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FOREST MANAGEMENT TRADEOFFS: EXAMINING RELATIONSHIPS BETWEEN TIMBER HARVEST, CARBON SEQUESTRATION AND STORAGE, BIOENERGY, AND WILDLIFE

A Dissertation Presented

by

Michelle L. Brown

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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 Doctor of Philosophy
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ABSTRACT

Timber harvesting is the leading cause of adult tree mortality in forests of the northeastern United States. While current rates of harvest are generally sustainable, there is considerable pressure to increase harvest to meet timber production, climate, and energy goals. Maximizing one of these values may compromise other forest resources, including a wide range of ecosystem services and the conservation of native species. This dissertation investigates the effects of timber harvest on carbon sequestration and storage, bioenergy, and wildlife. First, I estimated current harvest regimes for different forest types and regions across the U.S. states of New York, Vermont, New Hampshire, and Maine using data from the U.S. Forest Inventory and Analysis Program. I implemented the harvest regimes in SORTIE-ND, an individual-based model of forest dynamics, and simulated the effects of current harvest regimes and five additional harvest scenarios that varied by harvest frequency and intensity over 150 years. Second, I used the output from the forest dynamics model in combination with a greenhouse gas accounting tool, ForGATE, to estimate the carbon consequences of current and intensified timber harvest regimes in the northeastern U.S. I considered a range of carbon pools including forest ecosystem pools, forest product pools, and waste pools, along with different scenarios of feedstock production for biomass energy. Third, I examined the effect of the harvest regimes on the probability of occurrence of 12 forest-dwelling songbirds. I used expert elicitation to build occupancy models using a combination of field-based forest structure data and landscape-scale variables. Finally, in Chapter 4, I combined the results of the previous papers and assessed the tradeoffs between management alternatives using a multi-criteria decision analysis approach. I explored the possibilities of simultaneously meeting multiple objectives including wildlife occupancy, net carbon impact, harvested wood products, and biomass energy feedstock production. The results of this dissertation provide stakeholders with state and regional estimates of the benefits and impacts of timber harvest to sustainably manage for multiple forest values.

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CHAPTER 1: TIMBER HARVEST AS THE PREDOMINANT DISTURBANCE REGIME IN NORTHEASTERN U.S. FORESTS: EFFECTS OF HARVEST INTENSIFICATION

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1.1. Abstract

Harvesting is the leading cause of adult tree mortality in forests of the northeastern United States. While current rates of timber harvest are generally sustainable, there is considerable pressure to increase the contribution of forest biomass to meet renewable energy goals. We estimated current harvest regimes for different forest types and regions across the U.S. states of New York, Vermont, New Hampshire, and Maine using data from the U.S. Forest Inventory and Analysis Program. We implemented the harvest regimes in SORTIE-ND, an individual-based model of forest dynamics, and simulated the effects of current harvest regimes and five additional harvest scenarios that varied by harvest frequency and intensity over 150 years. The best statistical model for the harvest regime described the annual probability of harvest as a function of forest type/region, total plot basal area, and distance to the nearest improved road. Forests were predicted to increase in adult aboveground biomass in all harvest scenarios in all forest type and region combinations. The magnitude of the increase, however, varied dramatically - increasing from 3% to 120% above current landscape averages as harvest frequency and intensity decreased. The variation can be largely explained by the disproportionately high harvest rates estimated for Maine as compared with the rest of the region. Despite steady biomass accumulation across the landscape, stands that exhibited old-growth characteristics (defined as >=300 metric tons of biomass/hectare) were rare (8% or less of stands). Intensified harvest regimes had little effect on species composition due to widespread partial harvesting in all scenarios, resulting in dominance by late successional species over time. Our analyses indicate that forest biomass can represent a sustainable, if small, component of renewable energy portfolios in the region, although there are tradeoffs between carbon sequestration in forest biomass and sustainable feedstock supply. Integrating harvest regimes into a disturbance theory framework is critical to understanding the dynamics of forested landscapes, especially given the predominance of logging as a disturbance agent and the increasing pressure to meet renewable energy needs.

Key words: biomass energy; disturbance regimes; forest composition; forest structure; harvest regimes; logging; northeastern United States

1.2. Introduction

Harvesting is the leading source of canopy tree mortality in forests of the northeastern United States. It comprises more than half of all mortality (on a volume basis), making logging the predominant disturbance – natural or anthropogenic – affecting forest ecosystems in the region (Canham et al. 2013). Current harvest regimes are dominated by partial harvesting (Canham et al. 2013) in contrast to previous decades in which clearcutting was the most common silvicultural system (Kelty and D'Amato 2006, Masek et al. 2011).

Classical disturbance theory was developed to describe natural disturbances (Pickett and White 1985), but it is also a useful framework for studying anthropogenic disturbances such as logging (Oliver and Larson 1996, Seymour et al. 2002). As with natural disturbances like windthrow and fire, logging varies widely in terms of frequency and intensity. For instance, low intensity wind storms occur at much higher frequencies (decades) than catastrophic events (centuries to millennia) (Canham and Loucks 1984), just as low intensity logging occurs at higher frequencies than clearcutting (Seymour et al. 2002, Canham et al. 2013). Logging and natural disturbances can both be highly selective in mortality by species and size (Canham et al. 2001, Papaik and Canham 2006, Canham et al. 2013). In a recent paper, Canham et al. (2013) quantified current harvest regimes in terms of logging frequency and intensity by species and size within the northeastern United States. The statistical characterization of the harvest regimes represented the aggregate of stand-scale management across the landscape, just as natural disturbance regimes are characterized by the cumulative effect of individual disturbances (Pickett et al. 1989, Seymour et al. 2002).

Importantly, logging also differs from natural disturbance. Foremost, logging is driven by a wide range of socioeconomic factors and human decisions (Puettmann et al. 2009, Thompson et al. 2017a). There are more than 2 million forest landowners in the northeastern U.S. (USDA Forest Service 2016) and each landowner decides if, when, and how to manage their forests. Roughly half of current owners have logged their forests during their tenure for reasons including improving remaining stock, personal use of wood, increasing recreation and hunting opportunities, and financial gain (USDA Forest Service 2016). Logging regimes can also vary dramatically over short periods of time in response to market forces. For example, federal timber sale restrictions in the western U.S. accounted for an increase in private forest land harvest in the southern U.S. during the late 1980s and 1990s (Wear and Murray 2004), and harvest rates in the northeastern U.S. dropped significantly in response to the economic downturn in 2008.

Recent calls for increasing the use of forest biomass as a feedstock for the renewable energy industry underscore the importance of examining the effects of variation in the frequency and intensity of harvest on landscape-scale forest structure and composition. Many states are setting progressive renewable energy goals to increase energy independence and reduce carbon emissions (Energy Independence and Security Act 2007, Biomass Energy Resource Center 2013, Energy Information Administration 2015). For example, Vermont has set a goal of meeting 90% of the state’s energy needs through renewables by the year 2050 (Vermont Department of Public Service 2022), while New York aims to meet 50% of its electricity needs by the year 2030 from renewable energy (New York State Energy Plan 2015). New Hampshire is the first state in the region to require that a portion of its Renewable Portfolio Standard is met through thermal energy, and expects to increase forest bioenergy to achieve that goal (Hunter 2014). Despite these goals, the benefits of increasing timber harvest to meet energy needs are still being debated (IPCC 2014).

How would intensification of harvest affect both biomass feedstock supply and forest structure and composition in the region? Preliminary assessments by all four northern forest states (New York, Vermont, New Hampshire, and Maine), which are collectively 71% forested, have concluded that more intensive harvest regimes could yield additional sustainable feedstock supply (Maine Forest Service 2010, New Hampshire Department of Resources and Economic Development 2010, New York State Department of Environmental Conservation 2010, Vermont Agency of Natural Resources 2010). More detailed forest bioenergy assessments in different portions of this region have resulted in similar findings, however the predicted amount of feedstock that can be harvested sustainably varies considerably due to differing assumptions concerning technology, forest utilization, market forces, and available forest land base (Sherman 2007, Castellano et al. 2009, Biomass Thermal Energy Council 2010, Buchholz et al. 2011, Wojnar 2013).

These analyses, however, typically represent static analyses based on growth and yield from the current mix of forests within the landscape of a defined region, without considering the effects of changes in harvest regimes on the future composition, structure, and productivity of the forest landscape. In the analyses presented here, we use data from the U.S. Forest Service’s Forest Inventory and Analysis Program (FIA) (USDA Forest Service 2020) to characterize current harvest regimes for different regions and forest types across the northern forest states of New York, Vermont, New Hampshire, and

Maine. The harvest regimes are then implemented in SORTIE-ND, an individual-based model of forest dynamics (www.sortie-nd.org), to explore the effects of the current harvest regimes and five alternative harvest scenarios over the next 150 years. The model is initialized using current inventory data from existing FIA plots, which allows us to develop regional-scale predictions of the consequences of different harvest scenarios for forests in the region. Our analyses thus address two broad questions: (1) What are the current harvest regimes in different regions and forest types within New York, Vermont, New Hampshire, and Maine?, and (2) What are the effects of harvest intensification on biomass feedstock supply and long-term forest structure and composition over the next 150 years?

1.3. Methods

1.3.1. Study area

The study area includes all forest land in the states of New York, Vermont, New Hampshire, and Maine, which covers approximately 71% of the four-state region. FIA defines forest land as land that has at least ten percent live crown cover of trees of any size or past evidence of such a condition (USDA Forest Service 2020). Forest types in the region range from high elevation spruce-fir forests to oak-hickory forests; northern hardwood-conifer forests are the most widespread forest type. The temperate climate is diverse and characterized by warm summers and cold, frozen winters. Boreal conditions to the north and coastal conditions to the east influence temperature and precipitation patterns. Land ownership patterns are dominated by private woodland owners (80% of forest land) and while most of these owners are non-corporate (70%), industrial owners retain significant acreage particularly in Maine (Thompson et al. 2017a).

1.3.2. Analysis of regional variation in forest harvest regimes

Our analysis of regional variation in northern forest harvest regimes is an extension of statistical models developed by Canham et al. (2013). We used data from FIA plots from New York, Vermont, New Hampshire, and Maine that were censused at least two times using the new national standard plot design (Woudenberg et al. 2010), and were available for harvest, meaning not legally protected according to either FIA records or a more thorough secured lands database compiled by The Nature Conservancy (n = 4582) (Table 1.1) (Anderson and Olivero Sheldon 2011). Each FIA plot is classified by forest type; we grouped the plots into five main forest types for analysis: aspen-birch, bottomland, northern hardwood-conifer, oak-hickory, and spruce-fir. Because evidence suggests harvest rates in Maine are greater than the rest of the study area (Buchholz et al. 2011, Canham et al. 2013), we divided northern hardwood-conifer forests into two regions: Maine and a combined region of New York, Vermont, and New Hampshire. This resulted in six total forest type and region combinations.

For each of the six forest type/regions, we quantified two components of the harvest regime: (1) the annual probability that a plot was harvested, and (2) the total amount of basal area removed, if a plot was harvested. In the simplest statistical model, the annual probability of harvest and the fraction of basal area removed, if harvested, were assumed to vary solely as a function of the forest type/region and stand basal area.

Following Canham et al. (2013), we described the probability that a plot was harvested during a census interval as:

$$Prob(harvest_{ij}) = 1 - [a_j \, e^{-m_j X_{ij}^{b_j}}]^{Ni} \qquad \text{(Eqn. 1)}$$

where X_{ij} was adult tree basal area (m^2/ha) at the beginning of the census interval in the i^{th} plot of the j^{th} forest type/region, N_i was the census interval (in years) for that plot, and a_j, m_j, and b_j were estimated forest type/region specific parameters.

The mean percent of basal area removed (*BAR*) if a plot was logged during the census interval was also fit using an exponential model:

$$BAR_{ij} = \alpha_j e^{-\mu_j X_{ij}^{\beta_j}} \qquad \text{(Eqn. 2)}$$

where again X_{ij} was adult tree basal area (m^2/ha) at the beginning of the census interval in the i^{th} plot of the j^{th} forest type/region, and α_j, μ_j, and β_j were estimated forest type/region specific parameters. The β_j parameter allows a flexible form, but tests indicated that the data were best fit with a simple negative exponential form in which the β_j parameter was dropped.

There are clearly many other factors that influence landowner decisions whether to harvest, and with what intensity or silvicultural system (Butler et al. 2010). We tested a number of alternate models in which terms in Eqns. 1 and 2 were modified to take into account a suite of socioeconomic and biophysical aspects of the plot location. These included (1) distance to the nearest improved road (as measured in feet by seven classes defined by FIA: <=100, 101 - 300, 301 - 500, 501 - 1000, 1001 - 2640, 2641 - 5280, and >5280), (2) local population density at the county or smaller census tract scale, (3) land protection status, specifically presence of an easement that prevented development but allowed resource extraction, and (4) parcel size. Both land protection status and parcel size were assessed for a subset of the FIA plots, using a data layer compiled by The Nature Conservancy that covered roughly two-thirds of the region. Details of the modifications to test effects of population density, land protection status, and parcel size are given in Appendix S2. Based on visual examination of the data, road distance altered the probability of harvest but not the intensity when harvested. Thus, the model incorporating road distance replaced the intercept parameter a_j in Eqn. 1 with a vector of 7 parameters for each forest type/region, representing the 7 road distance classes. Our strategy for model comparison was to first examine raw data to determine whether there was variation in either harvest frequency or intensity as a function of any one of these factors, and then to test alternate models in which a factor was incorporated in one or more of the terms in the model.

As in Canham et al. (2013), the functions for probability of harvest and intensity if harvested were fit simultaneously using maximum likelihood methods. The analysis is effectively a mixture of a Bernoulli trial (whether or not a plot was harvested), and a gamma-distributed likelihood function to characterize the percent of basal area removed, if harvested. We solved for the maximum likelihood values of the parameters for both parts of the model using global optimization in the *likelihood* package in R version 3.1.1 (R Core Team 2014, Murphy 2015).

1.3.3. Development and implementation of alternate harvest regime scenarios

We developed six harvest scenarios that varied in magnitude and frequency of harvest (Table 1.2). The first scenario represents the current harvest regime characterized by the analyses described above, without any influence of climate change ("current harvest"). Given the inevitability of climate change, all other scenarios incorporate a nominal climate change based on regional climate assessments and IPCC scenarios (Horton et al. 2014). The climate change scenarios assumed that mean annual temperature increased linearly 3 degrees C over the next 100 years (and then stabilized), with a 10% increase in total annual precipitation over the same time period (Appendix S1). The second scenario is the current harvest regime with this climate change ("current harvest + climate"). The third scenario increases average harvest intensity by 50% ("current harvest + climate + intensity"). The fourth scenario increases the frequency of harvests by 75%, keeping the current distribution of harvest intensity ("current harvest + climate + frequency"). The fifth scenario increases average harvest intensity by 50% and harvest frequency by 100% ("current harvest + climate + intensity + frequency"). For reference, a sixth scenario included no harvests ("no harvest").

To increase the frequency of harvest over current levels, we adjusted the a and m parameters in Eqn. 1 for each forest type/region and road distance category as follows:

$$a' = a - (x*(1-a)) \qquad m' = m * (1+x)$$

where x is the proportion by which to increase harvest (e.g., 0.75 in the case of a 75% increase in harvest frequency). To increase the average intensity of a harvest regime, we shifted the observed distribution of harvest intensity by forest type/region upwards so that the average harvest intensity increased by the desired amount, but the approximate shape of the distribution of harvest intensity was maintained (details in Appendix S1).

1.3.4. Simulation of forest dynamics with SORTIE-ND

We implemented the six harvest scenarios in SORTIE-ND (Coates et al. 2003, Uriarte et al. 2009, Forsyth et al. 2015), a spatially-explicit individual-tree forest stand model that tracks the recruitment, growth, and mortality of all individual seedlings, saplings, and adult trees over time. The model has been parameterized from FIA data for the 50 most common tree species in the eastern U.S. (Canham and Murphy 2016a, b, Canham and Murphy 2017). Only 30 of the species are common in our study region and were used in our simulations (Appendix S1).

The structure of the model, including details on all behaviors in the model, and the statistical analyses used to parameterize behaviors for each of the species, are described in Appendix S1. A single scenario consists of 5000 separate runs of the model, with each run representing the predicted dynamics of a 4 ha stand initialized using the current structure and composition of one of 5000 randomly selected FIA plots within the study region (Fig. 1.1). Because FIA plots are themselves a randomly selected representative sample of forest land, output from the model, in aggregate, can be considered representative of the expected changes in the condition in forests across the landscape. The attributes of the FIA plots (e.g., state, forest type) can also be used to stratify and interpret variation in model predictions. Seedlings, saplings, and adult trees from the individual FIA plots are counted and categorized by species and size class, and scaled to number per hectare to initialize the 5000 individual SORTIE-ND runs (Fig.

1.1a). Each plot in every scenario except current harvest is assigned the climate change regime described above. Current mean annual temperature and precipitation data for each plot were extracted using bilinear interpolation from 800 m resolution PRISM climate data (http://www.prism.oregonstate.edu/) using true plot locations obtained under a security memorandum with the U.S. Forest Service. The climate data are combined with data on topography (for solar radiation calculations) and soil water storage capacity (from USDA soil databases) to calculate annual water deficits for each plot in each year. Given the environmental conditions of each plot over time, SORTIE-ND then implements a sequence of behaviors, including the harvest regime (described above) (Fig. 1.1b), tree growth (Fig. 1.1c), adult and sapling natural mortality (Fig. 1.1d), and seedling recruitment (Fig. 1.1e), and outputs detailed metrics on stand structure and composition, as well as harvest rates by species and size, annually for 150 years.

Growth. Individuals that are not harvested in a time step grow according to plot environmental and biotic conditions. Adult and sapling diameter growth are calculated as the average potential growth a tree can attain (cm/year), adjusted by several climate and neighborhood competition variables that limit tree growth (Fig. 1.1c). Tree size (Canham et al. 2006, Kunstler et al. 2009), precipitation, temperature, crowding (Canham et al. 2006), and nitrogen deposition (Thomas et al. 2010) are all factors that have the potential to limit adult and sapling growth, depending on species (details in Appendix S1). Parameter values are reported in Canham and Murphy (2016a) and based on empirical analyses of FIA data. There is no direct measurement of seedling growth in FIA data so sapling growth rates are applied to seedlings as well.

Natural Mortality. There are three different natural mortality behaviors that apply to different tree age classes: 1) adult and sapling mortality, 2) seedling mortality, and 3) size dependent large tree mortality (which increases mortality in very large trees) (Fig. 1.1d). Adult and sapling mortality is a function of climate, neighborhood competition, and nitrogen deposition, where the potential survival for each individual is reduced by variables that were observed to significantly reduce survivorship in analysis of FIA data, including tree size, soil water deficit, temperature, crowding, and nitrogen deposition (Canham and Murphy 2017). The seedling mortality behavior applies to seedlings of all species and is a function of mean annual temperature, soil water deficit, and total adult basal area within a 10 m-radius circle (details in Appendix S1). All parameter values are derived from empirical analyses of FIA data (Canham and Murphy 2016a, b, Canham and Murphy 2017). Lastly, a size-dependent logistic mortality function imposes an increased mortality in very large trees. This is necessary because FIA data contain too few large trees to estimate mortality rates for large trees (Canham and Murphy 2017).

Recruitment. Seedling recruitment is spatially-explicit in the model, and is a function of the total basal area of conspecific adult trees within a 10 m radius neighborhood. The recruitment functions were parameterized using FIA data (Canham and Murphy 2016b). SORTIE-ND then applies a temperature dependent colonization function to allow for establishment of seedlings when no adults are currently present in the plot (e.g., due to bath rain of seeds where no parents are present) (Fig. 1.1e) (details in Appendix S1).

1.4. Results

1.4.1. Analysis of regional variation in forest harvest regimes

The basic statistical model for the harvest regime characterized the annual probability of harvest and the intensity of harvest each as a function of forest type/region and total plot basal area. Of the four socioeconomic predictors examined, there was only strong support for including distance to the nearest improved road in the final model (Appendix S2). The average annual probability of harvest increased steadily with increasing plot basal area across all forest types/regions (Fig. 1.2A). Northern hardwood-conifer forests in Maine had the highest probability of annual harvest, followed by aspen-birch and spruce-fir forests, both of which are located predominantly in Maine. Northern hardwood-conifer forests in the New York, Vermont, and New Hampshire region were harvested at less than half of the frequency of the same forest type in Maine (Fig. 1.2A). Every forest type had a greater probability of harvest near improved roads (<100 feet) with one exception (Fig. 1.3). Bottomland forests were slightly more likely to be harvested at very large distances from roads (>1 mile) versus small distances from roads (<100 feet). The annual probability of logging approximately tripled for the Maine region of northern hardwood-conifer forests as the distance to the nearest road decreased from 0.5 miles to <100 feet (ranging from 4% to 12% in Maine) (Fig. 1.3).

Partial harvesting predominated in all forest types/regions. When a stand was logged, the fraction of basal area removed (at a given distance from the nearest road) was predicted to be nearly constant across stands with a wide range of basal area (Fig. 1.2B). The observed distributions of harvest intensity showed oak-hickory forests and northern hardwood-conifer forests in New York, Vermont, and New Hampshire were primarily harvested at very low intensities, whereas the percent of basal area removed varied less in other forest types (Fig. 1.4).

Local population density, land protection (easement) status, and parcel size were omitted from the harvest regimes implemented in the simulations because they either did not improve model fit relative to model complexity (Appendix S2), or the data were insufficient for robust parameter estimates (as indicated by very large support intervals). There was a weak effect of increasing local population density in census tracts on reducing intensity of harvest in northern hardwood–conifer forests only, but no effect on frequency of harvest in any of the forest types (Appendix S2). There were sufficient numbers of plots to test for an effect of land protection status in only the spruce-fir and northern hardwood-conifer forest types. Twenty-five percent of the plots in spruce-fir forests were under some form of easement, but a model that estimated separate parameters for easement plots was not superior to the simpler model that ignored protection status (AIC = 3410 vs. AIC = 3397 for the simpler model). Only 18% of plots in northern hardwood–conifer forests were under some form of easement. A model that estimated separate frequency and intensity of harvest for easement vs. non-easement lands was a very marginal improvement over the simpler model (ΔAIC = 1.07). Plots on easement lands were predicted to have slightly higher average fractions of basal area removed in a harvest, across the entire range of plot basal area, but the frequency of harvest was predicted to be slightly lower on easement lands, particularly for plots with high basal area (Appendix S2).

There was no effect of parcel size on frequency of harvest, but there was a very slight effect on harvest intensity (Appendix S2). Across all plots for which parcel size information was available (regardless of forest type) there was a predicted gradual increase in the average intensity of harvest with increasing parcel size up to an asymptote at approximately 1000 hectares (Appendix S2). The predicted responses by forest type varied widely, ranging from no effect of parcel size in oak-hickory forests to a step function in the intensity of harvest in spruce-fir forests when parcel size exceeded 2000 hectares. However, the model that estimated separate parameters for the parcel size effect by forest type was not superior to the simpler model that lumped all forest types together (AIC = 12118 vs. AIC = 12097 for the simpler model). Parcel size data were only available for roughly two-thirds of the study region, and the gaps in coverage were not randomly distributed. Because of this, combined with the uncertainty in parameter estimates and lack of support for forest-type specific effects, parcel size effects were not included in the harvest regimes used in the simulations.

1.4.2. Predicted impacts of alternate harvest regime scenarios

All forest types/regions are predicted to show increases in live aboveground tree biomass in all scenarios, but they differed widely in the total amount of biomass accumulated (Fig. 1.5). Northern hardwood-conifer forests in Maine accumulated the least amount of biomass in every scenario that included harvest (ranging from 41% to 3% above current landscape averages in the current harvest scenario and most intensive harvest scenario, respectively). This pattern can largely be explained by high harvest rates (Fig. 1.2A). Aspen-birch or bottomland forest types resulted in the highest percent increase in biomass in every scenario (ranging from 120% to 78% above current landscape averages in the current harvest scenario (bottomland forests) and most intensive harvest scenario (aspen-birch forests), respectively). Land that is legally reserved from logging in the region currently has almost 50% higher live tree biomass (averaging 134 metric tons/ha vs. 90.4 metric tons/ha), but our simulations predict that even these reserved forests have significant additional carbon sequestration potential over the next 100 years (Fig. 1.5). The sequestration potential would be even more dramatic on new reserves created on existing working forestland because current aboveground biomass on these lands is lower. Figure 1.5 shows aboveground biomass (a carbon pool), increasing over time resulting in net sequestration (a carbon flux). The capacity to store additional carbon over time reflects stand biomass and biomass growth rate, and the variation in regional stand biomass. The future biomass projections, which are directly proportional to carbon, incorporate growth and removals (harvest and natural mortality).

In all harvest intensification scenarios, the proportion of stands in young forest shifted toward more mature stands over time. Roughly 20% of the current (2012) landscape is comprised of forest stands with ≤40 mt/ha of live aboveground tree biomass. In the year 2120, the percent of the forested landscape in stands with ≤40 mt/ha biomass ranged from 5% in the current harvest scenario to 14% in the most intensive harvest scenario. Despite the steady biomass accumulation, however, only 8% or less of stands exhibited characteristics of old-growth forests (≥300 mt/ha) in the year 2120 under any of the regimes except the no harvest scenario. Thirty-seven percent of stands in the no harvest scenario had aboveground biomass ≥300 mt/ha by 2120, compared to < 1% in 2012 (Fig. 1.6).

Northern hardwood-conifer forests in Maine are currently the most heavily harvested forest type in the study region (Fig. 1.7). These forests have the highest annual probability of being harvested and when they are harvested, the amount of biomass removed is relatively large (Fig. 1.2) resulting in the highest harvest yields of all forest types in every scenario. Harvest yields from aspen-birch forests also increased significantly under all of the harvest regimes (Fig. 1.7) because both the rate of harvest and the percentage of biomass harvested when logged are relatively high for these forests (Fig. 1.2). Several forest type and harvest scenario combinations showed a decline in harvest yield over the first several decades before rising dramatically and eventually somewhat stabilizing in the last 50 years. This is due to changes in the frequency distribution of stand biomass (and therefore yield) across the forested landscape. Simply increasing the intensity of the harvest regimes did not have a large effect on the overall regional harvest yields because the rotation length increased in response.

While intensifying harvest had clear effects on both average stand biomass and the frequency distribution of stand biomass within a region or forest type, it had little effect on overall patterns of succession and stand development within a given forest type or region (Fig. 1.8 and Appendix S3). A general pattern of stands progressing toward later successional forests emerged across all harvest scenarios, owing to the high proportion of low biomass stands in the current landscape and the predominance of partial harvesting. Late successional species like sugar maple (*Acer saccharum*), American beech (*Fagus grandifolia*), and eastern hemlock (*Tsuga canadensis*) consistently represented high proportions of biomass in future northern hardwood-conifer forests (Fig. 1.8), while balsam fir (*Abies balsamea*) and red spruce (*Picea rubens*) comprised a large portion of the biomass in spruce-fir forests. Biomass of eastern white pine (*Pinus strobus*) is predicted to increase substantially in all forest type/regions and scenarios over time (Fig. 1.8). Quaking aspen (*Populus tremuloides*) and paper birch (*Betula papyrifera*), currently the two most common species in aspen-birch forests, decline steadily over time in that forest type, and are replaced as the most common species (on average) by balsam fir and red maple within 20 years (Appendix S3).

Comparing the current harvest regime with the current harvest + climate regime scenario isolates the effect of the projected climate change. Of the dominant species of these northern temperate forests, balsam fir was the most disproportionately affected by climate change (Appendix S3). Its abundance is predicted to begin to decline after 50 years in all of the scenarios that include climate change. Eastern hemlock was also predicted to decline in the face of climate change, although to a smaller degree. While balsam fir is a frequently harvested species (Canham et al. 2013), in the absence of climate change it recovers biomass rapidly following harvest. The effect of the decline in balsam fir was so great in Maine that total biomass at the landscape scale declined given the climate change scenario under the current harvest regime. In contrast, the climate change scenario predicted a slight increase in landscape average aboveground biomass under the current harvest regime in the other three states. Other species responded differentially to the climate change scenario: sugar maple, eastern white pine, and to a lesser extent American beech accumulated biomass at a greater rate under the climate change scenario (Appendix S3).

1.5. Discussion

1.5.1. Harvest effects on landscape structure and composition

Our analyses indicate that in every harvest scenario average forest biomass is expected to increase significantly over the next 150 years (ranging from 3% to 120% above current landscape averages), even in the most intensive harvest scenario. In contrast to studies predicting that the strength of the carbon sink in eastern U.S. forests is already or will soon begin to decline (Hurtt et al. 2002, Zheng et al. 2011, USDA Forest Service 2012, Wear and Coulston 2015), our results suggest that at least in terms of live tree biomass, the amount of carbon stored in northeastern forests will continue to increase significantly over the next century (Rhemtulla et al. 2009, Keeton et al. 2011, Davis et al. 2012, Dangal et al. 2014, McGarvey et al. 2015). One of the primary reasons for the growth in carbon storage is the legacy of past land-use, where land clearing and heavy harvest prevailed during the middle of last century (Thompson et al. 2011). The current forested landscape includes many stands with low biomass. These forests are predicted to accumulate significant additional biomass, although forest types/regions vary considerably in their contribution to the landscape-level increase in forest biomass (Fig. 1.5).

In terms of stand development, beyond the negative effects of climate change on balsam fir and eastern hemlock biomass, little difference was observed in successional dynamics under the different harvest scenarios (Fig. 1.8 and Appendix S3). Several studies have predicted a delayed effect of climate change on tree species composition (Iverson et al. 2004, Murphy et al. 2010, Bertrand et al. 2011, Wang et al. 2015). It is plausible that our 150-year simulations are too short to yield a more pronounced climate effect. In northern hardwood-conifer forests, our analyses predicted continued dominance by sugar maple and red maple (*Acer rubrum*), with eastern hemlock and American beech also showing increased relative and absolute abundance. The model parameterization for tree growth and mortality takes into account the fact that beech bark disease is endemic in the entire study region (Morin et al. 2007). Hemlock populations to the south of the study region are experiencing high mortality from the hemlock woolly adelgid (Morin et al. 2009), and climate change is expected to allow the insect to spread northward over time. Given uncertainty on that rate of spread, however, we did not attempt to account for this in the model. Albani et al. (2010) simulated the effects of the regional spread of the woolly adelgid in eastern U.S. forests and concluded that after several decades of reduced carbon sequestration due to hemlock mortality, uptake of carbon would subsequently be increased as hemlock was replaced by species with higher productivity. A host of subordinate species like black cherry (*Prunus serotina*), white ash (*Fraxinus americana*), red oak (*Quercus rubra*), and red and white spruce (*Picea rubens* and *Picea glauca*) remained at consistently low proportions in northern hardwood-conifer forests over the next 150 years. It is notable that the patterns of late-successional species response generally hold across all harvest regimes (albeit in different magnitudes). The early successional nature of the current landscape and the pervasiveness of partial harvesting result in a steadily maturing landscape (Thompson et al. 2011) where the partial harvest gaps are not large enough to promote shade intolerant species even in the intensive harvest scenarios.

Eastern white pine did surprisingly well and accumulated large amounts of biomass across nearly all harvest scenarios in all forest types/regions. While it is often considered a pioneer and gap specialist that is replaced by more shade-tolerant species, our analyses predict white pine to thrive under highly variable partial harvest regimes and canopy conditions that otherwise favor shade-tolerant species. The success of white pine recruitment (in both amount and duration) has been linked to disturbance intensity (Abrams 2001, Black and Abrams 2005), but our results suggest white pine will increase in seedling and sapling density as well as adult biomass across a wide range of disturbance regimes.

1.5.2. Integrating timber harvest regimes into disturbance theory

Logging is clearly the current dominant source of disturbance in northeastern forests (Canham et al. 2013); therefore, understanding the effects of harvest and integrating harvest with natural disturbance is critical for assessing the future of these forests. We show that northeastern forest harvest regimes vary as a function of stand basal area, forest type/region, and distance to roads. Partial harvesting predominates in all forest types/regions. At the scale of an individual stand there is a tremendous amount of variation in how much biomass is removed during a harvest (Fig. 1.2B). Numerous stands near roads (<100 feet) are lightly harvested across several forest types, likely due to firewood cutting, and almost every forest type/region has a greater probability of harvest near improved roads (Figs. 1.3 and 1.4).

At a landscape scale, the effects of harvest regimes are in many ways analogous to natural disturbance regimes (Gendreau-Berthiaume et al. 2012). Harvest regimes and natural disturbances are both predictable in terms of their frequency and intensity. The varying characteristics of individual harvests (i.e., frequency, severity, and scale) result in a spatially and temporally diverse landscape in a number of stand replacement stages, just as frequent, small-scale natural disturbances give rise to structurally heterogeneous small-and intermediate-scale canopy gaps (Payette et al. 1990, Frelich and Lorimer 1991, Seymour et al. 2002). Natural and anthropogenic disturbance are also both highly selective in mortality by species and size (Canham et al. 2001, Papaik and Canham 2006, Canham et al. 2013), which can result in widely diverging successional patterns depending on initial conditions at the time of a disturbance event and the severity of the disturbance (Uriarte et al. 2009).

The natural disturbance regime for much of the northeastern region is characterized by high frequency, low intensity partial disturbances and very low frequency catastrophic disturbances (Seymour et al. 2002). Prior to European settlement, this pattern resulted in a landscape predominated by old-growth conditions (Barton et al. 2012, Thompson et al. 2013). In contrast, characteristics of older forests may be completely absent or diminished in working forest landscapes (McGee et al. 1999, Lindenmayer and Franklin 2002, Angers et al. 2005, Keeton 2006, Bauhus et al. 2009, Keeton et al. 2011, Morrissey et al. 2014). Our analyses predict only a small fraction of stands with biomass levels characteristic of old-growth conditions after 150 years, despite an overall increase in aboveground biomass in all harvest scenarios (Fig. 1.6). The no harvest scenario corresponds closely to the growth and trajectory of biomass accumulation within a forested system driven by natural disturbance; stands with large amounts of live biomass (>= 300 mt/ha) are five times greater in the no harvest scenario. A similar pattern is observed in the average annual input of dead and downed woody debris due to natural mortality: the average input is almost twice as large in the no harvest scenario as in any of the harvest scenarios. These differences in inputs of coarse woody debris have implications for carbon storage, sequestration, and biodiversity conservation, and are exacerbated by increased harvest intensity (Lindenmayer and Franklin 2002, Nunery and Keeton 2010, Littlefield and Keeton 2012, Schwenk et al. 2012). In a landscape with limited protected lands (Table 1.1) and widespread partial harvesting, less intensive harvest regimes will result in more variability on working forest lands. As harvest regimes intensify, working forests will become less variable and the limited amount of protected lands will represent a greater proportion of the landscape in later successional stages and larger biomass classes.

1.5.3. Socioeconomic drivers of harvest disturbance regimes

The influence of human decision-making is a key difference between anthropogenic and natural disturbance regimes. A recent analysis illustrated that in addition to biophysical factors, regional harvest regimes are influenced by socioeconomic drivers like forest ownership type, household median income, and population density (Thompson et al. 2017a). Landowners determine the fate of their individual lands and they decide whether to harvest based on a complex array of economic factors (e.g., timber price, alleviating debt), management influences (e.g., attitudes toward forest land, objectives for land ownership, family tenure), and policy issues (e.g., access to timber harvest programs) (Silver et al. 2015, Butler et al. 2016). Landowner decision-making has significant reach as 80% of forest land in the northeastern United States is in private ownership (Thompson et al. 2017a), and changes ownership frequently. National surveys indicate that nearly 20% of family forest owners are likely to sell their forest land in the next decade (Butler et al. 2016).

Socioeconomic factors pose challenges with respect to integrating logging with natural disturbance regimes and predicting the future condition of northern forests. Our analyses do not explicitly include future changes in macroeconomic and social factors as predictor variables. The harvest regimes we implemented in the model reflect current landowner decision-making regarding the local conditions in a given stand. For example, in our scenarios, changing the average intensity of harvests generally did not change overall biomass accumulation because harvest decisions were fundamentally still based on stand basal area. Changing the intensity of a particular harvest simply increased the average rotation length until the next harvest. As biomass increases in a stand it becomes more likely the stand will be harvested. Under these conditions, the forest landscape eventually stabilizes when net growth equals net removals across the entire region, and the average biomass of forests in a region is inversely related to the average yield across the region.

From a climate perspective, the next two decades are the most important for sequestering and storing carbon to stabilize the climate (IPCC 2014). Thus, despite aboveground biomass being greater after a century of recovery and growth, any initial reduction in sequestration may be problematic. In several of our intensified harvest scenarios there is a decrease in aboveground biomass for the first 25 years before the trend reverses and eventually surpasses the initial biomass amounts. This is particularly evident in Maine northern hardwood-conifer forests and bottomland forests (Fig. 1.5). There is a clear tradeoff between higher intensity harvest regimes stabilizing at lower biomass but more productive forests. Currently, northeastern forests are an important offset for greenhouse gas emissions (Zheng et al. 2011). Our analyses predict there is enormous potential for continued carbon sequestration, even under intensified harvest regimes (Fig. 1.5). While this is consistent with several studies (Keeton et al. 2011, Davis et al. 2012, Dangal et al. 2014), there is serious debate as to the future direction and magnitude of the carbon sink in eastern U.S. forests (Hurtt et al. 2002, Zheng et al. 2011, USDA Forest Service 2012, Wear and Coulston 2015). Ultimately the potential contribution of forest bioenergy to meeting state renewable energy goals and reducing fossil fuel dependencies will vary broadly by state, renewable energy objectives, feedstock supply, fossil fuel conversation technologies, forest landowner objectives, and other social and economic factors.

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1.7. Tables and Figures

1.7.1. Tables

Table 1.1. Characteristics of the Forest Inventory and Analysis plots (USDA Forest Service) used to initialize SORTIE-ND model runs (n=5000).

State	Total Plots	Aspen-Birch	Bottomland	Northern Hardwood-Conifer	Oak-Hickory	Spruce-Fir	Average Remeasurement Period (year)	Percent Protected Plots
ME	2564	311	55	1225	103	870	4.96	3.79
NH	396	20	10	256	86	24	6.5	5.3
NY	1551	64	127	983	307	70	7.97	15.23
VT	489	31	9	391	21	37	6.33	12.47

Table 1.2. Harvest scenario descriptions.

Harvest Scenario Name	Harvest Scenario Definition
Current harvest	The current harvest regime characterized as a function of forest type/region, total plot basal area, and distance to the nearest improved road
Current harvest + climate	The current harvest regime plus a change in climate conditions that includes a 3 degree C increase in mean annual temperature and a 10% increase in total annual precipitation over the next 100 years
Current harvest + climate + intensity	The current harvest regime plus climate change and a 50% increase in average harvest intensity
Current harvest + climate + frequency	The current harvest regime plus climate change and a 75% increase in harvest frequency
Current harvest + climate + intensity + frequency	The current harvest regime plus climate change, a 50% increase in average harvest intensity, and a 100% increase in harvest frequency
No harvest	A no harvest scenario plus climate change

1.7.2. Figures

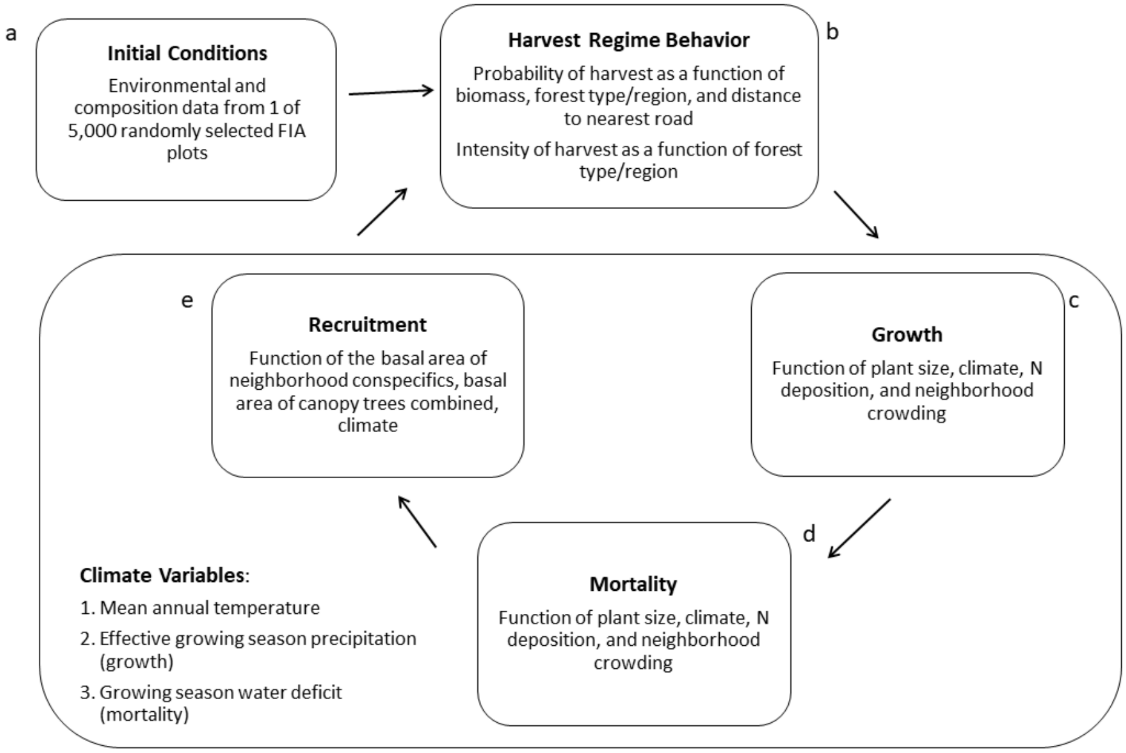

Figure 1.1. Schematic diagram of the SORTIE-ND forest simulation model. A detailed description of the model structure and parameterization is provided in Appendix S1.

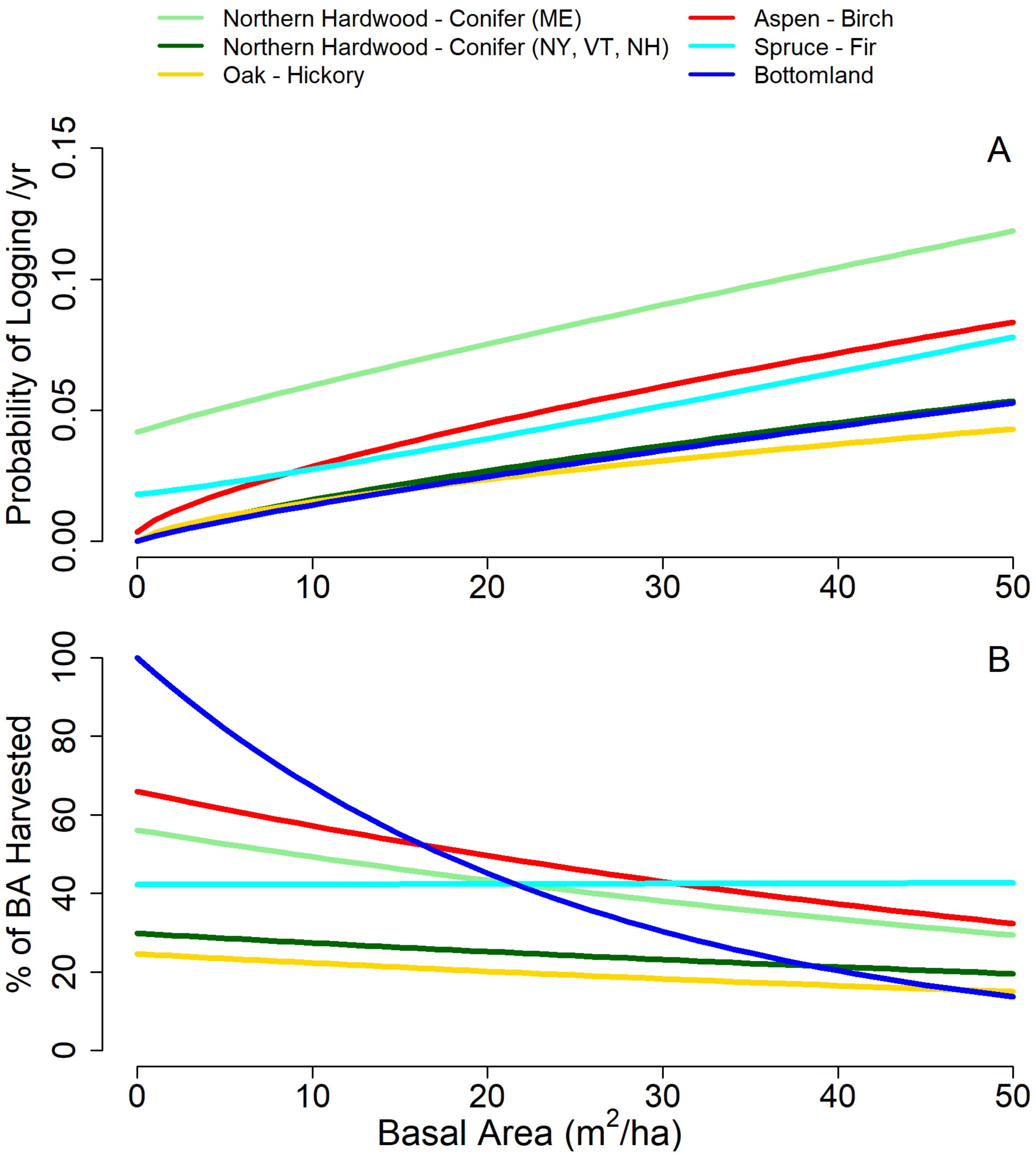

Figure 1.2. (A) Estimated annual probability that a plot is harvested, and (B) estimated percentage of basal area removed as a function of total stand basal area for six forest type/regions, shown at 300 – 500 feet from the nearest road.

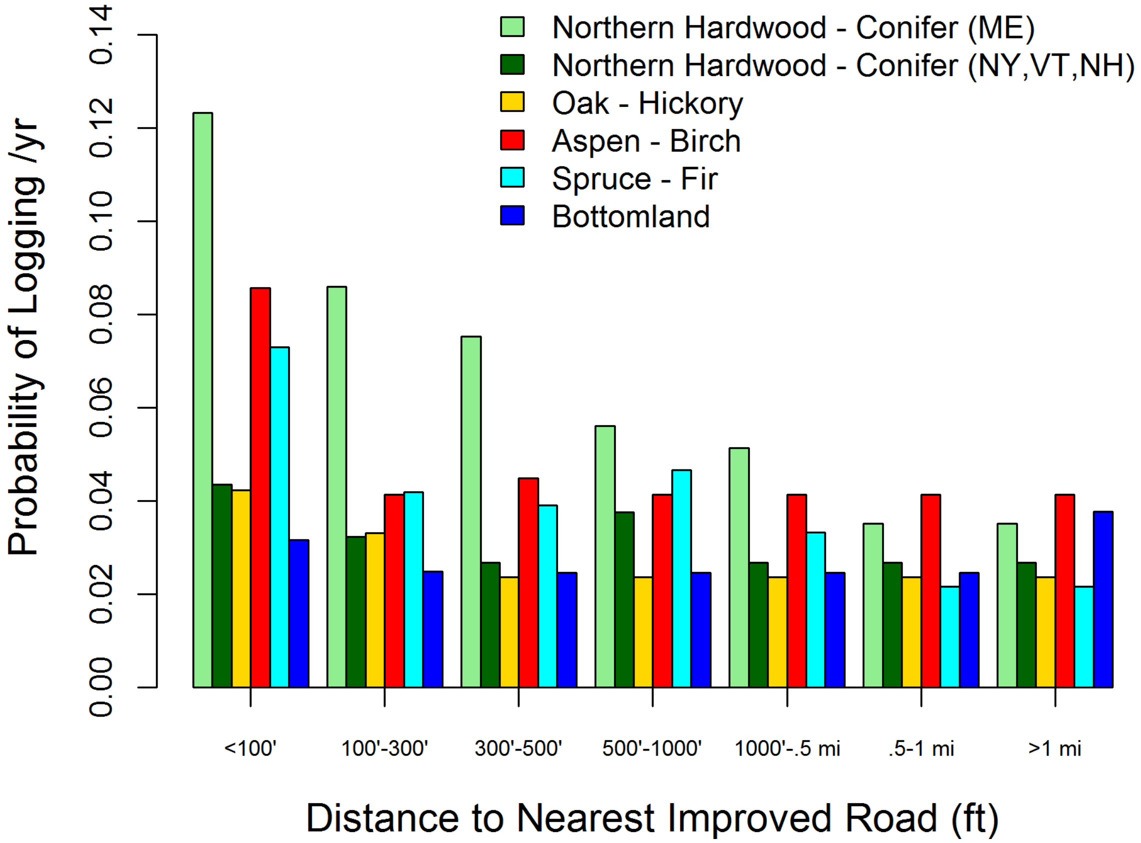

Figure 1.3. Estimated annual probability of harvest as a function of distance to nearest improved road for six forest type/regions, shown for a stand with 20 m^2/ha basal area.

