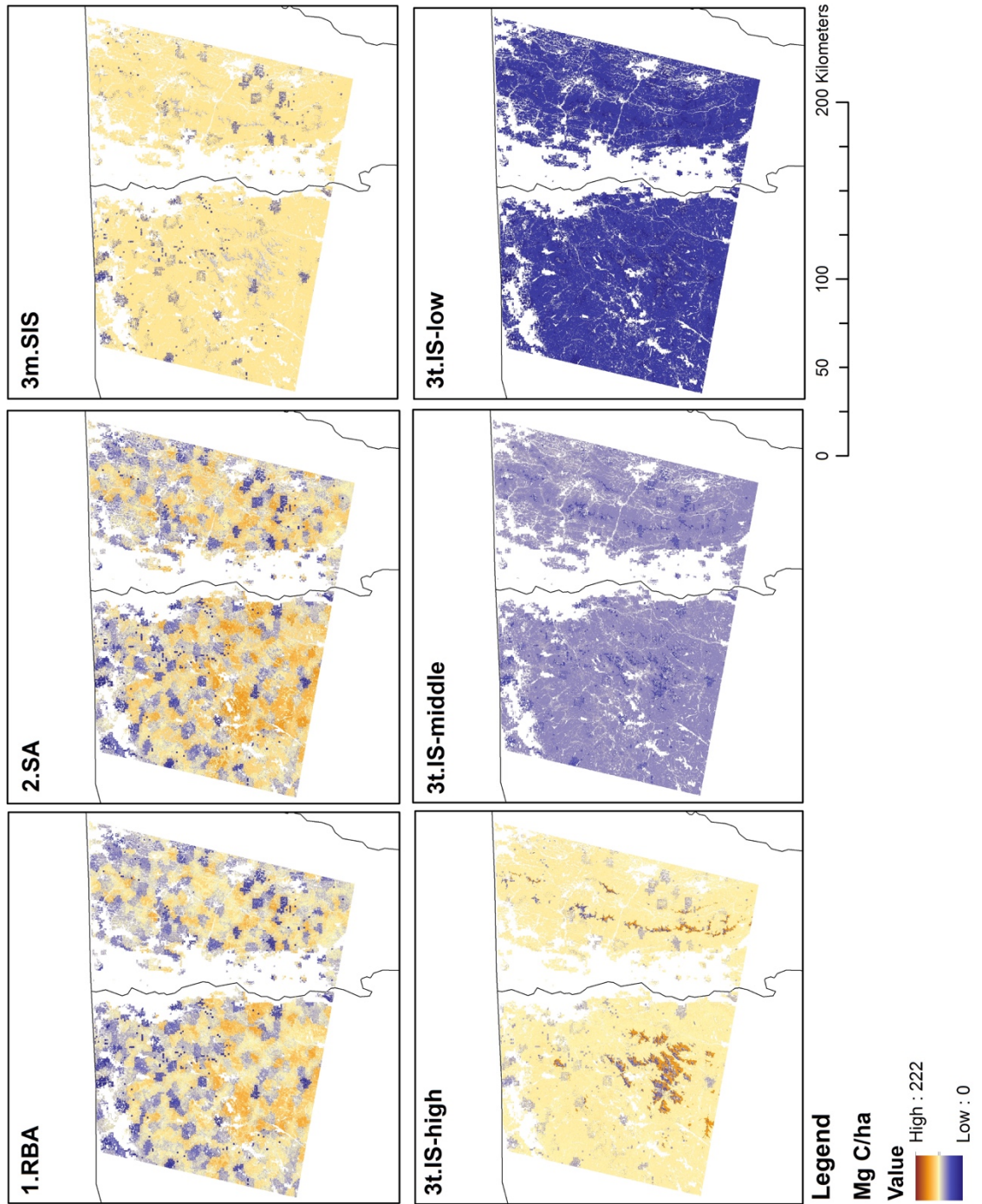
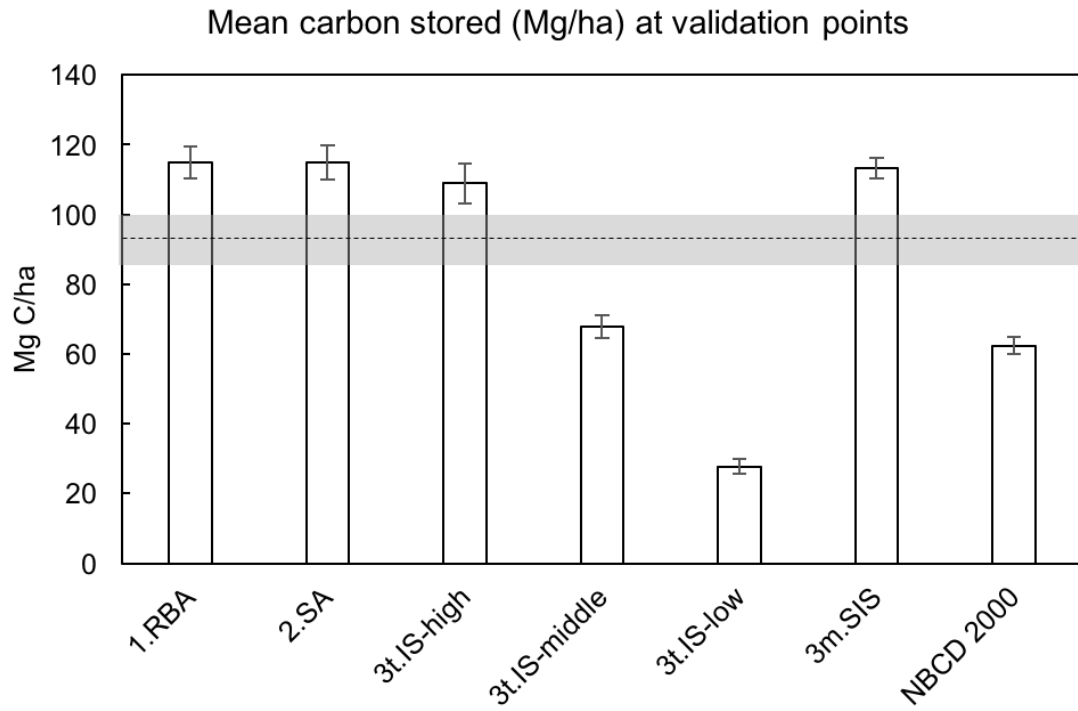


Fig. 9 Mean carbon stored per pixel by model type at the validation points. Horizontal dashed line represents the actual mean carbon storage across all inventory plots (93.6 Mg C/ha); shaded area is the standard error of the inventory plots



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