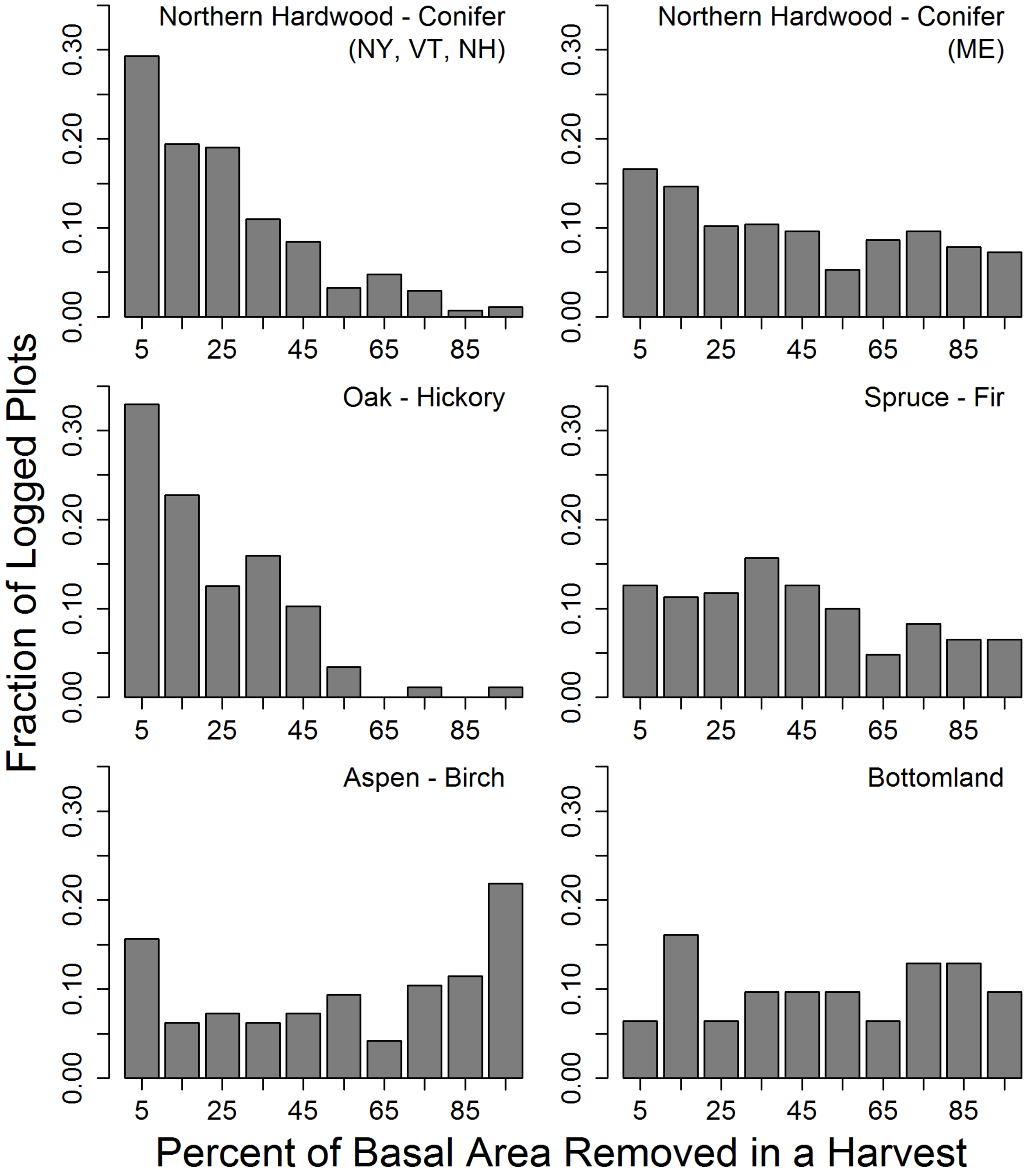

Figure 1.4. Frequency distribution of the percentage of tree basal area harvested in a given plot, for plots that experienced some level of harvest, for six forest type/regions.

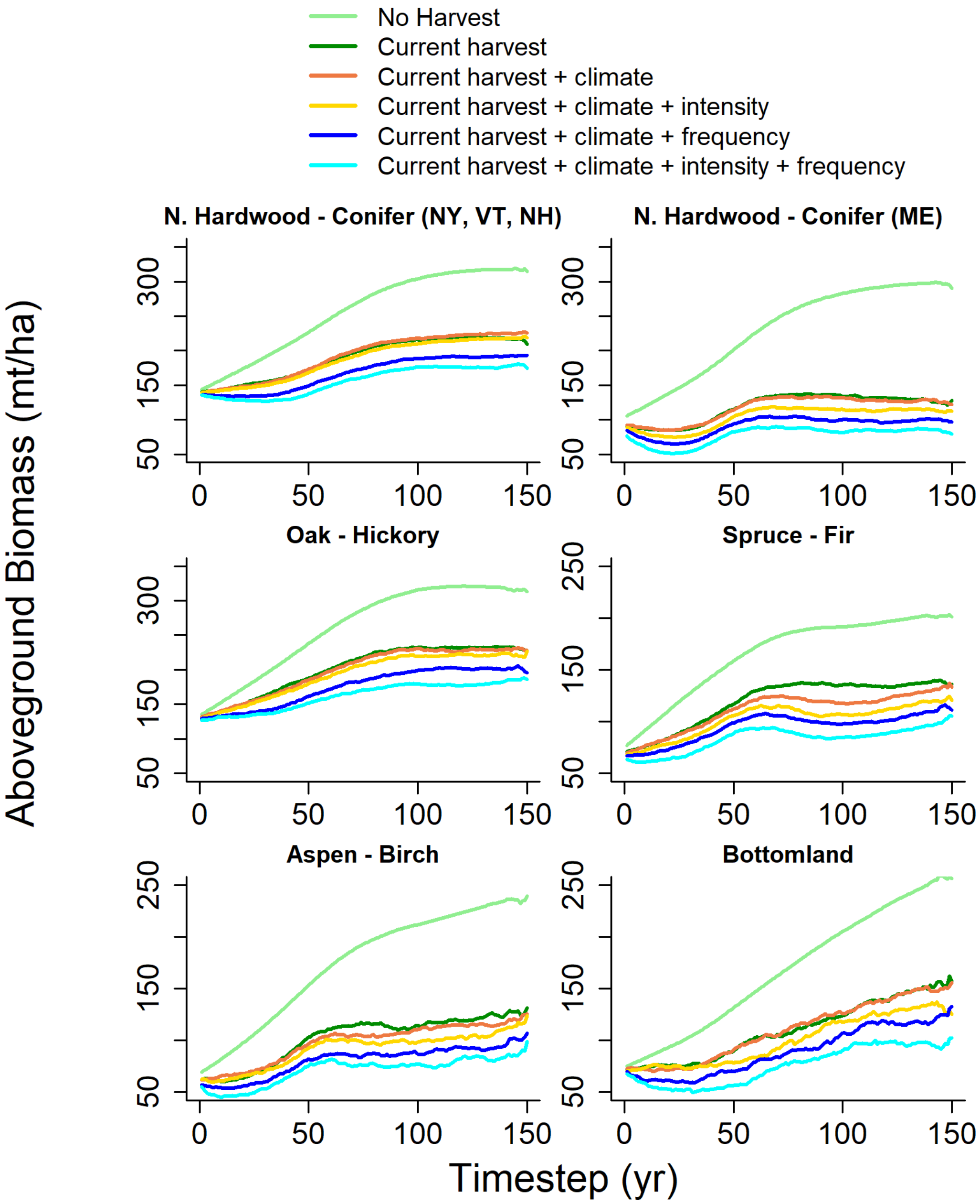

Figure 1.5. Estimates of adult aboveground biomass (metric tons/ha) for six harvest scenarios and six forest type/regions over the next 150 years. Timestep 1 corresponds to the year 2011.

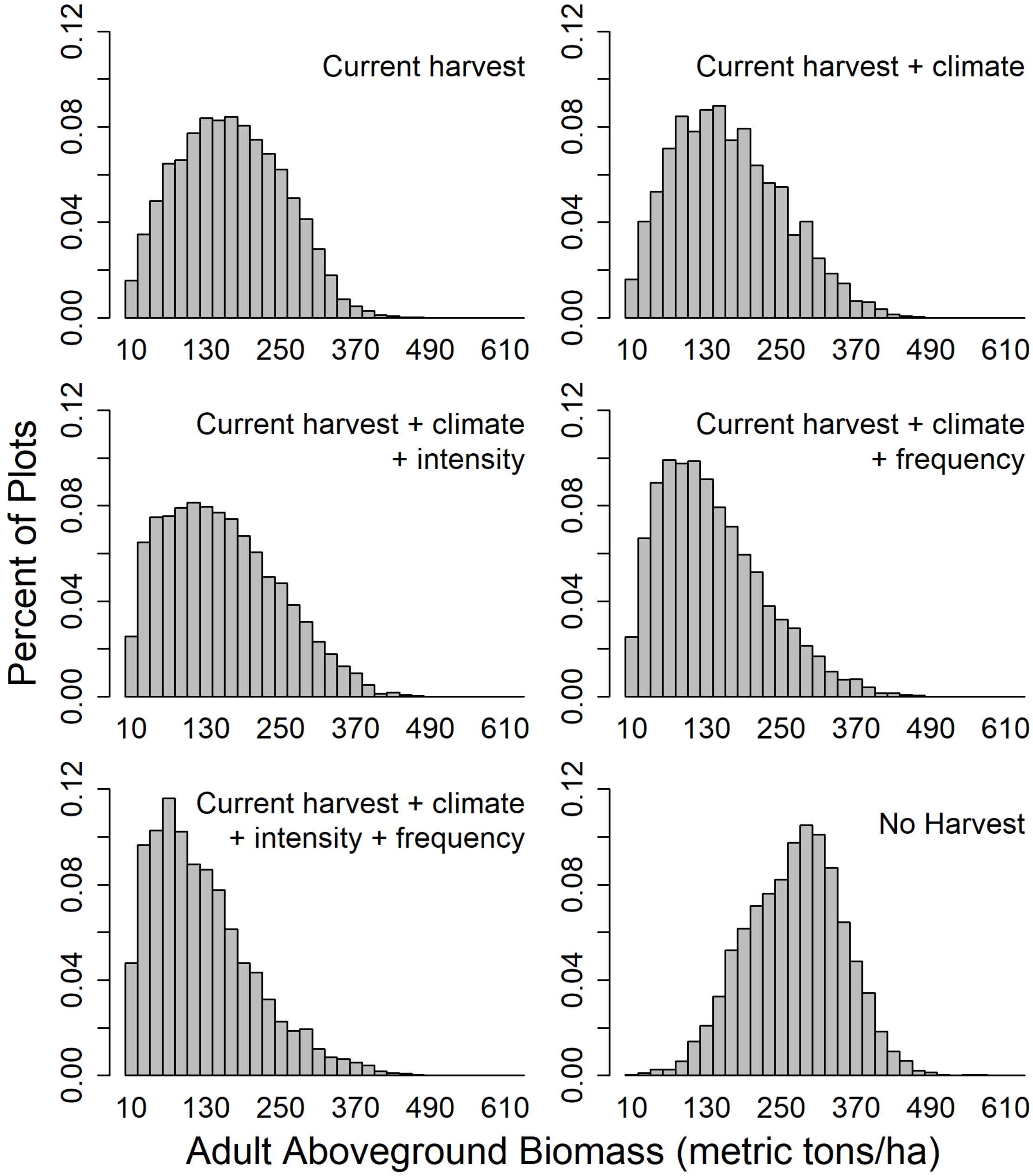

Figure 1.6. Percentage of plots in aboveground biomass classes in the year 2120 for six harvest scenarios. The “No Harvest” scenario includes effects of climate change.

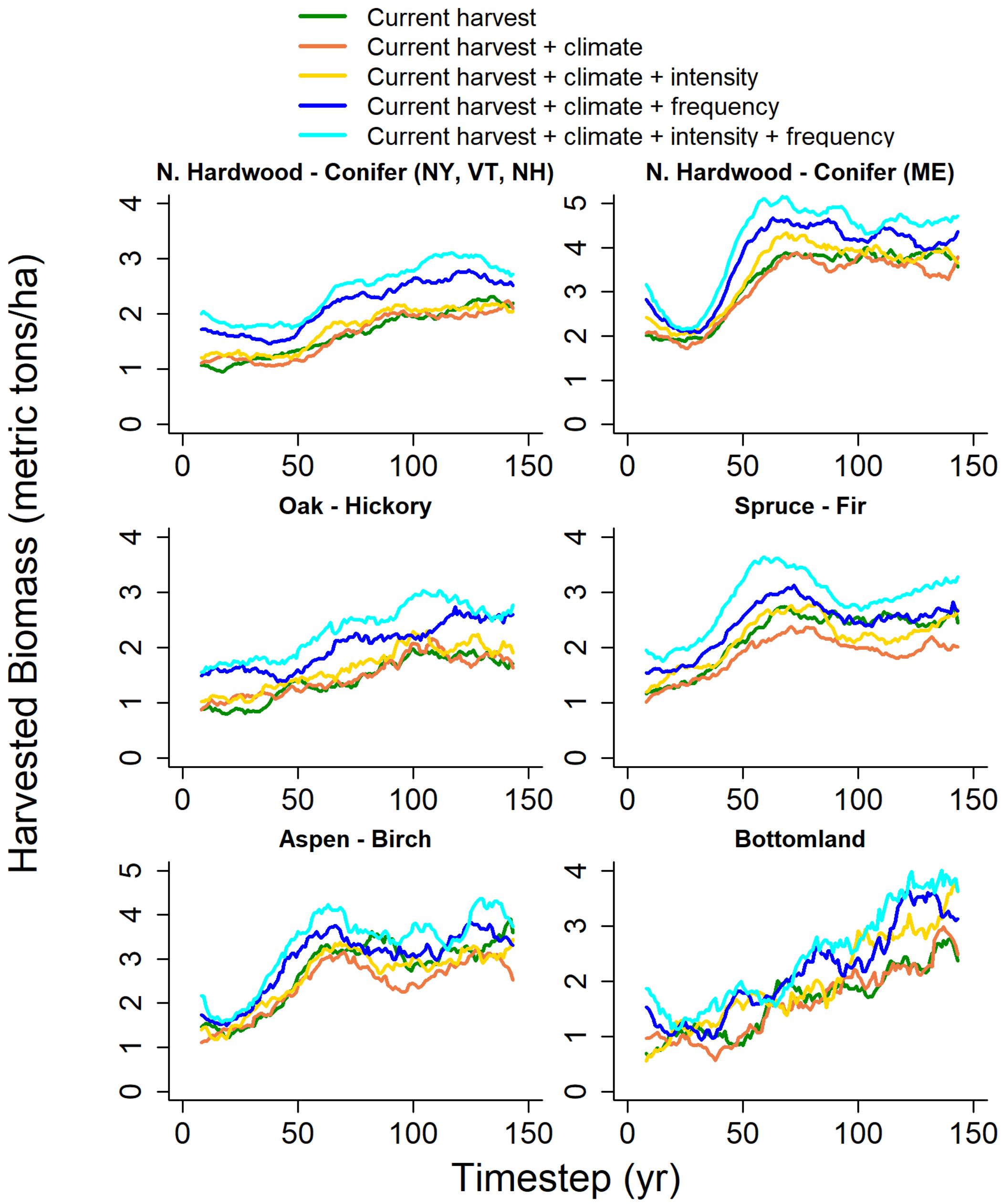

Figure 1.7. Amount of harvested biomass (15-year running averages) shown for five harvest scenarios and six forest type/regions. Timestep 1 corresponds to the year 2011.

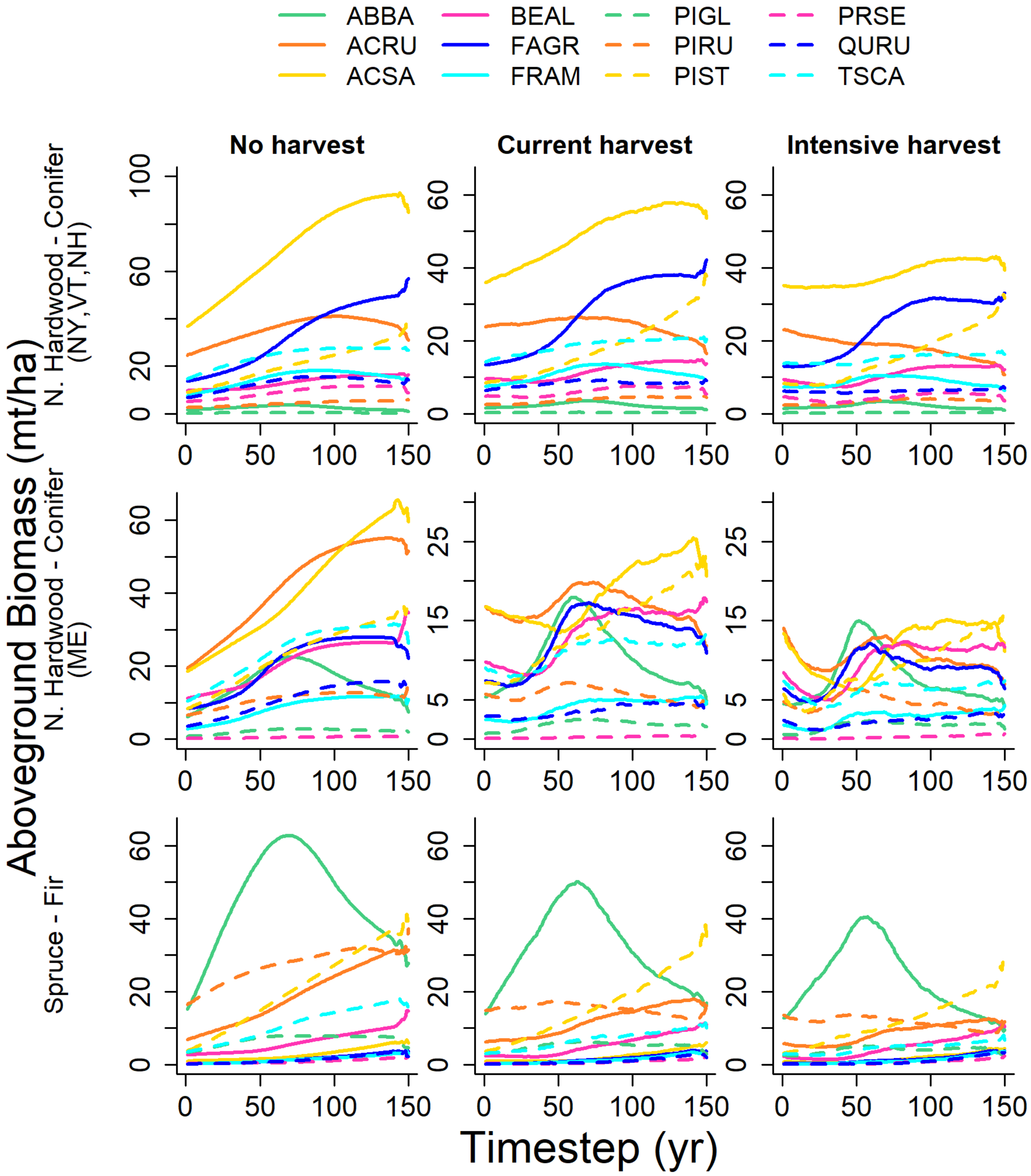

Figure 1.8. Species development over 150 years across three harvest regimes (columns): no harvest (with climate change), the current harvest regime but with climate change, and increased frequency and intensity of the current harvest regime with climate change; and three forest types/regions (rows): northern hardwood -conifer (New York, Vermont, New Hampshire), northern hardwood-conifer (Maine), and spruce-fir. Timestep 1 corresponds to the year 2011. Only twelve dominant species are shown: ABBA = *Abies balsamea*, ACRU = *Acer rubrum*, ACSA = *Acer saccharum*, BEAL = *Betula alleghaniensis*, FAGR = *Fagus grandifolia*, FRAM = *Fraxinus Americana*, PIGL = *Picea glauca*, PIRU = *Picea*

rubens, PIST = *Pinus strobes*, QURU = *Quercus rubra*, and TSCA = *Tsuga candensis.* Details for all of the forest types and all scenarios are given in Appendix S3.

1.8. References

Abrams, M. D. 2001. Eastern white pine versatility in the presettlement forest. BioScience **51**:967-979.

Albani, M., P. R. Moorcroft, A. M. Ellison, D. A. Orwig, and D. R. Foster. 2010. Predicting the impact of hemlock woolly adelgid on carbon dynamics of eastern United States forests. Canadian Journal of Forest Research **40**:119-133.

Anderson, M. G., and A. Olivero Sheldon. 2011. Conservation status of fish, wildlife, and natural habitats in the Northeast landscape: implementation of the Northeast Monitoring Framework. The Nature Conservancy, Eastern Conservation Science. 289 pp.

Angers, V. A., C. Messier, M. Beaudet, and A. Leduc. 2005. Comparing composition and structure in old-growth and harvested (selection and diameter-limit cuts) northern hardwood stands in Quebec. Forest Ecology and Management **217**:275-293.

Barton, A. M., A. S. White, and C. V. Cogbill. 2012. The changing nature of the Maine woods. University Press of New England, Lebanon, NH.

Bauhus, J., K. Puettmann, and C. Messier. 2009. Silviculture for old-growth attributes. Forest Ecology and Management **258**:525-537.

Bertrand, R., J. Lenoir, C. Piedallu, G. Riofrio-Dillon, P. de Ruffray, C. Vidal, J.-C. Pierrat, and J.-C. Gegout. 2011. Changes in plant community composition lag behind climate warming in lowland forests. Nature **479**:517-520.

Biomass Energy Resource Center. 2013. An overview of the biomass thermal energy policy opportunities in the Northern Forest region. Biomass Energy Resource Center at Vermont Energy Investment Corporation. Burlington, VT.

Biomass Thermal Energy Council. 2010. Heating the Northeast with renewable biomass: a vision for 2025. Biomass Thermal Energy Council, Washington, DC.

Black, B. A., and M. D. Abrams. 2005. Disturbance history and climate response in an old-growth hemlock-white pine forest, central Pennsylvania. The Journal of the Torrey Botanical Society **132**:103-114.

Buchholz, T., C. D. Canham, and S. P. Hamburg. 2011. Forest biomass and bioenergy: opportunities and constraints in the northeastern United States. Cary Institute of Ecosystem Studies, Milbrook, NY.

Butler, B. J., J. H. Hewes, B. J. Dickinson, K. Andrejczyk, S. M. Butler, and M. Markowski-Lindsay. 2016. Family forest ownerships of the United States, 2013: findings from the USDA Forest Service's National Woodland Owner Survey. Journal of Forestry **114**:638-647.

Butler, B. J., Z. Ma, D. B. Kittredge, and P. Catanzaro. 2010. Social versus biophysical availability of wood in the northern United States. Northern Journal of Applied Forestry **27**:151-159.

Canham, C. D., and O. L. Loucks. 1984. Catastrophic windthrow in the presettlement forests of Wisconsin. Ecology **65**:803-809.

Canham, C. D., and L. Murphy. 2016a. The demography of tree species response to climate: sapling and canopy tree growth. Ecosphere 7(10):e01474. 10.1002/ecs2.1474.

Canham, C. D., and L. Murphy. 2016b. The demography of tree species response to climate: seedling recruitment and survival. Ecosphere 7(8):e01424. 10.1002/ecs2.1424.

Canham, C. D., and L. Murphy. 2017. The demography of tree species response to climate: sapling and canopy tree survival. Ecosphere 8(2):e01701. 10.1002/ecs2.1701.

Canham, C. D., M. J. Papaik, and E. F. Latty. 2001. Interspecific variation in susceptibility to windthrow as a function of tree size and storm severity for northern temperate tree species. Canadian Journal of Forest Research **31**:1-10.

Canham, C. D., M. J. Papaik, M. Uriarte, W. H. McWilliams, J. C. Jenkins, and M. J. Twery. 2006. Neighborhood analyses of canopy tree competition along environmental gradients in New England forests. Ecological Applications **16**:540-554.

Canham, C. D., N. Rogers, and T. Buchholz. 2013. Regional variation in forest harvest regimes in the northeastern United States. Ecological Applications **23**:515-522.

Castellano, P. J., T. A. Volk, and L. P. Herrington. 2009. Estimates of technically available woody biomass feedstock from natural forests and willow biomass crops for two locations in New York State. Biomass and Bioenergy **33**:393-406.

Coates, K. D., C. D. Canham, M. Beaudet, D. L. Sachs, and C. Messier. 2003. Use of a spatially explicit individual-tree model (SORTIE/BC) to explore the implications of patchiness in structurally complex forests. Forest Ecology and Management **186**:297-310.

Dangal, S. R. S., B. S. Felzer, and M. D. Hurteau. 2014. Effects of agriculture and timber harvest on carbon sequestration in the eastern US forests. Journal of Geophysical Research: Biogeosciences **119**:35-54.

Davis, S. C., M. Dietze, E. DeLucia, C. Field, S. P. Hamburg, S. Loarie, W. Parton, M. Potts, B. Ramage, D. Wang, H. Youngs, and S. P. Long. 2012. Harvesting carbon from eastern US forests: opportunities and impacts of an expanding bioenergy industry. Forests **3**:370-397.

Energy Independence and Security Act. 2007. Public Law 110-140, 110th Congress.

Energy Information Administration. 2015. International Energy Outlook 2015 with projections to 2040. U.S. Energy Information Administration, Washington, DC.

Forsyth, D. M., D. J. Wilson, T. A. Easdale, G. Kunstler, C. D. Canham, W. A. Ruscoe, E. F. Wright, L. Murphy, A. M. Gormley, and A. Gaxiola. 2015. Century-scale effects of invasive deer and rodents on the dynamics of forests growing on soils of contrasting fertility. Ecological Monographs **85**:157-180.

Frelich, L. E., and C. G. Lorimer. 1991. Natural disturbance regimes in hemlock-hardwood forests of the Upper Great Lakes Region. Ecological Monographs **61**:145-164.

Gendreau-Berthiaume, B., D. D. Kneeshaw, and B. D. Harvey. 2012. Effects of partial cutting and partial disturbance by wind and insects on stand composition, structure and growth in boreal mixedwoods. Forestry: An International Journal of Forest Research **85**:551-565.

Horton, R., G. Yohe, W. Easterling, R. Kates, M. Ruth, E. Sussman, A. Whelchel, D. Wolfe, and F. Lipschultz. 2014. Ch. 16: Northeast. In Climate Change Impacts in the United States: The Third National Climate Assessment. J. M. Melillo, T.C.

Richmond, and G. W. Yohe, Eds. U.S. Global Change Research Program, 371-395, doi:10.7930/J0SF2T3P.

Hunter, L. 2014. Renewable energy in the 50 states: Northeast region. American Council on Renewable Energy (ACORE), Washington, DC.

Hurtt, G. C., S. W. Pacala, P. R. Moorcroft, J. Caspersen, E. Shevliakova, R. A. Houghton, and B. Moore. 2002. Projecting the future of the U.S. carbon sink. Proceedings of the National Academy of Sciences **99**:1389-1394.

IPCC. 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R. K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Iverson, L. R., M. W. Schwartz, and A. M. Prasad. 2004. Potential colonization of newly available tree-species habitat under climate change: an analysis for five eastern US species. Landscape Ecology **19**:787-799.

Keeton, W. S. 2006. Managing for late-successional/old-growth characteristics in northern hardwood-conifer forests. Forest Ecology and Management **235**:129-142.

Keeton, W. S., A. A. Whitman, G. C. McGee, and C. L. Goodale. 2011. Late-successional biomass development in northern hardwood-conifer forests of the northeastern United States. Forest Science **57**:489-505.

Kelty, M. J., and A. W. D'Amato. 2006. Historical perspective on diameter-limit cutting in northeastern forests. P. 3–15 in Proc. of the Conference on diameter-limit cutting in northeastern forests, Kenefic L.S., Nyland R.D. (eds.). USDA For. Serv., Gen. Tech. Rep. NE-342, Northeastern Research Station, Newtown Square, PA.

Kunstler, G., D. A. Coomes, and C. D. Canham. 2009. Size-dependence of growth and mortality influence the shade tolerance of trees in a lowland temperate rain forest. Journal of Ecology **97**:685-695.

Lindenmayer, D. B., and J. F. Franklin. 2002. Conserving forest biodiveristy: A comprehensive multiscaled approach. Island Press, Washington, D.C.

Littlefield, C. E., and W. S. Keeton. 2012. Bioenergy harvesting impacts on ecologically important stand structure and habitat characteristics. Ecological Applications **22**:1892-1909.

Maine Forest Service. 2010. Maine State Forest Assessment and Strategies. Maine Forest Service, Department of Conservation, Augusta, Maine. 225 pp.

Masek, J. G., W. B. Cohen, D. Leckie, M. A. Wulder, R. Vargas, B. de Jong, S. Healey, B. Law, R. Birdsey, R. A. Houghton, D. Mildrexler, S. Goward, and W. B. Smith. 2011. Recent rates of forest harvest and conversion in North America. Journal of Geophysical Research: Biogeosciences **116**:2156-2202.

McGarvey, J. C., J. R. Thompson, H. E. Epstein, and H. H. Shugart. 2015. Carbon storage in old-growth forests of the Mid-Atlantic: toward better understanding the eastern forest carbon sink. Ecology **96**:311-317.

McGee, G. G., D. J. Leopold, and R. D. Nyland. 1999. Structural characteristics of old-growth, maturing, and partially cut northern hardwood forests. Ecological Applications **9**:1316-1329.

Morin, R. S., A. M. Liebhold, and K. W. Gottschalk. 2009. Anisotropic spread of hemlock woolly adelgid in the eastern United States. Biological Invasions **11**:2341–2350.

Morin, R. S., A. M. Liebhold, P. C. Tobin, K. W. Gottschalk, and E. Luzader. 2007. Spread of beech bark disease in the eastern United States and its relationship to regional forest composition. Canadian Journal of Forest Research **37**:726-736.

Morrissey, R. C., M. A. Jenkins, and M. R. Saunders. 2014. Accumulation and connectivity of coarse woody debris in partial harvest and unmanaged relict forests. PLOS ONE 9(11): e113323. http://doi.org/10.1371/journal.pone.0113323.

Murphy, H. T., J. VanDerWal, and J. Lovett-Doust. 2010. Signatures of range expansion and erosion in eastern North American trees. Ecology Letters **13**:1233-1244.

Murphy, L. 2015. likelihood: Methods for Maximum Likelihood Estimation. R package version 1.7. http://CRAN.R-project.org/package=likelihood.

New Hampshire Department of Resources and Economic Development. 2010. New Hampshire Statewide Forest Resources Assessment – 2010. New Hampshire Department of Resources and Economic Development, Division of Forests and Lands, Concord, NH.

New York State Department of Environmental Conservation. 2010. New York State Forest Resource Assessment and Strategy. New York State Department of Environmental Conservation, Division of Lands and Forests, Albany, NY.

New York State Energy Plan. 2015. 2015 New York State Energy Plan. Albany, NY.

Nunery, J. S., and W. S. Keeton. 2010. Forest carbon storage in the northeastern United States: net effects of harvesting frequency, post-harvest retention, and wood products. Forest Ecology and Management **259**:1363-1375.

Oliver, C. D., and B. C. Larson. 1996. Forest Stand Dynamics. Wiley, New York.

Papaik, M. J., and C. D. Canham. 2006. Species resistance and community response to wind disturbance regimes in northern temperate forests. Journal of Ecology **94**:1011-1026.

Payette, S., L. Filion, and A. Delwaide. 1990. Disturbance regime of a cold temperate forest as deduced from tree-ring patterns: the Tantaré Ecological Reserve, Quebec. Canadian Journal of Forest Research **20**:1228-1241.

Pickett, S. T., and P. S. White. 1985. The Ecology of Natural Disturbance and Patch Dynamics. Academic Press, Inc., New York, New York.

Pickett, S. T. A., J. Kolasa, J. J. Armesto, and S. L. Collins. 1989. The ecological concept of disturbance and its expression at various hierarchical levels. Oikos **54**:129-136.

Puettmann, K. J., K. D. Coates, and C. Messier. 2009. A critique of silviculture: managing for complexity. Island Press, Washington, DC.

R Core Team. 2014. A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.

Rhemtulla, J. M., D. J. Mladenoff, and M. K. Clayton. 2009. Historical forest baselines reveal potential for continued carbon sequestration. Proceedings of the National Academy of Sciences **106**:6082-6087.

Schwenk, W. S., T. M. Donovan, W. S. Keeton, and J. S. Nunery. 2012. Carbon storage, timber production, and biodiversity: comparing ecosystem services with multi-criteria decision analysis. Ecological Applications **22**:1612-1627.

Seymour, R. S., A. S. White, and P. G. deMaynadier. 2002. Natural disturbance regimes in northeastern North America: evaluating silvicultural systems using natural scales and frequencies. Forest Ecology and Management **155**:357-367.

Sherman, A. R. 2007. Vermont wood fuel supply study - an examination of the availbility and reliability of wood fuel for biomass energy in Vermont. Biomass Energy Resources Center, Montpelier, VT.

Silver, E. J., J. E. Leahy, A. R. Weiskittel, C. L. Noblet, and D. B. Kittredge. 2015. An evidence-based review of timber harvesting behavior among private woodland owners. Journal of Forestry **113**:490-499.

Thomas, R. Q., C. D. Canham, K. C. Weathers, and C. L. Goodale. 2010. Increased tree carbon storage in response to nitrogen deposition in the US. Nature Geoscience **3**:13-17.

Thompson, J. R., C. D. Canham, L. Morreale, D. B. Kittredge, and B. Butler. 2017a. Social and biophysical variation in regional timber harvest regimes. Ecological Applications **27**:942-955.

Thompson, J. R., D. N. Carpenter, C. V. Cogbill, and D. R. Foster. 2013. Four centuries of change in northeastern United States forests. PLOS ONE 8(9): e72540. https://doi.org/10.1371/journal.pone.0072540.

Thompson, J. R., D. R. Foster, R. Scheller, and D. Kittredge. 2011. The influence of land use and climate change on forest biomass and composition in Massachusetts, USA. Ecological Applications **21**:2425-2444.

Uriarte, M., C. D. Canham, J. Thompson, J. K. Zimmerman, L. Murphy, A. M. Sabat, N. Fetcher, and B. L. Haines. 2009. Natural disturbance and human land use as determinants of tropical forest dynamics: results from a forest simulator. Ecological Monographs **79**:423-443.

USDA Forest Service. 2012. The future of America's forests and rangelands, Forest Service 2010 Resources Planning Act Assessment. USDA Forest Service, Washington, DC.

USDA Forest Service. 2016. National Woodland Owner Survey Table Maker version 3.0. Accessed January 3, 2017. https://apps.fs.usda.gov/nwos/tablemaker.jsp

USDA Forest Service. 2020. Forest Inventory and Analysis National Program. Accessed March 2022. http://www.fia.fs.fed.us/.

Vermont Agency of Natural Resources. 2010. 2010 Vermont Forest Resources Plan - State Assessment and Resources Strategies. Vermont Agency of Natural Resources, Department of Forests, Parks and Recreation, Montpelier, VT.

Vermont Department of Public Service. 2022. 2022 Vermont Comprehensive Energy Plan. Vermont Department of Public Service, Montpelier, VT.

Wang, W. J., H. S. He, F. R. Thompson, J. S. Fraser, B. B. Hanberry, and W. D. Dijak. 2015. Importance of succession, harvest, and climate change in determining future composition in U.S. central hardwood forests. Ecosphere **6**:1-18.

Wear, D. N., and J. W. Coulston. 2015. From sink to source: regional variation in U.S. forest carbon futures. Scientific Reports **5**:16518.

Wear, D. N., and B. C. Murray. 2004. Federal timber restrictions, interregional spillovers, and the impact on US softwood markets. Journal of Environmental Economics and Management **47**:307-330.

Wojnar, Z. 2013. Renewable fuels roadmap and sustainable biomass feedstock supply for New York, annual update #2. New York State Energy Research and Development Authority, Report 13-09, Albany, NY.

Woudenberg, S. W., B. L. Conkling, B. M. O'Connell, E. B. LaPoint, J. A. Turner, and K. L. Waddell. 2010. The Forest Inventory and Analysis Database: Database description and users manual version 4.0 for Phase 2. Gen. Tech. Rep. RMRS-GTR- 245. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 339 pp.

Zheng, D., L. S. Heath, M. J. Ducey, and J. E. Smith. 2011. Carbon changes in conterminous US forests associated with growth and major disturbances: 1992–2001. Environmental Research Letters. doi: 10.1088/1748-9326/6/1/014012.

CHAPTER 2: NET CARBON SEQUESTRATION IMPLICATIONS OF INTENSIFIED TIMBER HARVEST IN NORTHEASTERN U.S. FORESTS

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2.1. Abstract

U.S. forests, particularly in the eastern states, provide an important offset to greenhouse gas (GHG) emissions. Some have proposed that forest-based natural climate solutions can be strengthened via a number of strategies, including increases in production of forest biomass energy. We used output from a forest dynamics model [SORTIE-ND] in combination with a greenhouse gas accounting tool [ForGATE] to estimate the carbon consequences of current and intensified timber harvest regimes in the northeastern U.S. We considered a range of carbon pools including forest ecosystem pools, forest product pools, and waste pools, along with different scenarios of feedstock production for biomass energy. The business as usual (BAU) scenario, which represents current harvest practices derived from analysis of U.S. Forest Service Forest Inventory and Analysis data, sequestered more net CO_2 equivalents than any of the intensified harvest and feedstock utilization scenarios over the next decade, the most important time period for combatting climate change. Increasing the intensity of timber harvest increased total emissions and reduced landscape average forest carbon stocks, resulting in reduced net carbon sequestration relative to current harvest regimes. Net carbon sequestration "parity points," where the regional cumulative net carbon sequestration from alternate intensified harvest scenarios converge with and then exceed the business as usual baseline, ranged from 12 to 40 years. A "no harvest" scenario provides an estimate of an upper bound on forest carbon sequestration in the region given the expected successional dynamics of the region's forests, but ignores leakage. Regional net carbon sequestration is primarily influenced by (i) the harvest regime and amount of forest biomass removal, (ii) the degree to which bioenergy displaces fossil fuel use, and (iii) the proportion of biomass diverted to energy feedstocks versus wood products.

2.2. Introduction

Carbon sequestration in U.S. forests and forest products offsets approximately 11% of U.S. economy-wide greenhouse gas emissions annually (Domke et al. 2020), and recent studies have highlighted opportunities to enhance the role of forests in climate mitigation (Fargione et al. 2018, Drever et al. 2021). Forests in the eastern half of the country contribute a disproportionate share of the nation's forest carbon sequestration. Domke et al. (2020) estimate that forestland in the 31 eastern United States contained ~59% of the estimated total forest carbon stocks but provided 85% of the net carbon sequestration for the 48 conterminous states in 2018 (Domke et al. 2020).

Land use history and disturbance regimes clearly play a role in the magnitude of the eastern forest carbon sink, and a significant fraction of current forest land is the product of either afforestation of agricultural land abandoned during the past 200 years, or recovery following high rates of clearcutting in the late 19th and early 20th centuries. This has led to assumptions that forests of the region are even-aged and that rates of productivity and carbon sequestration will decline as those forests mature (e.g., Turner and Koerper 1995, Hurtt et al. 2002, Bradford and Kastendick 2010). Logging is by far the dominant disturbance in eastern forests (Canham et al. 2013, Brown et al. 2018a), and some studies have proposed that increases in overall harvest regimes could increase net carbon sequestration in forests and forest products (e.g., Peckham et al. 2012). Both of these assertions have been challenged and are the subject of ongoing debate (Rhemtulla et al. 2009, Nunery and Keeton 2010, Keeton et al. 2011, McGarvey et al. 2015, Keeton 2018). Keeton et. al (2011) conclude that northeastern U.S. forests have substantial potential to sequester and store carbon late into succession (350 - 400 years). Studies that combine forest ecosystem processes with wood product life cycles suggest that decreasing harvest intensity increases carbon sequestration (Nunery and Keeton 2010, Gunn and Buchholz 2018).

There has also been interest in the development of forest biomass energy as a component of the renewable energy portfolio of the northeastern U.S. (Milbrandt 2008, Perlack et al. 2008). While often touted as an inherently "carbon-neutral" energy source, it has become clear that a wide range of factors need to be considered to evaluate the net carbon and climate impact of biomass energy production (Schulze et al. 2012, Zanchi et al. 2012). To achieve a reduction in GHG emissions, many bioenergy policies assume that the emissions resulting from bioenergy combustion are balanced by plant regrowth and sequestration. A growing body of literature examines whether burning woody biomass for energy has a net positive or net negative carbon impact (Fargione et al. 2008, Searchinger et al. 2009, Malmsheimer et al. 2011, Haberl et al. 2012, Mika and Keeton 2013, 2015, Ter-Mikaelian et al. 2015, Buchholz et al. 2017, Searchinger et al. 2017, Birdsey et al. 2018, Gunn and Buchholz 2018, Sterman et al. 2018, Vance 2018, Dwivedi et al. 2019, Buchholz et al. 2021). Determining the actual impact of forest biomass energy on atmospheric carbon, however, must include emissions from land use change when biomass is harvested or grown for energy (Fargione et al. 2008, Searchinger et al. 2008), the source of the energy feedstock and its alternative fate, the time horizons needed to account for the full life cycle of forest growth, energy emissions associated with wood product supply chains and fossil fuel substitution, and forest carbon cycles (Haberl et al. 2012, Zanchi et al. 2012, Ter-Mikaelian et al. 2015, Birdsey et al. 2018). Accurately accounting for these often counteracting processes will determine the calculation of the net impact of forest biomass energy production on net GHG emissions or reductions.

In a separate study (Brown et al. 2018a), we characterized the current forest harvest regimes for the major forest types of the northern forest states from New York to Maine. We then used SORTIE-ND, a spatially-explicit individual-tree forest stand model (Coates et al. 2003, Uriarte et al. 2009, Forsyth et al. 2015), to project the effects of that regime and four alternative harvest regimes on forest structure, composition, and productivity over the next 150 years. Here, we take the results of that study and combine them with a simplified model of within-forest detrital carbon dynamics, and an analysis of the net carbon impacts (sequestration and emissions) of the flow of harvested wood through a range of forest products and biomass energy feedstocks. That analysis makes use of ForGATE, a forest-sector greenhouse gas accounting tool originally developed for the state of Maine (Hennigar et al. 2013). Specifically, we track forest ecosystem and harvested wood product carbon pools, and a full suite of emissions including forest decomposition, energy emissions, and waste emissions. Our results allow us to project the net carbon sequestration of a broad range of forest harvest regimes and biomass energy production over the next 100 years in the four northern forest states, combining both carbon dynamics in forests as well as in forest products and landfills.

2.3. Methods

2.3.1 Study area

The study area comprises all forest land as defined by the National Forest Inventory in the states of New York, Vermont, New Hampshire, and Maine, approximately 71% of the region (USDA Forest Service 2020). Forest types in the region vary from boreal spruce-fir (*Picea* sp. – *Abies* sp.) forests to dry temperate oak-hickory (*Quercus* sp. – *Carya* sp.) forests, with temperate northern hardwood-conifer forests being the most widespread. The temperate climate is defined by cold, snowy winters and warm summers. The terrain is predominately postglacial hills with intermixed mountain ranges and coastal lowlands. Eighty percent of forest land is owned by private owners. Most of these landowners are non-corporate (70%), however, industrial owners hold significant acreage particularly in Maine and northern New York (Thompson et al. 2017a).

2.3.2. Timber harvest scenarios and implementation in SORTIE-ND

Our analyses compare five harvest scenarios that varied in magnitude and frequency of harvest, described fully in Brown et al. (2018a) (Table 1). The first harvest scenario represents the current harvest regime and is the baseline for comparison (Brown et al. 2018a). We used U.S. Forest Service Forest Inventory and Analysis (FIA) data to estimate current harvest regimes for six different forest types and regions in the study area: aspen-birch (*Populus* sp. – *Betula* sp.), spruce-fir (*Picea* sp. – *Abies* sp.), bottomland, oak-hickory (*Quercus* sp. – *Carya* sp.), northern hardwood-conifer forests in Maine, and northern hardwood-conifer forests in the remaining three states (New York, Vermont, New Hampshire) (Canham et al. 2013, Brown et al. 2018a). For each of the six forest type/regions, Brown et al. (2018a) quantified two components of the harvest regime: (1) the annual probability that a plot was harvested, and (2) the total amount of basal area removed if a plot was harvested. Using these components, Brown et al.

(2018a) compared five harvest regimes that varied in magnitude and frequency of harvest (Table 1). The best statistical model characterized the annual probability of harvest as a function of forest type/region, total plot basal area, and distance to the nearest improved road. This harvest regime represents current practices and is the baseline harvest regime (H1) for comparison with the other regimes.

In addition to the current harvest regime (H1), four alternate harvest scenarios were examined (Table 1) (Brown et al. 2018a). The second scenario increases average harvest intensity by 50% ("current harvest + intensity"; H2). The third scenario increases the frequency of harvests by 75%, keeping the current distribution of harvest intensity ("current harvest + frequency"; H3). The fourth scenario increases average harvest intensity by 50% and harvest frequency by 100% ("current harvest + intensity + frequency"; H4). For reference, the fifth scenario is a no harvest scenario ("no harvest"; H0).

The five harvest scenarios were executed in SORTIE-ND, a spatially explicit model of forest dynamics. SORTIE-ND follows individual seedlings, saplings, and adult trees over time through a sequence of behaviors, including the harvest regime (described above), tree growth and natural mortality, and seedling recruitment. For each harvest scenario, species structure and composition data from 5000 randomly selected FIA plots were used to initialize 5000 individual SORTIE-ND runs. Each run represents the predicted dynamics of a 4 hectare forest stand. The simulations utilize the 30 most common species in the study region, which were parameterized from FIA data (Canham and Murphy 2016a, b, Canham and Murphy 2017, Brown et al. 2018a). Climate change was incorporated into all scenarios consisting of a 3 degree C increase in mean annual temperature and a 10% increase in total annual precipitation over 100 years followed by stabilization (Horton et al. 2014). Natural disturbances like ice storm damage and beech bark disease are included in the model to the extent that their impacts are picked up in FIA plot data, however stochastic events are not explicitly incorporated. Outputs include detailed metrics of stand structure and composition, as well as the magnitude of harvest by species and tree size (DBH). SORTIE-ND partitions harvested biomass into six harvest product carbon pools according to U.S. Forest Service Timber Products Output (TPO) studies: softwood sawlogs, hardwood sawlogs, softwood pulp, hardwood pulp, softwood residues, and hardwood residues (Fig. 1, column B).

2.3.3. Bioenergy feedstock scenarios

To understand how changes in timber harvest affect net GHG emissions, we considered two bioenergy feedstock scenarios that determine the proportion of harvest products (Fig. 1, column B) that are used as energy feedstocks, including logging residues, chips, and pellets (Fig. 1, column C; Table 1). Logging residues from SORTIE-ND either stay in the forest and eventually decompose (Fig. 1, columns A and B), or are used for one of the three energy feedstocks. We treat feedstock and energy pools as “pass-through” pools and assume there is no biomass feedstock storage and that the feedstock pools are completely diverted to energy production in the year of harvest. The first scenario (F1) diverts 5% of hardwood and softwood sawlogs, 20% of hardwood and softwood pulpwood, and 25% of logging residue to energy feedstocks (“low feedstock” scenario). The second feedstock scenario (F2) diverts 20% of hardwood and softwood sawlogs, 80% of hardwood and softwood pulpwood, and 50% of logging residue to energy feedstock ("high feedstock" scenario). In all scenarios, 25% of sawmill residues are used as pellet feedstock (Buchholz et al. 2017), and harvest residues are equally divided between pellet, chip, and residue feedstocks in the low and high feedstock scenarios. In total, 8 scenarios representing alternative combinations of harvest (Table 1, scenarios H1, H2, H3, and H4) and feedstock scenarios (Table 1, scenarios F1 and F2) were considered. The ninth scenario is the no harvest comparison (H0), which does not generate energy feedstocks or other wood products.

2.3.4. Greenhouse gas accounting for wood products utilizing ForGATE

The output from the SORTIE-ND analyses of the effects of the different harvest regimes on forests and harvest levels reported in Brown et al. (2018a) provided the inputs to our analyses reported here. Specifically, we used the forest carbon stocks and harvest data from SORTIE-ND (Fig. 1; columns A and B) as inputs to calculate carbon storage and emissions associated with finished wood products and landfills, based on the ForGATE model of Hennigar et al. (2013) (Fig. 1; columns C, D, and E). Carbon in the pulpwood and sawlog pools is transferred to mill waste, energy feedstocks, and primary finished products (i.e., lumber, plywood, oriented strand board (OSB), nonstructural panels, pulp/paper) (Fig. 1, column C). From there, carbon is combusted as energy or transferred to five end-use product pools (i.e., construction materials, furniture, shipping products, paper, other) (Fig. 1, column D). Finally, all remaining wood product pools end up in one of two waste stream pools: landfills or incineration (Fig. 1, column E). Parameters such as product half lives and mill efficiencies are described fully in ForGATE (Hennigar et al. 2013). We assume the harvest product pools and primary finished products are pass-through pools, meaning carbon is transferred through these pools in the year of harvest. Alternatively, the five end-use product pools can accumulate or lose carbon over time, functioning as long-term carbon storage. Carbon in these pools is transferred to the waste stream at a fixed percentage loss per year (Smith et al. 2006, in Hennigar et al. 2013). A fraction of the carbon is transferred to landfills, a sixth long-term carbon storage pool, and the remainder is incinerated and immediately released into the atmosphere (Fig. 1, column E).

2.3.5. Net carbon sequestration calculation

We calculated ten sources of carbon emissions from forest system dynamics (three emission sources) and the forest product sector (seven emission sources) (Fig. 1, denoted by clouds). We only considered CO_2 emissions in forests, but included CH_4 landfill emissions. Forest CO_2 emissions result from the decomposition of hardwood and softwood detritus and mineral soil organic matter (Fig. 1, column A). Detrital pools are comprised of standing and downed coarse woody debris, fine woody debris from branches, tops, and harvested residue, and belowground dead material like coarse and fine roots. To estimate initial hardwood and softwood detrital pool sizes (13.8 and 9.2 Mg C/ha, respectively), we used detrital pool estimates from Birdsey and Lewis (2003) and apportioned the values according to the relative abundance of live hardwood and softwood trees in forests of the study area (60% and 40%, respectively). We assumed annual decomposition rates of 0.069 and 0.039 for hardwood and softwood detrital pools, respectively (Russell et al. 2014, Tonitto et al. 2014), and diverted a fraction of carbon in the detrital pools (0.005) to the mineral soil pool each year (Crowley et al. 2016). We assumed a mineral soil pool decomposition rate of 0.00075 (Tonitto et al. 2014) and an initial pool size of 151.95 Mg C/ha (Birdsey and Lewis 2003).

The remaining seven carbon emission sources are from the forest products sector, via waste decomposition and incineration, mill waste combustion, and wood energy production (Fig. 1, columns C, D, and E). First, a fixed proportion of long-term forest products are diverted annually to the waste stream, with 19.6% of the waste stream incinerated and 80.4% sent to landfills (EPA 2019). We assume the incineration pool is transferred immediately to the atmosphere as CO_2 emissions, whereas in landfills the carbon pool can increase or decrease over time. Landfill forest carbon decomposes at a rate of 0.0495/yr (Fig. 1), and emissions include both CO_2 (54%) and CH_4 (46%) (Hennigar et al. 2013). We account for the proportion of landfill CH_4 emissions that are effectively captured (37%) (Hennigar et al. 2013). The initial landfill carbon pool is estimated to be 2.17 Mg C/ha of forest land, based on Birdsey and Lewis (2003). Second, mill waste emissions (CO_2) are generated from the combustion of mill waste, after sawmill residues have been diverted to pellet feedstock. While many mills utilize cogeneration to produce electricity on site, we did not include that on-site energy as a part of the fossil fuel offset. We also assume complete combustion of the annual mill waste pool. The final three sources of forest product emissions (CO_2) are from wood bioenergy production (Fig. 1, column D). We assume the energy pools (pellets, chips, and residues) are fully utilized during the year the feedstock is generated and transferred immediately into the atmosphere. Although the ForGATE tool allows users to account for manufacturing and harvest and transport emissions (Hennigar et al. 2013), we did not include these emissions here. Harvest and transport emissions are a small component of the total forest products sector emissions (Gunn and Buchholz 2018). Manufacturing emissions can be more significant particularly from pulp and paper (Gunn and Buchholz 2018), however, given the variability in electricity inputs and process heat sources between timber products, these emissions were not incorporated.

The ten emissions outputs in combination with sequestration estimates from the harvest scenarios are used to calculate net carbon impact (total sequestration - total emissions), where total sequestration equals gross forest growth plus the annual changes in the forest product and landfill pools, and total emissions equals the ten summed emission sources. We define gross forest growth as the carbon removed from the atmosphere by forest growth, including net biomass increment plus natural mortality and harvested biomass.

2.3.6. Fossil fuel displacement scenarios

Finally, we examine six fossil fuel displacement scenarios, ranging from no offset to 50%, 60%, 70%, 80% and 90% of fossil fuel emissions displaced. For an equal amount of energy production, we define fossil fuel displacement as the fossil fuel emissions that are supplanted by forest bioenergy emissions. Therefore, this flexible approach can account for any specific conversion technology efficiencies. Given the higher energy density and greater efficiency of fossil fuel utilization, each ton of CO_2 emitted from biomass feedstock combustion produces energy that could displace less than one ton of CO_2 emitted from fossil fuel combustion. For example, to produce 15 million GJ of energy, it takes roughly 1 million metric tons of forest biomass in the form of chip feedstocks utilized in a commercial boiler to produce industrial heat at a 75% efficiency.

The same amount of energy would require approximately 402 million m^3 of natural gas. There are 1.7 million metric tons of CO_2 and 1.0 million metric tons CO_2 emissions associated with this quantity of woody biomass and natural gas, respectively. Therefore, woody biomass energy displaces 59% of fossil fuel emissions in this example.

To present the results, we converted CO_2 and CH_4 (using a 100-year global warming potential of 25) to a carbon dioxide equivalent value (CO_2e). Results are presented as a combination of harvest scenarios (H), bioenergy feedstock scenarios (F), and when applicable, include fossil fuel displacement scenarios in percent (Table 1). For example, H1/F1/50 is a scenario comprised of the current baseline harvest regime (H1) with low biomass feedstock utilization (F1), and assuming 50% fossil fuel displacement by bioenergy. We refer to the H1/F1 scenario as the business-as-usual scenario (BAU).

All of our analyses were conducted in R version 4.1.2 (R Core Team 2021), including recoding the ForGATE model from a spreadsheet format to R code capable of accepting SORTIE-ND input.

2.4. Results

2.4.1. Predicted harvest effects on carbon pools

The cumulative amount of carbon stored in all pools is estimated to increase in every harvest/feedstock scenario over the 100 year period from 2020 - 2119 (Fig. 2). Live tree biomass is the largest carbon pool in all scenarios and is projected to increase between 53.4% in the most intensive harvest regime (H4) and 102.4% in the no harvest scenario (H0). Across the 18.4 million hectares of forest land in New York, Vermont, New Hampshire, and Maine, an average of 50.0 Mg C/ha will accumulate between 2020

– 2119 based on the BAU scenario (H1/F1). The live tree and detritus carbon pools increase and stabilize after approximately 50 and 90 years respectively, whereas the mineral soil, forest product, and landfill forest carbon pools increase steadily across the entire time period (Fig. 2). The only exception to this pattern is the no harvest scenario (H0). Because no wood products are removed from the forest, the forest product carbon pool stays at zero, and the landfill forest carbon pool declines due to the decomposition in landfills in combination with no new wood product additions (Fig. 2).

As harvest intensity increases, the amount of total carbon stored across all pools decreases. The most intensive harvest scenario (H4/F1) accumulates 13.2% less carbon during the 100 year period than the BAU scenario. Although the forest products and landfill pools are larger than in the BAU scenario under the most intensive harvest scenario (27.7% and 48.8% respectively), the proportion of stored carbon accumulated in forest pools (live trees, coarse woody debris, and forest floor detritus) declines from 92.3% in the BAU scenario to 80.2% in H4/F1). Thus, the decline in live and detrital biomass pools under more intensive harvests more than offsets the increases in forest products and landfill pools (Table 2, Fig. 3). Diverting additional harvested wood and residues to energy feedstocks further reduces the total amount of carbon stored in each harvest/feedstock scenario due to a reduction in the carbon additions to the forest floor detritus and mineral soil pools, as well as to the forest products and landfill forest carbon pools. The no harvest scenario (H0) predicts more accumulated carbon in live trees alone (99.9 Mg C/ha) than the total accumulated carbon pools in all other harvest/feedback scenarios (Fig. 3).

As more harvest residue is removed from the forest and diverted to energy feedstocks, the forest floor and mineral soil pools accumulate less biomass across the landscape (Fig. 4). After 100 years, the additional residue removals from the forest when comparing H1/F1 and H1/F2 are estimated to decrease carbon storage in the forest floor pool and mineral soil pool by 3.2% and 3.4%, respectively. While the percent decreases in these carbon pools appear relatively small, across the entire northern forest landscape, the carbon storage losses total 16.3 million metric tons of C. Reductions in detrital carbon pools are exacerbated further when intensifying harvest is combined with greater use of logging residues as energy feedstocks. Forest floor and mineral soil carbon pools decrease by 16.5% and 12.9%, respectively, when comparing the least intensive harvest and feedstock scenario (H1/F1) to the most intensive harvest and feedstock scenario (H4/F2) (Fig. 4).

2.4.2. Predicted greenhouse gas implications of alternative harvest regimes

Of the scenarios that include logging (H1 - H4), net carbon sequestration is maximized in the baseline harvest scenario (H1) over the next 50 years. Sequestration steadily declines from the least intensive H1/F1 scenario to the most intensive H4/F2 scenario (H1/F1 = 195.3 Mg CO_2e/ha cumulative sequestration and 3.9 Mg CO_2e/ha/year; H4/F2 = 156.5 Mg CO_2e/ha cumulative sequestration and 3.1 Mg CO_2e/ha/year) (Table 3). This pattern is altered when fossil fuel displacement is considered. Net carbon sequestration increases as more fossil fuels are displaced by wood bioenergy. Therefore, when fossil fuel emissions are displaced by biomass energy emissions, high biomass feedstock scenarios (F2) result in greater net carbon sequestration as compared to the low biomass feedstock (F1) alternatives because there is a greater opportunity for fossil fuel substitution (Table 3, Fig. 5). In both feedstock scenarios, however, less intensive harvests almost always result in greater net CO_2e sequestration. Although there is less woody biomass to displace fossil fuels, it is more carbon beneficial to harvest less and maximize carbon storage in the forest.

Over 100 years, similar patterns emerge. In all cases, high biomass feedstock scenarios (F2) sequester more net CO_2e than low biomass feedstock scenarios (F1) and greater fossil fuel displacement results in higher overall net CO_2e sequestration (Fig. 5). All scenarios result in net positive carbon sequestration. By the end of the 100 year period, however, the annual rate of net CO_2e sequestration drops in some cases below zero, indicating that emissions are higher than sequestration (starting around year 60 for the intensively harvested H4/F1/0 and around year 85 for the baseline harvest regime H1/F2/0) (Fig. 5). Although the rate of net forest ecosystem sequestration decreases slightly due to forest maturation, increases in harvest-related emissions are the primary driver of the reduction in net sequestration over time, specifically landfill forest product emissions (Fig. 6). Methane from landfill forest products emits more CO_2e than all other harvested wood product sources, over 40 times the emissions from residue energy after 100 years in the BAU scenario (Fig. 6). Forest ecosystem carbon emissions from forest floor detritus and soil decomposition far exceed emissions from all other forest product sources, but large amounts of forest growth counterbalance and surpass the impact of decomposition (Fig. 6).

The no harvest scenario sequesters more carbon than all other harvest/feedstock/fossil fuel displacement scenarios at 50 years and 100 years, totaling

289.8 Mg CO_2e/ha (average 5.8 Mg CO_2e/ha/year) and 473.7 Mg CO_2e/ha (average 4.7 Mg CO_2e/ha/year), respectively (Table 3, Fig. 5). Even though harvested wood products store carbon, the amount is far outweighed by the magnitude of carbon sequestered and stored in unharvested forests. Annually, there is between 44 times (H4/F1) and 79 times (H1/F2) more carbon sequestered and stored in forests versus harvested wood products, given the current distribution of harvested material to the different product pools. The average annual rate of carbon sequestration in live tree biomass is slightly lower in the no harvest scenario compared with the BAU scenarios. Foregoing timber harvest, however, is still significantly more carbon positive when all sequestration and emissions variables are considered, including fossil fuel emissions displacement. Sequestration in harvested wood products is simply too low to outweigh the emissions associated with those pools.

2.5. Discussion

2.5.1. Net carbon impact of variation in forest harvest regimes

Our results, which include forest ecosystem and harvested wood product dynamics, indicate that harvest intensification decreases net carbon sequestration. The BAU scenario results in an average annual net carbon sequestration of 3.91 Mg CO_2e/ha/year for forests in the 4 northeastern states over the next 50 years and outperforms all other low feedstock scenarios (Table 3). This represents our best approximation of future sequestration based on current forest inventory, forest growth, and harvest levels. Intensifying the baseline harvest regime reduces net carbon sequestration in almost all harvest/feedstock scenarios relative to this baseline (Table 3), yet all scenarios result in net positive carbon outcomes over the next 50 years. An increase in harvest emissions (landfill decay, waste incineration, mill processing, and bioenergy production) resulting from intensified management drives the reduction in overall net carbon sequestration. While harvested wood product sequestration grows substantially, it is not enough to counterbalance the rise in harvest emissions, especially landfill methane emissions (Fig. 5). Even though harvested wood product sequestration is 26% greater in the most intensive harvest regime (H4/F1) when compared to the baseline harvest regime (H1/F1), it only contributes about 2% percent of total sequestration. Contrary to studies that suggest more intensely managed forests reduce net CO_2e emissions (Malmsheimer et al. 2008, Peckham et al. 2012, Lundmark et al. 2014, Kilpeläinen et al. 2016), our results are consistent with other recent studies in the region and show that more intensive forest management regimes often result in worse carbon mitigation outcomes (Nunery and Keeton 2010, Mika and Keeton 2015, Buchholz et al. 2017, Gunn and Buchholz 2018). Specifically, Mika and Keeton (2015) demonstrated that wood bioenergy harvests increase net CO_2 emissions relative to timber management that does not contribute to bioenergy, although both scenarios result in net positive sequestration. Shifting management toward structural retention practices and decreasing harvest frequency can significantly increase C sequestration (Nunery and Keeton 2010).

Three critical components of our analyses interact and affect this conclusion: (i) the harvest regime and amount of forest biomass removal, (ii) the degree to which bioenergy displaces fossil fuel use, and (iii) the proportion of biomass diverted to energy feedstocks and wood products (Table 3, Fig. 5). The intensity of harvest and amount of biomass removal determine whether carbon pools grow or diminish. The cumulative amount of carbon storage increases in all harvest scenarios (Fig. 2), largely due to increases in forest biomass (live trees, forest floor detritus, and mineral soil organic matter), and may be sensitive to climate changes (Thom et al. 2019). Carbon stored in harvest pools (forest products and landfills) also increases, but to a much lesser degree (Fig. 2). Although every harvest scenario predicts substantial increases in cumulative carbon storage across all carbon pools over time (Fig. 2), intensified management reduces the magnitude of the increases (Fig. 3). More intensively harvested landscapes in this region will equilibrate at lower average forest carbon stocks than less intensively managed landscapes (Brown et al. 2018a). At the same time harvested wood products and associated bioenergy emissions increase (Figs. 2 and 3). Our results clearly indicate that reduced accumulation of forest carbon across the landscape from increased harvest outweighs additional forest product carbon storage (Nunery and Keeton 2010) and the potential benefits of fossil fuel displacement over the next 50 years. The one exception occurs when we assume a very high (90%) efficiency of fossil fuel emissions displacement. In that case, the most intensive harvest regime/high feedstock scenario (H4/F2/90) sequesters slightly more net CO_2e (0.05 Mg CO_2e/ha) on average than the baseline harvest/high feedstock scenario (H1/F2/90). This suggests that the benefits of fossil fuel displacement can overshadow the reduction of forest ecosystem carbon in some cases, although the current harvest regime (H1/F2/90) accumulates more carbon than the intensive harvest regime (H4/F2/90) for nearly four decades. Because this result is driven primarily by fossil fuel displacement it may be overly optimistic over longer time horizons. Fossil fuel displacement is expected to decline as fossil fuel use transitions to carbon-neutral energy sources (Liddle and Sadorsky 2017), and renewable energy use is predicted to increase annually over the next several decades (EIA 2022).

In scenarios that divert less biomass to energy production (F1 scenarios), more biomass is converted into wood products and consequently waste pools are larger. In these scenarios annual emissions eventually surpass sequestration, and the annual rate of net sequestration goes below zero (Fig. 5). That decrease in net sequestration over time is primarily due to a rise in emissions from harvested wood products, especially potent emissions of methane from landfills. Emissions surpass sequestration sooner in scenarios that divert more biomass to wood products and waste pools (F1 scenarios). For example, assuming 50% of fossil fuel emissions can be displaced by wood energy, the rate of sequestration shifts to negative after 64 years for the most intensive harvest scenario with low biomass energy diversion (H4/F1) and 78 years for the BAU scenario (H1/F1) (Fig. 5). A second factor contributing to the decline in the overall rate of net sequestration is forest maturation. Our BAU harvest regime models estimate that the distribution of stand biomass across the landscape equilibrates after about 60 years when forest gross growth roughly equals natural mortality plus harvest removals.

Timeframe becomes particularly important when considering forest climate mitigation. The point in time when an alternative harvest regime cumulatively sequesters more carbon than the baseline is known as the carbon sequestration parity point (Mitchell et al. 2012, Jonker et al. 2014). In our analysis, the BAU scenario is the most favorable throughout the entire time period when compared to other low feedstock utilization scenarios (F1 scenarios). As harvest intensity and/or energy feedstocks increase, sequestration rates vary and the carbon sequestration parity point ranges from 12 years (BAU scenario with greater feedstocks (H1/F2/50) to 40 years for the most intense harvest and feedstock scenario (H4/F2/50), respectively. This means that assuming 50%

fossil fuel emissions displacement the BAU scenario outperforms the higher feedstock scenario H1/F2/50 until year 2032. Notably, the no harvest scenario (H0) sequesters more carbon than all harvest/feedstock/displacement scenarios for all timeframes (Table 3, Fig. 5). We stress that the no harvest result is solely for comparative purposes and ignores the social and economic consequences of halting harvests across the study region, and that demand for forest products would be displaced to other regions ("leakage"), potentially with far worse carbon consequences.

2.5.2. Harvest effects on landscape forest carbon pools

The increase in cumulative carbon storage is largely due to the predicted increases in average forest biomass across the study area in all harvest scenarios. The current distribution of biomass in northeastern forests, which skews toward early and mid-successional biomass classes (Brown et al. 2018a), still reflects intensive land use from the nineteenth and twentieth centuries (Thompson et al. 2013). This, in addition to the partial harvest regimes characteristic of the northeastern U.S. (Brown et al. 2018a), allows for significant amounts of future projected carbon accumulation (Thompson et al. 2011, Duveneck et al. 2017, Wang et al. 2017, Brown et al. 2018a).

A key feature of our model is the incorporation of the baseline harvest regime, calculated using FIA data, and the harvest effects on future forest composition, structure, and productivity. The resulting regional-scale predictions account for the small percentage of lands that are being harvested each year and the majority of the forested landscape that continues to accumulate biomass (Fig. 2). This issue of scale is important. When a stand is logged to generate biomass energy, carbon is immediately released to the atmosphere through feedstock combustion, and more gradually through decomposition of logging residues, and then slowly removed from the atmosphere during forest regrowth. While this is true of an individual stand, it does not reflect the landscape-scale implications of harvest, forest growth, and biomass energy combustion. For the four northeastern states, roughly 3% of the non-reserved forestland is harvested in any given year, with a mean harvest intensity of approximately 30% of live biomass (Brown et al. 2018a). The emissions that year that are due to those harvests are more than balanced in the same year by the net sequestration of the remaining 97% of the forestland that was not harvested that year.

2.5.3. Carbon implications of use of logging residue as a biomass energy feedstock

Despite the predicted increase in overall forest biomass, any removal of harvest residue from the forest will decrease the forest floor and mineral soil carbon pools (Canham 2013). In contrast to several studies that suggest little or no carbon storage effects from residue feedstock utilization (Ranius et al. 2018), our analyses show a reduction in forest floor and mineral soil carbon pools as harvests intensify, greater amounts of feedstock are utilized for bioenergy, or both (Fig. 3). While the annual reductions in forest floor and mineral soil carbon storage are small, doubling the amount of harvest residue removed from the forest and used as energy feedstock from 25% to 50% results in a 16.3 million metric ton C loss in forest detritus over 100 years (Fig. 4). This is the equivalent of losing 0.1 metric tons of detrital carbon storage for every metric ton of biomass residue removed from the forest. Thus, there is a clear tradeoff between increasing the amount of residue available for energy feedstocks and decreasing carbon storage across the landscape.

At question is whether the utilization of logging residues results in a carbon positive outcome overall. Using logging residues as an energy feedstock has garnered special attention due to an assumption that its use is inherently carbon neutral. That assumption is based on the premise that the emissions released while converting residues to bioenergy would have been released anyway through decomposition, thereby making the practice carbon neutral. However, intensifying harvests to generate additional logging residues for biomass energy production does not offset the reduction in detrital carbon pools and results in net negative carbon outcomes (Table 3, Fig. 5). The carbon impact of utilizing greater amounts of logging residues for bioenergy within the BAU harvest regime is less obvious, however. Over a 100 year time period, 4.58 Mg C/ha of additional cumulative logging residues are available for energy production when comparing the baseline (BAU) harvest regime high (F2) and low (F1) feedstock scenarios. As more woody material is available to displace fossil fuel emissions and the displacement becomes more efficient, carbon benefits will increase (Table 3). Yet, solely increasing the use of residues as an energy feedstock yields an exceedingly small net carbon benefit (<1%) after 50 years, even when assuming maximum emissions displacement (Supplement 1). Furthermore, using additional residues for energy can only displace less than 1% of current fossil fuel consumption in NY, VT, NH, and ME (Supplement 1). We have focused here solely on the carbon consequences of removal and utilization of logging residues. In a broader context, those residues serve a wide array of ecological functions as a major input to detrital pools in northeastern forests (Aber et al. 1978).

Harvest effects on stand structure characteristics, such as downed woody debris, have implications for habitat function and biodiversity as well as co-varying landscape-scale carbon storage (Littlefield and Keeton 2012, Schwenk et al. 2012, Thom and Keeton 2019, Thom and Keeton 2020).

2.5.4. Forest biomass energy equivalent

Our results are fundamentally about tradeoffs. Intensified harvests yield more wood products, but reduce storage in live biomass in forests. Removal of logging residue (tops and limbs) reduces carbon storage in detrital pools, but can potentially provide limited displacement of fossil fuel emissions when used as a biomass energy feedstock. Net carbon sequestration is lower with intensified harvest, but is affected by the magnitude of fossil fuel substitution. The question must be asked – what is the potential energy return of all these tradeoffs? We project that the BAU scenario generates an average of 4.8 million metric tons of biomass energy feedstocks annually over the next 20 years in the 4-state region. Roughly 2.2% of current levels of fossil fuel energy use could be displaced by these biomass energy feedstocks by our estimates, assuming a biomass energy conversion efficiency of 0.8, which is consistent with combined heat and power plants producing electricity and residential and commercial heat (Supplement 1).

2.5.5. Limitations

We do not directly address leakage in this study. Because energy feedstocks increase at the expense of traditional wood products (F2 scenarios), there is a possibility that sourcing the replacement wood products could be driven outside of the study area. In addition to global implications of leakage, the bioenergy market in the northeast U.S. is currently not the driver of shifts in use of harvested wood products. Biomass harvests are almost always a by-product of integrated operations that include other products like timber and pulp (Buchholz et al. 2019, Quinn et al. 2020). Although the volume is substantial, the price for biomass is noncompetitive with other products, (Buchholz et al. 2019). Even so, studies show an appropriate leakage rate may be around 80% or even higher (Wear and Murray 2004, Gan and McCarl 2007, Pan et al. 2020), indicating that timber harvests could be reduced only slightly (< 20%) without triggering leakage. Based on the no harvest scenario (H0), we would expect a small reduction in harvest to yield higher net carbon sequestration than the BAU scenario, suggesting a role for forest conservation in climate mitigation policies (Gunn and Buchholz 2018).

While many studies choose a specific fossil fuel alternative to bioenergy for GHG analyses, we opted for a more flexible approach. Our analysis presents a range of potential displacement factors regardless of specific energy conversion technologies or comparisons with particular energy alternatives. It is worth emphasizing, however, that as fossil fuel use declines and renewable energy production increases, wood will compare less favorably as an energy substitution. This transition to renewables will reduce net carbon benefits as the energy mix becomes more carbon neutral and fossil fuel displacement becomes less relevant.

2.5.6. Conclusions

There is clearly a role for managed forests in mitigating greenhouse gas emissions (Griscom et al. 2017, Fargione et al. 2018, P.R. Shukla et al. 2019). The questions are to what degree and under what circumstances? Our analyses indicate that the BAU scenario in New York, Vermont, New Hampshire, and Maine sequesters more carbon over the next decade than any of the intensified harvest scenarios and increased feedstock utilization rates we examined. Modest reductions in harvest levels that do not trigger leakage would be expected to increase net carbon sequestration compared to current management. Our results suggest that any increase in the regional harvest regime will reduce net carbon sequestration in the landscape over climate policy-relevant time scales, even when more of the harvest is diverted to biomass energy production at very high assumed efficiency in displacing fossil fuel emissions. While all harvest/feedstock scenarios become more carbon competitive when fossil fuel emissions are displaced through wood energy, the transition to carbon-neutral energy sources will reduce the net carbon benefits of fossil fuel displacement over time.

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2.7. Tables and Figures

2.7.1. Tables

Table 2.1. Harvest and biomass feedstock scenarios.

Harvest or Biomass Feedstock Scenario	**Harvest or Biomass Feedstock Scenario Definition**
No harvest (H0)	No harvest regime
Current harvest (H1)	The current harvest regime characterized as a function of forest type/region, total plot basal area, and distance to the nearest improved road, including a 3 degree C increase in mean annual temperature and a 10% increase in total annual precipitation over the next 100 years (Brown et al. 2018)
Current harvest + intensity (H2)	The current harvest regime and a 50% increase in average harvest intensity
Current harvest + frequency (H3)	The current harvest regime and a 75% increase in harvest frequency
Current harvest + intensity + frequency (H4)	The current harvest regime, a 50% increase in average harvest intensity, and a 100% increase in harvest frequency
Low feedstock (F1)	5% of hardwood and softwood sawlogs diverted to chip and pellet energy feedstocks; 20% of hardwood and softwood pulpwood diverted to energy feedstocks; 25% of logging residue diverted to energy feedstocks
High feedstock (F2)	20% of hardwood and softwood sawlogs diverted to chip and pellet energy feedstocks; 80% of hardwood and softwood pulpwood diverted to energy feedstocks; 50% of logging residue diverted to energy feedstocks

Table 2.2. Carbon pools in each harvest/feedstock scenario after 100 years (metric tons C/ha). All carbon pools include the initial condition for each pool (average metric tons C/ha across the landscape at the start of each scenario) plus the accumulated carbon for 100 years, except the forest products pool. The forest products pool only includes accumulated carbon.

Carbon Pools	H0	H1F1	H1F2	H2F1	H2F2	H3F1	H3F2	H4F1	H4F2
Live Trees	172.6	117.7	117.7	113.2	113.2	105.5	105.5	99.0	99.0
CWD and Detritus	60.5	50.5	49.6	49.5	48.5	48.0	46.9	47.2	45.9
Mineral Soil	162.8	161.2	160.9	161.0	160.7	160.7	160.2	160.5	160.0
Forest Products	0.0	8.7	5.5	9.3	5.8	10.3	6.1	11.1	6.2
Landfill	0.0	6.2	3.7	6.7	3.9	7.5	4.1	8.2	4.1
Total	396.0	344.3	337.5	339.8	332.0	332.0	322.8	326.0	315.3

Table 2.3. Cumulative net CO2e sequestration (metric tons C/ha) resulting from nine harvest (H) and feedstock (F) scenarios after 50 years. The percent displacement refers to the amount of fossil fuel emissions that are displaced by wood biomass emissions.

Scenario	**No displacement**	**50% displacement**	**60% displacement**	**70% displacement**	**80% displacement**	**90% displacement**
H0	289.8	289.8	289.8	289.8	289.8	289.8
H1/F1	195.3	209.3	212.1	214.9	217.7	220.5
H1/F2	194.5	227.2	233.7	240.2	246.7	253.3
H2/F1	186.7	202.7	205.9	209.1	212.3	215.5
H2/F2	185.5	223.1	230.6	238.1	245.6	253.2
H3/F1	168.4	187.5	191.4	195.2	199.0	202.8
H3/F2	166.9	212.5	221.6	230.7	239.8	248.9
H4/F1	158.6	181.1	185.6	190.1	194.6	199.1
H4/F2	156.5	211.0	221.9	232.8	243.7	254.6

2.7.2. Figures

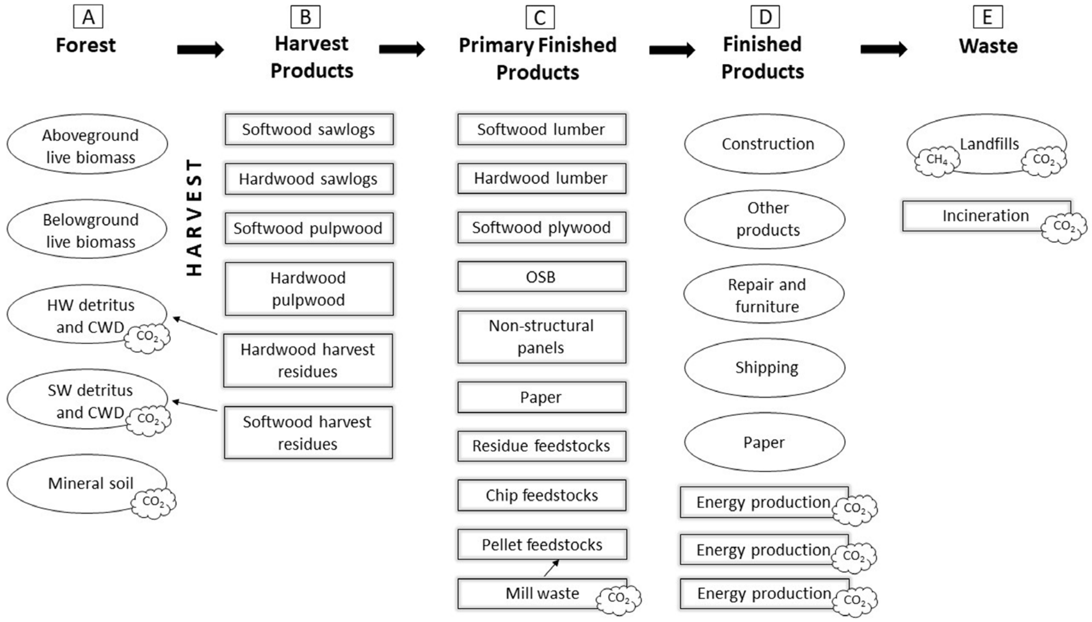

Figure 2.1. Carbon transfer from forest pools through waste pools and release to the atmosphere. Forest carbon (column A) is transferred to harvest products (column B) as defined by each harvest regime (Brown et al. 2018a). Carbon in harvest product pools (column B) is transferred to end products, waste pools, or the atmosphere (columns C, D, and E) based on ForGATE (Hennigar et al. 2013). Ovals indicate carbon pools that can accumulate or decline, rectangles represent annual pass-through pools, and clouds represent GHG emissions.

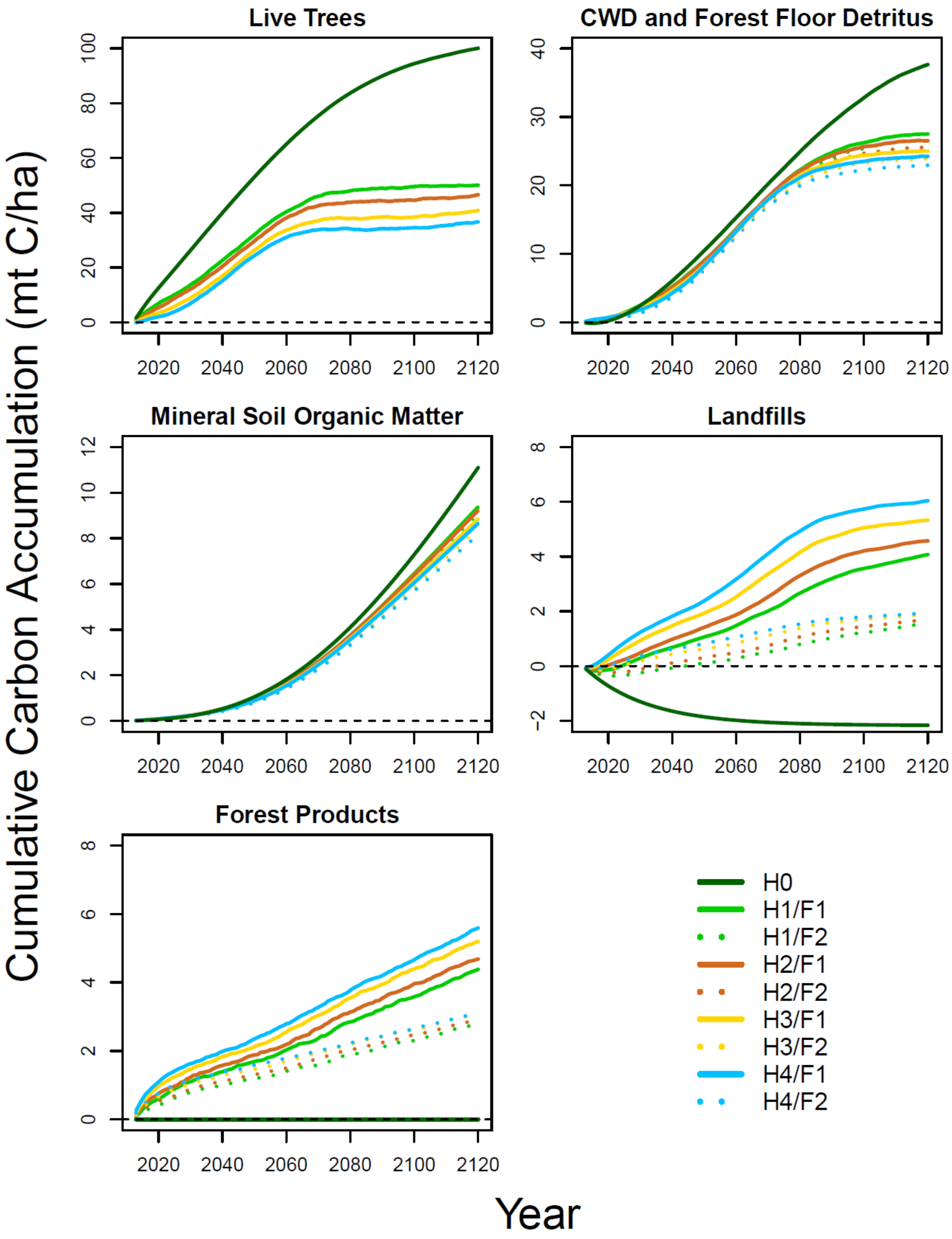

Figure 2.2. Carbon accumulation in all carbon pools over 100 years resulting from harvest (H) and feedstock (F) scenarios. The live tree panel shows overlapping results when the harvest scenarios are the same, but the feedstock scenarios differ. The harvest scenario determines the live tree biomass results, not the feedstock scenario.

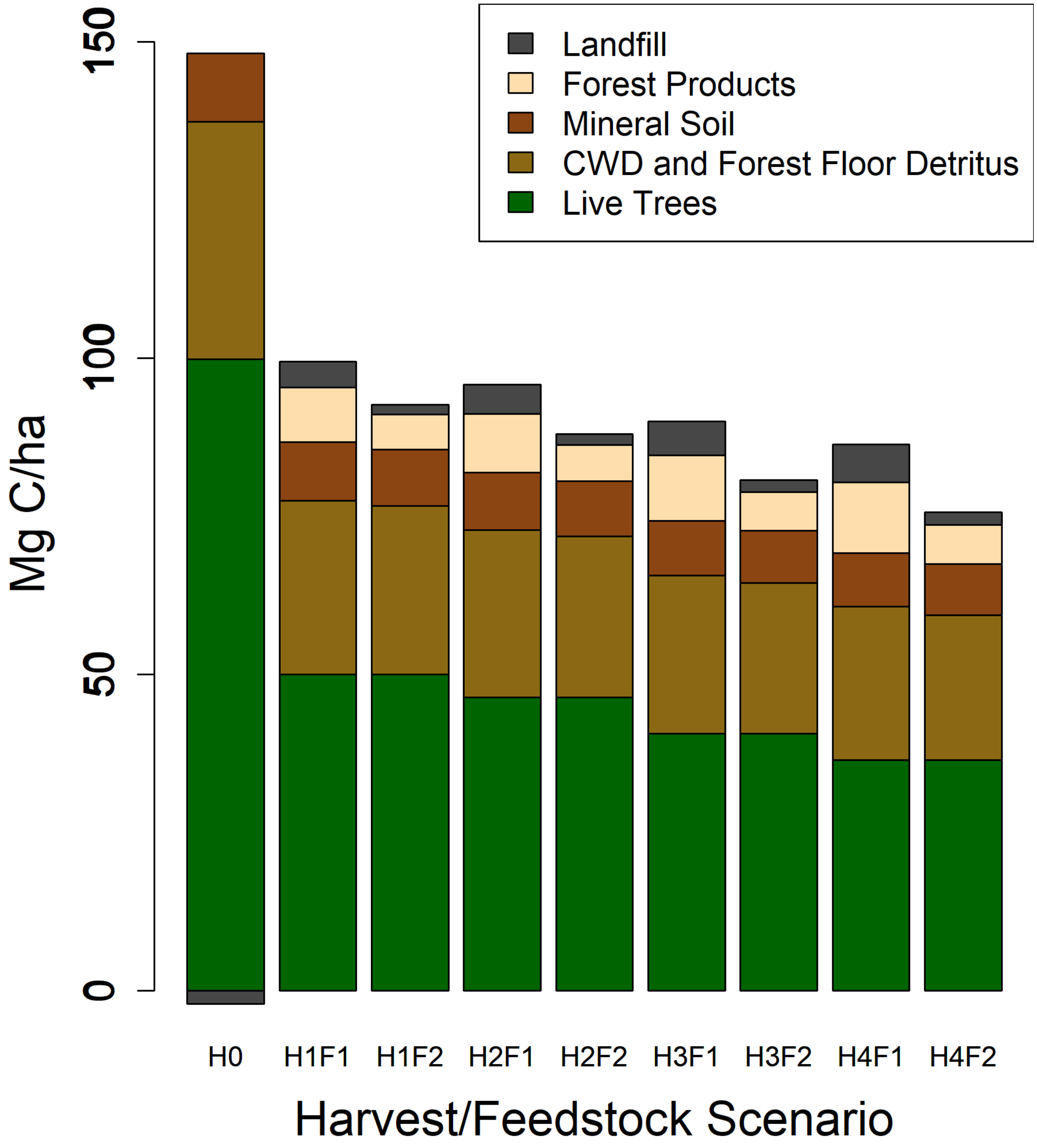

Figure 2.3. Total carbon (Mg/ha) stored in five pools - live trees, coarse woody debris and forest floor detritus, mineral soil, forest products, and landfill forest carbon pools - after 100 years resulting from nine harvest (H) and feedstock (F) scenarios.

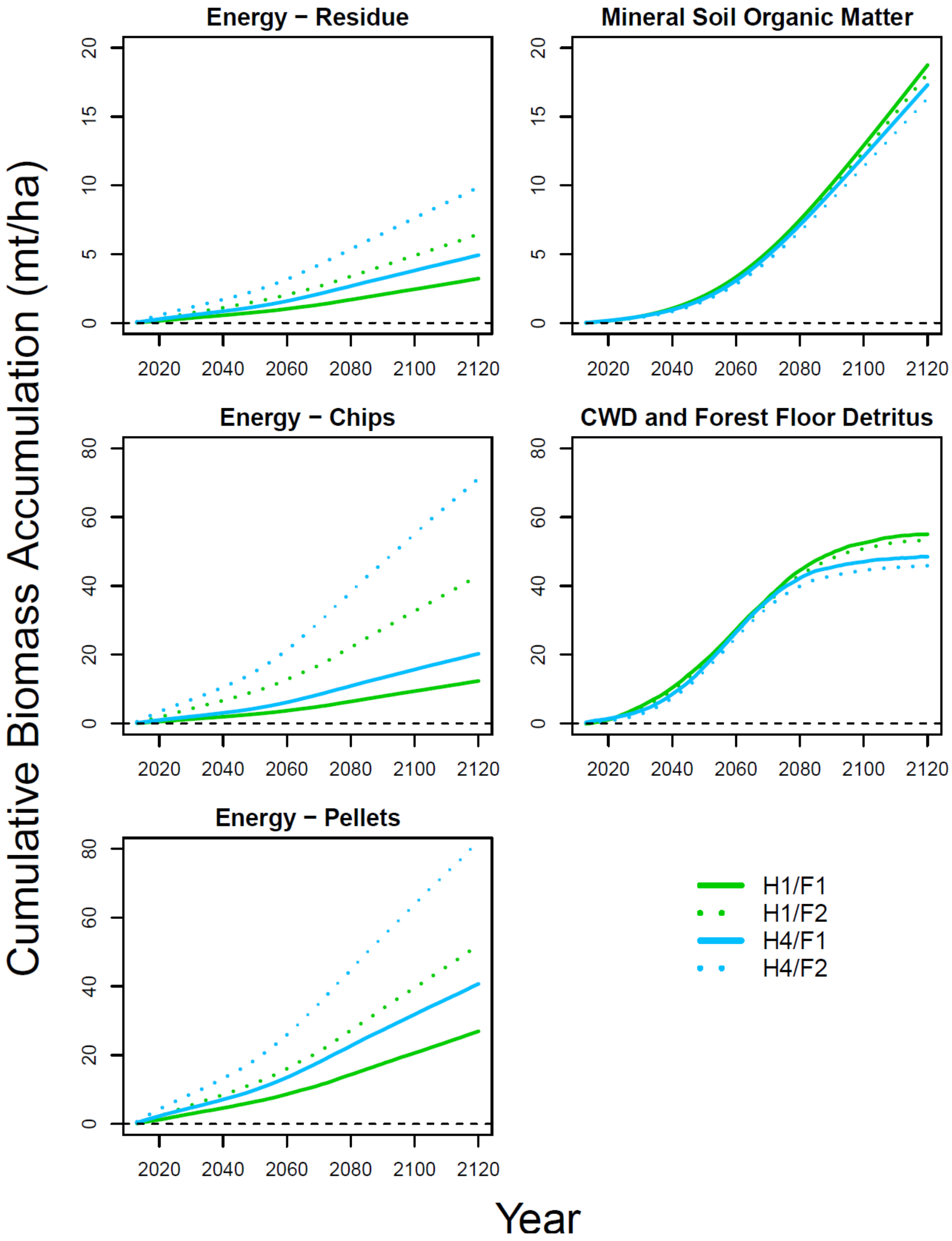

Figure 2.4. Biomass accumulation in coarse woody debris and forest floor detritus, mineral soil, and three energy feedstock carbon pools – logging residues, chips, and pellets – after 100 years. The baseline harvest regime (H1) is being compared with the most intensive harvest regime (H4) across two feedstock scenarios. F1 diverts 25% and F2 diverts 50% of logging residues from the forest to energy feedstocks.

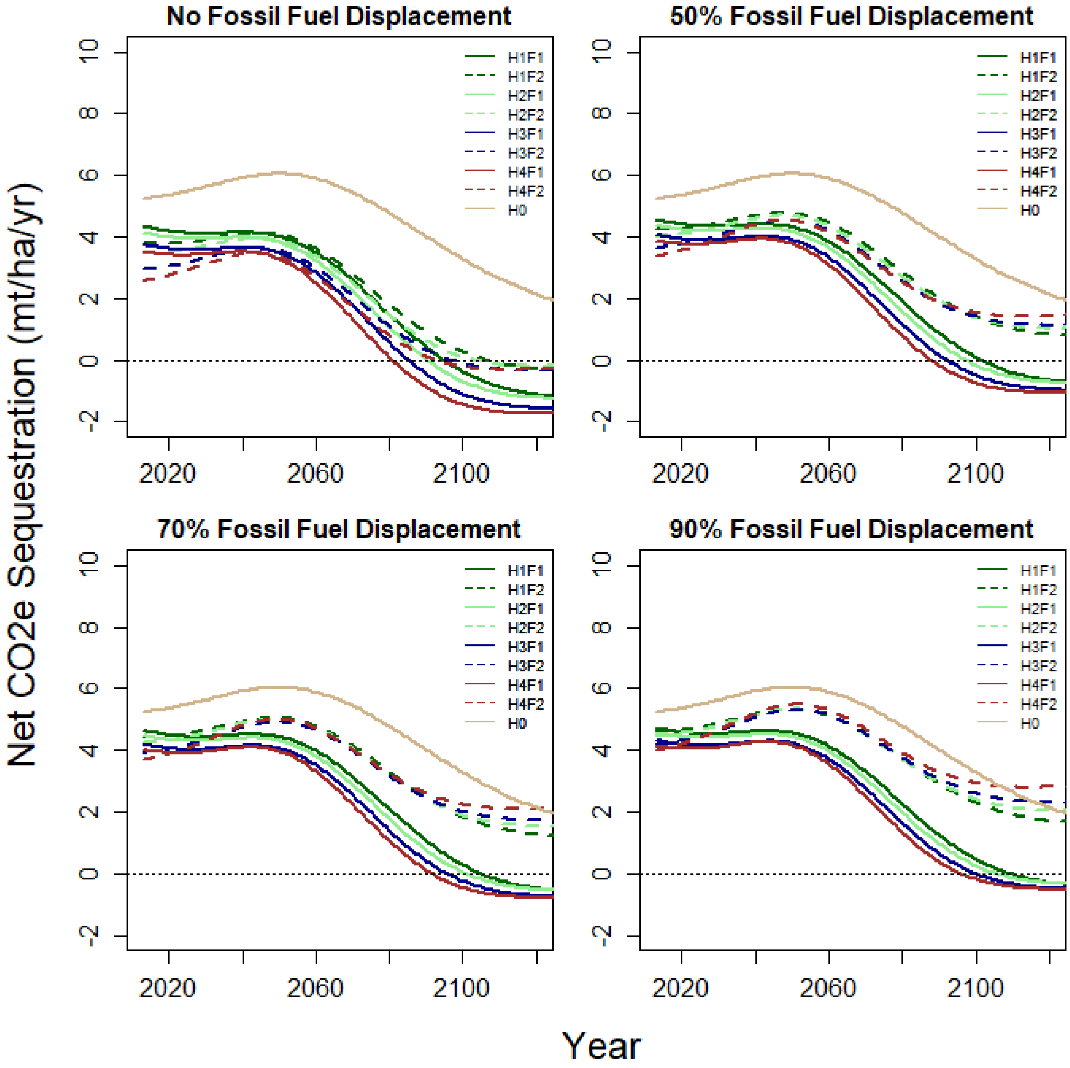

Figure 2.5. Net CO$_2$e sequestration (Mg C/ha/year) resulting from nine harvest (H) and feedstock (F) scenarios over 100 years. The percent displacement refers to the amount of fossil fuel emissions that are displaced by wood biomass emissions.

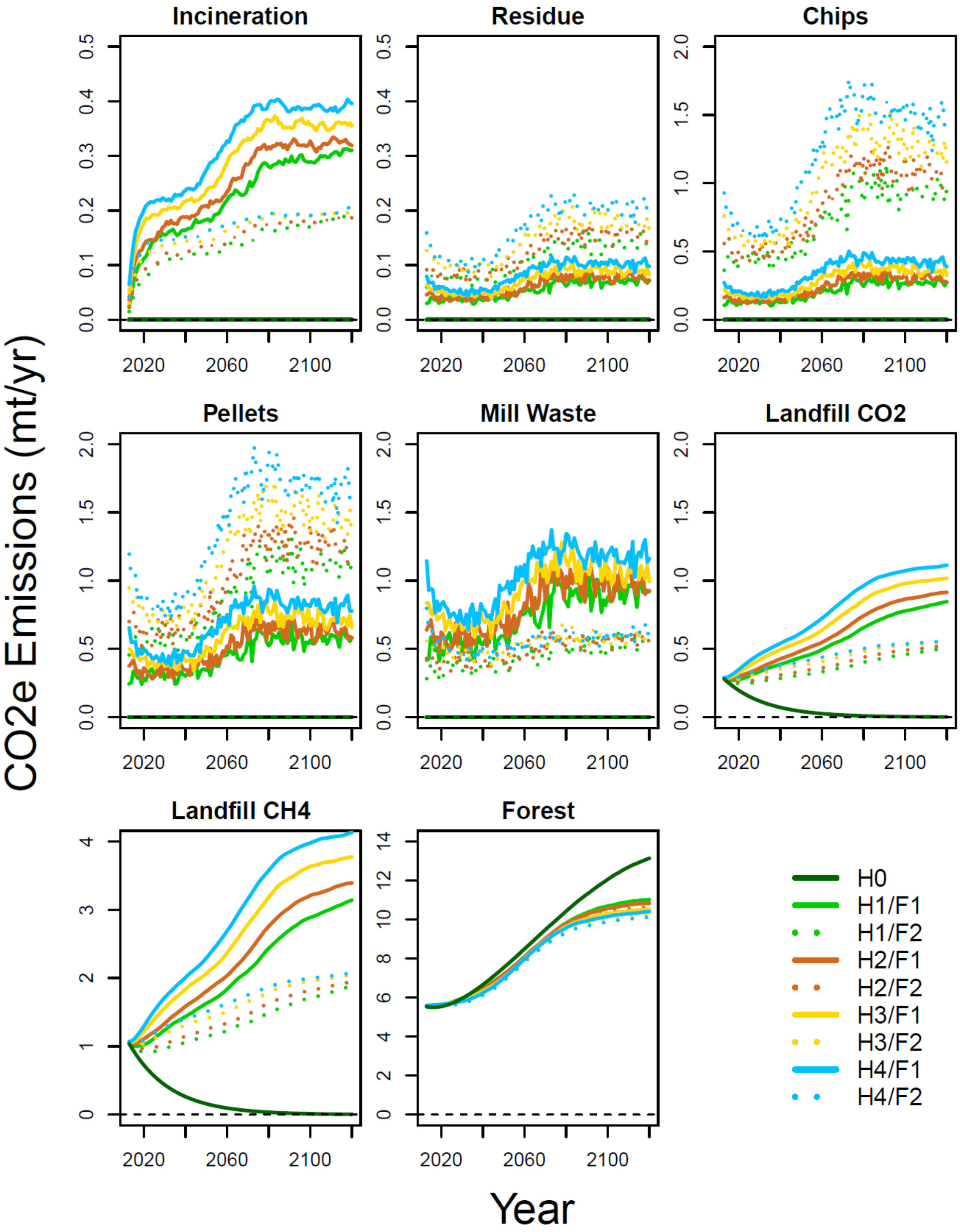

Figure 2.6. Emissions (Mg of CO_2e/year) from eight different sources resulting from harvest (H) and feedstock (F) scenarios over 100 years.

2.8. References

Aber, J. D., D. B. Botkin, and J. M. Melillo. 1978. Predicting effects of different harvesting regimes on forest floor dynamics in northern hardwoods. Canadian journal of forest Research-Revue Canadienne De Recherche Forestiere **8**:306-315.

Birdsey, R., P. Duffy, C. Smyth, W. A. Kurz, A. J. Dugan, and R. Houghton. 2018. Climate, economic, and environmental impacts of producing wood for bioenergy. Environmental Research Letters **13**:050201.

Birdsey, R. A., and B. M. Lewis. 2003. Carbon in U.S. forests and wood products, 1987–1997: state-by-state estimates. Gen. Tech. Rep. NE-310, Washington, DC: U.S. Department of Agriculture, Forest Service.

Bradford, J. B., and D. N. Kastendick. 2010. Age-related patterns of forest complexity and carbon storage in pine and aspen-birch ecosystems of northern Minnesota, USA. Canadian Journal of Forest Research **40**:401-409.

Brown, M. L., C. D. Canham, L. Murphy, and T. M. Donovan. 2018a. Timber harvest as the predominant disturbance regime in northeastern U.S. forests: effects of harvest intensification. Ecosphere **9**:e02062.

Buchholz, T., J. S. Gunn, and D. S. Saah. 2017. Greenhouse gas emissions of local wood pellet heat from northeastern US forests. Energy **141**:483-491.

Buchholz, T., J. S. Gunn, and B. Sharma. 2021. When Biomass Electricity Demand Prompts Thinnings in Southern US Pine Plantations: A Forest Sector Greenhouse Gas Emissions Case Study. Frontiers in Forests and Global Change **4**.

Buchholz, T., W. S. Keeton, and J. S. Gunn. 2019. Economics of integrated harvests with biomass for energy in non-industrial forests in the northeastern US forest. Forest Policy and Economics **109**:102023.

Canham, C. D. 2013. Carbon cycle implications of forest biomass energy production in the northeastern United States. In M. Jacobson and D. Ciolkosz, editors. Wood-based Energy in the Northern Forests. Pages 61-78. Springer, New York.

Canham, C. D., and L. Murphy. 2016a. The demography of tree species response to climate: sapling and canopy tree growth. Ecosphere 7(10):e01474. 10.1002/ecs2.1474.

Canham, C. D., and L. Murphy. 2016b. The demography of tree species response to climate: seedling recruitment and survival. Ecosphere 7(8):e01424. 10.1002/ecs2.1424.

Canham, C. D., and L. Murphy. 2017. The demography of tree species response to climate: sapling and canopy tree survival. Ecosphere 8(2):e01701. 10.1002/ecs2.1701.

Canham, C. D., N. Rogers, and T. Buchholz. 2013. Regional variation in forest harvest regimes in the northeastern United States. Ecological Applications **23**:515-522.

Coates, K. D., C. D. Canham, M. Beaudet, D. L. Sachs, and C. Messier. 2003. Use of a spatially explicit individual-tree model (SORTIE/BC) to explore the implications of patchiness in structurally complex forests. Forest Ecology and Management **186**:297-310.

Crowley, K. F., G. M. Lovett, M. A. Arthur, and K. C. Weathers. 2016. Long-term effects of pest-induced tree species change on carbon and nitrogen cycling in northeastern U.S. forests: A modeling analysis. Forest Ecology and Management **372**:269-290.

Domke, G. M., B. F. Walters, D. J. Nowak, J. E. Smith, S. M. Ogle, J. W. Coulston, and T. C. Wirth. 2020. Greenhouse gas emissions and removals from forest land, woodlands, and urban trees in the United States, 1990-2018. . Resource Update FS-227. Madison, WI: U.S. Department of Agriculture, Forest Service, Northern Research Station. 5 p.

Drever, C. R., S. C. Cook-Patton, F. Akhter, P. H. Badiou, G. L. Chmura, S. J. Davidson, R. L. Desjardins, A. Dyk, J. E. Fargione, M. Fellows, B. Filewod, M. Hessing-Lewis, S. Jayasundara, W.S. Keeton, T. Kroeger, T.J. Lark, E. Le, S.M. Leavitt, M.E. LeClerc, T.C. Lemprière, J. Metsaranta, B. McConkey, E. Neilson, G.P. St-Laurent1, D. Puric-Mladenovic, S. Rodrigue, R.Y. Soolanayakanahally, S.A. Spawn, M. Strack, C. Smyth, N. Thevathasan, M. Voicu, C.A. Williams, P.B. Woodbury, D.E. Worth, Z. Xu, S. Yeo, and W. A. Kurz. 2021. Natural climate solutions for Canada. Science Advances **7**:eabd6034.

Duveneck, M. J., J. R. Thompson, E. J. Gustafson, Y. Liang, and A. M. G. de Bruijn. 2017. Recovery dynamics and climate change effects to future New England forests. Landscape Ecology **32**:1385-1397.

Dwivedi, P., M. Khanna, and M. Fuller. 2019. Is wood pellet-based electricity less carbon-intensive than coal-based electricity? It depends on perspectives, baselines, feedstocks, and forest management practices. Environmental Research Letters **14**:024006.

EIA. 2022. Annual energy outlook 2022. U.S. Energy Information Administration, Washington, DC 20585.

EPA. 2019. National overview: Facts and figures on materials, wastes and recycling. United States Environmental Protection Agency. https://www.epa.gov/facts-and-figures-about-materials-waste-and-recycling/national-overview-facts-and-figures-materials#Combustion, accessed April 2019.

Fargione, J., J. Hill, D. Tilman, S. Polasky, and P. Hawthorne. 2008. Land Clearing and the Biofuel Carbon Debt. Science **319**:1235-1238.

Fargione, J. E., S. Bassett, T. Boucher, S. D. Bridgham, R. T. Conant, S. C. Cook-Patton, P. W. Ellis, A. Falcucci, J. W. Fourqurean, T. Gopalakrishna, H. Gu, B. Henderson, M. D. Hurteau, K. D. Kroeger, T. Kroeger, T. J. Lark, S. M. Leavitt, G. Lomax, R. I. McDonald, J. P. Megonigal, D. A. Miteva, C. J. Richardson, J. Sanderman, D. Shoch, S. A. Spawn, J. W. Veldman, C. A. Williams, P. B. Woodbury, C. Zganjar, M. Baranski, P. Elias, R. A. Houghton, E. Landis, E. McGlynn, W. H. Schlesinger, J. V. Siikamaki, A. E. Sutton-Grier, and B. W. Griscom. 2018. Natural climate solutions for the United States. Science Advances **4**:eaat1869.

Forsyth, D. M., D. J. Wilson, T. A. Easdale, G. Kunstler, C. D. Canham, W. A. Ruscoe, E. F. Wright, L. Murphy, A. M. Gormley, and A. Gaxiola. 2015. Century-scale effects of invasive deer and rodents on the dynamics of forests growing on soils of contrasting fertility. Ecological Monographs **85**:157-180.

Gan, J., and B. A. McCarl. 2007. Measuring transnational leakage of forest conservation. Ecological Economics **64**:423-432.

Griscom, B. W., J. Adams, P. W. Ellis, R. A. Houghton, G. Lomax, D. A. Miteva, W. H. Schlesinger, D. Shoch, J. V. Siikamäki, P. Smith, P. Woodbury, C. Zganjar, A. Blackman, J. Campari, R. T. Conant, C. Delgado, P. Elias, T. Gopalakrishna, M.

R. Hamsik, M. Herrero, J. Kiesecker, E. Landis, L. Laestadius, S. M. Leavitt, S. Minnemeyer, S. Polasky, P. Potapov, F. E. Putz, J. Sanderman, M. Silvius, E. Wollenberg, and J. Fargione. 2017. Natural climate solutions. Proceedings of the National Academy of Sciences **114**:11645.

Gunn, J. S., and T. Buchholz. 2018. Forest sector greenhouse gas emissions sensitivity to changes in forest management in Maine (USA). Forestry: An International Journal of Forest Research **91**:526-538.

Haberl, H., D. Sprinz, M. Bonazountas, P. Cocco, Y. Desaubies, M. Henze, O. Hertel, R. K. Johnson, U. Kastrup, P. Laconte, E. Lange, P. Novak, J. Paavola, A. Reenberg, S. van den Hove, T. Vermeire, P. Wadhams, and T. Searchinger. 2012. Correcting a fundamental error in greenhouse gas accounting related to bioenergy. Energy Policy **45**:18-23.

Hennigar, C., L. Amos-Binks, R. Cameron, J. S. Gunn, D. A. MacLean, and M. J. Twery. 2013. ForGATE - A Forest-sector GHG Assessment Tool for Maine: Calibration and Overview. Gen. Tech. Rep. NRS-116. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. 54pp.

Horton, R., G. Yohe, W. Easterling, R. Kates, M. Ruth, E. Sussman, A. Whelchel, D. Wolfe, and F. Lipschultz. 2014. Ch. 16: Northeast. In Climate Change Impacts in the United States: The Third National Climate Assessment. J. M. Melillo, T.C. Richmond, and G. W. Yohe, Eds. U.S. Global Change Research Program, 371-395, doi:10.7930/J0SF2T3P.

Hurtt, G. C., S. W. Pacala, P. R. Moorcroft, J. Caspersen, E. Shevliakova, R. A. Houghton, and B. Moore. 2002. Projecting the future of the U.S. carbon sink. Proceedings of the National Academy of Sciences **99**:1389-1394.

Jonker, J. G. G., M. Junginger, and A. Faaij. 2014. Carbon payback period and carbon offset parity point of wood pellet production in the South-eastern United States. GCB Bioenergy **6**:371-389.

Keeton, W. S. 2018. Source or sink? Carbon dynamics in old-growth forests and their role in climate change mitigation. Pages 267-288 in: Barton, A. and W.S. Keeton (eds.). Ecology and Recovery of Eastern Old-Growth Forests. Island Press, Washington, D.C. 340 pp.

Keeton, W. S., A. A. Whitman, G. C. McGee, and C. L. Goodale. 2011. Late-successional biomass development in northern hardwood-conifer forests of the northeastern United States. Forest Science **57**:489-505.

Kilpeläinen, A., A. Alam, P. Torssonen, H. Ruusuvuori, S. Kellomäki, and H. Peltola. 2016. Effects of intensive forest management on net climate impact of energy biomass utilisation from final felling of Norway spruce. Biomass and Bioenergy **87**:1-8.

Liddle, B., and P. Sadorsky. 2017. How much does increasing non-fossil fuels in electricity generation reduce carbon dioxide emissions? Applied Energy **197**:212-221.

Littlefield, C. E., and W. S. Keeton. 2012. Bioenergy harvesting impacts on ecologically important stand structure and habitat characteristics. Ecological Applications **22**:1892-1909.

Lundmark, T., J. Bergh, P. Hofer, A. Lundström, A. Nordin, B. Poudel, R. Sathre, R. Taverna, and F. Werner. 2014. Potential Roles of Swedish Forestry in the Context of Climate Change Mitigation. Forests **5**:557-578.

Malmsheimer, R. W., J. L. Bowyer, J. S. Fried, E. Gee, R. L. Izlar, R. A. Miner, I. A. Munn, E. Oneil, and W. C. Stewart. 2011. Managing forests because carbon matters: integrating energy, products, and land management policy. Journal of Forestry.

Malmsheimer, R. W., P. Heffernan, S. Brink, D. Crandall, F. Deneke, C. Galik, Gee, E., J. A. Helms, N. McClure, N. Mortimer, S. Ruddell, M. Smith, and J. Stewart. 2008. Preventing GHG emissions through wood substitution. Journal of Forestry **106**:132–135.

McGarvey, J. C., J. R. Thompson, H. E. Epstein, and H. H. Shugart. 2015. Carbon storage in old-growth forests of the Mid-Atlantic: toward better understanding the eastern forest carbon sink. Ecology **96**:311-317.

Mika, A. M., and W. S. Keeton. 2013. Factors contributing to carbon fluxes from bioenergy harvests in the U.S. Northeast: an analysis using field data. GCB Bioenergy **5**:290-305.

Mika, A. M., and W. S. Keeton. 2015. Net carbon fluxes at stand and landscape scales from wood bioenergy harvests in the US Northeast. GCB Bioenergy **7**:438-454.

Milbrandt, A. 2008. A Geographic Perspective on the Current Biomass Resource Availability in the United States. Technical Report NREL/TP-560-39181 2008 update, 70 p.

Mitchell, S. R., M. E. Harmon, and K. E. B. O'Connell. 2012. Carbon debt and carbon sequestration parity in forest bioenergy production. GCB Bioenergy **4**:818-827.

Nunery, J. S., and W. S. Keeton. 2010. Forest carbon storage in the northeastern United States: net effects of harvesting frequency, post-harvest retention, and wood products. Forest Ecology and Management **259**:1363-1375.

P.R. Shukla, J. Skea, R. Slade, R. van Diemen, E. Haughey, J. Malley, M. Pathak, and J. P. P. (eds.). 2019. Technical Summary. In: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems [P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M, Belkacemi, J. Malley, (eds.)]. In press.

Pan, W., M.-K. Kim, Z. Ning, and H. Yang. 2020. Carbon leakage in energy/forest sectors and climate policy implications using meta-analysis. Forest Policy and Economics **115**:102161.

Peckham, S. D., S. T. Gower, and J. Buongiorno. 2012. Estimating the carbon budget and maximizing future carbon uptake for a temperate forest region in the U.S. Carbon Balance and Management **7**:6.

Perlack, R. D., L. L. Wright, A. Turhollow, R. L. Graham, B. Stokes, and D. C. Erbach. 2008. Biomass as Feedstock for a Bioenergy and Bioproducts Industry: The Technical Feasibility of a Billion-Ton Annual Supply. Study prepared by Oak Ridge National Laboratory for the U.S. Department of Agriculture and the U.S. Department of Energy. 2008 update.

Quinn, R. J., H. Ha, T. A. Volk, T. R. Brown, S. Bick, R. W. Malmsheimer, and M. O. P. Fortier. 2020. Life cycle assessment of forest biomass energy feedstock in the Northeast United States. GCB Bioenergy **12**:728-741.

Ranius, T., A. Hämäläinen, G. Egnell, B. Olsson, K. Eklöf, J. Stendahl, J. Rudolphi, A. Sténs, and A. Felton. 2018. The effects of logging residue extraction for energy on ecosystem services and biodiversity: A synthesis. Journal of Environmental Management **209**:409-425.

Rhemtulla, J. M., D. J. Mladenoff, and M. K. Clayton. 2009. Historical forest baselines reveal potential for continued carbon sequestration. Proceedings of the National Academy of Sciences **106**:6082-6087.

Russell, M. B., C. W. Woodall, S. Fraver, A. W. D'Amato, G. M. Domke, and K. E. Skog. 2014. Residence Times and Decay Rates of Downed Woody Debris Biomass/Carbon in Eastern US Forests. Ecosystems **17**:765-777.

Schulze, E.-D., C. Körner, B. E. Law, H. Haberl, and S. Luyssaert. 2012. Large-scale bioenergy from additional harvest of forest biomass is neither sustainable nor greenhouse gas neutral. GCB Bioenergy **4**:611-616.

Schwenk, W. S., T. M. Donovan, W. S. Keeton, and J. S. Nunery. 2012. Carbon storage, timber production, and biodiversity: comparing ecosystem services with multi-criteria decision analysis. Ecological Applications **22**:1612-1627.

Searchinger, T., R. Heimlich, R. A. Houghton, F. Dong, A. Elobeid, J. Fabiosa, S. Tokgoz, D. Hayes, and T.-H. Yu. 2008. Use of U.S. Croplands for Biofuels Increases Greenhouse Gases Through Emissions from Land-Use Change. Science **319**:1238.

Searchinger, T. D., T. Beringer, and A. Strong. 2017. Does the world have low-carbon bioenergy potential from the dedicated use of land? Energy Policy **110**:434-446.

Searchinger, T. D., S. P. Hamburg, J. Melillo, W. Chameides, P. Havlik, D. M. Kammen, G. E. Likens, R. N. Lubowski, M. Obersteiner, and M. Oppenheimer. 2009. Fixing a critical climate accounting error. Science **326**:527.

Smith, J. E., L. S. Heath, K. E. Skog, and R. A. Birdsey. 2006. Methods for calculating forest ecosystem and harvested carbon, with standard estimates for forest types of the United States. Gen. Tech. Rep. NE-343. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northeastern Research Station. 216 p.

Sterman, J. D., L. Siegel, and J. N. Rooney-Varga. 2018. Does replacing coal with wood lower CO2 emissions? Dynamic lifecycle analysis of wood bioenergy. Environmental Research Letters **13**:015007.

Ter-Mikaelian, M. T., S. J. Colombo, and J. Chen. 2015. The Burning Question: Does Forest Bioenergy Reduce Carbon Emissions? A Review of Common Misconceptions about Forest Carbon Accounting. Journal of Forestry **113**:57-68.

Thom, D., and W. S. Keeton. 2019. Stand structure drives disparities in carbon storage in northern hardwood-conifer forests. Forest Ecology and Management **442**:10-20.

Thom, D., and W. S. Keeton. 2020. Disturbance-based silviculture for habitat diversification: Effects on forest structure, dynamics, and carbon storage. Forest Ecology and Management **469**:118132.

Thom, D., M. Golivets, L. Edling, G.W. Meigs, J.D. Gourevitch, L.J. Sonter, G. L. Galford, and W. S. Keeton. 2019. Climate sensitivity of carbon, timber, and species richness in the boreal-temperate ecotone co-varies with forest development. Global Change Biology **25**:2446–2458.

Thompson, J. R., C. D. Canham, L. Morreale, D. B. Kittredge, and B. Butler. 2017a. Social and biophysical variation in regional timber harvest regimes. Ecological Applications **27**:942-955.

Thompson, J. R., D. N. Carpenter, C. V. Cogbill, and D. R. Foster. 2013. Four centuries of change in northeastern United States forests. PLOS ONE 8(9): e72540. https://doi.org/10.1371/journal.pone.0072540.

Thompson, J. R., D. R. Foster, R. Scheller, and D. Kittredge. 2011. The influence of land use and climate change on forest biomass and composition in Massachusetts, USA. Ecological Applications **21**:2425-2444.

Tonitto, C., C. L. Goodale, M. S. Weiss, S. D. Frey, and S. V. Ollinger. 2014. The effect of nitrogen addition on soil organic matter dynamics: a model analysis of the Harvard Forest Chronic Nitrogen Amendment Study and soil carbon response to anthropogenic N deposition. Biogeochemistry **117**:431-454.

Turner, D. P., and G. J. Koerper. 1995. Carbon sequestration by forests of the United States. Current status and projections to the year 2040. Tellus 47:232–239. Tellus **47**:232–239.

Uriarte, M., C. D. Canham, J. Thompson, J. K. Zimmerman, L. Murphy, A. M. Sabat, N. Fetcher, and B. L. Haines. 2009. Natural disturbance and human land use as determinants of tropical forest dynamics: results from a forest simulator. Ecological Monographs **79**:423-443.

USDA Forest Service. 2020. Forest Inventory and Analysis National Program. Accessed March 2022. http://www.fia.fs.fed.us/.

Vance, E. D. 2018. Conclusions and caveats from studies of managed forest carbon budgets. Forest Ecology and Management **427**:350-354.

Wang, W. J., H. S. He, F. R. Thompson, J. S. Fraser, and W. D. Dijak. 2017. Changes in forest biomass and tree species distribution under climate change in the northeastern United States. Landscape Ecology **32**:1399-1413.

Wear, D. N., and B. C. Murray. 2004. Federal timber restrictions, interregional spillovers, and the impact on US softwood markets. Journal of Environmental Economics and Management **47**:307-330.

Zanchi, G., N. Pena, and N. Bird. 2012. Is woody bioenergy carbon neutral? A comparative assessment of emissions from consumption of woody bioenergy and fossil fuel. GCB Bioenergy **4**:761-772.

CHAPTER 3: PREDICTING REGIONAL-SCALE EFFECTS OF FOREST MANGEMENT ON SONGBIRDS WITH EXPERT ELICITATION

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3.1. Abstract

Global timber demand is on the rise, driven by wood product and energy needs. Wildlife must be considered as the allocation of forest resources are debated. We used expert elicitation techniques and generalized linear mixed modeling approaches to estimate the probability of occurrence of 12 forest-dependent bird species across the northeastern U.S. under changing forest conditions. We combined bird occupancy models with 5 timber harvest scenarios to estimate changes in bird species occupancy over 100 years. A total of 2588 occupancy probabilities at 377 sites were collected via 37 experts across New York, Vermont, New Hampshire, and Maine. Harvest intensification led to a decline in occupancy for 9 species, ranging from 1% (mourning warbler and veery) to 12% (black-throated green warbler). Three species increased in occupancy probability with harvest intensification, including Canada warbler (6%), chestnut-sided warbler (2%), and white-throated sparrow (9%). At the end of the 100-year simulation period, most species (n = 9) in our study were predicted to increase in occurrence probability within the same harvest regime. Every harvest scenario, even the most intensely managed, resulted in an increase in average basal area, and many bird species responded to that increase over time. The results of this study provide valuable information about the future distribution of bird species that should be considered when evaluating the tradeoffs between timber harvest and other forest values.

3.2. Introduction

Global timber demand is forecasted to increase by more than a third over the next several decades (FAO 2022). This demand comes from multiple sources. In the northeastern U.S., where 74% of the landscape is forested, there has been interest in expanding the use of forest biomass for energy to offset fossil fuel energy use (Biomass Energy Resource Center 2013, Maine Governor's Energy Office 2015, New Hampshire Department of Energy 2022, Vermont Department of Public Service 2022). Others call for increased timber harvest in this region to maximize carbon sequestration under the assumption that as forests mature their rate of sequestration declines (Maine Forest Carbon Task Force 2021, New York Climate Action Council 2021). Still others call for increased harvest to substitute wood for high carbon emitting products like steel and concrete, which form the basis of the built environment (Comnick et al. 2022).

Each of these reasons is not without debate. A growing body of literature suggests that burning woody biomass for energy can have a net negative effect on atmospheric carbon (Mika and Keeton 2015, Brown et al. in review-a). The results of these studies can be hard to compare however, because different authors use different net carbon accounting equations (Helin et al. 2013, Buchholz et al. 2016). Calls to increase harvest to maximize carbon sequestration are countered by studies that demonstrate eastern forests sequester carbon very late into stand development and contain aboveground biomass levels that are well above current regional averages (Keeton et al. 2011, Brown et al. 2018a). The potential benefits of increasing harvest for wood product substitution have been muted by authors who suggest the accounting of product substitution is flawed (e.g., overestimated displacement factors) and the market potential for these new wood products inflated (Harmon 2019, Leturcq 2020).

To address these issues, several authors use scenario-based approaches to examine how forest management affect both forest sustainability and carbon sequestration (Nunery and Keeton 2010, Mika and Keeton 2015, Brown et al. 2018a, Gunn and Buchholz 2018). For example, Brown et al. (2018) developed 5 timber harvest scenarios for the 6 most common forest types/regions across New York, Vermont, New Hampshire, and Maine (hereafter, the Northeast U.S., Figure 1), including a no harvest scenario (H0) (Table 1). Scenario one (H1) represented the current harvest regime, calculated using U.S. Forest Service Forest Inventory and Analysis (FIA) data (Canham et al. 2013, Brown et al. 2018a). Additionally, four alternative harvest scenarios were examined (Table 1) (Brown et al. 2018). These included increasing average harvest intensity by 50% ("current harvest + intensity"; H2), increasing harvest frequency by 75% while maintaining current harvest intensity ("current harvest + frequency"; H3), and increasing harvest intensity by 50% and harvest frequency by 100% ("current harvest + intensity + frequency"; H4). The final scenario is a no harvest scenario ("no harvest"; H0; Table 1). Each scenario included a 3 degree C increase in mean annual temperature and a 10% increase in total annual precipitation over the 100 year simulation (Horton et al. 2014).

Key results from Brown et al. (2018) and other authors suggest that maintaining current harvest regimes can allow for sustainable forest growth, timber production, and a modest amount of energy supply (Mika and Keeton 2015, Gunn and Buchholz 2018, Brown et al. in review-a). Even in intensified timber harvest scenarios, aboveground biomass is projected to increase in this region (Nunery and Keeton 2010, Brown et al. 2018a) due to the current distribution of biomass in northeastern forests resulting largely from farm abandonment and substantial harvest in the late nineteenth century (Thompson et al. 2013). Despite this, intensified harvest scenarios sequester less net CO_2e (carbon dioxide equivalent) than current harvest practices when forest ecosystem and forest product dynamics are considered (Mika and Keeton 2015, Brown et al. 2018a, Gunn and Buchholz 2018).

In these debates, forest-dependent birds are a silent stakeholder whose distribution patterns may be greatly altered by forest timber management (DeGraaf et al. 1998, King and DeGraaf 2000, DeGraaf and Yamasaki 2003). The response of biodiversity to timber harvest varies widely depending on species, harvest intensity, stand type, time since harvest, and can be positive, negative, or neutral (Annand and Thompson 1997, Janowiak and Webster 2010, Riffell et al. 2011, Verschuyl et al. 2011, Schwenk et al. 2012). The impacts of forest harvest on forest-dependent birds can be direct (e.g., reduced nesting cavities from biomass removal (Sallabanks and Arnett 2005)) or indirect (Littlefield and Keeton 2012) (e.g., changes in canopy structure may enhance foraging opportunities for songbirds (Hagar et al. 2004)).

While timber harvest effects on forest birds are well studied, the results are often difficult to aggregate at regional scales, stymying predictions of how regional-scale forest management scenarios will affect the distribution patterns into the future. Although birds are among the most studied wildlife species, with national inventories like the Breeding Bird Survey (BBS) (Sauer et al. 2017) and public repositories like eBird (Sullivan et al. 2009) storing thousands of data observations in time and space, forest conditions associated with such observations are often lacking, including key forest metrics such as tree density, live and dead basal area, and species composition. Instead, regional scale bird models often rely on remote variables that can be mapped at coarser levels (e.g., 30x30 meter pixel landcover data) as opposed to on-the-ground metrics (Schwenk and Donovan 2011, Brown et al. 2014). A number of studies link bird distribution to forest metrics, yet these are typically done at smaller spatial scales and with different methodologies, creating modeling aggregation challenges (e.g., Engstrom et al. 1984, King et al. 1997, DeGraaf et al. 1998, King and DeGraaf 2000, Bakermans et al. 2012, Perry and Thill 2013, Perry et al. 2018)).

Managers and policy makers charged with conserving viable populations of wildlife need to understand the implications of timber harvest practices. Birds in particular are sensitive to changing forests conditions (DeGraaf and Yamasaki 2003, Perry et al. 2018), and many forest birds are of conservation concern (Table 2). A recent study reported widespread reductions in avifauna, on the order of billions of individual birds, across North America over the last 50 years (Rosenberg et al. 2019). In addition to expected declines in rare and threatened species, common species across most habitat types, including Eastern forests, are also in decline, potentially altering ecosystem function (Rosenberg et al. 2019). Virtually every Wildlife Action Plan in the Northeast cite logging and wood harvesting as threats to species of conservation concern (Maine Department of Inland Fisheries and Wildlife 2015, New Hampshire Fish and Game Department 2015, New York State Department of Environmental Conservation 2015, Vermont Fish & Wildlife Department 2015). As timber demand is on the rise, it is timely for managers and decision makers to ask how wildlife will be affected.

To address these challenges, we used expert elicitation to develop occupancy models for 12 forest-nesting birds and combined them with the 5 timber harvest scenarios described above (Brown et al. 2018a). Our goal was to predict how songbirds will respond under the 5 different forest management regimes. Specifically, our objectives were to: (1) Conduct a regional expert survey to elicit bird species occupancy probabilities across the Northeast U.S., (2) Build occupancy models from expert data, and (3) Apply occupancy models to 5 timber harvest scenarios to predict changes in bird distribution patterns.

3.3. Methods

3.3.1. Study Area

Our study area included forests in the states of New York, Vermont, New Hampshire, and Maine, where the landscape is roughly 74% forest, 6% scrub-shrub, 9% wetlands, 4% open water, 4% agriculture (pasture/hay), 3% development, and 1% grassland (Figure 1) (U.S. Geological Survey 2014). The dominant forest type is northern hardwood-conifer forest followed by spruce-fir forest. The region is distinguished by inland mountain ranges and extensive coastlines, and the climate is characterized by warm summers and cold, snowy winters. Overall, the forested landscape is roughly 9% protected, the majority of which is in New York (Brown et al. 2018a).

Within this study area, we used the 5 harvest scenarios previously mentioned by Brown et al. (2018) as the basis for describing regional forest condition for the next 100 years. Brown et al. (2018) implemented the 5 harvest scenarios in SORTIE-ND, a spatially explicit individual-tree forest stand model. Individual seedlings, saplings, and adult trees were tracked over time through growth, mortality, and recruitment behaviors. FIA data were used to parameterize the 30 most common tree species in the study region (Canham and Murphy 2016a, b, Canham and Murphy 2017, Brown et al. 2018a). The complete model structure and parameterization is described fully in Brown et al. (2018). Five thousand FIA plots were randomly selected across the landscape, which included plots that were inventoried between 1999 and 2012 (Figure 1) (Brown et al. 2018a). For every harvest scenario, forest composition and structure data from each of the 5000 FIA plots were summarized and scaled to number per hectare to initialize 5000 SORTIE-ND runs. Given the environmental conditions of each site, SORTIE-ND then implemented several forest dynamic behaviors, including harvest regime, growth, natural mortality, and seedling recruitment, annually for 100 years. Outputs include detailed forest stand structure and composition metrics by species and tree size at each of the 5000 points (e.g., Figure 2).

3.3.2. Focal Species

To understand how each harvest scenario may affect the distribution of forest-dependent birds, we selected 12 songbird species that prefer a range of forest conditions, including differing forest composition and structure, edge tolerance, and canopy cover preferences (Table 2) (Hagenbuch et al. 2011, Schwenk and Donovan 2011, Schwenk et al. 2012). All of the focal species were forest dwelling birds that are sensitive to changes in forest condition, broadly nesting in three habitats: 1) forest interior and closed canopy, 2) intermediate forest landscapes and intermediate percent forest cover, and 3) early successional open canopy.

3.3.3. Objective 1. Conduct a regional expert survey to elicit bird species occupancy probabilities across the Northeast U.S.

Build the elicitation survey

We developed a web-based survey to collect the opinions of 37 experts regarding the probability of occurrence of the 12 focal species at randomly selected FIA points, drawn from the pool of 5000 selected FIA plots across the study area (Figure 1). Because the exact locations of FIA plots are legally restricted, we used the perturbed locations to represent survey sites (McRoberts et al. 2005). For each plot, we compiled a comprehensive list of forest structure, forest composition, and landscape variables representing potential drivers of species occurrence based on literature and professional experience. We recruited bird experts based on qualifications and expertise in the states of New York, Vermont, New Hampshire, and Maine. Experts were required to have strong knowledge of one or more focal species in the region and a background in conservation, wildlife management or a related field. Additional experts were identified by their extensive field-based birding knowledge and through expert nomination. We found experts through their academic research, state and regional birding databases, state agencies, Audubon, birding list-serves, professional contacts, and recommendations by other experts. Each expert self-selected and all participation was voluntary; survey protocols were approved by the University of Vermont Institutional Research Board (IRB 17–0417).

Implement bird expert elicitation survey

The bird survey was administered through a web-based interface designed to elicit expert opinion of bird probability of occurrence mimicking an elicitation tool known as

Elicitator (James et al. 2010, Low Choy et al. 2012).

There were three sections to the survey, including the introduction/presurvey, the expert elicitation survey, and the exit questionnaire. Prior to starting the survey, we met with each expert and walked them through how to complete each section. The first section introduced the expert to the elicitation process. Each expert identified their geographic expertise by selecting one or more states (NY, VT, NH, ME) on a map of the study area. Experts were also asked to select the focal species in which they had expertise and could select any number of the 12 bird species.

The second section was the elicitation survey (Figure 3). Given the expert's geographic expertise, the application randomly generated 10 survey points within the selected geography through a k-means clustering approach that utilized the covariates presented to the experts (Likas et al. 2003). This stratified the survey locations to ensure that selected sites encompassed a full range of forest covariate values. For example, if an expert indicated their expertise was limited to Maine, the survey generated 10 random points in Maine. If an expert was comfortable assessing locations across the entire study area, the application generated 10 random sites across all four states. Individual experts could not survey the same site twice, however, it was possible for two experts to be randomly assigned the same plots.

For each survey site, the expert was provided with an interactive satellite image (Google Map; Figure 3A), a table of site-specific covariates (Table 3, Figure 3B), and two site-specific figures (Figure 3C). The Google Map satellite image depicted a circle that encompassed the survey site and provided the expert with the overall landscape context. Due to FIA privacy restrictions, the exact location of the site was unmarked, but users understood that the site was most likely within the circular boundary. The tabular information (Figure 3B, Table 3) described forest structure variables as well as landscape metrics that are known to affect forest bird occupancy (Schwenk and Donovan 2011, Schwenk et al. 2012). The first figure showed a bar chart of the proportion of basal area per species for adult trees and saplings, and the second figure showed two histograms of adult and sapling basal area across all 5000 site locations with a line representing the site-specific data on the histogram (Figure 3C).

Given this information, at each survey site the expert used sliders to parameterize a beta distribution (α and β) that provides the average probability of occupancy and the confidence in their occupancy estimates ranging from 0 to 1 (Figure 3D). The confidence estimates represented the range of occupancy probabilities that experts believed were plausible. Experts provided predictions for as many sites as they were willing, but we requested the completion of at least 10 sites. After the tenth site, the expert was prompted to respond to an additional 10 sites and could decline at any time.

The final section of the survey asked experts to rank the importance of the covariates in terms of their influence (positive, negative, or neutral) on bird distribution. Further, experts could identify additional variables that they believed affected species occupancy (Table 3).

3.3.4. Objective 2. Build occupancy models from expert data

Data

Survey responses were downloaded and included the occupancy beta distribution parameters (α, β) for each expert-surveyed species and site combination, along with site-specific covariate data. Total sample size for each species was the number of sites in which experts provided an opinion about occurrence (Table 2).

For each response, we calculated the mean of the expert's beta distribution as

$$E[X] = \alpha / (\alpha + \beta)$$

and variance as

$$\mathrm{var}[X] = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$$

Site-specific covariate data included the variables from the web survey (n = 10; Table 3) and additional variables that the experts identified as important in the post-survey (n = 7; Table 3). In addition to these variables, 62 variables from the SORTIE-ND output were available for each site, mostly adding relative density data for individual tree species at each site. Ecoregion was also included as a potential random effect based on literature (Pearman-Gillman et al. 2020), for a total of 80 site-specific covariates.

Model covariate reduction

We reduced the full list of 80 covariates to a final covariate set to be used in the species-specific models. First, we retained variables that were correlated with the probability of occupancy (r >= 0.35) and met a coefficient of variation threshold (cv >= 0.25). Second, we retained all variables that were identified by experts as being the most important for a species of interest (from the list in Table 3), and then removed any variables that were correlated with them (r >= 0.5). From this remaining list, we retained only those variables that were most strongly correlated with occupancy and purged any variables that were correlated with them (r >= 0.5). Finally, we included percent forest cover (1 km radius) and the proportion of coniferous basal area in the development of all models as they are commonly cited in the literature as important. The severe trimming resulted in between 3-9 variables for species-specific occupancy modeling.

Model development

Generalized linear mixed modeling approaches were used to develop species-specific distribution models via the R package lme4 (Bates et al. 2015). For all models, the response variable was mean probability of occurrence. Fixed effects included the forest condition variables retained from the trimming exercise described above (section 2.2). For each species, we evaluated two alternative models that had the same fixed effects but varied in their random effects: expert or expert + ecoregion. To incorporate expert uncertainty, we used the weighted approach in the *glmer* function in R and weighted by the inverse of the expert's standard deviation (the spread of the expert's original beta distribution for a given site). In practice, this allowed for high confidence occurrence estimates to have more weight than low confidence estimates. We used Akaike's Information Criteria (AIC, Burnham and Anderson, 2002) to compare the two alternative models for each species and retained the model that had the lowest AIC score and successfully converged to a solution without error. We further used the *qqnorm* function in R to examine the assumption of normally distributed model error terms. We plotted the residuals for each model against a theoretical normal distribution. The results indicated that the residuals for all final models were normally distributed.

Model Validation

We used leave-one-out cross validation methods to evaluate the performance of each species' final model. This method systematically removed one observation from the dataset at a time, creating a new training dataset. The glmer model was then updated using the training data only, and the resulting model was used to predict the response value of the observation left out of the model. The process results in *N* predictions (Table 2) that were used in model assessment. For each sample, we assigned a “1” to model predictions or expert responses that were > 0.5, representing species presence. Otherwise we assigned “0”, representing species absence. We then created a confusion matrix to assess the sensitivity (true positive rate), specificity (true negative rate), and overall success rate of the model. For example, the hypothetical confusion matrix below compares expert responses at a site (0 or 1) with model predictions at that site (0 or 1).

		Expert Occurrence		
		0	1	
Predicted Occurrence	0	55	10	65
	1	15	45	60
		70	55	

Sensitivity is the probability of a positive test, conditioned on truly being positive. In this case, it is the agreement between the expert and model “1” records, calculated as

$$Sensitivity = \frac{\text{\# of true positives}}{\text{\# of true positives} + \text{\# of false negatives}}$$

The hypothetical sensitivity in this case is 0.82 (45/55), which can be interpreted as the model performing well to predict species presence when the experts identified the species as present (occupancy probability > 0.5). Specificity is the probability of a negative test, conditioned on truly being negative. In this case, it is the agreement between the expert and model “0” records, calculated as

$$Specificity = \frac{\text{\# of true negatives}}{\text{\# of true negatives} + \text{\# of false positives}}$$

The hypothetical specificity in this example is 0.79 (55/70), which can be interpreted as the model performing well to predict species absence when the experts identified the species as absent (occupancy probability < 0.5).

We also reported on success rate for each species, which is the number of times the expert responses matched the model predictions divided by the total number of expert responses.

3.3.5. Objective 3. Apply occupancy models to 5 timber harvest scenarios to predict changes in bird distribution patterns

We input each species' final model to the *predict* function in R to obtain predictions of forest bird occupancy rates at the 5000 FIA points under each of the five harvest scenarios. We updated the top species' models using covariate values for the 50 year and 100 year future timeframes and generated new occupancy probabilities. For the variables that did not have future values, namely the landscape-scale GIS variables like percent forest cover, we held the values constant.

3.4. Results

3.4.1. Objective 1. Conduct a regional expert survey to elicit bird species occupancy probabilities across the Northeast U.S.

A total of 2588 occupancy probabilities at 377 sites were collected between March and May 2018. Occupancy estimates were recorded for American redstart (n = 187), blackburnian warbler (n = 219), black-throated blue warbler (n = 272), black-throated green warbler (n = 217), Canada warbler (n = 217), chestnut-sided warbler (n = 271), mourning warbler (n = 198), ovenbird (n = 261), scarlet tanager (n = 171), veery (n = 193), white-throated sparrow (n = 182), and wood thrush (n = 200). Thirty-seven experts voluntarily participated in the elicitation survey across the states of New York (n = 692), Vermont (n = 672), New Hampshire (n = 463), and Maine (n = 761) (Table 2).

3.4.2. Objective 2. Build occupancy models from expert data

The final covariate set included 20 variables that likely influence occupancy probability across species. Ten variables were forest structure and composition variables, and 10 variables were landscape-scale attributes (Table 3). Expert was included in all models as a random effect. An additional random effect of ecoregion was further included in 8 of the top species' models. The top performing species' models contained between 3 and 9 fixed effects from the final covariate set (Table 4, Table 5). Every model contained a mix of landscape-scale variables and on-the-ground forest structure and composition variables. Besides percent forest cover and proportion of coniferous basal area that were included in all models, adult basal area and sapling density were the most common covariates used in model development, 9 and 8 times, respectively (Table 4). While suggested by experts and supported in the literature, percent wetland cover was not significant in our models (Table 5).

The results from the leave-one-out cross validation revealed overall success rates between 0.64 (scarlet tanager) and 0.82 (Canada warbler) (Table 6). This indicated our models perform well overall in predicting expert-estimated occupancy probabilities. Sensitivity results ranged between 0.17 (mourning warbler) to 0.86 (white-throated sparrow), although most species' sensitivities were > 0.6. The two outlier sensitivity results, 0.17 (mourning warbler) and 0.41 (Canada warbler), indicate poor ability of the models to predict species presence. In both cases, however, the specificity results for those species were extremely high, 0.94 and 0.95, respectively, suggesting that the models for mourning warbler and Canada warbler were very good at correctly predicting species absence. The distribution of responses for those species were skewed heavily to species' absences, likely influencing the sensitivity results. Overall, the specificity results indicated well performing models (>= 0.57) (Table 6).

3.4.3. Objective 3. Apply occupancy models to 5 timber harvest scenarios to predict changes in bird distribution patterns

Harvest intensification led to a decline in occupancy for 9 species, including American redstart, blackburnian warbler, black-throated blue warbler, black-throated green warbler, mourning warbler, ovenbird, scarlet tanager, veery, and wood thrush (Figure 4). When comparing the business-as-usual scenario (H1) to the most intensive harvest regime (H4), occupancy declined between 0.01 (mourning warbler and veery) and 0.12 (black-throated green warbler) among this group. For every species except mourning warbler, the decline in occupancy due to harvest intensification was greater in 2120 than 2070. Three species increased in occupancy probability with harvest intensification, including Canada warbler, chestnut-sided warbler, and white-throated sparrow. Occupancy increases ranged from 0.02 (chestnut-sided warbler) to 0.09 (white-throated sparrow) and were greater in 2120 than 2070 (Figure 4).

Future occupancy predictions for the years 2070 and 2120 varied among species and harvest scenarios. Occupancy probabilities increased over time in every harvest scenario (e.g., H1 in 2070 compared to H1 in 2120) for 6 species, including American redstart, blackburnian warbler, black-throated blue warbler, black-throated green warbler, mourning warbler, and scarlet tanager (Figure 4). Veery and white-throated sparrow declined in occupancy between 2070-2120 across most harvest scenarios. Wood thrush and ovenbird increased in occupancy in every harvest scenario over time except the most intensive harvest scenario (H4) where there was <1% decline. Alternatively, chestnut-sided warbler and Canada warbler increased in occupancy probabilities in all harvest scenarios except no harvest (H0) and additionally the business-as-usual (H1) for chestnut-sided warbler (Figure 4).

The largest changes in occupancy in terms of magnitude resulted from the no harvest scenario (H0) and the most intensive harvest scenario (H4). Under the no harvest scenario, white-throated sparrow and Canada warbler occupancy probability declined by 0.09 and 0.06 over time, respectively. Alternatively, occupancy for black-throated green warbler and blackburnian warbler increased by 0.09 and 0.08, respectively, over time under the same scenario. Under the most intensive harvest scenario, mourning warbler occupancy increased 0.12 (Figure 4).

3.5. Discussion

We used expert elicitation methods to develop 12 forest-dependent bird occupancy models across the states of New York, Vermont, New Hampshire, and Maine to predict how species distribution patterns may change in response to 5 regional forest management scenarios. Our models performed well at predicting species occurrence, demonstrating a new technique for linking species data with existing forest structure data collected through the FIA program and summarized in SORTIE-ND. We integrated our occupancy models with 5 forest harvest simulations and estimated changes in species' distributions over 50- and 100-year timeframes. These approaches can help inform climate, and conservation and management plans, especially as the potential to increase timber harvest is debated.

3.5.1. Expert Elicitation

Linking bird occupancy with site-specific on-the-ground forest metrics was key to our study, which limited the applicability of widely available public datasets like BBS and eBird. These programs tend to amass observations in places that are easy to access and on public lands. FIA plot locations, on the other hand, are most often on private lands in this region and therefore inaccessible. Our solution was to use expert elicitation at FIA plots, a solution employed by many other conservation and wildlife studies (White et al. 2005, Welsh et al. 2006, Zielinski et al. 2006, Wilcox et al. 2016, Pearman-Gillman et al. 2020). Expert elicitation can be especially useful in studies that require numerous sites across large geographies, historic or current management information, when time and resources are limited, and when data are generally lacking (White et al. 2005, Wilcox et al. 2016, Riskas et al. 2018, Pearman-Gillman et al. 2020, Agu et al. 2021, Camus et al. 2022). Importantly, in our study experts provided responses that reflected an overall probability of occurrence in response to forest metrics, aggregating their personal observations over time and space (Low Choy et al. 2009). As a result, annual anomalies that can affect field inventories, like unusually poor reproductive years or extreme weather during the breeding season, do not impact our results (Marcelino et al. 2020).

While expert elicitation alleviates many challenges, the utility of expert opinion has been debated (Pearce et al. 2001, Clevenger et al. 2002, Johnson and Gillingham 2004, Seoane et al. 2005). The introduction of expert bias, uncertainty, and inaccurate data collection are commonly cited concerns of expert elicitation (Low Choy et al. 2009, Martin et al. 2012). However, when expert opinion is effectively elicited through approaches that capture both opinion and uncertainty, using experts has been shown to improve model predictability (Martin et al. 2005, Low Choy et al. 2009, Murray et al. 2009). The results demonstrate substantial agreement between our experts, ranging from 0.64 to 0.82 agreement, for species occupancy estimates at sites. Two species, mourning warbler and Canada warbler, exhibited tradeoffs between low sensitivity scores and high specificity scores, resulting in many false negatives relative to the number of positive agreements, but few false positives. While overall our models performed well according to these methods, we did not have access to real observational bird data to validate our models.

3.5.2. Effect of harvest scenarios on bird occupancy – modeling approach

Many authors have focused on the impacts of clearcut management on bird species, and several others report on the relationship of bird presence and other silvicultural practices like shelterwood harvests and group selection (Hagan et al. 1997, DeGraaf and Yamasaki 2003, Campbell et al. 2007, Schwenk et al. 2012, Perry et al. 2018). However, Brown et al. (2018) demonstrated that strict silvicultural practices such as these have given way to variable partial harvest practices. The baseline harvest regime used in this study characterizes current partial harvest regimes, and therefore provides insight into the future occurrence of 12 forest birds based on the current practices across the region (H1).

Importantly, our results represent regional average changes in bird species occurrence. In our models, birds respond to both on-the-ground forest structure data and landscape attributes surrounding the plots. Each of the sites is in a different stage of forest stand development resulting from the harvest regime and other behaviors built into the forest simulation model (e.g., neighborhood crowding and site characteristics) but summarized across the entire landscape. This contrasts with many studies that are focused on stand level harvest treatments and shorter-term changes. One advantage of our approach is our ability to report on average bird response across landscape-scale forest dynamics. For example, at a stand scale, harvest treatments may only affect mature-preferring forest bird species short term (< 16 years) (Perry et al. 2018). Our approach factors in multitudes of forest stand development stages, capturing a full range of conditions across the landscape and providing a regional understanding of distribution trends over time.

3.5.3. Effect of harvest scenarios on bird occupancy – key findings

Our modeling approach resulted in two key findings. First, the majority of the forest birds in our study declined in distribution as timber harvest intensified, ranging between a 12% decline in black-throated green warbler to a 1% decline in mourning warbler and veery. While distribution declines were expected in species that prefer closed canopies and interior forest (e.g., black-throated green warbler, ovenbird, blackburnian warbler), we were surprised that the suite of more intermediate and edge tolerant species also declined (e.g., veery, American redstart). In contrast to other studies that have suggested that even bird species that prefer mature habitat often respond positively to timber harvest (Perry et al. 2018), our results show a decline in bird species distribution over time that prefer mature and intermediate forests. Several birds in our study did respond positively to intensified management. Canada warbler, chestnut-sided warbler, and white-throated sparrow distributions increased as harvest intensity increased. These species prefer open canopies (< 30% canopy closure) and utilize early successional forest habitat that is more abundant in the more intensely harvested landscapes in our study.

Second, most species in our study increased in occurrence probability between years 50 and 100 under the current harvest regime (H1) (n=9). Even species that declined with harvest intensity, had slight increases in their distributions over time. For example, black-throated green warbler decreased in occupancy by 12% when harvest regimes intensified from the current harvest (H1) to the most intensified harvest (H4). Over time, however, black-throated green warbler increased its occupancy by 3% under the current harvest regime (H1) between years 50 and 100. Almost all species whose distributions declined with harvest intensity, increased in occupancy over time. This is because basal area increased across all harvest scenarios, even the most intensified management scenario (Brown et al. 2018a). The majority of bird species whose distributions increased responded positively to adult basal area (Table 5).

3.5.4. Considerations

Changes in occupancy resulting from harvest intensification ranged from +9% (white-throated sparrow) to -12% (black-throated green warbler). While these changes are substantial, there are two reasons our estimates may appear conservative. First, small changes in occupancy probabilities can translate to large changes in landscape carrying capacity (N_k), the maximum number of breeding territories a landscape can support (Brown et al. 2018b). In this study for example, N_k would represent the potential number of viable bird territories within the region given underlying forested conditions. Population metrics such as these can provide a more direct picture of wildlife population trends (e.g., Rosenberg et al. 2019). Brown et al. (2018) predicted that ovenbird occupancy in rural landscapes would decrease by less than 2% in the face of future development, while landscape carrying capacity would decrease by 20%. While the previous study focused on development pressures, we would expect forest management intensity to also have a larger effect on landscape carrying capacity than changes in species distribution. Second, in our study we assume that forested plots remain forested throughout the 100-year timeframe. We do not account for land use conversion, but it is reasonable to expect some amount of future forest loss in the study region (Brown et al. 2014, Thompson et al. 2017b).

3.5.6. Conclusion

As demand for timber resources increase, wildlife considerations must be evaluated alongside other forest uses like timber production and carbon sequestration and storage. This study estimates the impact of different timber harvest regimes on bird species occupancy and provides managers with quantitative estimates and trends of regional species' distributions. Future research could systematically evaluate the tradeoffs of these results with alternative management objectives to effectively conserve and manage sustainable forested landscapes long term.

3.6. Tables and Figures

3.6.1. Tables

Table 3.1. Harvest scenario description (from Brown et al. 2018a).

Harvest Scenario	Harvest Scenario Definition
No harvest (H0)	No harvest
Current harvest (H1)	The current harvest regime characterized as a function of forest type/region, total plot basal area, and distance to the nearest improved road, including a 3 degree C increase in mean annual temperature and a 10% increase in total annual precipitation over the next 100 years (Brown et al 2018)
Current harvest + intensity (H2)	The current harvest regime and a 50% increase in average harvest intensity
Current harvest + frequency (H3)	The current harvest regime and a 75% increase in harvest frequency
Current harvest + intensity + frequency (H4)	The current harvest regime, a 50% increase in average harvest intensity, and a 100% increase in harvest frequency

Table 3.2. Characteristics of focal species. Canopy closure categories are defined as: (1) Open = canopy closure < 30%, (2) Intermediate = canopy closure between 30% - 80% and (3) Closed = canopy closure > 80% (Hagenbuch et al. 2011). Guild categories are defined as: (1) Interior = species increase as percent forest cover and distance to edge increases, (2) Mixed = species increase as percent forest cover increases and have positive associations with evergreen forest, (3) Deciduous, edge tolerant = species increase near edges and peak mostly in forested areas, (4) Intermediate = species peak at intermediate forest cover, (5) Forest edge = species decrease as road density increases, (6) Evergreen and mixed = species increase near edges and as percent forest cover increases; positive association with evergreen forest (Schwenk and Donovan 2011). Cluster categories are defined as: (1) Interior = species increase with high percent forest cover, (2) Coniferous = species increase with high percent forest cover and higher coniferous basal area, (3) Intermediate = species increase with intermediate forest cover, (4) Early successional within forest matrix = species increase with early successional habitat within forested landscapes (Schwenk et al. 2012).

Species	**Canopy Closure** (Hagenbuch et al. 2011)	**Guild** (Schwenk and Donovan 2011)	**Cluster** (Schwenk et al 2012)	**Birds of Conservation Concern** (state Audubon chapters, state wildlife action plans)	**Sample Size**
Black-throated blue warbler	Intermediate	Interior	Interior	NY, VT, ME	272
Black-throated green warbler	Closed	Interior	Interior	VT, ME	217
Blackburnian warbler	Closed	Mixed	Coniferous	VT, ME	219
Ovenbird	Closed	Interior	Interior	VT, ME	261
Veery	Intermediate	Deciduous, edge tolerant	Intermediate	VT, NH, ME	193
Wood thrush	Intermediate	Intermediate	Intermediate	NY, VT, NH, ME	200
Scarlet tanager	Closed	Intermediate	Intermediate	NY, VT, NH, ME	171
American redstart	Intermediate	Deciduous, edge tolerant	Intermediate		187
Mourning warbler	Open	Forest edge	Early successional within forest matrix	VT, ME	198
Canada warbler	Intermediate	Mixed	Early successional within forest matrix	NY, VT, NH, ME	217
Chestnut-sided warbler	Open	Forest edge	Early successional within forest matrix	VT, ME	271
White-throated sparrow	Open	Evergreen and mixed	Early successional within forest matrix	VT	182

Table 3.3. Final covariate list used in the development of 12 bird occupancy models, including covariates available in the expert survey and identified as important by experts. Variables included in the expert survey are shown in column 4. Expert-identified variables are shown in column 5.

Variable	Covariate name	Description	Included in elicitation survey?	Experts identified as important?	Source	
					Current	Future
Adult density	Adult density	Average number of adult trees per hectare (stems/ha)	Yes	Yes	SORTIE-ND	SORTIE-ND
Adult tree basal area	Adult BA	Average adult tree area per hectare (m^2/ha)	Yes	Yes	SORTIE-ND	SORTIE-ND
Balsam fir (*Abies balsama*) sapling relative density	ABBA density	Relative density of balsam fir saplings			SORTIE-ND	SORTIE-ND
Dead tree basal area	Dead BA	Average dead adult tree area per hectare (m^2/ha)	Yes	Yes	SORTIE-ND	SORTIE-ND
Distance to edge	Edge distance	Distance to the nearest edge of a different land cover type as measured by the National Land Cover Database (m)	Yes	Yes	U.S. Geological Survey	
Distance to stream	Stream distance	Distance to the nearest stream (m) defined by the National Hydrography Dataset		Yes	U.S. Geological Survey	
Eastern hemlock (*Tsuga canadensis*) basal area	TSCA BA	Average adult tree area per hectare (m^2/ha) of Eastern hemlock		Yes	SORTIE-ND	SORTIE-ND
Ecoregion	Ecoregion	Ecoregions and subregions of the United States			Bailey 2016	
Habitat type	Habitat type	Majority of habitat type within a 1 km window around the site as classified by the Northeastern Terrestrial Wildlife Habitat Classification	Yes	Yes	Ferree and Anderson 2013	
Harvest treatment	Harvest	Presence of a harvest treatment within the last 10 years (1/0)		Yes	FIA	SORTIE-ND
Percent evergreen forest cover	Evergreen cover	Amount of forest cover within a 300 m window around the site as measured by the National Land Cover Database and classified as coniferous forest	Yes	Yes	U.S. Geological Survey	
Percent forest cover	Forest cover	Amount of forest cover within a 1 km window around the site as measured by the National Land Cover Database and classified as deciduous, coniferous, or mixed forest	Yes	Yes	U.S. Geological Survey	
Percent shrub cover	Shrub cover	Amount of shrub cover within a 1 km window around the site as measured by the National Land Cover Database and classified as shrub/scrub		Yes	U.S. Geological Survey	
Percent wetland cover	Wetland cover	Amount of wetland cover within a 1 km window around the site as measured by the National Land Cover Database and classified as emergent herbaceous or woody wetlands		Yes	U.S. Geological Survey	
Percent woody wetland cover	Woody wetland cover	Amount of wetland cover within a 1 km window around the site as measured by the National Land Cover Database and classified as woody wetland		Yes	U.S. Geological Survey	
Proportion conifer trees	Conifer proportion	The proportion of total coniferous tree basal area			SORTIE-ND	SORTIE-ND
Road density	Road density	Cumluative length of all roads per 1 km area around the site (km/km^2) as measured by TIGER roads	Yes	Yes	U.S. Census Bureau	
Sapling basal area	Sapling BA	Average sapling area per hectare (m^2/ha)	Yes	Yes	SORTIE-ND	SORTIE-ND
Sapling density	Sapling density	Average number of saplings per hectare (stems/ha)	Yes	Yes	SORTIE-ND	SORTIE-ND
Seedling density	Seedling density	Average number of seedlings per hectare (stems/ha)		Yes	SORTIE-ND	SORTIE-ND

Table 3.4. Final occupancy models for focal bird species in the Northeast U.S. Models were developed using expert elicited data and generalized linear mixed modeling. Random effects are denoted by parentheses.

Species	**Model formula**
American redstart	Mean ~ Forest cover + Adult BA + Sapling BA + Conifer proportion + (1 | Expert)
Blackburnian warbler	Mean ~ Wetland cover + Adult BA + TSCA BA + Conifer proportion + Forest cover + (1 | Expert) + (1 | Ecoregion)
Black-throated blue warbler	Mean ~ Forest cover + Shrub cover + Adult BA + Sapling BA + Conifer proportion + (1 | Expert) + (1 | Ecoregion)
Black-throated green warbler	Mean ~ Forest cover + Adult BA + Conifer proportion + (1 | Expert) + (1 | Ecoregion)
Canada warbler	Mean ~ Forest cover + Road density + Shrub cover + Woody wetland cover + Adult BA + Sapling BA + Seedling density + ABBA density + Conifer proportion + (1 | Expert)
Chestnut-sided warbler	Mean ~ Edge distance + Forest cover + Road density + Shrub cover + Sapling BA + Conifer proportion + (1 | Expert) + (1 | Ecoregion)
Mourning warbler	Mean ~ Edge distance + Shrub cover + Harvest + Adult BA + Sapling BA + Seedling density + Forest cover + Conifer proportion + (1 | Expert) + (1 | Ecoregion)
Ovenbird	Mean ~ Forest cover + Road density + Adult BA + Sapling BA + Conifer proportion + (1 | Expert) + (1 | Ecoregion)
Scarlet tanager	Mean ~ Forest cover + Adult BA + Conifer proportion + (1 | Expert) + (1 | Ecoregion)
Veery	Mean ~ Shrub cover + Stream distance + Adult density + Sapling BA + Forest cover + Conifer proportion + (1 | Expert)
White-throated sparrow	Mean ~ Edge distance + Forest cover + Harvest + Adult BA + Sapling BA + Seedling density + ABBA density + Conifer proportion + (1 | Expert) + (1 | Ecoregion)
Wood thrush	Mean ~ Forest cover + Road density + Adult density + Sapling BA + Conifer proportion + (1 | Expert)

Table 3.5. Fixed effect parameter estimates with standard error and p-values for 12 bird occupancy models in the Northeast U.S.

Species	Covariate	Estimate	Standard error	P-value
American redstart	(Intercept)	0.14	0.49	0.7762
	Adult BA	1.19	0.42	0.0047
	Forest cover	-0.13	0.45	0.7634
	Sapling density	-0.28	0.33	0.3960
	Conifer proportion	-0.83	0.27	0.0023
Blackburnian warbler	(Intercept)	-2.12	0.50	0.0000
	Adult BA	1.16	0.45	0.0099
	Wetland cover	0.27	0.44	0.5378
	Forest cover	1.07	0.45	0.0171
	Conifer proportion	2.46	0.28	0.0000
	TSCA BA	0.85	0.75	0.2537
Black-throated blue warbler	(Intercept)	-2.40	0.45	0.0000
	Adult BA	1.12	0.38	0.0029
	Forest cover	2.69	0.42	0.0000
	Sapling density	0.32	0.36	0.3761
	Shrub cover	0.62	0.45	0.1755
	Conifer proportion	-0.24	0.22	0.2698
Black-throated green warbler	(Intercept)	-2.52	0.45	0.0000
	Adult BA	2.22	0.38	0.0000
	Forest cover	1.67	0.43	0.0001
	Conifer proportion	1.34	0.23	0.0000
Canada warbler	(Intercept)	-2.56	0.60	0.0000
	Adult BA	-0.49	0.47	0.2990
	Forest cover	0.92	0.55	0.0932
	Road density	-0.55	0.62	0.3755
	ABBA density	0.92	0.32	0.0047
	Sapling density	0.48	0.48	0.3124
	Seedling density	1.51	0.54	0.0048
	Shrub cover	1.33	0.55	0.0160
	Conifer proportion	0.29	0.27	0.2962
	Woody wetland cover	1.30	0.50	0.0094
Chestnut-sided warbler	(Intercept)	-0.21	0.50	0.6695
	Edge distance	-0.70	0.58	0.2299
	Forest cover	-0.28	0.48	0.5547
	Road density	1.56	0.53	0.0033
	Sapling density	0.87	0.39	0.0275
	Shrub cover	0.70	0.46	0.1318
	Conifer proportion	-0.34	0.22	0.1193

Species	Covariate	Estimate	Standard error	P-value
Mourning warbler	(Intercept)	-1.14	0.58	0.0485
	Adult BA	-0.10	0.63	0.8694
	Edge distance	-4.75	1.04	0.0000
	Forest cover	-0.47	0.64	0.4654
	Sapling density	0.78	0.57	0.1732
	Seedling density	2.20	0.53	0.0000
	Shrub cover	-0.48	0.57	0.3942
	Conifer proportion	-0.59	0.33	0.0720
	Harvest	-0.63	0.29	0.0304
Ovenbird	(Intercept)	-0.11	0.54	0.8460
	Adult BA	3.09	0.53	0.0000
	Forest cover	1.52	0.50	0.0025
	Road density	-1.58	0.54	0.0035
	Sapling density	-1.49	0.46	0.0013
	Conifer proportion	-0.59	0.26	0.0239
Scarlet tanager	(Intercept)	-1.16	0.51	0.0225
	Adult BA	1.51	0.38	0.0001
	Forest cover	1.85	0.54	0.0006
	Conifer proportion	-1.92	0.26	0.0000
Veery	(Intercept)	-0.06	0.42	0.8899
	Adult density	0.78	0.47	0.0951
	Forest cover	0.84	0.41	0.0412
	Sapling density	-1.10	0.41	0.0072
	Shrub cover	-1.33	0.55	0.0159
	Stream distance	-1.80	0.53	0.0008
	Conifer proportion	-0.56	0.25	0.0254
White-throated sparrow	(Intercept)	-0.20	0.53	0.7028
	Adult BA	-0.74	0.47	0.1129
	Edge distance	-1.97	0.89	0.0273
	Forest cover	-0.46	0.64	0.4767
	ABBA density	0.65	0.38	0.0823
	Sapling BA	1.11	0.64	0.0803
	Seedling density	2.51	0.64	0.0001
	Conifer proportion	1.11	0.30	0.0002
	Harvest	-0.10	0.27	0.7108
Wood thrush	(Intercept)	-2.04	0.53	0.0001
	Adult density	0.00	0.00	0.6887
	Forest cover	3.30	0.47	0.0000
	Road density	0.62	0.59	0.2936
	Sapling density	-2.02	0.43	0.0000
	Conifer proportion	-1.04	0.27	0.0001

Table 3.6. Leave one out cross validation results for 12 bird occupancy models in the Northeast U.S. The confusion matrices compare expert responses at a site with model predictions at that site. “0” indicates species absence; “1” indicates species presence. Success rate = (number of true positives + number of true negatives) / total number of responses; Sensitivity = number of true positives / (number of true positives + number of false negatives; Specificity = number of true negatives / (number of true negatives + number of false positives).

American redstart

		Expert		
		0	1	
Model	0	52	28	80
	1	32	75	107
		84	103	

Success rate = 0.68

Sensitivity = 0.73

Specificity = 0.62

Blackburnian warbler

		Expert		
		0	1	
Model	0	87	27	114
	1	30	75	105
		117	102	

Success rate = 0.74

Sensitivity = 0.74

Specificity = 0.74

Black-throated blue warbler

		Expert		
		0	1	
Model	0	88	49	137
	1	40	95	135
		128	144	

Success rate = 0.67

Sensitivity = 0.66

Specificity = 0.69

Black-throated green warbler

		Expert		
		0	1	
Model	0	54	34	88
	1	35	94	129
		89	128	

Success rate = 0.68

Sensitivity = 0.73

Specificity = 0.61

Canada warbler

		Expert		
		0	1	
Model	0	159	29	188
	1	9	20	29
		168	49	

Success rate = 0.82

Sensitivity = 0.41

Specificity = 0.95

Chestnut-sided warbler

		Expert		
		0	1	
Model	0	135	29	164
	1	32	75	107
		167	104	

Success rate = 0.77

Sensitivity = 0.72

Specificity = 0.81

Mourning warbler

		Expert		
		0	1	
Model	0	147	34	181
	1	10	7	17
		157	41	

Success rate = 0.78

Sensitivity = 0.17

Specificity = 0.94

Ovenbird

		Expert		
		0	1	
Model	0	42	30	72
	1	32	157	189
		74	187	

Success rate = 0.76

Sensitivity = 0.84

Specificity = 0.57

Scarlet tanager

		Expert		
		0	1	
Model	0	48	31	79
	1	30	62	92
		78	93	

Success rate = 0.64

Sensitivity = 0.67

Specificity = 0.62

Veery

		Expert		
		0	1	
Model	0	74	34	108
	1	32	53	85
		106	87	

Success rate = 0.66

Sensitivity = 0.61

Specificity = 0.70

White-throated sparrow

		Expert		
		0	1	
Model	0	68	13	81
	1	24	77	101
		92	90	

Success rate = 0.80

Sensitivity = 0.86

Specificity = 0.74

Wood thrush

		Expert			
		0	1		
Model	0	86	30	116	
	1	29	55	84	
		115	85		118

Success rate = 0.71

Sensitivity = 0.65

Specificity = 0.75

3.6.2. Figures

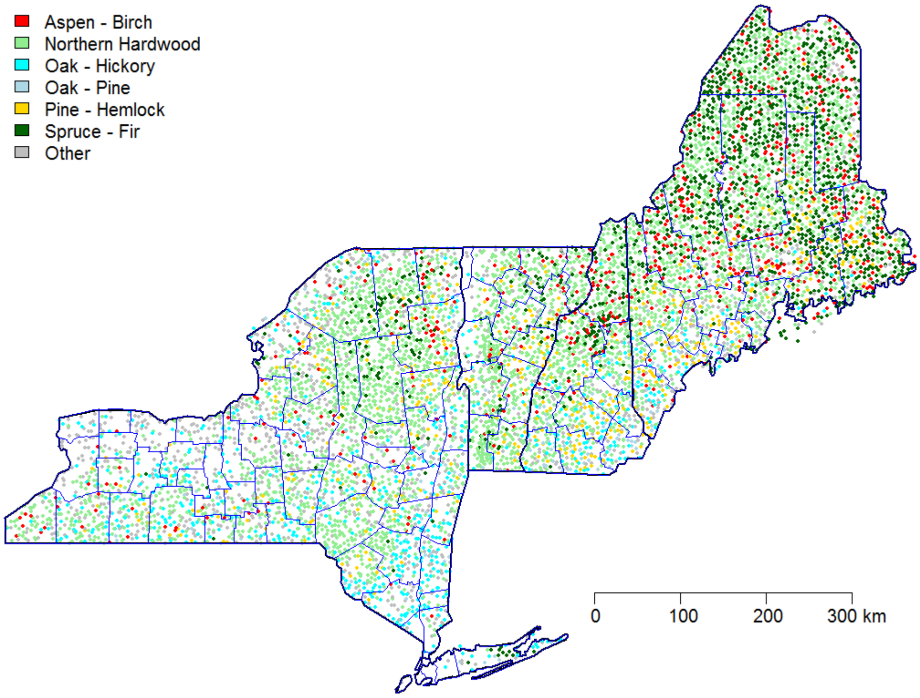


Figure 3.1. Regional map of the study area showing the 5000 FIA points by forest type.

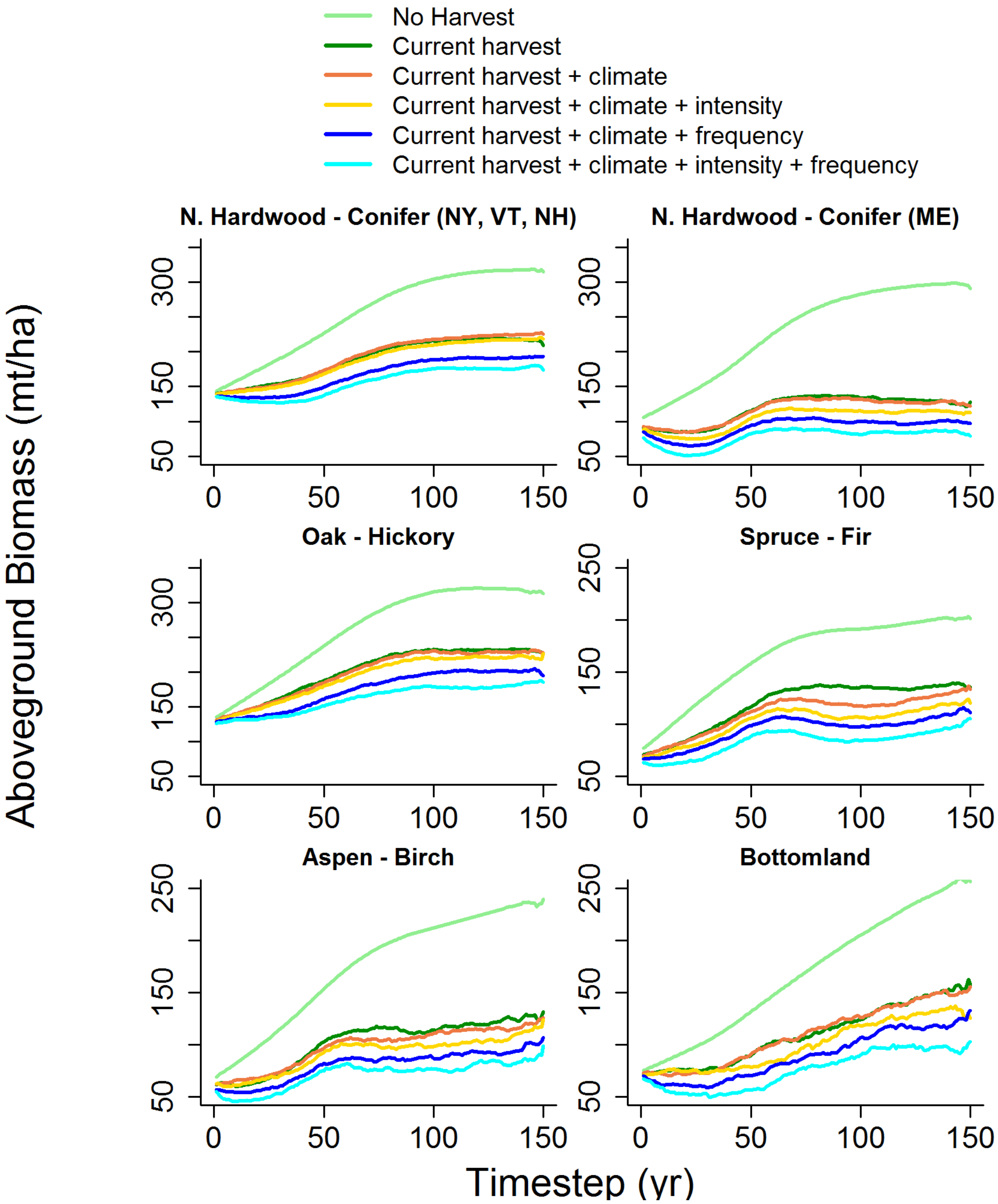
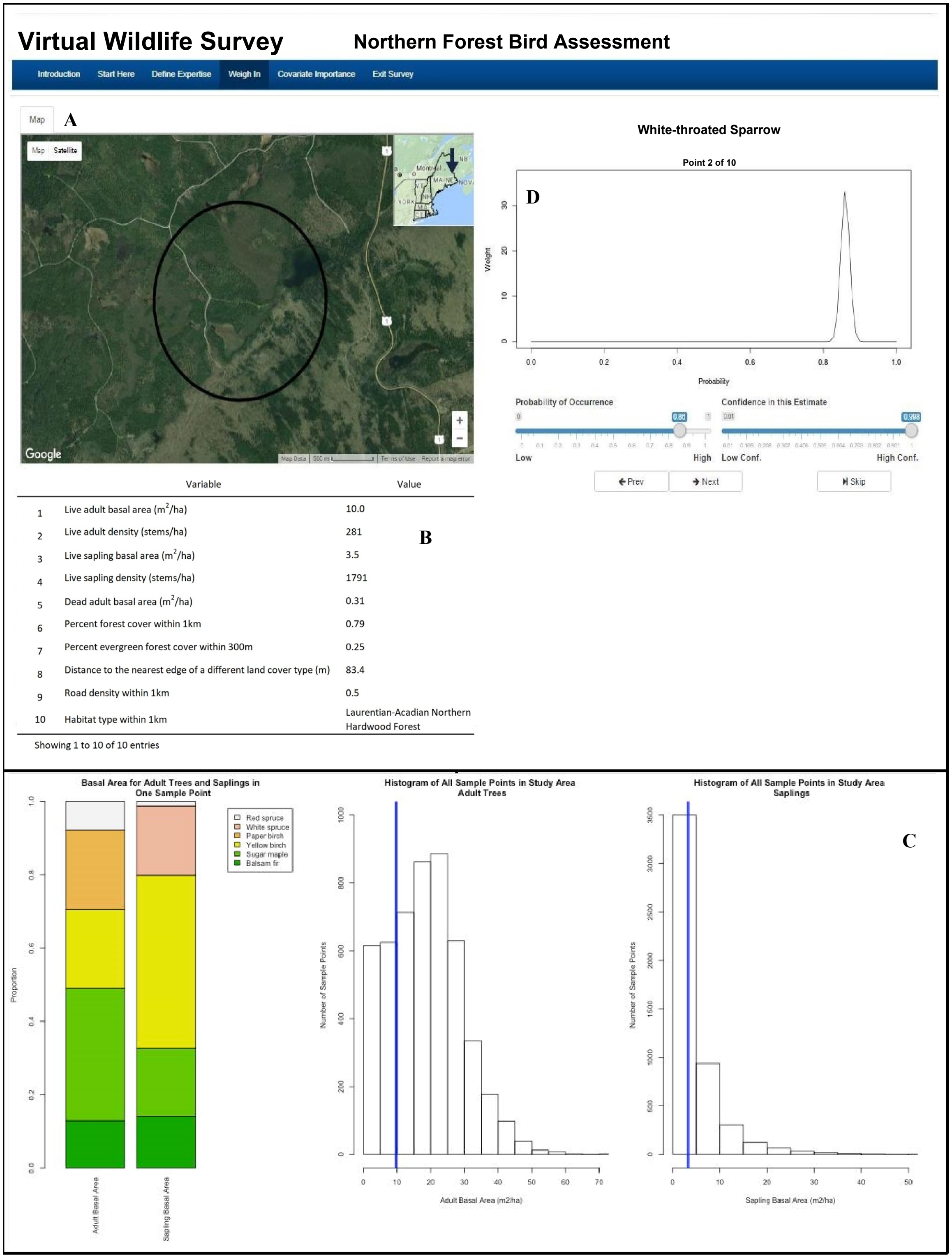


Figure 3.2. Example SORTIE-ND output showing adult tree aboveground biomass estimates for six harvest scenarios across six forest types/regions (from Brown et al. 2018).



Probability of Occurrence: 0.86

Confidence in this Estimate: 0.998

	Variable	Value
1	Live adult basal area (m^2/ha)	10.0
2	Live adult density (stems/ha)	281
3	Live sapling basal area (m^2/ha)	3.5
4	Live sapling density (stems/ha)	1791
5	Dead adult basal area (m^2/ha)	0.31
6	Percent forest cover within 1km	0.79
7	Percent evergreen forest cover within 300m	0.25
8	Distance to the nearest edge of a different land cover type (m)	83.4
9	Road density within 1km	0.5
10	Habitat type within 1km	Laurentian-Acadian Northern Hardwood Forest

Showing 1 to 10 of 10 entries

Figure 3.3. Example of the elicitation survey interface designed to collect bird occurrence data for 12 species. A) Interactive satellite map, B) Site covariate values for the survey site locations, C) Supplementary forest structure and composition data for the survey sites, D) Sliders where experts recorded occupancy estimates and confidence in their estimates.

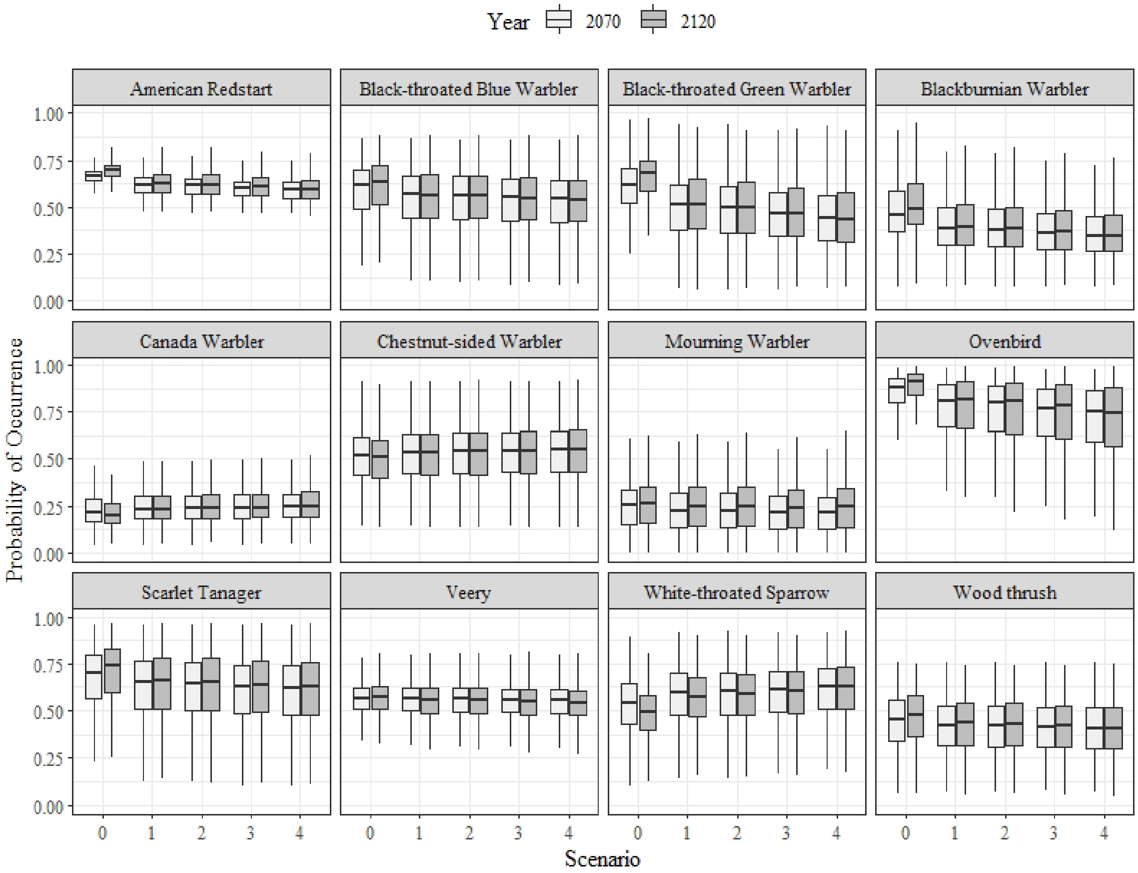


Figure 3.4. Box plots for 12 bird species models showing future probability of occurrence estimates in years 2070 and 2120 (y-axis). Each of the 12 boxplots show the estimated median for the 2 timeframes. The lower and upper hinges demark the 25th and 75th percentiles for the 5 harvest scenarios (x-axis). The 5 harvest scenarios represent no harvest (Scenario 0), current harvest (Scenario 1), and 3 harvest intensification scenarios (Scenarios 2-4) (Table 1).

3.7. References

Agu, H. U., C. Andrew, and M. L. Gore. 2021. Mapping Terra Incognita: An Expert Elicitation of Women's Roles in Wildlife Trafficking. Frontiers in Conservation Science **2**.

Annand, E. M., and F. R. Thompson, III. 1997. Forest Bird Response to Regeneration Practices in Central Hardwood Forests. The Journal of Wildlife Management **61**:159-171.

Bakermans, M. H., A. D. Rodewald, and A. C. Vitz. 2012. Influence of forest structure on density and nest success of mature forest birds in managed landscapes. The Journal of Wildlife Management **76**:1225-1234.

Bates, D., M. Mächler, B. Bolker, and S. Walker. 2015. Fitting Linear Mixed-Effects Models Using lme4. Journal of Statistical Software **67**:1-48.

Biomass Energy Resource Center. 2013. An overview of the biomass thermal energy policy opportunities in the Northern Forest region. Biomass Energy Resource Center at Vermont Energy Investment Corporation. Burlington, VT.

Brown, M. L., C. D. Canham, T. Buchholz, J. S. Gunn, and T. M. Donovan. in review-a. Net carbon sequestration implications of intensified timber harvest in northeastern U.S. forests.

Brown, M. L., C. D. Canham, L. Murphy, and T. M. Donovan. 2018a. Timber harvest as the predominant disturbance regime in northeastern U.S. forests: effects of harvest intensification. Ecosphere **9**:e02062.

Brown, M. L., T. M. Donovan, R. M. Mickey, G. S. Warrington, W. S. Schwenk, and D. M. Theobald. 2018b. Predicting effects of future development on a territorial forest songbird: methodology matters. Landscape Ecology **33**:93-108.

Brown, M. L., T. M. Donovan, W. S. Schwenk, and D. M. Theobald. 2014. Predicting impacts of future human population growth and development on occupancy rates of forest-dependent birds. Biological Conservation **179**:311-320.

Buchholz, T., M. D. Hurteau, J. Gunn, and D. Saah. 2016. A global meta-analysis of forest bioenergy greenhouse gas emission accounting studies. GCB Bioenergy **8**:281-289.

Campbell, S. P., J. W. Witham, and M. L. Hunter Jr. 2007. Long-Term Effects of Group-Selection Timber Harvesting on Abundance of Forest Birds. Conservation Biology **21**:1218-1229.

Camus, E. B., J. R. Rhodes, C. A. McAlpine, D. Lunney, J. Callaghan, R. Goldingay, A. Brace, M. Hall, S. B. Hetherington, M. Hopkins, M. J. Druzdzel, and H. J. Mayfield. 2022. Using expert elicitation to identify effective combinations of management actions for koala conservation in different regional landscapes. Wildlife Research.

Canham, C. D., and L. Murphy. 2016a. The demography of tree species response to climate: sapling and canopy tree growth. Ecosphere 7(10):e01474. 10.1002/ecs2.1474.

Canham, C. D., and L. Murphy. 2016b. The demography of tree species response to climate: seedling recruitment and survival. Ecosphere 7(8):e01424. 10.1002/ecs2.1424.

Canham, C. D., and L. Murphy. 2017. The demography of tree species response to climate: sapling and canopy tree survival. Ecosphere 8(2):e01701. 10.1002/ecs2.1701.

Canham, C. D., N. Rogers, and T. Buchholz. 2013. Regional variation in forest harvest regimes in the northeastern United States. Ecological Applications **23**:515-522.

Clevenger, A. P., J. Wierzchowski, B. Chruszcz, and K. Gunson. 2002. GIS-Generated, Expert-Based Models for Identifying Wildlife Habitat Linkages and Planning Mitigation Passages. Conservation Biology **16**:503-514.

Comnick, J., L. Rogers, and K. Wheiler. 2022. Increasing Mass Timber Consumption in the U.S. and Sustainable Timber Supply. Sustainability.

DeGraaf, R. M., J. B. Hestbeck, and M. Yamasaki. 1998. Associations between breeding bird abundance and stand structure in the White Mountains, New Hampshire and Maine, USA. Forest Ecology and Management **103**:217-233.

DeGraaf, R. M., and M. Yamasaki. 2003. Options for managing early-successional forest and shrubland bird habitats in the northeastern United States. Forest Ecology and Management **185**:179-191.

Engstrom, R. T., R. L. Crawford, and W. W. Baker. 1984. Breeding Bird Populations in Relation to Changing Forest Structure following Fire Exclusion: A 15-Year Study. The Wilson Bulletin **96**:437-450.

FAO. 2022. Global forest sector outlook 2050: Assessing future demand and sources of timber for a sustainable economy – Background paper for The State of the World's Forests 2022. Food and Agriculture Organization of the United Nations Forestry Working Paper, No. 31. Rome. Provisional. https://doi.org/10.4060/cc2265en.

Gunn, J. S., and T. Buchholz. 2018. Forest sector greenhouse gas emissions sensitivity to changes in forest management in Maine (USA). Forestry: An International Journal of Forest Research **91**:526-538.

Hagan, J. M., P. S. McKinley, A. L. Meehan, and S. L. Grove. 1997. Diversity and Abundance of Landbirds in a Northeastern Industrial Forest. The Journal of Wildlife Management **61**:718-735.

Hagar, J., S. Howlin, and L. Ganio. 2004. Short-term response of songbirds to experimental thinning of young Douglas-fir forests in the Oregon Cascades. Forest Ecology and Management **199**:333-347.

Hagenbuch, S., K. Manaras, J. Shallow, K. Sharpless, and M. Snyder. 2011. Forest bird habitat assessment: A guide to integrating bird habitat data into a Vermont Forest Inventory. Created and published by Audubon Vermont, Huntington, Vermont, 05642.

Harmon, M. E. 2019. Have product substitution carbon benefits been overestimated? A sensitivity analysis of key assumptions. Environmental Research Letters **14**:065008.

Helin, T., L. Sokka, S. Soimakallio, K. Pingoud, and T. Pajula. 2013. Approaches for inclusion of forest carbon cycle in life cycle assessment – a review. GCB Bioenergy **5**:475-486.

Horton, R., G. Yohe, W. Easterling, R. Kates, M. Ruth, E. Sussman, A. Whelchel, D. Wolfe, and F. Lipschultz. 2014. Ch. 16: Northeast. In Climate Change Impacts in the United States: The Third National Climate Assessment. J. M. Melillo, T.C.

Richmond, and G. W. Yohe, Eds. U.S. Global Change Research Program, 371-395, doi:10.7930/J0SF2T3P.

James, A., S. L. Choy, and K. Mengersen. 2010. Elicitator: An expert elicitation tool for regression in ecology. Environmental Modelling & Software **25**:129-145.

Janowiak, M. K., and C. R. Webster. 2010. Promoting Ecological Sustainability in Woody Biomass Harvesting. Journal of Forestry **108**:16-23.

Johnson, C. J., and M. P. Gillingham. 2004. Mapping uncertainty: sensitivity of wildlife habitat ratings to expert opinion. Journal of Applied Ecology **41**:1032-1041.

Keeton, W. S., A. A. Whitman, G. C. McGee, and C. L. Goodale. 2011. Late-successional biomass development in northern hardwood-conifer forests of the northeastern United States. Forest Science **57**:489-505.

King, D. I., and R. M. DeGraaf. 2000. Bird species diversity and nesting success in mature, clearcut and shelterwood forest in northern New Hampshire, USA. Forest Ecology and Management **129**:227-235.

King, D. I., C. R. Griffin, and R. M. DeGraaf. 1997. Effect of Clearcut Borders on Distribution and Abundance of Forest Birds in Northern New Hampshire. The Wilson Bulletin **109**:239-245.

Leturcq, P. 2020. GHG displacement factors of harvested wood products: the myth of substitution. Scientific Reports **10**:20752.

Likas, A., N. Vlassis, and J. J. Verbeek. 2003. The global k-means clustering algorithm. Pattern recognition **36**:451-461.

Littlefield, C. E., and W. S. Keeton. 2012. Bioenergy harvesting impacts on ecologically important stand structure and habitat characteristics. Ecological Applications **22**:1892-1909.

Low Choy, S., A. James, and K. Mengersen. 2009. Expert elicitation and its interface with technology: a review with a view to designing Elicitator. Pages 4269-4275 *in* 18th World IMACS Congress and MODSIM09 International Congress on Modelling and Simulation.

Low Choy, S., A. James, J. Murray, and K. Mengersen. 2012. Elicitator: A User-Friendly, Interactive Tool to Support Scenario-Based Elicitation of Expert Knowledge. Pages 39-67 *in* A. H. Perera, C. A. Drew, and C. J. Johnson, editors. Expert Knowledge and Its Application in Landscape Ecology. Springer New York.

Maine Department of Inland Fisheries and Wildlife. 2015. Maine's wildlife action plan. Maine Department of Inland Fisheries and Wildlife, Augusta, ME.

Maine Forest Carbon Task Force. 2021. Governor’s Task Force on the Creation of a Forest Carbon Program. Maine Forest Carbon Task Force, Augusta, Maine.

Maine Governor's Energy Office. 2015. Maine Comprehensive Energy Plan Update 2015. Governor's Energy Office, State of Maine, Augusta, ME.

Marcelino, J., J. P. Silva, J. Gameiro, A. Silva, F. C. Rego, F. Moreira, and I. Catry. 2020. Extreme events are more likely to affect the breeding success of lesser kestrels than average climate change. Scientific Reports **10**:7207.

Martin, T. G., M. A. Burgman, F. Fidler, P. M. Kuhnert, S. Low-Choy, M. McBride, and K. Mengersen. 2012. Eliciting Expert Knowledge in Conservation Science. Conservation Biology **26**:29-38.

Martin, T. G., P. M. Kuhnert, K. Mengersen, and H. P. Possingham. 2005. THE POWER OF EXPERT OPINION IN ECOLOGICAL MODELS USING BAYESIAN METHODS: IMPACT OF GRAZING ON BIRDS. Ecological Applications **15**:266-280.

McRoberts, R. E., G. R. Holden, M. D. Nelson, G. C. Liknes, W. K. Moser, A. J. Lister, S. L. King, E. B. LaPoint, J. W. Coulston, W. B. Smith, and G. A. Reams. 2005. Estimating and Circumventing the Effects of Perturbing and Swapping Inventory Plot Locations. Journal of Forestry **103**:275-279.

Mika, A. M., and W. S. Keeton. 2015. Net carbon fluxes at stand and landscape scales from wood bioenergy harvests in the US Northeast. GCB Bioenergy **7**:438-454.

Murray, J. V., A. W. Goldizen, R. A. O'Leary, C. A. McAlpine, H. P. Possingham, and S. L. Choy. 2009. How useful is expert opinion for predicting the distribution of a species within and beyond the region of expertise? A case study using brush-tailed rock-wallabies Petrogale penicillata. Journal of Applied Ecology **46**:842-851.

New Hampshire Department of Energy. 2022. New Hampshire 10-year State Energy Strategy. New Hampshire Department of Energy, Concord, NH.

New Hampshire Fish and Game Department. 2015. New Hampshire Wildlife Action Plan, 2015 Revised Edition. New Hampshire Fish and Game Department, Concord, NH.

New York Climate Action Council. 2021. New York State Climate Action Council Draft Scoping Plan. New York Climate Action Council, Albany, NY.

New York State Department of Environmental Conservation. 2015. New York State Wildlife Action Plan. 2015. New York State Department of Environmental Conservation. Albany, NY. http://www.dec.ny.gov/docs/wildlife_pdf/swapfinaldraft2015.pdf.

Nunery, J. S., and W. S. Keeton. 2010. Forest carbon storage in the northeastern United States: net effects of harvesting frequency, post-harvest retention, and wood products. Forest Ecology and Management **259**:1363-1375.

Pearce, J. L., K. Cherry, D. M, F. S, and G. Whish. 2001. Incorporating expert opinion and fine-scale vegetation mapping into statistical models of faunal distribution. Journal of Applied Ecology **38**:412-424.

Pearman-Gillman, S. B., J. E. Katz, R. M. Mickey, J. D. Murdoch, and T. M. Donovan. 2020. Predicting wildlife distribution patterns in New England USA with expert elicitation techniques. Global Ecology and Conservation **21**:e00853.

Perry, R. W., J. M. A. Jenkins, R. E. Thill, and F. R. Thompson, III. 2018. Long-term effects of different forest regeneration methods on mature forest birds. Forest Ecology and Management. 408: 183-194 **408**:183-194.

Perry, R. W., and R. E. Thill. 2013. Long-term responses of disturbance-associated birds after different timber harvests. Forest Ecology and Management 307:274–283. **307**:274-283.

Riffell, S., J. Verschuyl, D. Miller, and T. B. Wigley. 2011. Biofuel harvests, coarse woody debris, and biodiversity – A meta-analysis. Forest Ecology and Management **261**:878-887.

Riskas, K. A., R. C. Tobin, M. M. P. B. Fuentes, and M. Hamann. 2018. Evaluating the threat of IUU fishing to sea turtles in the Indian Ocean and Southeast Asia using expert elicitation. Biological Conservation **217**:232-239.

Rosenberg, K. V., A. M. Dokter, P. J. Blancher, J. R. Sauer, A. C. Smith, P. A. Smith, J. C. Stanton, A. Panjabi, L. Helft, M. Parr, and P. P. Marra. 2019. Decline of the North American avifauna. Science **366**:120-124.

Sallabanks, R., and E. B. Arnett. 2005. Accommodating birds in managed forests of North America: a review of bird–forestry relationships. U.S. Department of Agriculture, Forest Service, Pacific Northwest Region, Portland, Oregon, U.S.

Sauer, J. R., K. L. Pardieck, D. J. Ziolkowski, Jr., A. C. Smith, M.-A. R. Hudson, V. Rodriguez, H. Berlanga, D. K. Niven, and W. A. Link. 2017. The first 50 years of the North American Breeding Bird Survey. The Condor **119**:576-593.

Schwenk, W. S., and T. M. Donovan. 2011. A multi-species framework for landscape conservation planning. Conservation Biology **25**:1010-1021.

Schwenk, W. S., T. M. Donovan, W. S. Keeton, and J. S. Nunery. 2012. Carbon storage, timber production, and biodiversity: comparing ecosystem services with multi-criteria decision analysis. Ecological Applications **22**:1612-1627.

Seoane, J., J. Bustamante, and R. DÍAz-Delgado. 2005. Effect of Expert Opinion on the Predictive Ability of Environmental Models of Bird Distribution. Conservation Biology **19**:512-522.

Sullivan, B. L., C. L. Wood, M. J. Iliff, R. E. Bonney, D. Fink, and S. Kelling. 2009. eBird: A citizen-based bird observation network in the biological sciences. Biological Conservation **142**:2282-2292.

Thompson, J. R., D. N. Carpenter, C. V. Cogbill, and D. R. Foster. 2013. Four centuries of change in northeastern United States forests. PLOS ONE 8(9): e72540. https://doi.org/10.1371/journal.pone.0072540.

Thompson, J. R., J. S. Plisinski, P. Olofsson, C. E. Holden, and M. J. Duveneck. 2017b. Forest loss in New England: A projection of recent trends. PLoS ONE **12**:e0189636.

U.S. Geological Survey. 2014. National Land Cover Database (NLCD) 2011 Land Cover Conterminous United States: U.S. Geological Survey data release, https://doi.org/10.5066/P97S2IID.

Vermont Department of Public Service. 2022. 2022 Vermont Comprehensive Energy Plan. Vermont Department of Public Service, Montpelier, VT.

Vermont Fish & Wildlife Department. 2015. Vermont Wildlife Action Plan 2015. Vermont Fish & Wildlife Department. Montpelier, VT. https://vtfishandwildlife.com/node/551

Verschuyl, J., S. Riffell, D. Miller, and T. B. Wigley. 2011. Biodiversity response to intensive biomass production from forest thinning in North American forests – A meta-analysis. Forest Ecology and Management **261**:221-232.

Welsh, H. H., J. R. Dunk, and W. J. Zielinski. 2006. Developing and Applying Habitat Models Using Forest Inventory Data: An Example Using a Terrestrial Salamander. Journal of Wildlife Management **70**:671-681.

White, P. C. L., N. V. Jennings, A. R. Renwick, and N. H. L. Barker. 2005. REVIEW: Questionnaires in ecology: a review of past use and recommendations for best practice. Journal of Applied Ecology **42**:421-430.

Wilcox, C., N. J. Mallos, G. H. Leonard, A. Rodriguez, and B. D. Hardesty. 2016. Using expert elicitation to estimate the impacts of plastic pollution on marine wildlife. Marine Policy **65**:107-114.

Zielinski, W. J., R. L. Truex, J. R. Dunk, and T. Gaman. 2006. Using Forest Inventory Data To Assess Fisher Resting Habitat Suitability In California. Ecological Applications **16**:1010-1025.

CHAPTER 4: USING MULTI-CRITERIA ANALYSIS TO EVALUTATE FOREST RESOURCE TRADEOFFS IN THE NORTHEASTERN USA

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4.1. Abstract

Forest systems face increasing pressure to simultaneously provide multiple ecosystem services, which are often in conflict and challenging to maximize concurrently. We used a Multi-Criteria Decision Analysis (MCDA) approach to consider four objectives: 1) net carbon impact, 2) timber production, 3) bioenergy feedstock supply, and 4) sustaining forest bird biodiversity. We used SORTIE-ND, a forest dynamics model, to simulate five forest management alternatives over 100 years across New York, Vermont, New Hampshire, and Maine. To estimate the effects of each harvest alternative on net carbon impact, timber production, and bioenergy feedstock, we combined the outputs of SORTIE-ND with a greenhouse gas accounting tool, ForGATE., and estimated biodiversity levels using occupancy models derived through expert elicitation for 12 forest-dwelling bird species. We used the Simple Multi-Attribute Rating Technique to combine outcomes across objectives, resulting in a single, overall utility score for each harvest alternative. No one forest management alternative resulted in the greatest utility across all objectives. More intensive harvest alternatives achieved higher timber and bioenergy feedstock production, whereas the net carbon impact and biodiversity objectives were better served by less intensive harvest regimes. When all of the objectives were weighted equally in terms of importance, the forest management alternatives resulted in similar overall utility scores, emphasizing the role of decision maker and stakeholder values in MCDA approaches, allowing for the clear distinguishment of science and values. Our study that combined MCDA with forest dynamics, greenhouse gas accounting, and occupancy modeling provides a valuable approach for systematically evaluating natural resource tradeoffs.

4.2. Introduction

Forest systems face increasing pressure to simultaneously provide multiple ecosystem services. First, the importance of sequestering and storing carbon in forests continues to grow as atmospheric carbon rises to the highest levels in human history (IPCC 2014). Forests serve as a major global carbon sink. In the United States alone, forests currently sequester about 16% of carbon dioxide emissions (USFS), and governments are counting on forest sequestration to help meet climate goals. Second, timber product and wood energy consumption are projected to increase by more than a third over the next several decades (FAO 2022). Along with demand for traditional forest products and wood energy, wood product substitution for non-renewable materials is expected to grow substantially, largely motivated by climate change concerns (Nepal et al. 2021, FAO 2022). Increased timber product demand will also likely increase local and global forest economies and associated jobs (World Bank). Third, forest ecosystems provide habitat for most of the world's terrestrial biodiversity (Pillay et al. 2022, Shvidenko et al. 2005). Yet, degradation of forests has contributed to a precipitous decline in biodiversity and associated ecosystem functions (Rosenberg et al. 2019, Betts et al. 2022).

Timber harvest directly affects the provisioning of all of these ecosystem services. Several authors have demonstrated the tradeoffs between intensified forest management and net carbon sequestration. Some studies conclude that net sequestration declines as harvest intensity increases, even when harvested wood product carbon storage is accounted for (Mika and Keeton 2015, Gunn and Buchholz 2018, Brown et al. in review-a). Other studies conclude the opposite and suggest that harvesting increases net sequestration (Malmsheimer et al. 2008, Bradford and Kastendick 2010, Ruddell et al. 2007). These results are heavily influenced by the total number of carbon pools and carbon emissions sources included in each analysis (Buchholz et al. 2016). Harvest intensity also directly affects the magnitude of wood products and energy feedstocks available. As more raw materials are removed from the forest, wood-based fuel and timber products can be made available. While some studies demonstrate renewable wood energy production can help reduce atmospheric carbon, bioenergy harvest goals may conflict with biodiversity conservation goals because timber harvest shapes species distribution patterns on the landscape (Littlefield and Keeton 2012, Work et al. 2014). For example, when evaluating the effect of timber harvest on over fifty species of northeastern breeding birds, Schwenk et al. (2012) found that harvest intensity and management prescription determined whether individual birds increased, decreased, or exhibited no change in occupancy probability. Avian loss in North American forest biomes has been significant over the last several decades, on the order of a billion birds (Rosenberg et al. 2019). This includes species of conservation concern and species that are dependent on mature forests (Rosenberg et al. 2019, Betts et al. 2022).

Multi-Criteria Decision Analysis (MCDA) is one approach for evaluating complicated tradeoffs associated with forest management decisions. MCDA is a formal approach to decision-making (Belton and Stewart 2002), and has been utilized for several decades in natural resource management, where most decisions include multiple, and often competing, objectives (e.g., maximize harvest income while maximizing forest carbon storage). Assessing tradeoffs between management alternatives requires tools that can account for conflicting objectives, diverse stakeholders, uncertainty, different types of data, and multiple units of analysis (Kiker et al. 2005, Wolfslehner and Seidl 2010). An MCDA framework can help cut through the complexity and inherent uncertainty of many types of problems in a systematic way (Mendoza and Martins 2006, Diaz-Balteiro and Romero 2008, Wang et al. 2009, Kareiva and Marvier 2012). Sustainable forestry problems are particularly appropriate for MCDA given the inherent challenges to simultaneously meeting economic, social, and environmental goals (Buchholz et al. 2009, Schwenk et al. 2012).

Understanding these forest management tradeoffs is pressing in the northeastern U.S., where state governments are actively debating the role of forests in meeting climate goals, renewable energy goals, and biodiversity goals (Biomass Energy Resource Center 2013, Maine Governor's Energy Office 2015, New York Climate Action Council 2021, New Hampshire Department of Energy 2022, Vermont Department of Public Service 2022). Timber harvest is generally sustainable, but in a geography that is predominantly forested (74%), and a political landscape that is setting ambitious, economy-wide climate-neutral goals, forest resources are being targeted to simultaneously increase carbon sequestration, provide timber resources and renewable energy feedstocks, and protect biodiversity including forest-dependent birds.

To examine these tradeoffs, we developed a SMART (Simple Multi-Attribute Ranking Technique (Edwards 1977, Edwards and Barron 1994) MCDA framework, that predicts the consequences that alternative forest harvest scenarios (i.e., decision alternatives) will have with respect to competing forest management objectives (i.e., decision objectives) (Fig. 1). Specifically, our objectives, which follow common steps in MCDA analysis, were to: 1) Identify forest management decision objectives, 2) Identify forest management decision alternatives, 3) Estimate the consequences of each decision alternative relative to each decision objective, 4) Evaluate tradeoffs among the decision objectives.

4.3. Methods

4.3.1. Study Area

Our study area comprised the forested regions of the states of New York, Vermont, New Hampshire, and Maine, USA. The landscape is roughly 71% forest, the majority of which is northern hardwood-conifer forest. This forest type is characterized by sugar maple (*Acer saccharum*), American beech (*Fagus grandifolia*), and yellow birch (*Betula alleghaniensis*) with Eastern hemlock (*Tsuga canadensis*), white ash (*Fraxinus americana*), and red spruce (*Picea rubens*) occurring as common canopy associates on some sites. The climate ranges from warm summers to cold, snowy winters with average annual precipitation ranging between 102 cm and 124 cm.

4.3.2. Objective 1. Identify forest management decision objectives (Figure 1A).

We selected four commonly described forest management objectives for use as fundamental decision objectives, the objectives that decision makers ultimately value, in an MCDA framework: 1) maximize net carbon impact, 2) maximize timber production, 3) maximize energy feedstock production, and 4) maximize biodiversity (Figure 1A). We established performance measures for each objective.

1.1. Maximize net carbon impact. Net carbon impact refers to the total net sequestration that results from forest ecosystem dynamics and harvested wood product processes for a given forest management alternative (described in Objective 2). Here, we measured net carbon impact (metric tons CO2e/ha) as total sequestration minus total emissions, where total sequestration equals gross forest growth plus the annual changes in the forest product and landfill carbon pools, and total emissions equals the summed emission sources (decomposition, mill waste, bioenergy production, incineration, and landfill decomposition).

1.2. Maximize timber production. Timber production represents the amount of wood products that result from harvest operations and manufacturing. Typically, hardwood and softwood saw timber and pulpwood are manufactured into primary finished wood products, like timber lumber or plywood (Figure 2, columns B and C). Then, those primary finished wood products are transferred into end-use products like houses and furniture (Figure 2, column D). Here, we measured timber production as the metric tons of end-use wood products per ha, where end-use wood products equal construction materials (including houses), shipping materials, furniture, paper, and other nonresidential construction (Figure 2, column D).

1.3. Maximize bioenergy feedstock production. Bioenergy feedstock production refers to the amount of harvested forest material used to produce energy. Generally, a portion of harvest products like pulpwood and logging residue (tops and branches left onsite after a harvest operation) are utilized as energy feedstocks in the form of chips, pellets, or residues (Figure 2, columns B and C). We measured bioenergy feedstock production as the cumulative metric tons of biomass from all bioenergy feedstocks per hectare.

1.4. Maximize biodiversity. We measured biodiversity as the probability of occurrence of 12 forest-dwelling songbirds across the study area. The suite of birds are all sensitive to changing forest conditions, but they prefer a range of habitat features like canopy cover and forest structure (Table 1). We considered the 12 bird species as subobjectives of the biodiversity objective, which allowed us to examine the effect of individual bird species on the decision outcome (Figure 1B).

4.3.3. Objective 2. Identify forest management decision alternatives (Figure 1C).

We utilized 5 timber harvest scenarios as our decision alternatives (Brown et al. 2018a) (Figure 1C, Table 2). These forest management alternatives represent different harvest regimes that affect each decision objective – maximizing carbon impact, timber and energy feedstock production, and biodiversity – to varying degrees. Fully described in Brown et al. 2018, current harvest regimes were estimated for 6 different forest types and regions using FIA data, including aspen-birch, spruce-fir, bottomland, oak-hickory, northern hardwood-conifer forests in Maine, and northern hardwood-conifer forests in New York, Vermont, and New Hampshire. The harvest regimes were quantified by first establishing the annual probability that a plot was harvested, and second, if a plot was harvested, calculating the total amount of basal area removed (Canham et al. 2013, Brown et al. 2018a). In addition to the current harvest regime (H1), four other harvest regimes were analyzed (Brown et al. 2018a). The second harvest regime increases average harvest intensity by 50% ("current harvest + intensity"; H2). The third scenario increases the frequency of harvests by 75%, keeping the current distribution of harvest intensity ("current harvest + frequency"; H3). The fourth harvest regime increases average harvest intensity by 50% and harvest frequency by 100% ("current harvest + intensity + frequency"; H4). The fifth scenario is a no harvest scenario ("no harvest"; H0) (Table 2).

The five forest management alternatives were implemented in SORTIE-ND (Brown et al. 2018a). This model, described fully in Brown et al. 2018, calculates the population dynamics for all tree species in a stand. SORTIE-ND is an individual-based, spatially explicit model, that tracks the fate of individual seedlings, saplings, and adult trees and their interactions with the environment annually over 100 years. U.S. Forest Service Forest Inventory and Analysis (FIA) program data were used to parameterize the model for the 30 most common tree species in the study region. Model behaviors describing tree growth, natural mortality, forest management, and recruitment determine the trajectory of the forest over time. Every modeling scenario consists of 5000 individual SORTIE-ND runs that are initialized using forest data from 5000 random FIA plots within the study area. This represents the current condition of the landscape at time step 0. The outputs of the model for application in this study include harvest, forest structure, and forest composition metrics for each forest management alternative (H0, H1, H2, H3, H4), time period (years 2070 and 2120), and state/region (New York, Vermont, New Hampshire, Maine, and New England) (Brown et al. 2018a).

4.3.4. Objective 3. Estimate the consequences of each decision alternative relative to each decision objective (Figure 1D).

Consequences are the predicted result of each decision alternative for each decision objective. Three models were used to estimate consequences in this study: 1)

SORTIE-ND, a forest dynamics model (Pacala et al. 1996, Coates et al. 2003, Brown et al. 2018a), 2) ForGATE, a greenhouse gas accounting tool (Hennigar et al. 2013, Brown et al. in review-a), and 3) bird species occupancy models (Brown et al. in review-b). The consequences for each decision objective are considered partial utilities (Figure 1D), whereas the total utility is a one score summary across all four decision objectives (Objective 4, Figure 1F). We projected the consequences (net carbon impact, timber production, bioenergy feedstock production, biodiversity) of the five forest management alternatives (H0, H1, H2, H3, H4) for two time periods (years 2070 and 2120) and five states/region (New York, Vermont, New Hampshire, Maine, and New England).

3.1 Net Carbon Impact. Net carbon impact was the total net sequestration (total sequestration - total emissions) that results from forest ecosystem dynamics, like forest growth and decomposition, and the production and disposal of harvested wood products. The modeling framework combined a forest dynamics model, SORTIE-ND, with a greenhouse gas accounting tool, ForGATE, to track carbon pools and fluxes over 100 years (Brown et al. in review-a). The authors tracked a range of carbon pools including forest ecosystem pools (aboveground and belowground biomass, hardwood and softwood detritus and coarse woody debris, mineral soil) (Figure 2, column A), forest product pools (construction materials, furniture, shipping materials, paper, and residue, chip, and pellet bioenergy feedstocks) (Figure 2, columns C and D), and waste pools (landfills and incinerated waste) (Figure 2, column E). Emissions sources (decomposition, mill waste, bioenergy production, incineration, and landfill decomposition) were also tracked (Figure 2).

The forest carbon pool and harvest data from SORTIE-ND were used as inputs to calculate carbon storage and emissions associated with wood products and landfills based on ForGATE, a greenhouse gas account tool (Hennigar et al. 2013, Brown et al. in review-a) (Figure 2). Described fully in Hennigar et al. 2013, ForGATE tracks the harvested wood from SORTIE-ND (Figure 2, column A) and transfers the carbon to pulpwood and sawlog pools (Figure 2, Column B). Next, carbon in these pools is transferred to primary finished products (i.e., lumber, plywood, oriented strand board (OSB), nonstructural panels, pulp/paper) via manufacturing (Figure 2, column C). Finally, carbon is combusted as energy or mill waste, or transferred to five end-use product pools (i.e., housing construction, furniture, shipping products, paper, other nonresidential construction) (Figure 2, column D). The authors assumed that 50% of the emissions from bioenergy combustion displaces fossil fuel emissions. Finally, the end-use wood product pools terminated in one of two waste stream pools: 1) landfills, which both store carbon long term and emit carbon through decay, or 2) incineration (Figure 2, column E). The net carbon impact (metric tons CO2e/ha total sequestration - metric tons CO2e/ha total emissions) calculated from forest ecosystem dynamics and harvested wood product processes were recorded in the consequence table as partial utilities for each forest management alternative (Figure 1D).

3.2 Timber Production. We utilized timber production data from Brown et al. in review. As described above, the forest dynamics model, SORTIE-ND, derives the amount of harvested biomass given a forest management alternative. Hardwood and softwood harvested biomass is apportioned to sawlogs, pulpwood or residue pools according to Timber Product Output (TPO) data (Brown et al. in review-a) (Figure 2, columns A and B). TPO studies are conducted by the U.S. Forest Service and estimate the use of roundwood from timber harvest through targeted nationwide mill surveys. Once harvested biomass is apportioned to sawlogs, pulpwood, or residue, it is tracked via ForGATE through the manufacturing and production of end-use wood products (Brown et al. in review-a) (Figure 2, columns C and D). We recorded the cumulative amount of end-use finished wood products (metric tons of wood products/ha) as partial utilities for each forest management alternative.

3.3 Bioenergy feedstock production. Bioenergy feedstock production represents the amount of harvested forest material used to produce energy, given forest management alternatives. We utilized bioenergy feedstock production data from Brown et al., in review. The authors allocated a proportion of the harvested material resulting from SORTIE-ND model runs to bioenergy feedstocks (Figure 2, columns A, B and C). The feedstock scenario assumed 5% of hardwood and softwood sawlogs are diverted to chip and pellet energy feedstocks, 20% of hardwood and softwood pulpwood are diverted to energy feedstocks, and 25% of logging residues are diverted to energy feedstocks. Here, we utilized the annual amount of total bioenergy feedstock supply for three feedstock products, chips, pellets, and residues (metric tons of bioenergy feedstocks/ha), as consequences for each forest management alternative (Figure 1D). Brown et al., in review assumed that all energy feedstocks were combusted in the year they were produced.

3.4 Biodiversity. We used forest bird occupancy data to represent biodiversity levels, described fully in Brown et al. in review-b. The authors used expert elicitation techniques and generalized linear mixed modeling approaches to estimate the probability of occurrence of 12 forest-dependent songbirds across the study region (Table 1). Many of these species are identified as species of concern and are associated with different seral stages of forest development. Thirty-seven experts voluntarily estimated occupancy probability via a web survey for the 12 bird species based on a survey site map, site covariates, and supplemental figures describing basal area and composition for adult trees and saplings. Species-specific occupancy models were generated through generalized linear mixed modeling methods, where the mean probability of occurrence was the response variable, fixed effects included on-the-ground covariates from SORTIE-ND as well as landscape-scale covariates derived from GIS, and random effects included expert and/or ecoregion (ref). The bird models were projected out 100 years under changing forest conditions derived from the forest management alternatives. Partial utilities were calculated for each individual bird species (Figure 1D).

4.3.5. Objective 4. Evaluate tradeoffs among the decision objectives (Figure 1F).

Because the decision objectives vary in scale (e.g., net carbon impact is not directly comparable with biodiversity level), we normalized the data within the partial utilities from Objective 3 using a maxi-min approach (ref). This method rescales each row in the consequence table between 0 and 1, where the best harvest alternative for a given objective is scored 1, the worst harvest alternative is scored 0, and the remaining alternatives are scored between 0 and 1 based on their distances from the optimum. Within this method, we calculated the total utility of each alternative by adding the scaled values across all four foundational objectives. The resulting total utility scores provide a quantifiable “consequence” of each forest management scenario (Figure 1F). Decision makers use these results to inform their decisions, often selecting the alternative that provides the overall highest utility.

The total utility scores imply that all four decision objectives are equally important. However, diverse stakeholders will value these objectives differently. For example, state representatives who are charged with meeting climate goals may value net carbon impact more than biodiversity. MCDA allows these values to be incorporated as weights through a formal process (Figure 1E). These weights represent the social value that stakeholders place on each objective and have no bearing on the data within the consequence table (thus separating "values" from "science" in the decision problem). The challenge lies in rigorously assessing the weights so that they reflect the values of stakeholders.

Here, we examined a full range of weighting options across all decision objectives. We systematically calculated the total utility of each harvest scenario under all combinations of weighting schemes, where each decision objective was weighted with five different values (0, 0.25, 0.5, 0.75, and 1), resulting in 625 possible weighting schemes for each region (ME, NH, NY, VT, Northeast) and timeframe (2070 and 2120) combination. We retained only those weighting schemes whose values summed to 1 (n = 35/625), resulting in 350 different weighting schemes in total (35 schemes * 6 regions * 2 timeframes). This approach allowed us to examine the resulting utility scores for each harvest scenario across a full range of hypothetical stakeholder values. The total utility of each decision alternative is the value in the consequence table, multiplied by the weight (or value preference) for each decision objective (Fig. 1F).

We further examined the biodiversity objective because it is comprised of 12 forest-dwelling songbird subobjectives (Figure 1B). All of the songbirds are sensitive to changes in forest condition, but they prefer different forest niches for nesting. We tested the sensitivity of the subobjective weighting by grouping the songbirds into three categories of habitat preference: 1) forest interior, closed canopy (blackburnian warbler, black-throated green warbler, ovenbird, scarlet tanager), 2) intermediate canopy cover (American redstart, black-throated blue warbler, veery, wood thrush), and 3) early successional, open canopy (Canada warbler, chestnut-sided warbler, mourning warbler, white-throated sparrow). We systematically shifted the total weight assigned to the biodiversity objective to each group of birds and compared the resulting utility scores.

4.4. Results

4.4.1. Consequences

We calculated the consequences of 50 different combinations of forest management decision alternatives (harvest scenarios H0, H1, H2, H3, H4), years (2070 and 2120), and state/region (New York, Vermont, New Hampshire, Maine, New England) (Appendix S4). The results for each decision objective varied over time and space. Net carbon impact values ranged from 110.4 metric tons CO2e/ha (harvest scenario H4, year 2070, NY) to 555.0 metric tons CO2e/ha (harvest scenario H0, year 2120, NH). As the forest management alternatives intensified in harvest, net carbon impact decreased (Figure 3). Harvested wood product values ranged from 0 to 25.2 metric tons harvested wood products/ha (harvest scenario H4, year 2120, ME). All scenarios that included the no forest management decision alternative (H0) resulted in no harvested wood products and no energy feedstock production. The amount of harvested wood products increased as harvest intensity increased. Bioenergy feedstock production ranged from 0 to 1.0 metric tons bioenergy feedstocks/ha/yr (harvest scenario H4, year 2070, ME) and increased as harvest intensity increased (Figure 3). The biodiversity values ranged from 0.17 to 0.94 and varied significantly by species (Figure 4). Canada warbler and mourning warbler were among the species with the lowest occupancy scores; ovenbird and scarlet tanager were among the species with the highest occupancy scores.

4.4.2. Tradeoffs

We calculated utility scores for 350 different weighting schemes. When each of the four objectives was weighed the same, utility scores varied by geography and year (Figure 5). A single result is highlighted in Table 3, which illustrates the calculations of the total utility score for the region-wide scenario in the year 2120 when the foundational objectives were weighted equally (weight = 0.25) and the forest-bird subobjectives were weighted equally (weight = 0.021). Table 3A shows the consequences, or partial utilities, representing the scientific predictions from models that estimated the effects of the forest management alternatives on carbon impact, timber and energy feedstock production, and biodiversity. To compare the tradeoffs between objectives, the consequence table results were scaled such that the best alternative for a given objective was scored 1, the worst alternative was scored 0, and the remaining scenarios were scored between 0 and 1 based on their distances from the optimum (Table 3B). Total utility equals the dot product of the partial utilities and the weights of each objective and subobjective, revealing utility scores of 0.50, 0.52, 0.50, 0.49, and 0.50 for harvest scenarios H0, H1, H2, H3, and H4 respectively (Table 3B). Harvest alternative H1 has the highest total utility in terms of overall rank (Table 3B), but other alternatives are in contention. This same example is illustrated in Figure 5. The partial utilities of each objective (Table 3B) are graphed in the New England panel (Figure 5, top left). The cumulative bars are representative of the overall rank of the harvest alternative utility scores, although to calculate total utility, the partial utilities were multiplied by objective weight. In this example, harvest alternative H1 represents the highest total utility (Figure 5, top left).

When all weights were assigned to one decision objective (weight = 1), the no management alternative (H0) resulted in the highest utility for maximizing biodiversity and maximizing net carbon impact. The most intensive harvest regime (H4) resulted in the highest utility for maximizing timber products. This same alternative (H4) also yielded the highest utility score for the majority of state and year combinations when maximizing energy feedstock production. There was a large gap in utility score between the no management alternative (H1) and the harvested management alternatives (H1-H4) whose values were clustered more closely together. This gap was consistent when the no management alternative had both the highest and lowest utility scores.

Across all weighting scenarios, the no harvest forest management alternative (H0) most frequently resulted in the highest utility score (Figure 6). This same forest management alternative (H0) also resulted in the lowest utility score most often (Figure 6). Similarly, the most intensive timber management scenario (H4) resulted in frequent high and low utility scores (Figure 6). These results are due, in part, to the relationship between harvest, timber products, and bioenergy feedstock production. As harvest intensity increases, the amount of timber products and energy feedstocks also increase (Figure 3), which is reflected in the partial utility scores for those objectives. On the other hand, the utility score for the no harvest alternative (H0) is driven by the values of net carbon impact and forest bird biodiversity. Because the H0 alternative generates no harvested wood products, it receives no partial utility for timber production or bioenergy feedstocks when the foundational objectives are weighted equally. Therefore, the H0 total utility score is often the lowest decision alternative score despite the large net carbon impact partial utility.

Twelve forest-dwelling songbirds comprise the biodiversity decision objective. Holding the state/region, year, and fundamental objective weighting constant at Northeast, 2120, and 0.25 for each foundational objective, respectively, we calculated the sensitivity of the individual bird subobjectives relative to the overall utility score for the forest management alternatives. Weighting the 12 birds equally resulted in the current harvest regime having the highest utility score, ranging from 0.49 (H3) to 0.52 (H1). We shifted all the biodiversity weight to each group of habitat-preferring birds by weighting each bird in the group 0.063 (n = 4) and the remainder of the birds 0 (n = 8) (Table 1). When both the closed canopy bird group and the intermediate canopy bird group were highly valued, the current harvest regime (H1) resulted in the highest utility. When the early successional, open canopy group was preferred, the most intensive harvest regime (H4) scored the highest in utility. Importantly, the range of utility scores was minimal across the forest management alternatives when valuing closed canopy and intermediate forest birds (closed canopy bird range = 0.49 (H3) to 0.52 (H1) and intermediate forest birds range = 0.49 (H3) to 0.53 (H1)). Within the early successional open canopy, the spread of utility scores was much greater, ranging between 0.25 (H0) to 0.75 (H4).

4.5. Discussion

We used an MCDA framework to evaluate forest management alternatives relative to maximizing net carbon impact, timber and bioenergy feedstock production, and biodiversity objectives. No one forest management alternative resulted in the greatest utility across all scenarios, due to the varying effects of timber harvest activities and weighting on the decision objectives. This means that the values of decision makers will have a large influence over the utility outcomes and tradeoffs will be required.

These results underscore a key feature of MCDA. The process allows for the systematic evaluation of tradeoffs between multiple important and competing objectives. This was the case in our study where the no harvest scenario (H0) was both the most frequent highest performing forest management alternative as well as the most frequent lowest performing alternative, making up roughly 40% of all weighting combinations (Figure 5). Examining the effects of the forest management alternatives on the individual decision objectives and maximally weighting each objective highlighted the juxtaposition of several goals. First, net carbon sequestration declines as forest intensity increases. Even though more intensified timber harvest increases the amount of carbon stored in wood products, that does not make up for the loss in average carbon storage across the landscape and the emissions associated with the production and disposal of harvested wood products. This means that the highest utility forest management alternative for net carbon impact (H0) is the lowest utility forest management alternative for timber production. The opposite is also true in that the highest utility forest management alternative for timber production (H4) is the lowest utility forest management alternative for net carbon impact. Second, bioenergy feedstock production is similarly related to the intensity of harvest and the amount of woody material diverted to energy feedstocks. It follows that forest management alternatives that are most beneficial for bioenergy feedstock production (H4) are most detrimental for net carbon impact, even when factoring in fossil fuel emissions displacement by forest bioenergy. In practice, it is impossible to simultaneously maximize competing objectives.

The MCDA process cuts through the impasse of competing objectives by formally incorporating the perspectives of decision makers or stakeholders. There is a clear separation of science, the results of which are factually reported without bias in the consequence table, and values, which are incorporated through the weighting of decision objectives (Adem Esmail and Geneletti 2018). Weighting is a crucial step in MCDA as it directly influences the scoring of the preferred alternatives. Integral to the process is making value judgements explicit and ideally incorporating stakeholder input (Adem Esmail and Geneletti 2018). While we were unable to incorporate stakeholders into our study, we calculated the utility scores for 350 different weighting combinations so as not to influence the utility outcomes according to our own values or the hypothetical values of decision makers.

We explored the sensitivity of weighting by examining the effect of the biodiversity subobjective weights on the total utility score. Utility scores were sensitive to the habitat preferences of three bird groupings: 1) forest interior, closed canopy, 2) intermediate forest cover, and 3) early successional, open canopy (Table 1). When birds that prefer closed and intermediate canopy cover were prioritized, the current harvest regime (H1) resulted in the highest utility score. Alternatively, when birds associated with open canopies were highly valued, the most intensive harvest regime (H4) was the preferred alternative. Perspectives vary widely on whether forest management should favor early seral habitats that support declining early successional bird populations (King and Schlossberg 2014, Litvaitis et al. 2021) or late-successional habitats that are underrepresented in the landscape (Brown et al. 2018a) and promote structural complexity co-benefits like carbon storage and biodiversity (Ford and Keeton 2017, McGee 2018, Thom and Keeton 2020). These are value differences and MCDA frameworks allow for the incorporation of these opposing viewpoints.

Notably, the range of total utility scores is minimal across the forest management alternatives when closed and intermediate canopy cover preferring bird groups were valued (closed canopy bird range = 0.49 (H3) to 0.52 (H1) and intermediate forest bird range = 0.49 (H3) to 0.53 (H1)). Absolute differences between forest management alternatives should be interpreted cautiously when the range of utility scores is so minimal. In our presentation of the bird sensitivity results, equal weight was assigned to the foundational objectives (weight = 0.25). When more weight is assigned to maximizing biodiversity, the spread of utility scores is greater across the forest management objective. This means that the no harvest (H0) and current harvest scenarios (H1) become the preferred forest management alternatives by a wider margin as the overall biodiversity objective weight increases and closed and intermediate canopy birds are valued. While a strength of MCDA is its ability to evaluate tradeoffs between conflicting values and objectives, the sensitivity of the weighting schemes could heavily influence the utility score outcomes, which should be evaluated relative to the utility scores of all alternatives.

Decision makers develop solutions based at least in part on their values. The MCDA framework explicitly accounts for this component of the decision-making process. In our study there were several examples of the utility scores for forest management alternatives being similar across all alternatives. For example, in Table 3, the objectives and subobjectives were set equally, and the resulting utility scores were nearly equal across the forest management alternatives, ranging from 0.49 (H3) to 0.52 (H1). There is no clear timber harvest alternative that will equally meet carbon, timber and energy production, and biodiversity goals, which emphasizes the importance of both science and values in natural resource decision making.

We used one MCDA approach, Simple Multi-Attribute Rating Technique (SMART) (Edwards 1977, Edwards and Barron 1994). Several different approaches can be classified as MCDA methods, but they all utilize multiple criteria to make decisions and the decision-makers are always individuals or groups of individuals (Belton and Stewart 2002, Mendoza and Martins 2006). As a framework for forest management and other types of complex natural resource decision problems that aspire to meet multiple objectives, MCDA is a favorable process. Forest management in the U.S. is increasingly vying to meet multiple objectives, and an MCDA framework can aid in evaluating tradeoffs between different harvest regimes. One strength of MCDA approaches is the possible aggregation of different types of quantitative data with normative opinions. The framework strips out the complexity of assessing criteria with multiple units (e.g., comparing tons of carbon against species occurrence), providing stakeholders with a uniform rating scheme upon which to establish preferences. Overall the approach is flexible, not only resulting in preferred alternatives, but also improved understanding of the tradeoffs through changing weighting preferences.

Alternatively, when applying MCDA frameworks there are several pitfalls that may lead to suboptimal outcomes (Adem Esmail and Geneletti 2018). Of particular relevance is the crucial element of weighting. Successful MCDA processes understand the implication of weighting, convey the importance of weighting to relevant stakeholders, and use sensitivity analyses to examine the robustness of the results (Adem Esmail and Geneletti 2018). And the results of an MCDA approach are only as good as the objectives and alternatives presented to stakeholders. Additionally, MCDA processes may not capture the full range of values across whole populations, as they are particularly good at targeting decision maker values (Saarikoski et al. 2016). A failure to consider the values of all stakeholders can undermine progress toward achieving MCDA goals and objectives (Armitage et al. 2020).

Federal and state governments are increasingly identifying the critical role forests play in meeting climate, energy, biodiversity, and timber production goals. All of these objectives cannot be maximized concurrently. Our study exemplified these complexities by bringing together models of forest dynamics, greenhouse gas accounting, and species occupancy to evaluate forest management tradeoffs on four decision objectives. No one solution is the best alternative for all objectives, thereby emphasizing the importance of decision maker preferences. MCDA provides a formal process for integrating quantitative data and stakeholder values to identify solutions that meet multiple objectives, while explicitly identifying tradeoffs.

4.6. Tables and Figures

4.6.1. Tables

Table 4.1. Characteristics of focal species and subobjective categories. Canopy closure categories are defined as: (1) Open = canopy closure < 30%, (2) Intermediate = canopy closure between 30% - 80% and (3) Closed = canopy closure > 80% (Hagenbuch et al. 2011). Guild categories are defined as: (1) Interior = species increase as percent forest cover and distance to edge increases, (2) Mixed = species increase as percent forest cover increases and have positive associations with evergreen forest, (3) Deciduous, edge tolerant = species increase near edges and peak mostly in forested areas, (4) Intermediate = species peak at intermediate forest cover, (5) Forest edge = species decrease as road density increases, (6) Evergreen and mixed = species increase near edges and as percent forest cover increases; positive association with evergreen forest (Schwenk and Donovan 2011). Cluster categories are defined as: (1) Interior = species increase with high percent forest cover, (2) Coniferous = species increase with high percent forest cover and higher coniferous basal area, (3) Intermediate = species increase with intermediate forest cover, (4) Early successional within forest matrix = species increase with early successional habitat within forested landscapes (Schwenk et al. 2012) (from Brown et al. in review-b).

Subobjective group	**Species**	**Canopy Closure** (Audubon Vermont 2011)	**Guild** (Schwenk and Donovan 2011)	**Cluster** (Schwenk et al 2012)	**Birds of Conservation Concern** (state Audubon chapters, state wildlife action plans)
Forest interior, closed canopy	Blackburnian warbler	Closed (> 80%)	Mixed	Coniferous	NY, ME
Forest interior, closed canopy	Black-throated green warbler	Closed (> 80%)	Interior	Interior	NY, VT, ME
Forest interior, closed canopy	Ovenbird	Closed (> 80%)	Interior	Interior	
Forest interior, closed canopy	Scarlet tanager	Closed (> 80%)	Intermediate	Intermediate	NY, VT, NH, ME
Intermediate canopy cover	American redstart	Intermediate (30 - 80%)	Deciduous, tolerant of edges	Intermediate	NY, ME
Intermediate canopy cover	Black-throated blue warbler	Intermediate (30 - 80%)	Interior	Interior	NY, VT, ME
Intermediate canopy cover	Veery	Intermediate (30 - 80%)	Deciduous, tolerant of edges	Intermediate	NY, VT, NH, ME
Intermediate canopy cover	Wood thrush	Intermediate (30 - 80%)	Intermediate	Intermediate	NY, VT, NH, ME
Early successional, open canopy	Canada warbler	Intermediate (30 - 80%)	Mixed	Early successional within forest matrix	NY, VT, NH, ME
Early successional, open canopy	Chestnut-sided warbler	Open (< 30%)	Forest edge, early successional	Early successional within forest matrix	NY, VT, ME
Early successional, open canopy	Mourning warbler	Open (< 30%)	Forest edge, early successional	Early successional within forest matrix	ME
Early successional, open canopy	White-throated sparrow	Open (< 30%)	Evergreen and mixed	Early successional within forest matrix	VT, ME

Table 4.2. Timber harvest scenarios.

Harvest Scenario	Harvest Scenario Definition
No harvest (H0)	No harvest
Current harvest (H1)	The current harvest regime characterized as a function of forest type/region, total plot basal area, and distance to the nearest improved road, including a 3 degree C increase in mean annual temperature and a 10% increase in total annual precipitation over the next 100 years (Brown et al 2018)
Current harvest + intensity (H2)	The current harvest regime and a 50% increase in average harvest intensity
Current harvest + frequency (H3)	The current harvest regime and a 75% increase in harvest frequency
Current harvest + intensity + frequency (H4)	The current harvest regime, a 50% increase in average harvest intensity, and a 100% increase in harvest frequency

Table 4.3. Example of Multi-Criteria Decision Analysis consequence table and tradeoff results. Consequences, or partial utilities, represent the effect of forest management harvest alternatives on the objectives, and are generated from models of forest dynamics, greenhouse gas accounting, and forest bird occupancy (Table A). To examine tradeoffs between the various objectives, these values must be scaled (Table B). They can also be weighted to incorporate stakeholder values (Table B). One final utility score results for each forest management alternative (Table B).

Geography = New England
Timeframe = 2120

A

				Forest Management Alternative				
Foundational Objective	**Weight**	**Subobjective**	**Weight**	**H0**	**H1**	**H2**	**H3**	**H4**
Maximize net carbon impact	0.25		0.250	473.67	239.75	218.41	185.66	164.53
Maximize timber production	0.25		0.250	0.00	17.54	18.74	20.78	22.37
Maximize energy feedstock production	0.25		0.250	0.00	0.51	0.50	0.58	0.69
Maximize biodiversity	0.25	AMRE	0.021	0.69	0.63	0.62	0.61	0.60
		BTBW	0.021	0.61	0.55	0.55	0.54	0.53
		BTNW	0.021	0.65	0.51	0.50	0.47	0.45
		BLBW	0.021	0.51	0.41	0.40	0.39	0.37
		CAWA	0.021	0.22	0.25	0.25	0.26	0.26
		CSWA	0.021	0.50	0.52	0.53	0.53	0.54
		MOWA	0.021	0.26	0.25	0.25	0.24	0.25
		OVEN	0.021	0.88	0.77	0.75	0.73	0.71
		SCTA	0.021	0.70	0.64	0.63	0.62	0.61
		VEER	0.021	0.56	0.55	0.54	0.54	0.53
		WOTH	0.021	0.46	0.43	0.42	0.41	0.40
		WTSP	0.021	0.48	0.56	0.58	0.59	0.61

B

				Forest Management Alternative				
Foundational Objective	**Weight**	**Subobjective**	**Weight**	**H0**	**H1**	**H2**	**H3**	**H4**
Maximize net carbon impact	0.25		0.250	1.00	0.24	0.17	0.07	0.00
Maximize timber production	0.25		0.250	0.00	0.78	0.84	0.93	1.00
Maximize energy feedstock production	0.25		0.250	0.00	0.74	0.73	0.84	1.00
Maximize biodiversity	0.25		0.250	1.00	0.32	0.24	0.13	0.00
			UTILITY ->	0.50	0.52	0.50	0.49	0.50

4.6.2. Figures

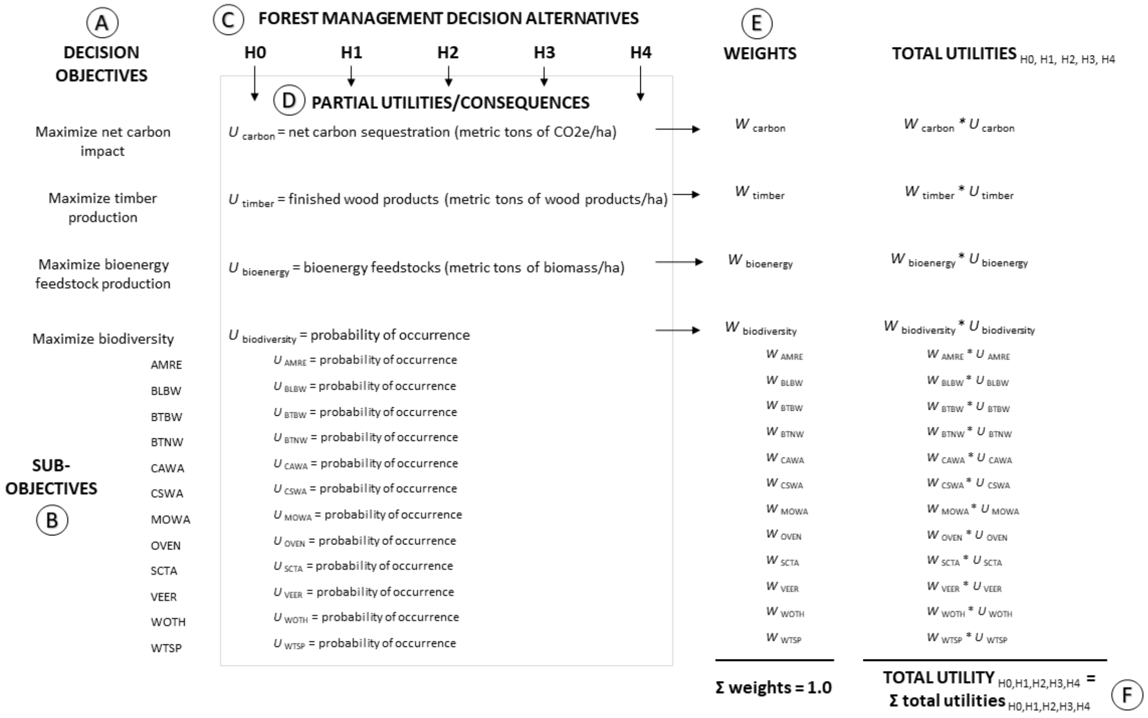


Figure 4.1. Multi-Criteria Decision Analysis (MCDA) framework. Key components include the identification of decision objectives and decision alternatives (A, B, C). From there, consequences are calculated and represent the effect of decision alternatives (C) relative to the objectives (D). Weighing schemes (E) are applied to the consequence results to generate a total utility score for each decision alternative (F).

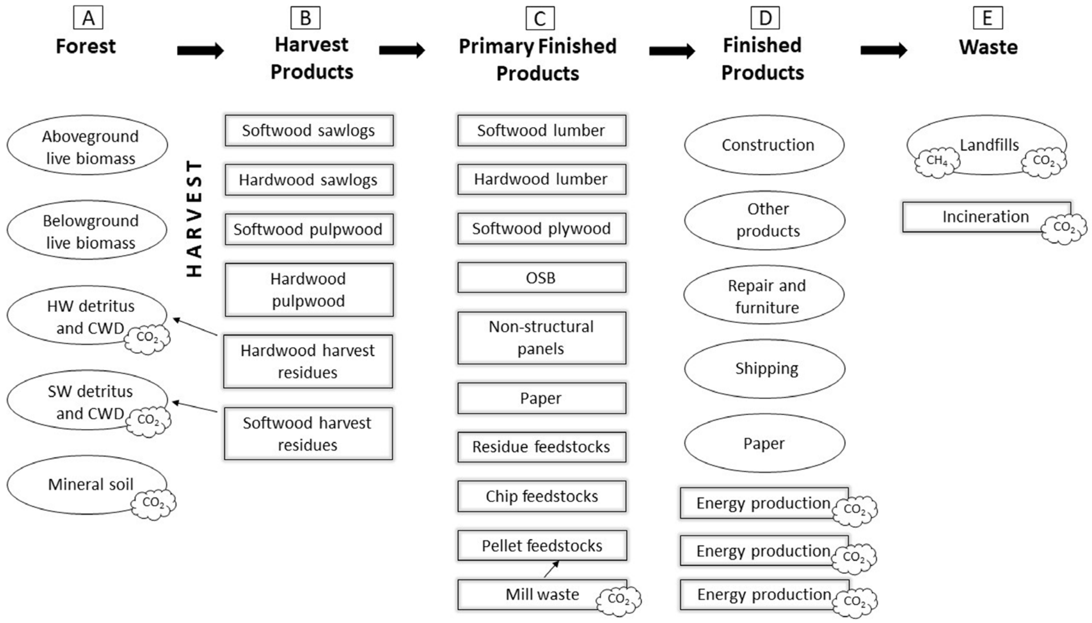


Figure 4.2. Carbon transfer from forest pools through waste pools and release to the atmosphere. Forest carbon (column A) is transferred to harvest products (column B) as defined by each harvest regime (Brown et al. 2018a). Carbon in harvest product pools (column B) is transferred to end products, waste pools, or the atmosphere (columns C, D, and E) based on ForGATE (Hennigar et al. 2013). Ovals indicate carbon pools that can accumulate or decline, rectangles represent annual pass-through pools, and clouds represent GHG emissions (from Brown et al. in review-a).

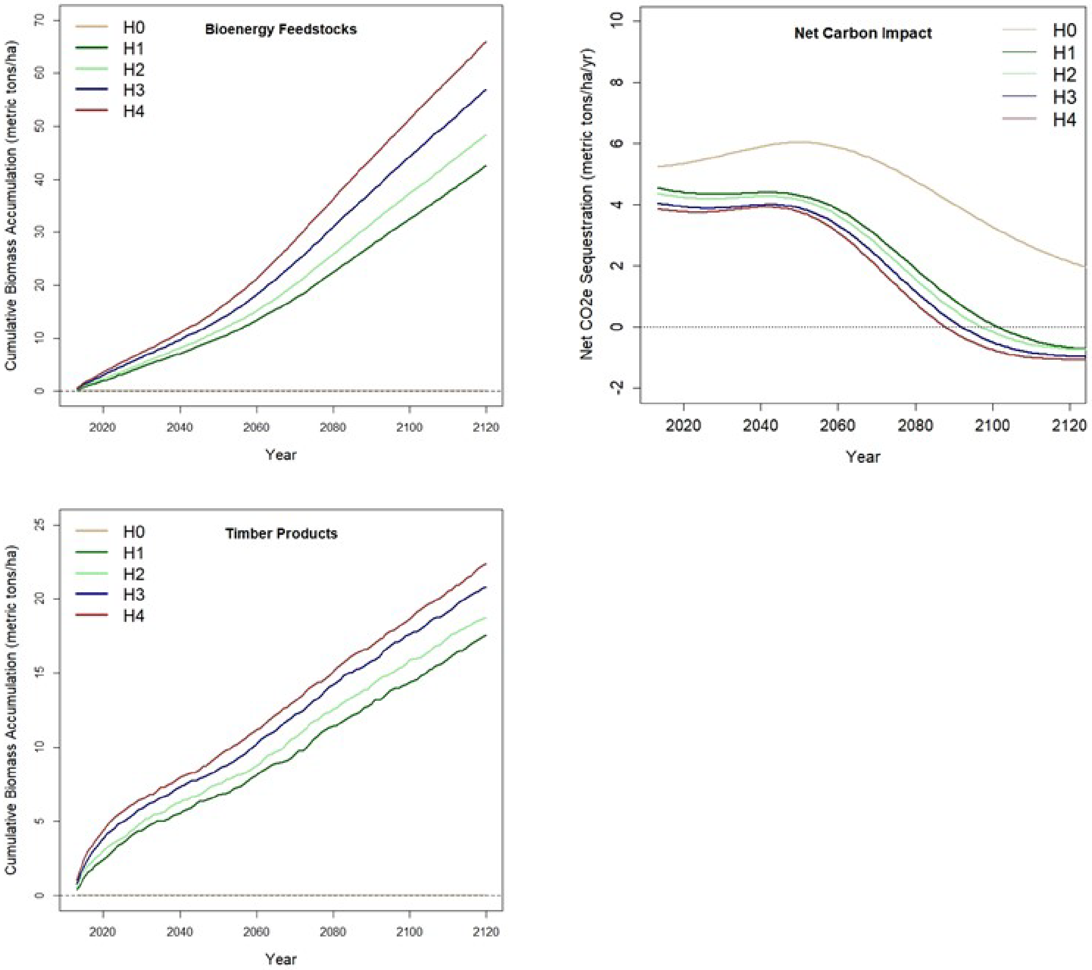


Figure 4.3. SORTIE-ND outputs for five forest management alternatives varying by harvest frequency and intensity illustrating the accumulation of (1) biomass energy feedstocks (upper left), (2) net carbon impact (upper right), and (3) timber products (from Brown et al. in review-a).

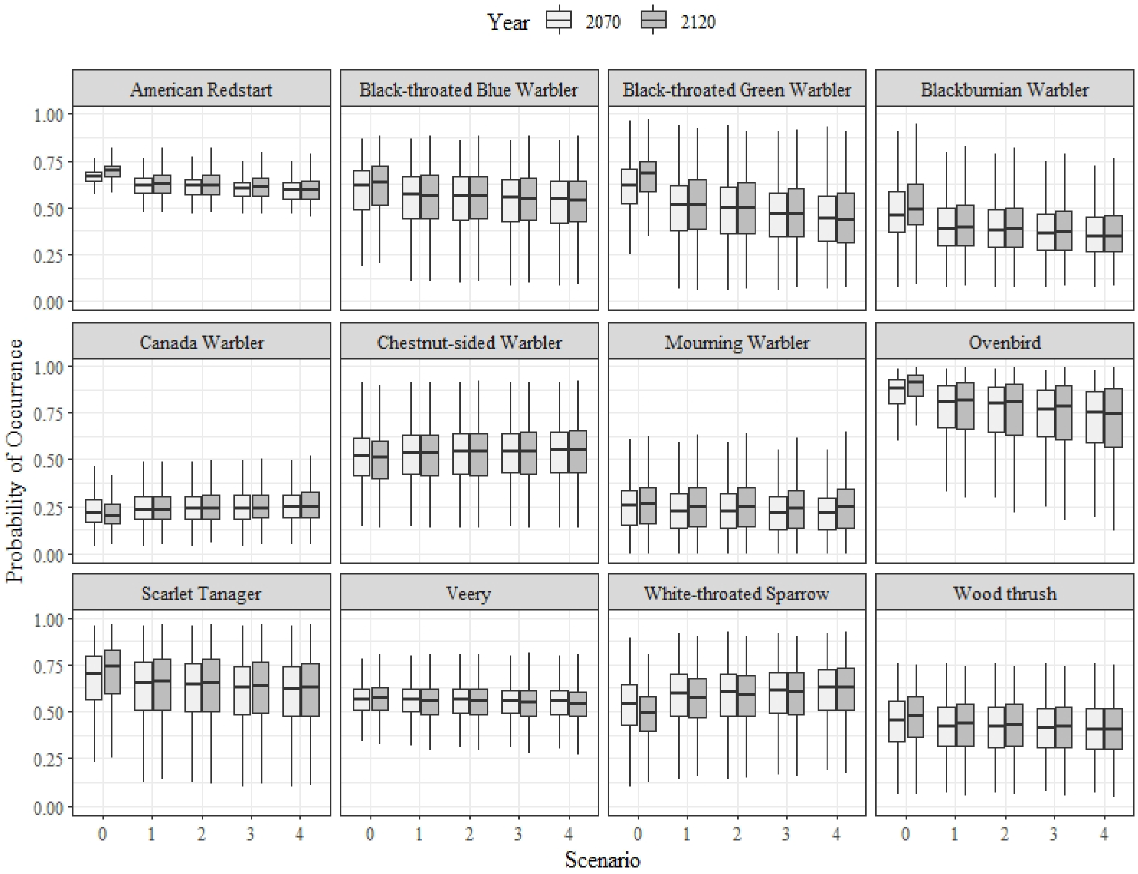


Figure 4.4. Box plots for 12 bird species models showing future probability of occurrence estimates in years 2070 and 2120 (y-axis). Each of the 12 boxplots show the estimated median for the 2 timeframes. The lower and upper hinges demark the 25th and 75th percentiles for the 5 harvest scenarios (x-axis). The 5 harvest scenarios represent no harvest (Scenario 0), current harvest (Scenario 1), and 3 harvest intensification scenarios (Scenarios 2-4) (Table 1) (from Brown et al. in review-b).

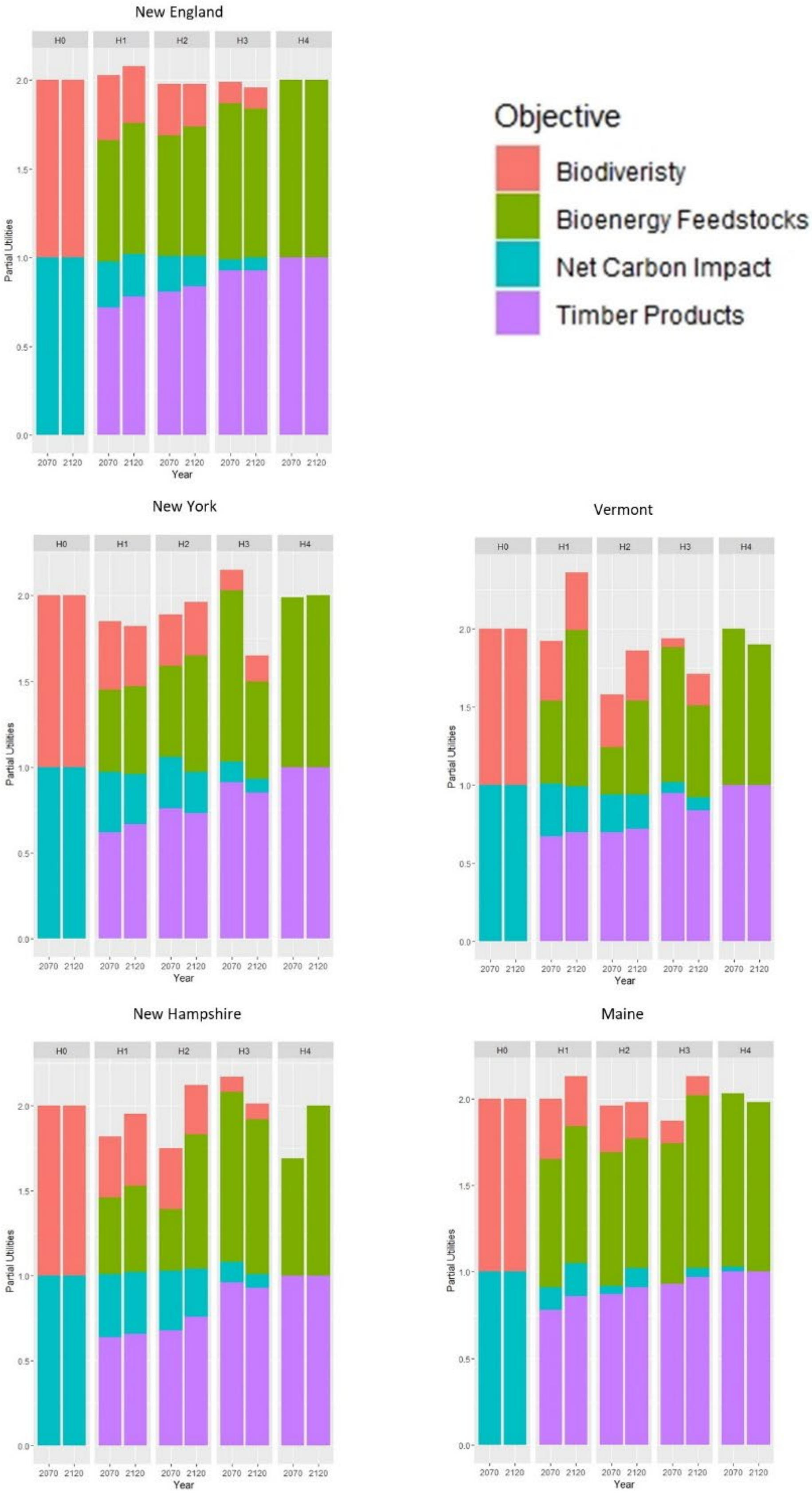

New England
New York
Vermont
New Hampshire
Maine
H0
H1
H2
H3
H4
Partial Utilities
0.0
0.5
1.0
1.5
2.0
2070
2120
Year
Objective
Biodiveristy
Bioenergy Feedstocks
Net Carbon Impact
Timber Products

Figure 4.5. Partial scaled utilities for each forest management alternative relative to four decision objectives – maximizing net carbon impact, maximizing timber production, maximizing bioenergy feedstock supplies, and maximizing biodiversity.

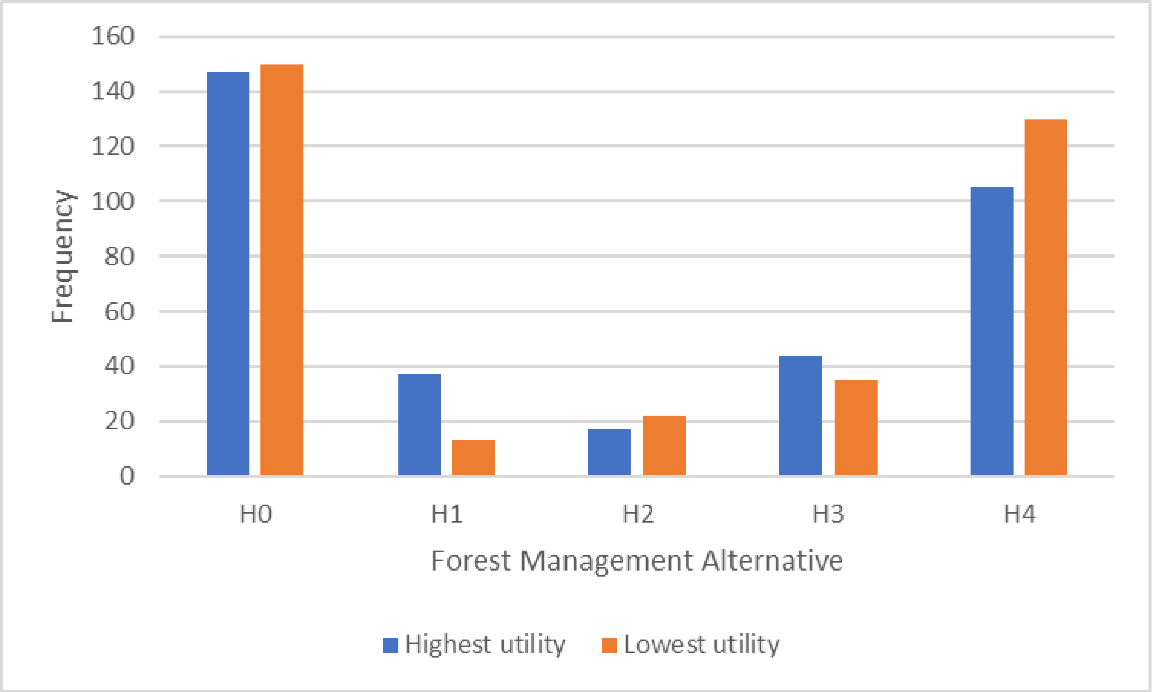


Figure 4.6. The frequency of the highest and lowest utility scores for five forest management alternatives (n=350 for both utility categories).

4.7. References

Adem Esmail, B., and D. Geneletti. 2018. Multi-criteria decision analysis for nature conservation: A review of 20 years of applications. Methods in Ecology and Evolution **9**:42-53.

Armitage, D., P. Mbatha, E. K. Muhl, W. Rice, and M. Sowman. 2020. Governance principles for community-centered conservation in the post-2020 global biodiversity framework. Conservation Science and Practice **2**:e160.

Belton, S., and T. S. Stewart. 2002. Multiple Criteria Decision Analysis. An Integrated Approach. Kluwer Academic Publishers, Massachusetts.

Betts, M. G., Z. Yang, A. S. Hadley, A. C. Smith, J. S. Rousseau, J. M. Northrup, J. J. Nocera, N. Gorelick, and B. D. Gerber. 2022. Forest degradation drives widespread avian habitat and population declines. Nature Ecology & Evolution **6**:709-719.

Biomass Energy Resource Center. 2013. An overview of the biomass thermal energy policy opportunities in the Northern Forest region. Biomass Energy Resource Center at Vermont Energy Investment Corporation. Burlington, VT.

Bradford, J. B., and D. N. Kastendick. 2010. Age-related patterns of forest complexity and carbon storage in pine and aspen-birch ecosystems of northern Minnesota, USA. Canadian Journal of Forest Research **40**:401-409.

Brown, M. L., C. D. Canham, T. Buchholz, J. S. Gunn, and T. M. Donovan. in review-a. Net carbon sequestration implications of intensified timber harvest in northeastern U.S. forests.

Brown, M. L., C. D. Canham, L. Murphy, and T. M. Donovan. 2018a. Timber harvest as the predominant disturbance regime in northeastern U.S. forests: effects of harvest intensification. Ecosphere **9**:e02062.

Brown, M. L., T. M. Donovan, R. Mickey, and J. Katz. in review-b. Predicting regional-scale effects of forest management on songbirds with expert elicitation

Buchholz, T., M. D. Hurteau, J. Gunn, and D. Saah. 2016. A global meta-analysis of forest bioenergy greenhouse gas emission accounting studies. GCB Bioenergy **8**:281-289.

Buchholz, T., E. Rametsteiner, T. A. Volk, and V. A. Luzadis. 2009. Multi Criteria Analysis for bioenergy systems assessments. Energy Policy **37**:484-495.

Canham, C. D., N. Rogers, and T. Buchholz. 2013. Regional variation in forest harvest regimes in the northeastern United States. Ecological Applications **23**:515-522.

Coates, K. D., C. D. Canham, M. Beaudet, D. L. Sachs, and C. Messier. 2003. Use of a spatially explicit individual-tree model (SORTIE/BC) to explore the implications of patchiness in structurally complex forests. Forest Ecology and Management **186**:297-310.

Diaz-Balteiro, L., and C. Romero. 2008. Making forestry decisions with multiple criteria: A review and an assessment. Forest Ecology and Management **255**:3222-3241.

Edwards, W. 1977. How to use multiattribute utility measurement for social decision making. IEEE Transactions on Systems, Man, and Cybernetics. SMC-7:326-340.

Edwards, W., and F. H. Barron. 1994. SMARTS and SMARTER: Improved simple methods for multiattribute utility measurement. Organizational behavior and human decision processes **60**:306-325.

FAO. 2022. Global forest sector outlook 2050: Assessing future demand and sources of timber for a sustainable economy – Background paper for The State of the World's Forests 2022. Food and Agriculture Organization of the United Nations Forestry Working Paper, No. 31. Rome. Provisional. https://doi.org/10.4060/cc2265en.

Ford, S. E., and W. S. Keeton. 2017. Enhanced carbon storage through management for old-growth characteristics in northern hardwood-conifer forests. Ecosphere **8**:e01721.

Gunn, J. S., and T. Buchholz. 2018. Forest sector greenhouse gas emissions sensitivity to changes in forest management in Maine (USA). Forestry: An International Journal of Forest Research **91**:526-538.

Hennigar, C., L. Amos-Binks, R. Cameron, J. S. Gunn, D. A. MacLean, and M. J. Twery. 2013. ForGATE - A Forest-sector GHG Assessment Tool for Maine: Calibration and Overview. Gen. Tech. Rep. NRS-116. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. 54pp.

IPCC. 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R. K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Kareiva, P., and M. Marvier. 2012. What Is Conservation Science? BioScience **62**:962-969.

Kiker, G. A., T. S. Bridges, A. Varghese, T. P. Seager, and I. Linkov. 2005. Application of multicriteria decision analysis in environmental decision making. Integrated Environmental Assessment and Management **1**:95-108.

King, D. I., and S. Schlossberg. 2014. Synthesis of the conservation value of the early-successional stage in forests of eastern North America. Forest Ecology and Management **324**:186-195.

Littlefield, C. E., and W. S. Keeton. 2012. Bioenergy harvesting impacts on ecologically important stand structure and habitat characteristics. Ecological Applications **22**:1892-1909.

Litvaitis, J. A., J. L. Larkin, D. J. McNeil, D. Keirstead, and B. Costanzo. 2021. Addressing the Early-Successional Habitat Needs of At-Risk Species on Privately Owned Lands in the Eastern United States. Land **10**:1116.

Maine Governor's Energy Office. 2015. Maine Comprehensive Energy Plan Update 2015. Governor's Energy Office, State of Maine, Augusta, ME.

Malmsheimer, R. W., P. Heffernan, S. Brink, D. Crandall, F. Deneke, C. Galik, Gee, E., J. A. Helms, N. McClure, N. Mortimer, S. Ruddell, M. Smith, and J. Stewart. 2008. Preventing GHG emissions through wood substitution. Journal of Forestry **106**:132–135.

McGee, G. G. 2018. Biological Diversity in Eastern Old Growth. Pages 197-216 *in* A. M. Barton and W. S. Keeton, editors. Ecology and Recovery of Eastern Old-Growth Forests. Island Press/Center for Resource Economics, Washington, DC.

Mendoza, G. A., and H. Martins. 2006. Multi-criteria decision analysis in natural resource management: A critical review of methods and new modelling paradigms. Forest Ecology and Management **230**:1-22.

Mika, A. M., and W. S. Keeton. 2015. Net carbon fluxes at stand and landscape scales from wood bioenergy harvests in the US Northeast. GCB Bioenergy **7**:438-454.

Nepal, P., C. Johnston, and I. Ganguly. 2021. Effects on Global Forests and Wood Product Markets of Increased Demand for Mass Timber. Sustainability **13**:13943.

New Hampshire Department of Energy. 2022. New Hampshire 10-year State Energy Strategy. New Hampshire Department of Energy, Concord, NH.

New York Climate Action Council. 2021. New York State Climate Action Council Draft Scoping Plan. New York Climate Action Council, Albany, NY.

Pacala, S. W., C. D. Canham, J. Saponara, J. A. Silander, R. K. Kobe, and E. Ribbens. 1996. Forest Models Defined by Field Measurements: Estimation, Error Analysis and Dynamics. Ecological Monographs **66**:1-43.

Pillay, R., M. Venter, J. Aragon-Osejo, P. González-del-Pliego, A. J. Hansen, J. E. M. Watson, and O. Venter. 2022. Tropical forests are home to over half of the world's vertebrate species. Frontiers in Ecology and the Environment **20**:10-15.

Rosenberg, K. V., A. M. Dokter, P. J. Blancher, J. R. Sauer, A. C. Smith, P. A. Smith, J. C. Stanton, A. Panjabi, L. Helft, M. Parr, and P. P. Marra. 2019. Decline of the North American avifauna. Science **366**:120-124.

Ruddell, S., R. Sampson, M. Smith, R. Giffen, J. Cathcart, J. Hagan, D. Sosland, J. Godbee, J. Heissenbuttel, S. Lovett, J. Helms, W. Price, and R. Simpson. 2007. The role for sustainably managed forests in climate change mitigation. . Journal of Forestry **105**: 314–319.

Saarikoski, H., J. Mustajoki, D. N. Barton, D. Geneletti, J. Langemeyer, E. Gomez-Baggethun, M. Marttunen, P. Antunes, H. Keune, and R. Santos. 2016. Multi-Criteria Decision Analysis and Cost-Benefit Analysis: Comparing alternative frameworks for integrated valuation of ecosystem services. Ecosystem Services **22**:238-249.

Schwenk, W. S., T. M. Donovan, W. S. Keeton, and J. S. Nunery. 2012. Carbon storage, timber production, and biodiversity: comparing ecosystem services with multi-criteria decision analysis. Ecological Applications **22**:1612-1627.

Shvidenko, A., C. V. Barber, R. Persson, P. Gonzalez, and R. Hassan. 2005. Forest andwoodland systems. In: Millennium Ecosystem Assessment (Ed.), Ecosystemsand Human Well-Being: Current State and Trends, Washington,DC.

Thom, D., and W. S. Keeton. 2020. Disturbance-based silviculture for habitat diversification: Effects on forest structure, dynamics, and carbon storage. Forest Ecology and Management **469**:118132.

Vermont Department of Public Service. 2022. 2022 Vermont Comprehensive Energy Plan. Vermont Department of Public Service, Montpelier, VT.

Wang, J.-J., Y.-Y. Jing, C.-F. Zhang, and J.-H. Zhao. 2009. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renewable and Sustainable Energy Reviews **13**:2263-2278.

Wolfslehner, B., and R. Seidl. 2010. Harnessing Ecosystem Models and Multi-Criteria Decision Analysis for the Support of Forest Management. Environmental Management **46**:850-861.

Work, T. T., S. Brais, and B. D. Harvey. 2014. Reductions in downed deadwood from biomass harvesting alter composition of spiders and ground beetle assemblages in jack-pine forests of Western Quebec. Forest Ecology and Management **321**:19-28.

5.0 COMPREHENSIVE BIBLIOGRAPHY

Aber, J. D., D. B. Botkin, and J. M. Melillo. 1978. Predicting effects of different harvesting regimes on forest floor dynamics in northern hardwoods. Canadian journal of forest Research-Revue Canadienne De Recherche Forestiere **8**:306-315.

Abrams, M. D. 2001. Eastern white pine versatility in the presettlement forest. BioScience **51**:967-979.

Adem Esmail, B., and D. Geneletti. 2018. Multi-criteria decision analysis for nature conservation: A review of 20 years of applications. Methods in Ecology and Evolution **9**:42-53.

Agu, H. U., C. Andrew, and M. L. Gore. 2021. Mapping Terra Incognita: An Expert Elicitation of Women's Roles in Wildlife Trafficking. Frontiers in Conservation Science **2**.

Albani, M., P. R. Moorcroft, A. M. Ellison, D. A. Orwig, and D. R. Foster. 2010. Predicting the impact of hemlock woolly adelgid on carbon dynamics of eastern United States forests. Canadian Journal of Forest Research **40**:119-133.

Anderson, M. G., and A. Olivero Sheldon. 2011. Conservation status of fish, wildlife, and natural habitats in the Northeast landscape: implementation of the Northeast Monitoring Framework. The Nature Conservancy, Eastern Conservation Science. 289 pp.

Angers, V. A., C. Messier, M. Beaudet, and A. Leduc. 2005. Comparing composition and structure in old-growth and harvested (selection and diameter-limit cuts) northern hardwood stands in Quebec. Forest Ecology and Management **217**:275-293.

Annand, E. M., and F. R. Thompson, III. 1997. Forest Bird Response to Regeneration Practices in Central Hardwood Forests. The Journal of Wildlife Management **61**:159-171.

Armitage, D., P. Mbatha, E. K. Muhl, W. Rice, and M. Sowman. 2020. Governance principles for community-centered conservation in the post-2020 global biodiversity framework. Conservation Science and Practice **2**:e160.

Bakermans, M. H., A. D. Rodewald, and A. C. Vitz. 2012. Influence of forest structure on density and nest success of mature forest birds in managed landscapes. The Journal of Wildlife Management **76**:1225-1234.

Barton, A. M., A. S. White, and C. V. Cogbill. 2012. The changing nature of the Maine woods. University Press of New England, Lebanon, NH.

Bates, D., M. Mächler, B. Bolker, and S. Walker. 2015. Fitting Linear Mixed-Effects Models Using lme4. Journal of Statistical Software **67**:1-48.

Bauhus, J., K. Puettmann, and C. Messier. 2009. Silviculture for old-growth attributes. Forest Ecology and Management **258**:525-537.

Belton, S., and T. S. Stewart. 2002. Multiple Criteria Decision Analysis. An Integrated Approach. Kluwer Academic Publishers, Massachusetts.

Bertrand, R., J. Lenoir, C. Piedallu, G. Riofrio-Dillon, P. de Ruffray, C. Vidal, J.-C. Pierrat, and J.-C. Gegout. 2011. Changes in plant community composition lag behind climate warming in lowland forests. Nature **479**:517-520.

Betts, M. G., Z. Yang, A. S. Hadley, A. C. Smith, J. S. Rousseau, J. M. Northrup, J. J. Nocera, N. Gorelick, and B. D. Gerber. 2022. Forest degradation drives widespread avian habitat and population declines. Nature Ecology & Evolution **6**:709-719.

Biomass Energy Resource Center. 2013. An overview of the biomass thermal energy policy opportunities in the Northern Forest region. Biomass Energy Resource Center at Vermont Energy Investment Corporation. Burlington, VT.

Biomass Thermal Energy Council. 2010. Heating the Northeast with renewable biomass: a vision for 2025. Biomass Thermal Energy Council, Washington, DC.

Birdsey, R., P. Duffy, C. Smyth, W. A. Kurz, A. J. Dugan, and R. Houghton. 2018. Climate, economic, and environmental impacts of producing wood for bioenergy. Environmental Research Letters **13**:050201.

Birdsey, R. A., and B. M. Lewis. 2003. Carbon in U.S. forests and wood products, 1987–1997: state-by-state estimates. Gen. Tech. Rep. NE-310, Washington, DC: U.S. Department of Agriculture, Forest Service.

Black, B. A., and M. D. Abrams. 2005. Disturbance history and climate response in an old-growth hemlock-white pine forest, central Pennsylvania. The Journal of the Torrey Botanical Society **132**:103-114.

Bradford, J. B., and D. N. Kastendick. 2010. Age-related patterns of forest complexity and carbon storage in pine and aspen-birch ecosystems of northern Minnesota, USA. Canadian Journal of Forest Research **40**:401-409.

Brown, M. L., C. D. Canham, T. Buchholz, J. S. Gunn, and T. M. Donovan. in review-a. Net carbon sequestration implications of intensified timber harvest in northeastern U.S. forests.

Brown, M. L., C. D. Canham, L. Murphy, and T. M. Donovan. 2018a. Timber harvest as the predominant disturbance regime in northeastern U.S. forests: effects of harvest intensification. Ecosphere **9**:e02062.

Brown, M. L., T. M. Donovan, R. Mickey, and J. Katz. in review-b. Predicting regional-scale effects of forest management on songbirds with expert elicitation

Brown, M. L., T. M. Donovan, R. M. Mickey, G. S. Warrington, W. S. Schwenk, and D. M. Theobald. 2018b. Predicting effects of future development on a territorial forest songbird: methodology matters. Landscape Ecology **33**:93-108.

Brown, M. L., T. M. Donovan, W. S. Schwenk, and D. M. Theobald. 2014. Predicting impacts of future human population growth and development on occupancy rates of forest-dependent birds. Biological Conservation **179**:311-320.

Buchholz, T., C. D. Canham, and S. P. Hamburg. 2011. Forest biomass and bioenergy: opportunities and constraints in the northeastern United States. Cary Institute of Ecosystem Studies, Milbrook, NY.

Buchholz, T., J. S. Gunn, and D. S. Saah. 2017. Greenhouse gas emissions of local wood pellet heat from northeastern US forests. Energy **141**:483-491.

Buchholz, T., J. S. Gunn, and B. Sharma. 2021. When Biomass Electricity Demand Prompts Thinnings in Southern US Pine Plantations: A Forest Sector Greenhouse Gas Emissions Case Study. Frontiers in Forests and Global Change **4**.

Buchholz, T., M. D. Hurteau, J. Gunn, and D. Saah. 2016. A global meta-analysis of forest bioenergy greenhouse gas emission accounting studies. GCB Bioenergy **8**:281-289.

Buchholz, T., W. S. Keeton, and J. S. Gunn. 2019. Economics of integrated harvests with biomass for energy in non-industrial forests in the northeastern US forest. Forest Policy and Economics **109**:102023.

Buchholz, T., E. Rametsteiner, T. A. Volk, and V. A. Luzadis. 2009. Multi Criteria Analysis for bioenergy systems assessments. Energy Policy **37**:484-495.

Butler, B. J., J. H. Hewes, B. J. Dickinson, K. Andrejczyk, S. M. Butler, and M. Markowski-Lindsay. 2016. Family forest ownerships of the United States, 2013: findings from the USDA Forest Service's National Woodland Owner Survey. Journal of Forestry **114**:638-647.

Butler, B. J., Z. Ma, D. B. Kittredge, and P. Catanzaro. 2010. Social versus biophysical availability of wood in the northern United States. Northern Journal of Applied Forestry **27**:151-159.

Campbell, S. P., J. W. Witham, and M. L. Hunter Jr. 2007. Long-Term Effects of Group-Selection Timber Harvesting on Abundance of Forest Birds. Conservation Biology **21**:1218-1229.

Camus, E. B., J. R. Rhodes, C. A. McAlpine, D. Lunney, J. Callaghan, R. Goldingay, A. Brace, M. Hall, S. B. Hetherington, M. Hopkins, M. J. Druzdzel, and H. J. Mayfield. 2022. Using expert elicitation to identify effective combinations of management actions for koala conservation in different regional landscapes. Wildlife Research.

Canham, C. D. 2013. Carbon cycle implications of forest biomass energy production in the northeastern United States. In M. Jacobson and D. Ciolkosz, editors. Wood-based Energy in the Northern Forests. Pages 61-78. Springer, New York.

Canham, C. D., and O. L. Loucks. 1984. Catastrophic windthrow in the presettlement forests of Wisconsin. Ecology **65**:803-809.

Canham, C. D., and L. Murphy. 2016a. The demography of tree species response to climate: sapling and canopy tree growth. Ecosphere 7(10):e01474. 10.1002/ecs2.1474.

Canham, C. D., and L. Murphy. 2016b. The demography of tree species response to climate: seedling recruitment and survival. Ecosphere 7(8):e01424. 10.1002/ecs2.1424.

Canham, C. D., and L. Murphy. 2017. The demography of tree species response to climate: sapling and canopy tree survival. Ecosphere 8(2):e01701. 10.1002/ecs2.1701.

Canham, C. D., M. J. Papaik, and E. F. Latty. 2001. Interspecific variation in susceptibility to windthrow as a function of tree size and storm severity for northern temperate tree species. Canadian Journal of Forest Research **31**:1-10.

Canham, C. D., M. J. Papaik, M. Uriarte, W. H. McWilliams, J. C. Jenkins, and M. J. Twery. 2006. Neighborhood analyses of canopy tree competition along environmental gradients in New England forests. Ecological Applications **16**:540-554.

Canham, C. D., N. Rogers, and T. Buchholz. 2013. Regional variation in forest harvest regimes in the northeastern United States. Ecological Applications **23**:515-522.

Castellano, P. J., T. A. Volk, and L. P. Herrington. 2009. Estimates of technically available woody biomass feedstock from natural forests and willow biomass crops for two locations in New York State. Biomass and Bioenergy **33**:393-406.

Clevenger, A. P., J. Wierzchowski, B. Chruszcz, and K. Gunson. 2002. GIS-Generated, Expert-Based Models for Identifying Wildlife Habitat Linkages and Planning Mitigation Passages. Conservation Biology **16**:503-514.

Coates, K. D., C. D. Canham, M. Beaudet, D. L. Sachs, and C. Messier. 2003. Use of a spatially explicit individual-tree model (SORTIE/BC) to explore the implications of patchiness in structurally complex forests. Forest Ecology and Management **186**:297-310.

Comnick, J., L. Rogers, and K. Wheiler. 2022. Increasing Mass Timber Consumption in the U.S. and Sustainable Timber Supply. Sustainability.

Crowley, K. F., G. M. Lovett, M. A. Arthur, and K. C. Weathers. 2016. Long-term effects of pest-induced tree species change on carbon and nitrogen cycling in northeastern U.S. forests: A modeling analysis. Forest Ecology and Management **372**:269-290.

Dangal, S. R. S., B. S. Felzer, and M. D. Hurteau. 2014. Effects of agriculture and timber harvest on carbon sequestration in the eastern US forests. Journal of Geophysical Research: Biogeosciences **119**:35-54.

Davis, S. C., M. Dietze, E. DeLucia, C. Field, S. P. Hamburg, S. Loarie, W. Parton, M. Potts, B. Ramage, D. Wang, H. Youngs, and S. P. Long. 2012. Harvesting carbon from eastern US forests: opportunities and impacts of an expanding bioenergy industry. Forests **3**:370-397.

DeGraaf, R. M., J. B. Hestbeck, and M. Yamasaki. 1998. Associations between breeding bird abundance and stand structure in the White Mountains, New Hampshire and Maine, USA. Forest Ecology and Management **103**:217-233.

DeGraaf, R. M., and M. Yamasaki. 2003. Options for managing early-successional forest and shrubland bird habitats in the northeastern United States. Forest Ecology and Management **185**:179-191.

Diaz-Balteiro, L., and C. Romero. 2008. Making forestry decisions with multiple criteria: A review and an assessment. Forest Ecology and Management **255**:3222-3241.

Domke, G. M., B. F. Walters, D. J. Nowak, J. E. Smith, S. M. Ogle, J. W. Coulston, and T. C. Wirth. 2020. Greenhouse gas emissions and removals from forest land, woodlands, and urban trees in the United States, 1990-2018. . Resource Update FS-227. Madison, WI: U.S. Department of Agriculture, Forest Service, Northern Research Station. 5 p.

Drever, C. R., S. C. Cook-Patton, F. Akhter, P. H. Badiou, G. L. Chmura, S. J. Davidson, R. L. Desjardins, A. Dyk, J. E. Fargione, M. Fellows, B. Filewod, M. Hessing-Lewis, S. Jayasundara, W.S. Keeton, T. Kroeger, T.J. Lark, E. Le, S.M. Leavitt, M.E. LeClerc, T.C. Lemprière, J. Metsaranta, B. McConkey, E. Neilson, G.P. St-Laurent1, D. Puric-Mladenovic, S. Rodrigue, R.Y. Soolanayakanahally, S.A. Spawn, M. Strack, C. Smyth, N. Thevathasan, M. Voicu, C.A. Williams, P.B. Woodbury, D.E. Worth, Z. Xu, S. Yeo, and W. A. Kurz. 2021. Natural climate solutions for Canada. Science Advances **7**:eabd6034.

Duveneck, M. J., J. R. Thompson, E. J. Gustafson, Y. Liang, and A. M. G. de Bruijn. 2017. Recovery dynamics and climate change effects to future New England forests. Landscape Ecology **32**:1385-1397.

Dwivedi, P., M. Khanna, and M. Fuller. 2019. Is wood pellet-based electricity less carbon-intensive than coal-based electricity? It depends on perspectives, baselines, feedstocks, and forest management practices. Environmental Research Letters **14**:024006.

Edwards, W. 1977. How to use multiattribute utility measurement for social decision making. IEEE Transactions on Systems, Man, and Cybernetics. SMC-7:326-340.

Edwards, W., and F. H. Barron. 1994. SMARTS and SMARTER: Improved simple methods for multiattribute utility measurement. Organizational behavior and human decision processes **60**:306-325.

EIA. 2022. Annual energy outlook 2022. U.S. Energy Information Administration, Washington, DC 20585.

Energy Independence and Security Act. 2007. Public Law 110-140, 110th Congress.

Energy Information Administration. 2015. International Energy Outlook 2015 with projections to 2040. U.S. Energy Information Administration, Washington, DC.

Engstrom, R. T., R. L. Crawford, and W. W. Baker. 1984. Breeding Bird Populations in Relation to Changing Forest Structure following Fire Exclusion: A 15-Year Study. The Wilson Bulletin **96**:437-450.

EPA. 2019. National overview: Facts and figures on materials, wastes and recycling. United States Environmental Protection Agency. https://www.epa.gov/facts-and-figures-about-materials-waste-and-recycling/national-overview-facts-and-figures-materials#Combustion, accessed April 2019.

FAO. 2022. Global forest sector outlook 2050: Assessing future demand and sources of timber for a sustainable economy – Background paper for The State of the World's Forests 2022. Food and Agriculture Organization of the United Nations Forestry Working Paper, No. 31. Rome. Provisional. https://doi.org/10.4060/cc2265en.

Fargione, J., J. Hill, D. Tilman, S. Polasky, and P. Hawthorne. 2008. Land Clearing and the Biofuel Carbon Debt. Science **319**:1235-1238.

Fargione, J. E., S. Bassett, T. Boucher, S. D. Bridgham, R. T. Conant, S. C. Cook-Patton, P. W. Ellis, A. Falcucci, J. W. Fourqurean, T. Gopalakrishna, H. Gu, B. Henderson, M. D. Hurteau, K. D. Kroeger, T. Kroeger, T. J. Lark, S. M. Leavitt, G. Lomax, R. I. McDonald, J. P. Megonigal, D. A. Miteva, C. J. Richardson, J. Sanderman, D. Shoch, S. A. Spawn, J. W. Veldman, C. A. Williams, P. B. Woodbury, C. Zganjar, M. Baranski, P. Elias, R. A. Houghton, E. Landis, E. McGlynn, W. H. Schlesinger, J. V. Siikamaki, A. E. Sutton-Grier, and B. W. Griscom. 2018. Natural climate solutions for the United States. Science Advances **4**:eaat1869.

Ford, S. E., and W. S. Keeton. 2017. Enhanced carbon storage through management for old-growth characteristics in northern hardwood-conifer forests. Ecosphere **8**:e01721.

Forsyth, D. M., D. J. Wilson, T. A. Easdale, G. Kunstler, C. D. Canham, W. A. Ruscoe, E. F. Wright, L. Murphy, A. M. Gormley, and A. Gaxiola. 2015. Century-scale effects of invasive deer and rodents on the dynamics of forests growing on soils of contrasting fertility. Ecological Monographs **85**:157-180.

Frelich, L. E., and C. G. Lorimer. 1991. Natural disturbance regimes in hemlock-hardwood forests of the Upper Great Lakes Region. Ecological Monographs **61**:145-164.

Gan, J., and B. A. McCarl. 2007. Measuring transnational leakage of forest conservation. Ecological Economics **64**:423-432.

Gendreau-Berthiaume, B., D. D. Kneeshaw, and B. D. Harvey. 2012. Effects of partial cutting and partial disturbance by wind and insects on stand composition, structure and growth in boreal mixedwoods. Forestry: An International Journal of Forest Research **85**:551-565.

Griscom, B. W., J. Adams, P. W. Ellis, R. A. Houghton, G. Lomax, D. A. Miteva, W. H. Schlesinger, D. Shoch, J. V. Siikamäki, P. Smith, P. Woodbury, C. Zganjar, A. Blackman, J. Campari, R. T. Conant, C. Delgado, P. Elias, T. Gopalakrishna, M. R. Hamsik, M. Herrero, J. Kiesecker, E. Landis, L. Laestadius, S. M. Leavitt, S. Minnemeyer, S. Polasky, P. Potapov, F. E. Putz, J. Sanderman, M. Silvius, E. Wollenberg, and J. Fargione. 2017. Natural climate solutions. Proceedings of the National Academy of Sciences **114**:11645.

Gunn, J. S., and T. Buchholz. 2018. Forest sector greenhouse gas emissions sensitivity to changes in forest management in Maine (USA). Forestry: An International Journal of Forest Research **91**:526-538.

Haberl, H., D. Sprinz, M. Bonazountas, P. Cocco, Y. Desaubies, M. Henze, O. Hertel, R. K. Johnson, U. Kastrup, P. Laconte, E. Lange, P. Novak, J. Paavola, A. Reenberg, S. van den Hove, T. Vermeire, P. Wadhams, and T. Searchinger. 2012. Correcting a fundamental error in greenhouse gas accounting related to bioenergy. Energy Policy **45**:18-23.

Hagan, J. M., P. S. McKinley, A. L. Meehan, and S. L. Grove. 1997. Diversity and Abundance of Landbirds in a Northeastern Industrial Forest. The Journal of Wildlife Management **61**:718-735.

Hagar, J., S. Howlin, and L. Ganio. 2004. Short-term response of songbirds to experimental thinning of young Douglas-fir forests in the Oregon Cascades. Forest Ecology and Management **199**:333-347.

Hagenbuch, S., K. Manaras, J. Shallow, K. Sharpless, and M. Snyder. 2011. Forest bird habitat assessment: A guide to integrating bird habitat data into a Vermont Forest Inventory. Created and published by Audubon Vermont, Huntington, Vermont, 05642.

Harmon, M. E. 2019. Have product substitution carbon benefits been overestimated? A sensitivity analysis of key assumptions. Environmental Research Letters **14**:065008.

Helin, T., L. Sokka, S. Soimakallio, K. Pingoud, and T. Pajula. 2013. Approaches for inclusion of forest carbon cycle in life cycle assessment – a review. GCB Bioenergy **5**:475-486.

Hennigar, C., L. Amos-Binks, R. Cameron, J. S. Gunn, D. A. MacLean, and M. J. Twery. 2013. ForGATE - A Forest-sector GHG Assessment Tool for Maine: Calibration and Overview. Gen. Tech. Rep. NRS-116. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. 54pp.

Horton, R., G. Yohe, W. Easterling, R. Kates, M. Ruth, E. Sussman, A. Whelchel, D. Wolfe, and F. Lipschultz. 2014. Ch. 16: Northeast. In Climate Change Impacts in the United States: The Third National Climate Assessment. J. M. Melillo, T.C. Richmond, and G. W. Yohe, Eds. U.S. Global Change Research Program, 371-395, doi:10.7930/J0SF2T3P.

Hunter, L. 2014. Renewable energy in the 50 states: Northeast region. American Council on Renewable Energy (ACORE), Washington, DC.

Hurtt, G. C., S. W. Pacala, P. R. Moorcroft, J. Caspersen, E. Shevliakova, R. A. Houghton, and B. Moore. 2002. Projecting the future of the U.S. carbon sink. Proceedings of the National Academy of Sciences **99**:1389-1394.

IPCC. 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R. K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Iverson, L. R., M. W. Schwartz, and A. M. Prasad. 2004. Potential colonization of newly available tree-species habitat under climate change: an analysis for five eastern US species. Landscape Ecology **19**:787-799.

James, A., S. L. Choy, and K. Mengersen. 2010. Elicitator: An expert elicitation tool for regression in ecology. Environmental Modelling & Software **25**:129-145.

Janowiak, M. K., and C. R. Webster. 2010. Promoting Ecological Sustainability in Woody Biomass Harvesting. Journal of Forestry **108**:16-23.

Johnson, C. J., and M. P. Gillingham. 2004. Mapping uncertainty: sensitivity of wildlife habitat ratings to expert opinion. Journal of Applied Ecology **41**:1032-1041.

Jonker, J. G. G., M. Junginger, and A. Faaij. 2014. Carbon payback period and carbon offset parity point of wood pellet production in the South-eastern United States. GCB Bioenergy **6**:371-389.

Kareiva, P., and M. Marvier. 2012. What Is Conservation Science? BioScience **62**:962-969.

Keeton, W. S. 2006. Managing for late-successional/old-growth characteristics in northern hardwood-conifer forests. Forest Ecology and Management **235**:129-142.

Keeton, W. S. 2018. Source or sink? Carbon dynamics in old-growth forests and their role in climate change mitigation. Pages 267-288 in: Barton, A. and W.S. Keeton (eds.). Ecology and Recovery of Eastern Old-Growth Forests. Island Press, Washington, D.C. 340 pp.

Keeton, W. S., A. A. Whitman, G. C. McGee, and C. L. Goodale. 2011. Late-successional biomass development in northern hardwood-conifer forests of the northeastern United States. Forest Science **57**:489-505.

Kelty, M. J., and A. W. D'Amato. 2006. Historical perspective on diameter-limit cutting in northeastern forests. P. 3–15 in Proc. of the Conference on diameter-limit cutting in northeastern forests, Kenefic L.S., Nyland R.D. (eds.). USDA For. Serv., Gen. Tech. Rep. NE-342, Northeastern Research Station, Newtown Square, PA.

Kiker, G. A., T. S. Bridges, A. Varghese, T. P. Seager, and I. Linkov. 2005. Application of multicriteria decision analysis in environmental decision making. Integrated Environmental Assessment and Management **1**:95-108.

Kilpeläinen, A., A. Alam, P. Torssonen, H. Ruusuvuori, S. Kellomäki, and H. Peltola. 2016. Effects of intensive forest management on net climate impact of energy biomass utilisation from final felling of Norway spruce. Biomass and Bioenergy **87**:1-8.

King, D. I., and R. M. DeGraaf. 2000. Bird species diversity and nesting success in mature, clearcut and shelterwood forest in northern New Hampshire, USA. Forest Ecology and Management **129**:227-235.

King, D. I., C. R. Griffin, and R. M. DeGraaf. 1997. Effect of Clearcut Borders on Distribution and Abundance of Forest Birds in Northern New Hampshire. The Wilson Bulletin **109**:239-245.

King, D. I., and S. Schlossberg. 2014. Synthesis of the conservation value of the early-successional stage in forests of eastern North America. Forest Ecology and Management **324**:186-195.

Kunstler, G., D. A. Coomes, and C. D. Canham. 2009. Size-dependence of growth and mortality influence the shade tolerance of trees in a lowland temperate rain forest. Journal of Ecology **97**:685-695.

Leturcq, P. 2020. GHG displacement factors of harvested wood products: the myth of substitution. Scientific Reports **10**:20752.

Liddle, B., and P. Sadorsky. 2017. How much does increasing non-fossil fuels in electricity generation reduce carbon dioxide emissions? Applied Energy **197**:212-221.

Likas, A., N. Vlassis, and J. J. Verbeek. 2003. The global k-means clustering algorithm. Pattern recognition **36**:451-461.

Lindenmayer, D. B., and J. F. Franklin. 2002. Conserving forest biodiveristy: A comprehensive multiscaled approach. Island Press, Washington, D.C.

Littlefield, C. E., and W. S. Keeton. 2012. Bioenergy harvesting impacts on ecologically important stand structure and habitat characteristics. Ecological Applications **22**:1892-1909.

Litvaitis, J. A., J. L. Larkin, D. J. McNeil, D. Keirstead, and B. Costanzo. 2021. Addressing the Early-Successional Habitat Needs of At-Risk Species on Privately Owned Lands in the Eastern United States. Land **10**:1116.

Low Choy, S., A. James, and K. Mengersen. 2009. Expert elicitation and its interface with technology: a review with a view to designing Elicitator. Pages 4269-4275 *in* 18th World IMACS Congress and MODSIM09 International Congress on Modelling and Simulation.

Low Choy, S., A. James, J. Murray, and K. Mengersen. 2012. Elicitator: A User-Friendly, Interactive Tool to Support Scenario-Based Elicitation of Expert Knowledge. Pages 39-67 *in* A. H. Perera, C. A. Drew, and C. J. Johnson, editors. Expert Knowledge and Its Application in Landscape Ecology. Springer New York.

Lundmark, T., J. Bergh, P. Hofer, A. Lundström, A. Nordin, B. Poudel, R. Sathre, R. Taverna, and F. Werner. 2014. Potential Roles of Swedish Forestry in the Context of Climate Change Mitigation. Forests **5**:557-578.

Maine Department of Inland Fisheries and Wildlife. 2015. Maine's wildlife action plan. Maine Department of Inland Fisheries and Wildlife, Augusta, ME.

Maine Forest Carbon Task Force. 2021. Governor’s Task Force on the Creation of a Forest Carbon Program. Maine Forest Carbon Task Force, Augusta, Maine.

Maine Forest Service. 2010. Maine State Forest Assessment and Strategies. Maine Forest Service, Department of Conservation, Augusta, Maine. 225 pp.

Maine Governor's Energy Office. 2015. Maine Comprehensive Energy Plan Update 2015. Governor's Energy Office, State of Maine, Augusta, ME.

Malmsheimer, R. W., J. L. Bowyer, J. S. Fried, E. Gee, R. L. Izlar, R. A. Miner, I. A. Munn, E. Oneil, and W. C. Stewart. 2011. Managing forests because carbon matters: integrating energy, products, and land management policy. Journal of Forestry.

Malmsheimer, R. W., P. Heffernan, S. Brink, D. Crandall, F. Deneke, C. Galik, Gee, E., J. A. Helms, N. McClure, N. Mortimer, S. Ruddell, M. Smith, and J. Stewart. 2008. Preventing GHG emissions through wood substitution. Journal of Forestry **106**:132–135.

Marcelino, J., J. P. Silva, J. Gameiro, A. Silva, F. C. Rego, F. Moreira, and I. Catry. 2020. Extreme events are more likely to affect the breeding success of lesser kestrels than average climate change. Scientific Reports **10**:7207.

Martin, T. G., M. A. Burgman, F. Fidler, P. M. Kuhnert, S. Low-Choy, M. McBride, and K. Mengersen. 2012. Eliciting Expert Knowledge in Conservation Science. Conservation Biology **26**:29-38.

Martin, T. G., P. M. Kuhnert, K. Mengersen, and H. P. Possingham. 2005. THE POWER OF EXPERT OPINION IN ECOLOGICAL MODELS USING BAYESIAN METHODS: IMPACT OF GRAZING ON BIRDS. Ecological Applications **15**:266-280.

Masek, J. G., W. B. Cohen, D. Leckie, M. A. Wulder, R. Vargas, B. de Jong, S. Healey, B. Law, R. Birdsey, R. A. Houghton, D. Mildrexler, S. Goward, and W. B. Smith. 2011. Recent rates of forest harvest and conversion in North America. Journal of Geophysical Research: Biogeosciences **116**:2156-2202.

McGarvey, J. C., J. R. Thompson, H. E. Epstein, and H. H. Shugart. 2015. Carbon storage in old-growth forests of the Mid-Atlantic: toward better understanding the eastern forest carbon sink. Ecology **96**:311-317.

McGee, G. G. 2018. Biological Diversity in Eastern Old Growth. Pages 197-216 *in* A. M. Barton and W. S. Keeton, editors. Ecology and Recovery of Eastern Old-Growth Forests. Island Press/Center for Resource Economics, Washington, DC.

McGee, G. G., D. J. Leopold, and R. D. Nyland. 1999. Structural characteristics of old-growth, maturing, and partially cut northern hardwood forests. Ecological Applications **9**:1316-1329.

McRoberts, R. E., G. R. Holden, M. D. Nelson, G. C. Liknes, W. K. Moser, A. J. Lister, S. L. King, E. B. LaPoint, J. W. Coulston, W. B. Smith, and G. A. Reams. 2005. Estimating and Circumventing the Effects of Perturbing and Swapping Inventory Plot Locations. Journal of Forestry **103**:275-279.

Mendoza, G. A., and H. Martins. 2006. Multi-criteria decision analysis in natural resource management: A critical review of methods and new modelling paradigms. Forest Ecology and Management **230**:1-22.

Mika, A. M., and W. S. Keeton. 2013. Factors contributing to carbon fluxes from bioenergy harvests in the U.S. Northeast: an analysis using field data. GCB Bioenergy **5**:290-305.

Mika, A. M., and W. S. Keeton. 2015. Net carbon fluxes at stand and landscape scales from wood bioenergy harvests in the US Northeast. GCB Bioenergy **7**:438-454.

Milbrandt, A. 2008. A Geographic Perspective on the Current Biomass Resource Availability in the United States. Technical Report NREL/TP-560-39181 2008 update, 70 p.

Mitchell, S. R., M. E. Harmon, and K. E. B. O'Connell. 2012. Carbon debt and carbon sequestration parity in forest bioenergy production. GCB Bioenergy **4**:818-827.

Morin, R. S., A. M. Liebhold, and K. W. Gottschalk. 2009. Anisotropic spread of hemlock woolly adelgid in the eastern United States. Biological Invasions **11**:2341–2350.

Morin, R. S., A. M. Liebhold, P. C. Tobin, K. W. Gottschalk, and E. Luzader. 2007. Spread of beech bark disease in the eastern United States and its relationship to regional forest composition. Canadian Journal of Forest Research **37**:726-736.

Morrissey, R. C., M. A. Jenkins, and M. R. Saunders. 2014. Accumulation and connectivity of coarse woody debris in partial harvest and unmanaged relict forests. PLOS ONE 9(11): e113323. http://doi.org/10.1371/journal.pone.0113323.

Murphy, H. T., J. VanDerWal, and J. Lovett-Doust. 2010. Signatures of range expansion and erosion in eastern North American trees. Ecology Letters **13**:1233-1244.

Murphy, L. 2015. likelihood: Methods for Maximum Likelihood Estimation. R package version 1.7. http://CRAN.R-project.org/package=likelihood.

Murray, J. V., A. W. Goldizen, R. A. O'Leary, C. A. McAlpine, H. P. Possingham, and S. L. Choy. 2009. How useful is expert opinion for predicting the distribution of a species within and beyond the region of expertise? A case study using brush-tailed rock-wallabies Petrogale penicillata. Journal of Applied Ecology **46**:842-851.

Nepal, P., C. Johnston, and I. Ganguly. 2021. Effects on Global Forests and Wood Product Markets of Increased Demand for Mass Timber. Sustainability **13**:13943.

New Hampshire Department of Energy. 2022. New Hampshire 10-year State Energy Strategy. New Hampshire Department of Energy, Concord, NH.

New Hampshire Department of Resources and Economic Development. 2010. New Hampshire Statewide Forest Resources Assessment – 2010. New Hampshire Department of Resources and Economic Development, Division of Forests and Lands, Concord, NH.

New Hampshire Fish and Game Department. 2015. New Hampshire Wildlife Action Plan, 2015 Revised Edition. New Hampshire Fish and Game Department, Concord, NH.

New York Climate Action Council. 2021. New York State Climate Action Council Draft Scoping Plan. New York Climate Action Council, Albany, NY.

New York State Department of Environmental Conservation. 2010. New York State Forest Resource Assessment and Strategy. New York State Department of Environmental Conservation, Division of Lands and Forests, Albany, NY.

New York State Department of Environmental Conservation. 2015. New York State Wildlife Action Plan. 2015. New York State Department of Environmental Conservation. Albany, NY. http://www.dec.ny.gov/docs/wildlife_pdf/swapfinaldraft2015.pdf.

New York State Energy Plan. 2015. 2015 New York State Energy Plan. Albany, NY.

Nunery, J. S., and W. S. Keeton. 2010. Forest carbon storage in the northeastern United States: net effects of harvesting frequency, post-harvest retention, and wood products. Forest Ecology and Management **259**:1363-1375.

Oliver, C. D., and B. C. Larson. 1996. Forest Stand Dynamics. Wiley, New York.

P.R. Shukla, J. Skea, R. Slade, R. van Diemen, E. Haughey, J. Malley, M. Pathak, and J. P. P. (eds.). 2019. Technical Summary. In: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems [P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M, Belkacemi, J. Malley, (eds.)]. In press.

Pacala, S. W., C. D. Canham, J. Saponara, J. A. Silander, R. K. Kobe, and E. Ribbens. 1996. Forest Models Defined by Field Measurements: Estimation, Error Analysis and Dynamics. Ecological Monographs **66**:1-43.

Pan, W., M.-K. Kim, Z. Ning, and H. Yang. 2020. Carbon leakage in energy/forest sectors and climate policy implications using meta-analysis. Forest Policy and Economics **115**:102161.

Papaik, M. J., and C. D. Canham. 2006. Species resistance and community response to wind disturbance regimes in northern temperate forests. Journal of Ecology **94**:1011-1026.

Payette, S., L. Filion, and A. Delwaide. 1990. Disturbance regime of a cold temperate forest as deduced from tree-ring patterns: the Tantaré Ecological Reserve, Quebec. Canadian Journal of Forest Research **20**:1228-1241.

Pearce, J. L., K. Cherry, D. M, F. S, and G. Whish. 2001. Incorporating expert opinion and fine-scale vegetation mapping into statistical models of faunal distribution. Journal of Applied Ecology **38**:412-424.

Pearman-Gillman, S. B., J. E. Katz, R. M. Mickey, J. D. Murdoch, and T. M. Donovan. 2020. Predicting wildlife distribution patterns in New England USA with expert elicitation techniques. Global Ecology and Conservation **21**:e00853.

Peckham, S. D., S. T. Gower, and J. Buongiorno. 2012. Estimating the carbon budget and maximizing future carbon uptake for a temperate forest region in the U.S. Carbon Balance and Management **7**:6.

Perlack, R. D., L. L. Wright, A. Turhollow, R. L. Graham, B. Stokes, and D. C. Erbach. 2008. Biomass as Feedstock for a Bioenergy and Bioproducts Industry: The Technical Feasibility of a Billion-Ton Annual Supply. Study prepared by Oak Ridge National Laboratory for the U.S. Department of Agriculture and the U.S. Department of Energy. 2008 update.

Perry, R. W., J. M. A. Jenkins, R. E. Thill, and F. R. Thompson, III. 2018. Long-term effects of different forest regeneration methods on mature forest birds. Forest Ecology and Management. 408: 183-194 **408**:183-194.

Perry, R. W., and R. E. Thill. 2013. Long-term responses of disturbance-associated birds after different timber harvests. Forest Ecology and Management 307:274–283. **307**:274-283.

Pickett, S. T., and P. S. White. 1985. The Ecology of Natural Disturbance and Patch Dynamics. Academic Press, Inc., New York, New York.

Pickett, S. T. A., J. Kolasa, J. J. Armesto, and S. L. Collins. 1989. The ecological concept of disturbance and its expression at various hierarchical levels. Oikos **54**:129-136.

Pillay, R., M. Venter, J. Aragon-Osejo, P. González-del-Pliego, A. J. Hansen, J. E. M. Watson, and O. Venter. 2022. Tropical forests are home to over half of the world's vertebrate species. Frontiers in Ecology and the Environment **20**:10-15.

Puettmann, K. J., K. D. Coates, and C. Messier. 2009. A critique of silviculture: managing for complexity. Island Press, Washington, DC.

Quinn, R. J., H. Ha, T. A. Volk, T. R. Brown, S. Bick, R. W. Malmsheimer, and M. O. P. Fortier. 2020. Life cycle assessment of forest biomass energy feedstock in the Northeast United States. GCB Bioenergy **12**:728-741.

R Core Team. 2014. A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.

Ranius, T., A. Hämäläinen, G. Egnell, B. Olsson, K. Eklöf, J. Stendahl, J. Rudolphi, A. Sténs, and A. Felton. 2018. The effects of logging residue extraction for energy on ecosystem services and biodiversity: A synthesis. Journal of Environmental Management **209**:409-425.

Rhemtulla, J. M., D. J. Mladenoff, and M. K. Clayton. 2009. Historical forest baselines reveal potential for continued carbon sequestration. Proceedings of the National Academy of Sciences **106**:6082-6087.

Riffell, S., J. Verschuyl, D. Miller, and T. B. Wigley. 2011. Biofuel harvests, coarse woody debris, and biodiversity – A meta-analysis. Forest Ecology and Management **261**:878-887.

Riskas, K. A., R. C. Tobin, M. M. P. B. Fuentes, and M. Hamann. 2018. Evaluating the threat of IUU fishing to sea turtles in the Indian Ocean and Southeast Asia using expert elicitation. Biological Conservation **217**:232-239.

Rosenberg, K. V., A. M. Dokter, P. J. Blancher, J. R. Sauer, A. C. Smith, P. A. Smith, J. C. Stanton, A. Panjabi, L. Helft, M. Parr, and P. P. Marra. 2019. Decline of the North American avifauna. Science **366**:120-124.

Ruddell, S., R. Sampson, M. Smith, R. Giffen, J. Cathcart, J. Hagan, D. Sosland, J. Godbee, J. Heissenbuttel, S. Lovett, J. Helms, W. Price, and R. Simpson. 2007. The role for sustainably managed forests in climate change mitigation. . Journal of Forestry **105**: 314–319.

Russell, M. B., C. W. Woodall, S. Fraver, A. W. D'Amato, G. M. Domke, and K. E. Skog. 2014. Residence Times and Decay Rates of Downed Woody Debris Biomass/Carbon in Eastern US Forests. Ecosystems **17**:765-777.

Saarikoski, H., J. Mustajoki, D. N. Barton, D. Geneletti, J. Langemeyer, E. Gomez-Baggethun, M. Marttunen, P. Antunes, H. Keune, and R. Santos. 2016. Multi-Criteria Decision Analysis and Cost-Benefit Analysis: Comparing alternative frameworks for integrated valuation of ecosystem services. Ecosystem Services **22**:238-249.

Sallabanks, R., and E. B. Arnett. 2005. Accommodating birds in managed forests of North America: a review of bird–forestry relationships. U.S. Department of Agriculture, Forest Service, Pacific Northwest Region, Portland, Oregon, U.S.

Sauer, J. R., K. L. Pardieck, D. J. Ziolkowski, Jr., A. C. Smith, M.-A. R. Hudson, V. Rodriguez, H. Berlanga, D. K. Niven, and W. A. Link. 2017. The first 50 years of the North American Breeding Bird Survey. The Condor **119**:576-593.

Schulze, E.-D., C. Körner, B. E. Law, H. Haberl, and S. Luyssaert. 2012. Large-scale bioenergy from additional harvest of forest biomass is neither sustainable nor greenhouse gas neutral. GCB Bioenergy **4**:611-616.

Schwenk, W. S., and T. M. Donovan. 2011. A multi-species framework for landscape conservation planning. Conservation Biology **25**:1010-1021.

Schwenk, W. S., T. M. Donovan, W. S. Keeton, and J. S. Nunery. 2012. Carbon storage, timber production, and biodiversity: comparing ecosystem services with multi-criteria decision analysis. Ecological Applications **22**:1612-1627.

Searchinger, T., R. Heimlich, R. A. Houghton, F. Dong, A. Elobeid, J. Fabiosa, S. Tokgoz, D. Hayes, and T.-H. Yu. 2008. Use of U.S. Croplands for Biofuels Increases Greenhouse Gases Through Emissions from Land-Use Change. Science **319**:1238.

Searchinger, T. D., T. Beringer, and A. Strong. 2017. Does the world have low-carbon bioenergy potential from the dedicated use of land? Energy Policy **110**:434-446.

Searchinger, T. D., S. P. Hamburg, J. Melillo, W. Chameides, P. Havlik, D. M. Kammen, G. E. Likens, R. N. Lubowski, M. Obersteiner, and M. Oppenheimer. 2009. Fixing a critical climate accounting error. Science **326**:527.

Seoane, J., J. Bustamante, and R. DÍAz-Delgado. 2005. Effect of Expert Opinion on the Predictive Ability of Environmental Models of Bird Distribution. Conservation Biology **19**:512-522.

Seymour, R. S., A. S. White, and P. G. deMaynadier. 2002. Natural disturbance regimes in northeastern North America: evaluating silvicultural systems using natural scales and frequencies. Forest Ecology and Management **155**:357-367.

Sherman, A. R. 2007. Vermont wood fuel supply study - an examination of the availbility and reliability of wood fuel for biomass energy in Vermont. Biomass Energy Resources Center, Montpelier, VT.

Shvidenko, A., C. V. Barber, R. Persson, P. Gonzalez, and R. Hassan. 2005. Forest andwoodland systems. In: Millennium Ecosystem Assessment (Ed.), Ecosystemsand Human Well-Being: Current State and Trends, Washington,DC.

Silver, E. J., J. E. Leahy, A. R. Weiskittel, C. L. Noblet, and D. B. Kittredge. 2015. An evidence-based review of timber harvesting behavior among private woodland owners. Journal of Forestry **113**:490-499.

Smith, J. E., L. S. Heath, K. E. Skog, and R. A. Birdsey. 2006. Methods for calculating forest ecosystem and harvested carbon, with standard estimates for forest types of the United States. Gen. Tech. Rep. NE-343. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northeastern Research Station. 216 p.

Sterman, J. D., L. Siegel, and J. N. Rooney-Varga. 2018. Does replacing coal with wood lower CO2 emissions? Dynamic lifecycle analysis of wood bioenergy. Environmental Research Letters **13**:015007.

Sullivan, B. L., C. L. Wood, M. J. Iliff, R. E. Bonney, D. Fink, and S. Kelling. 2009. eBird: A citizen-based bird observation network in the biological sciences. Biological Conservation **142**:2282-2292.

Ter-Mikaelian, M. T., S. J. Colombo, and J. Chen. 2015. The Burning Question: Does Forest Bioenergy Reduce Carbon Emissions? A Review of Common Misconceptions about Forest Carbon Accounting. Journal of Forestry **113**:57-68.

Thom, D., and W. S. Keeton. 2019. Stand structure drives disparities in carbon storage in northern hardwood-conifer forests. Forest Ecology and Management **442**:10-20.

Thom, D., and W. S. Keeton. 2020. Disturbance-based silviculture for habitat diversification: Effects on forest structure, dynamics, and carbon storage. Forest Ecology and Management **469**:118132.

Thom, D., M. Golivets, L. Edling, G.W. Meigs, J.D. Gourevitch, L.J. Sonter, G. L. Galford, and W. S. Keeton. 2019. Climate sensitivity of carbon, timber, and species richness in the boreal-temperate ecotone co-varies with forest development. Global Change Biology **25**:2446–2458.

Thomas, R. Q., C. D. Canham, K. C. Weathers, and C. L. Goodale. 2010. Increased tree carbon storage in response to nitrogen deposition in the US. Nature Geoscience **3**:13-17.

Thompson, J. R., C. D. Canham, L. Morreale, D. B. Kittredge, and B. Butler. 2017a. Social and biophysical variation in regional timber harvest regimes. Ecological Applications **27**:942-955.

Thompson, J. R., D. N. Carpenter, C. V. Cogbill, and D. R. Foster. 2013. Four centuries of change in northeastern United States forests. PLOS ONE 8(9): e72540. https://doi.org/10.1371/journal.pone.0072540.

Thompson, J. R., D. R. Foster, R. Scheller, and D. Kittredge. 2011. The influence of land use and climate change on forest biomass and composition in Massachusetts, USA. Ecological Applications **21**:2425-2444.

Thompson, J. R., J. S. Plisinski, P. Olofsson, C. E. Holden, and M. J. Duveneck. 2017b. Forest loss in New England: A projection of recent trends. PLoS ONE **12**:e0189636.

Tonitto, C., C. L. Goodale, M. S. Weiss, S. D. Frey, and S. V. Ollinger. 2014. The effect of nitrogen addition on soil organic matter dynamics: a model analysis of the Harvard Forest Chronic Nitrogen Amendment Study and soil carbon response to anthropogenic N deposition. Biogeochemistry **117**:431-454.

Turner, D. P., and G. J. Koerper. 1995. Carbon sequestration by forests of the United States. Current status and projections to the year 2040. Tellus 47:232–239. Tellus **47**:232–239.

U.S. Geological Survey. 2014. National Land Cover Database (NLCD) 2011 Land Cover Conterminous United States: U.S. Geological Survey data release, https://doi.org/10.5066/P97S2IID.

Uriarte, M., C. D. Canham, J. Thompson, J. K. Zimmerman, L. Murphy, A. M. Sabat, N. Fetcher, and B. L. Haines. 2009. Natural disturbance and human land use as determinants of tropical forest dynamics: results from a forest simulator. Ecological Monographs **79**:423-443.

USDA Forest Service. 2012. The future of America's forests and rangelands, Forest Service 2010 Resources Planning Act Assessment. USDA Forest Service, Washington, DC.

USDA Forest Service. 2016. National Woodland Owner Survey Table Maker version 3.0. Accessed January 3, 2017. https://apps.fs.usda.gov/nwos/tablemaker.jsp

USDA Forest Service. 2020. Forest Inventory and Analysis National Program. Accessed March 2022. http://www.fia.fs.fed.us/.

Vance, E. D. 2018. Conclusions and caveats from studies of managed forest carbon budgets. Forest Ecology and Management **427**:350-354.

Vermont Agency of Natural Resources. 2010. 2010 Vermont Forest Resources Plan - State Assessment and Resources Strategies. Vermont Agency of Natural Resources, Department of Forests, Parks and Recreation, Montpelier, VT.

Vermont Department of Public Service. 2022. 2022 Vermont Comprehensive Energy Plan. Vermont Department of Public Service, Montpelier, VT.

Vermont Fish & Wildlife Department. 2015. Vermont Wildlife Action Plan 2015. Vermont Fish & Wildlife Department. Montpelier, VT. https://vtfishandwildlife.com/node/551

Verschuyl, J., S. Riffell, D. Miller, and T. B. Wigley. 2011. Biodiversity response to intensive biomass production from forest thinning in North American forests – A meta-analysis. Forest Ecology and Management **261**:221-232.

Wang, J.-J., Y.-Y. Jing, C.-F. Zhang, and J.-H. Zhao. 2009. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renewable and Sustainable Energy Reviews **13**:2263-2278.

Wang, W. J., H. S. He, F. R. Thompson, J. S. Fraser, and W. D. Dijak. 2017. Changes in forest biomass and tree species distribution under climate change in the northeastern United States. Landscape Ecology **32**:1399-1413.

Wang, W. J., H. S. He, F. R. Thompson, J. S. Fraser, B. B. Hanberry, and W. D. Dijak. 2015. Importance of succession, harvest, and climate change in determining future composition in U.S. central hardwood forests. Ecosphere **6**:1-18.

Wear, D. N., and J. W. Coulston. 2015. From sink to source: regional variation in U.S. forest carbon futures. Scientific Reports **5**:16518.

Wear, D. N., and B. C. Murray. 2004. Federal timber restrictions, interregional spillovers, and the impact on US softwood markets. Journal of Environmental Economics and Management **47**:307-330.

Welsh, H. H., J. R. Dunk, and W. J. Zielinski. 2006. Developing and Applying Habitat Models Using Forest Inventory Data: An Example Using a Terrestrial Salamander. Journal of Wildlife Management **70**:671-681.

White, P. C. L., N. V. Jennings, A. R. Renwick, and N. H. L. Barker. 2005. REVIEW: Questionnaires in ecology: a review of past use and recommendations for best practice. Journal of Applied Ecology **42**:421-430.

Wilcox, C., N. J. Mallos, G. H. Leonard, A. Rodriguez, and B. D. Hardesty. 2016. Using expert elicitation to estimate the impacts of plastic pollution on marine wildlife. Marine Policy **65**:107-114.

Wojnar, Z. 2013. Renewable fuels roadmap and sustainable biomass feedstock supply for New York, annual update #2. New York State Energy Research and Development Authority, Report 13-09, Albany, NY.

Wolfslehner, B., and R. Seidl. 2010. Harnessing Ecosystem Models and Multi-Criteria Decision Analysis for the Support of Forest Management. Environmental Management **46**:850-861.

Work, T. T., S. Brais, and B. D. Harvey. 2014. Reductions in downed deadwood from biomass harvesting alter composition of spiders and ground beetle assemblages in jack-pine forests of Western Quebec. Forest Ecology and Management **321**:19-28.

Woudenberg, S. W., B. L. Conkling, B. M. O'Connell, E. B. LaPoint, J. A. Turner, and K. L. Waddell. 2010. The Forest Inventory and Analysis Database: Database description and users manual version 4.0 for Phase 2. Gen. Tech. Rep. RMRS-GTR- 245. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 339 pp.

Zanchi, G., N. Pena, and N. Bird. 2012. Is woody bioenergy carbon neutral? A comparative assessment of emissions from consumption of woody bioenergy and fossil fuel. GCB Bioenergy **4**:761-772.

Zheng, D., L. S. Heath, M. J. Ducey, and J. E. Smith. 2011. Carbon changes in conterminous US forests associated with growth and major disturbances: 1992–2001. Environmental Research Letters. doi: 10.1088/1748-9326/6/1/014012.

Zielinski, W. J., R. L. Truex, J. R. Dunk, and T. Gaman. 2006. Using Forest Inventory Data To Assess Fisher Resting Habitat Suitability In California. Ecological Applications **16**:1010-1025.

6.0 APPENDICES

6.1. Appendix S1

Appendix S1: SORTIE-ND Documentation

Contents

SORTIE-ND Overview

SORTIE-ND is an individual-based, spatially-explicit model of forest stand dynamics. It is a successor to the earlier SORTIE model (Pacala et al. 1996), using a new software architecture that allows users to create and invoke a wide range of "behaviors" (subroutines) that apply each timestep in a user-defined sequence, and act on either "individuals" of tree species in user-defined life history stages - typically seedlings, saplings and adult trees - or "grids" – rasters of defined grid-cell size in which properties of the grid cell are defined and altered by behaviors. As an example, to reduce computational demand, seedling counts are managed as simply a density, by species and size class, within each grid cell. As seedlings grow into the sapling size classes, they are subsequently treated as individuals.

A more general description of model, including detailed documentation for both users and programmers, and sample parameter files, can be found on the model's website – www.sortie-nd.org.

Recent peer-reviewed papers based on use of the model include Uriarte et al. (2009), Kuntsler et al. (2013), and Forsyth et al. (2015).

Project Overview and Study Region

The implementation of SORTIE-ND used in this study is based on a larger project led by C. D. Canham and Lora Murphy that is designed to assess the effects of a suite of anthropogenic impacts on forests of the eastern United States. Those impacts include (1) climate change, (2) introduced forest pests and pathogens, (3) nitrogen deposition, and (4) logging. Parameterization of the model uses data from the U.S. Forest Service Forest Inventory and Analysis (FIA) network for the 31 eastern states. The data and statistical analyses used to parameterize each of the key demographic processes (seedling recruitment, and sapling growth and mortality) for the 50 most common tree species in the eastern US are described in the sections for the corresponding model behaviors, below.

The current study focuses on just the four northern states of New York, Vermont, New Hampshire, and Maine, and includes a new analysis of the harvest regimes in that region.

Tree Species included in the Model

The 30 most common tree species in the four-state study region (New York, Vermont, New Hampshire, and Maine) were included in the runs used for this study. The species are listed in Table 1 (below).

Table 1.

SPECIES CODE	FIA SPP #	GENUS	SPECIES
ABBA	12	*Abies*	*balsamea*
ACRU	316	*Acer*	*rubrum*
ACSA	318	*Acer*	*saccharum*
BEAL	371	*Betula*	*alleghaniensis*

SPECIES CODE	FIA SPP #	GENUS	SPECIES
BELE	372	*Betula*	*lenta*
BEPA	375	*Betula*	*papyrifera*
CAAL	409	*Carya*	*alba*
CAGL	403	*Carya*	*glabra*
CAOV	407	*Carya*	*ovata*
FAGR	531	*Fagus*	*grandifolia*
FRAM	541	*Fraxinus*	*americana*
LITU	621	*Liriodendron*	*tulipifera*
OSVI	701	*Ostrya*	*virginiana*
PIGL	94	*Picea*	*glauca*
PIRU	97	*Picea*	*rubens*
PIRE	125	*Pinus*	*resinosa*
PIST	129	*Pinus*	*strobus*
POBA	741	*Populus*	*balsamifera*
POGR	743	*Populus*	*grandidentata*
POTR	746	*Populus*	*tremuloides*
PRSE	762	*Prunus*	*serotina*
QUAL	802	*Quercus*	*alba*
QUCO	806	*Quercus*	*coccinea*
QUPR	832	*Quercus*	*prinus*
QURU	833	*Quercus*	*rubra*
QUVE	837	*Quercus*	*velutina*
THOC	241	*Thuja*	*occidentalis*
TIAM	951	*Tilia*	*americana*
TSCA	261	*Tsuga*	*canadensis*
ULAM	972	*Ulmus*	*americana*

Summary of Alternate Scenarios

Scenario 1: "Current Harvest" - No climate change and baseline harvest regime

This scenario represents a baseline of expected dynamics in the northern forest, under no climate change and continuation of the existing regional harvest regime.

The scenario involves the following list of behaviors:

1. Generalized Harvest Regime
2. Neighborhood Competition Index (NCI) growth, applied to saplings and adults of all species
3. NCI quadrat growth, applied to seedlings of all species
4. NCI mortality, applied to saplings and adults of all species
5. Climate and Competition Dependent Neighborhood Survival, applied to seedlings of all species
6. Size dependent logistic mortality (senescence), applied to saplings and adults of all species
7. Stochastic Double-Logistic Temperature Dependent Neighborhood Disperse + establishment, applied to all species

8. Proportional Seed Survival, applied to all species

Scenario 2: "Current Harvest + Climate" - Climate change and baseline harvest regime

This scenario projects forest dynamics and harvest characteristics under a continuation of the existing regional harvest regime, but under a climate change scenario in which mean annual temperature increases linearly a total of 3 degrees C over the next 100 years, and in which annual precipitation increases a total of 10% over the same time period. All of the subsequent scenarios involve this nominal climate change scenario

The scenario involves the following sequence of behaviors:

1. Temperature Climate Change
2. Precipitation Climate Change
3. Seasonal water deficit climate change
4. Generalized Harvest Regime
5. NCI growth, applied to saplings and adults of all species
6. NCI quadrat growth, applied to seedlings of all species
7. NCI mortality, applied to saplings and adults of all species
8. Size dependent logistic mortality (senescence), applied to saplings and adults of all species
9. Climate and Competition Dependent Neighborhood Survival, applied to seedlings of all species
10. Stochastic Double-Logistic Temperature Dependent Neighborhood Disperse + establishment, applied to all species
11. Proportional Seed Survival, applied to all species

Scenario 3: "Current Harvest + Climate + Intensity" - Climate change and a 50% increase in harvest intensity

This scenario projects forest dynamics and harvest characteristics under the nominal climate change but with an approximately 50% increase in the average intensity of individual harvests (over the current harvest regime).

The scenario involves the following sequence of behaviors:

1. Temperature Climate Change
2. Precipitation Climate Change
3. Seasonal water deficit climate change
4. Generalized Harvest Regime
5. NCI growth, applied to saplings and adults of all species
6. NCI quadrat growth, applied to seedlings of all species
7. NCI mortality, applied to saplings and adults of all species
8. Size dependent logistic mortality (senescence), applied to saplings and adults of all species
9. Climate and Competition Dependent Neighborhood Survival, applied to seedlings of all species
10. Stochastic Double-Logistic Temperature Dependent Neighborhood Disperse + establishment, applied to all species
11. Proportional Seed Survival, applied to all species

Scenario 4: "Current Harvest + Climate + Frequency" - Climate change and a 75% increase in harvest frequency

This scenario projects forest dynamics and harvest characteristics under the nominal climate change but with an approximately 75% increase in the frequency of harvests (over the current harvest regime).

The scenario involves the following sequence of behaviors:

1. Temperature Climate Change
2. Precipitation Climate Change
3. Seasonal water deficit climate change
4. Generalized Harvest Regime
5. NCI growth, applied to saplings and adults of all species
6. NCI quadrat growth, applied to seedlings of all species
7. NCI mortality, applied to saplings and adults of all species
8. Size dependent logistic mortality (senescence), applied to saplings and adults of all species
9. Climate and Competition Dependent Neighborhood Survival, applied to seedlings of all species
10. Stochastic Double-Logistic Temperature Dependent Neighborhood Disperse + establishment, applied to all species
11. Proportional Seed Survival, applied to all species

Scenario 5: "Current Harvest + Climate + Intensity + Frequency" - Climate change and a 50% increase in harvest intensity and a 100% increase in harvest frequency

This scenario projects forest dynamics and harvest characteristics under the nominal climate change but with an approximately 50% increase in average intensity of individual harvests and a doubling of the frequency of harvests (over the current harvest regime).

The scenario involves the following sequence of behaviors:

1. Temperature Climate Change
2. Precipitation Climate Change
3. Seasonal water deficit climate change
4. Generalized Harvest Regime
5. NCI growth, applied to saplings and adults of all species
6. NCI quadrat growth, applied to seedlings of all species
7. NCI mortality, applied to saplings and adults of all species
8. Size dependent logistic mortality (senescence), applied to saplings and adults of all species
9. Climate and Competition Dependent Neighborhood Survival, applied to seedlings of all species
10. Stochastic Double-Logistic Temperature Dependent Neighborhood Disperse + establishment, applied to all species
11. Proportional Seed Survival, applied to all species

Scenario 6: "No Harvest" - Climate change and no harvest

This scenario projects forest dynamics under the nominal climate change, and with no harvest at all. It provides a reference baseline for forest conditions expected on reserved forestland.

The scenario involves the following sequence of behaviors:

1. Temperature Climate Change
2. Precipitation Climate Change
3. Seasonal water deficit climate change

4. NCI growth, applied to saplings and adults of all species
5. NCI quadrat growth, applied to seedlings of all species
6. NCI mortality, applied to saplings and adults of all species
7. Size dependent logistic mortality (senescence), applied to saplings and adults of all species
8. Climate and Competition Dependent Neighborhood Survival, applied to seedlings of all species
9. Stochastic Double-Logistic Temperature Dependent Neighborhood Disperse + establishment, applied to all species
10. Proportional Seed Survival, applied to all species

Initial Densities of Seedlings, Saplings, and Adults

Each scenario consists of 5,000 individual runs of the SORTIE-ND model, with the individual runs initialized with conditions in one of 5,000 randomly selected FIA plots within the 4-state study region. This includes information about current climate, soils, and topography of the plot, and, more critically, data for the current abundance, by species and size class, of seedlings, saplings, and adult trees.

Seedlings

Seedling numbers for a given plot are taken directly from the NE FIA records for that plot as recorded in [STATE]_SEEDLING.csv, summed by species across subplots. This number is scaled to #/ha. Only species on the list above are included. The seedlings are randomly distributed across the plot.

SORTIE-ND creates the seedlings by randomly drawing on a uniform height distribution from the smallest possible seedling height (the height of a seedling with a d10 of 0.2 cm) up to 133 cm height. This upper bound value is slightly arbitrary; SORTIE-ND works with three seedling height classes for the purposes of initial conditions and this allows for the definition of the other two at 134 and 135 cm. These larger classes remain empty.

Saplings

Sapling size classes are set from 0 – 12 cm DBH, in 2 cm increments. For a plot, the total number of live saplings (trees with a DBH > 2.54 cm and < 12.7 cm as recorded in the [STATE]_TREE.CSV file) are counted by species and scaled to #/ha. We used a matrix of size class frequencies to distribute these values into the 0-12 cm size classes. Saplings that are not of a species on the above list are ignored.

Adults

Adult size classes are set from 12-15, and then 15–65 cm DBH, in 5 cm increments. For a plot, the adult trees (trees with a DBH >= 12.7 cm as recorded in the [STATE]_TREE.CSV file) are tallied by species and size class. Adult trees of a species not on the above list are randomly re-assigned to one of those species and tallied as well. Adults larger than the largest size class are ignored because they are so rare. This size distribution is scaled to #/ha and passed to SORTIE-ND in the parameter file.

Temperature Climate Change

Description

This behavior implements change in plot mean annual temperature, using a simple climate change scenario with a **3 degree C increase over the first 100 years of the run,** starting with whatever calendar year the first timestep represents. The temperature increase is linear, and then capped at 100 years with no further increase.

Data Sources:

PRISM data were used to calculate the average mean annual temperature during the approximately 5 years between the last two censuses for a plot. This value was used as the mean annual temperature for the plot at the beginning of the run.

Precipitation Climate Change

Description

This behavior implements annual change in total annual precipitation, in mm. Climate models are far less certain of projected changes in precipitation for the northeastern US over the next century, but generally predict a slight increase in total annual precipitation. The simulations used in this study assume an increase in precipitation uniformly across the study region by **10% above current levels at any given location, over the first 100 years of the run,** starting with whatever calendar year the first timestep represents. The precipitation increase will be linear, and then capped at 100 years with no further increase.

This calculates the proportion of change in the annual precipitation, then adjusts seasonal precipitation by the same amount.

Data Sources

The 800 m resolution PRISM climate data were used to calculate the average total annual precipitation at the location of a plot, averaged across the period between the two most recent censuses of that plot (approximately 5 years).

Seasonal Water Deficit Calculation

Description

This behavior calculates growing season cumulative water deficit each year.

Annual precipitation is first partitioned by month, by multiplying the total by the fraction of precipitation that falls in each month based on seasonal distributions of precipitation determined for each plot location from PRISM climate data. Then monthly temperature is calculated, by multiplying annual mean temperature by the ratio of the month’s mean to annual mean (entered as a parameter). This preserves current patterns of seasonal variation in temperature and precipitation.

PET (monthly potential evapotranspiration) is calculated as:

$$PET_i = \begin{cases} 0.013\left[\dfrac{T}{T+15}\right](R_s + 50) & if\ T > 0 \\ 0 & if\ T \leq 0 \end{cases}$$

Where

- PET is monthly potential evapotranspiration in mm

- T is mean monthly temperature in °C
- R_s is monthly global radiation received at the earth's surface, in cal cm^{-2} (entered as a parameter)

Monthly soil moisture storage is calculated as:

$$sms_i = 0 < sms_{i-1} + precip_i - PET_i < MaxAWS$$

where:

- $precip_i$ is the monthly precipitation (mm) for the previous month
- PET_i is for the previous month
- MaxAWS is the available soil water storage, in mm (entered as a parameter)

Monthly actual evapotranspiration (AET) is calculated as:

$$AET_i = \begin{cases} sms_i + precip_i & if\ sms_{i+1} \leq 0 \\ PET_i & if\ sms_{i+1} > 0 \end{cases}$$

Then

$$AET = \sum_{i=1}^{12} AET_i$$

and

$$PET = \sum_{i=1}^{12} PET_i$$

and Annual Water Deficit = PET – AET.

Data Sources

Initial plot monthly precipitation and temperature patterns were derived from bi-linear interpolation of 800 m resolution PRISM data extracted at the true location of the desired FIA plot.

Monthly solar radiation values for each plot were calculated using solar radiation functions in ArcGIS, using the USGS 10m resolution seamless digital elevation model.

Generalized Harvest Regime

Description

This behavior decides when harvests will occur and how much to cut based on forest type, total plot adult basal area and distance from the nearest improved road, then chooses trees to cut with the help of a preference algorithm. The basic approach is outlined in Canham et al. (2013). Parameters for the current study were derived from an analysis of harvest data from FIA plots in the study region (the states of NY, VT, NH, and ME).

In each timestep, the behavior begins by deciding whether or not a harvest will occur. The probability of harvest is a function of total plot adult basal area, as follows:

$$P = 1 - a * e^{-mBA^{b}}$$

Where P is the probability that the plot will be harvested this time step, *BA* is the total plot adult basal area, in m^2/ha, and *a*, *m*, and *b* are parameters.

A random number is compared to this probability to decide whether or not harvest will occur. The frequency of harvest in previous time steps is not taken into account.

If a harvest is to occur, the target removal amount is drawn from a user-defined probability distribution function. There are 10 equal harvest intensity classes (0-10%, 11-20%, ...) and an associated probability for each. The behavior turns the probabilities for all the classes into a cumulative probability function. A random number drawn on the uniform distribution between 0 and 1 is used against the cumulative probabilities to determine which class the harvest falls into. Then a second uniform random draw on the range of values in that class is used to choose the target proportion of adult basal area to remove.

The plot basal area in the equations above is the total adult basal area for all species. All species are considered in determining harvest levels must participate in harvest, and only adults are counted and cut.

Once a basal area removal target has been established, the individuals to cut must be selected. A preference function determines the probability that an individual will be cut, as follows:

$$P_i = \left[1 - \gamma_i * e^{-\beta_i BAR^{\alpha_i}}\right] * \left[e^{-0.5\left(\frac{DBH-\mu_i}{\sigma}\right)^2}\right]$$

Where P_i is the probability that individual i will be cut, *BAR* is the percent of total adult basal area to remove, *DBH* is the individual's DBH, and α_i, β_i, γ_i, and μ_i are parameters for the species of individual i.

The term σ is:

$$\sigma = a + b * BAR^{c}$$

where *a*, *b*, and *c* are parameters and *BAR* is the percent of total adult basal area to remove. Parameters for these species-specific functions are drawn from analyses in Canham et al. (2013).

An individual's probability of removal is compared with a random number to determine if that individual is cut.

Data Sources

Removal data from most recent recensuses in FIA plots in the 4-state NSRC study region were analyzed using the statistical models outlined in Canham et al. (2013).

Analyses

The manuscript describes the specific harvest analyses and results for this study. There are separate parameters for each of 6 different combinations of forest type and region. There are also separate values of the *a* parameter for each of 7 different categories of distance to nearest improved road (based on the FIA RDDISTCD code).

Scenarios

The parameters described above represent the nominal (baseline) scenario.

In Scenarios 3 and 5, harvest intensity is increased by 50%. Harvest intensity is increased by shifting the probability distribution over the 10 harvest intensity classes upwards by 50%. The original distribution was simply the histogram of observed harvest intensities. To shift this distribution, the following method was used:

1. Perform a large number of random draws on this distribution and find their mean (which is the distribution mean)
2. Multiply this mean by 1.5
3. Shift all intensity class upper bounds upwards by the difference in the old and new mean
4. Perform a large number of random draws on this new distribution
5. Bin these draws into the old intensity classes

This process cannot perfectly preserve the shape of the distributions, since it is bounded between 0 and 1. The highest intensity class (i.e. clearcuts) will increase disproportionately. This was judged acceptable.

In scenarios 4 and 5, harvest frequency is increased. This is achieved by adjusting the value of the "a" and "m" parameters in the probability of harvest:

$$P = 1 - a * e^{-mBA^{b}}$$

The values are

a' = a – (x*(1-a))
m' = m * (1+x)

where x is the proportion by which to increase harvest (i.e. 0.75 in the case of a 75% increase).

NCI growth

Applied to

Saplings and adults of all species. Saplings are described as individuals taller than 1.35 m and < 12.7 cm DBH (5").

Analyses

Parameters are based on results of analyses of FIA data described in Canham and Murphy (2016a).

Diameter growth (**in mm/yr**) is a function of:

1. Size: with a shifted lognormal functional form
2. Temperature: with a double logistic, using mean annual temperature
3. Precipitation: with a double logistic, using seasonal precipitation
4. Competition: based on the total basal area of all sapling and adult neighbors within a 7.32 m radius circle (the size of the FIA plot), and includes a gamma term applied to the ratio of mean basal area of neighbors to target basal area.
5. Nitrogen deposition: using a simple 2-parameter Gaussian, based on plot average total wet N deposition

6. Site index: we grouped the FIA site index code into 3 categories, and estimate a separate potential growth for each category
7. Life history stage: separate parameters were estimated for juveniles and adults

Parameters

Parameter values are reported in Canham and Murphy (2016a). Those analyses generated separate parameter values for saplings and adults. Model comparison methods were used to test 4 alternate models based on presence/absence of temperature and precipitation effects (i.e. both temperature and precipitation effects, no precipitation effect, no temperature effect, or no climate effects).

Description

For a tree, the amount of diameter growth per year is calculated as:

*Growth = Max Growth * Size Effect * Precipitation Effect * Crowding Effect * Temperature Effect * Nitrogen Effect * Pest Effect*

Max Growth is the maximum diameter growth the tree can attain, in **cm/yr**, entered as the **Weibull Climate Growth - Max Potential Growth (cm/yr)** parameter. The other effects are all factors which act to reduce the maximum growth rate and will vary depending on the conditions a tree is in. Each of these effects is a value between 0 and 1.

Size Effect is calculated with a shifted lognormal function, as follows:

$$SE = exp\left(-0.5\left[\frac{ln\left({(DBH + X_p)}/{X_0}\right)}{X_b}\right]^2\right)$$

Where *DBH* is of the target tree, in cm, and X_0, X_p, and X_b are parameters.

There is a minimum DBH for the size effect in the **Size Effect Minimum DBH** parameter, set to 2.5 cm. Any target tree whose DBH is less than this value will get a size effect based on the minimum DBH instead. This allows us to avoid problems with very small trees that can occur because of the shape of the lognormal function.

Precipitation Effect is calculated as:

$$PE = \left(a_l + \frac{1 - a_l}{1 + \left({b_l}/{ppt}\right)^{c_l}}\right) * \left(a_h + \frac{1 - a_h}{1 + \left({ppt}/{b_h}\right)^{c_h}}\right)$$

Where *ppt* is the plot's effective growing season precipitation (see Canham and Murphy 2016a), in millimeters, for that timestep, and a_l, b_l, c_l, a_h, b_h, and c_h are parameters.

Temperature Effect is calculated as:

$$TE = \left(a_l + \frac{1 - a_l}{1 + \left({}^{b_l}/_{T} \right)^{c_l}} \right) * \left(a_h + \frac{1 - a_h}{1 + \left({}^{T}/_{b_h} \right)^{c_h}} \right)$$

Where *T* is the plot's annual mean temperature, in degrees Celsius, for that timestep, and a_l, b_l, c_l, a_h, b_h, and c_h are parameters.

The *Crowding Effect* is calculated as:

$$CE = e^{-C*BA.RATIO^{\gamma}*TOT.BA^{D}}$$

Where:

- *TOT.BA* is the total basal area of adult and sapling neighbors with a DBH greater than the target tree's DBH, out to a maximum distance
    - For adults, the distance is 7.32 m, the size of the FIA plots (24')
    - For saplings, the distance is 2.073 m, the size of the FIA microplots (6.8')
- *BA.RATIO* is the ratio of the mean BA of neighbors (the same individuals that went into calculation of *TOT.BA*) to the BA of the target tree
- *C*, *D*, and γ are species-specific parameters.

The *Nitrogen Effect* is calculated as a Gaussian function of average annual dry nitrogen deposition (in kg/ha/yr; see Canham and Murphy 2016a for methods of calculating N deposition at each plot location):

$$NE = e^{-0.5\left(\frac{N - X_0}{X_b}\right)^2}$$

Where *N* is the nitrogen deposition estimated for the plot location, and X_0 and X_b are parameters.

The equation defines the expected (mean) diameter growth. Actual growth of an individual is a random draw from a normal distribution using the estimated species-specific standard deviation (SD) parameter. Growth is truncated at zero to avoid negative values.

NCI Quadrat Growth

Applied to

Seedlings of all species

Description

This is the same as "NCI growth" with the following exceptions:

- All of the terms are calculated on a per-quadrat basis and applied to all seedlings within the quadrat; the final growth term is used as the mean on a normal random draw with standard deviation equal to the "sd" parameter in the NCI Growth behavior
- BA.RATIO for competition is calculated with a constant BA based on a DBH of 1 cm
- Size effect is pre-calculated for each species for a 2.5 cm DBH and multiplied into the max growth term

Parameters

There are no direct measurements of growth on seedlings in FIA data, so we apply sapling growth rates to seedling sizes (calculated assuming a size of 2.5 cm DBH), and use the parameters from saplings.

NCI survival

Applied to

Saplings and adults of all species

Parameters

Parameter values are reported in Canham and Murphy (2017). Those analyses generated separate parameter values for saplings and adults. Model comparison methods were used to test 4 alternate models based on presence/absence of temperature and precipitation effects (i.e. both temperature and precipitation effects, no precipitation effect, no temperature effect, or no climate effects).

Data and Analysis Source

FIA data from the eastern 31 states were compiled to estimate species-specific probabilities of sapling and adult mortality as a function of size, crowding, nitrogen deposition, and climate. Results of the analysis are described in Canham and Murphy (*in prep)*, and follow the same general analytical framework used to model growth rates (as described in Canham and Murphy 2016a)

Description

As with all behaviors based on our analysis of FIA data, the behavior incorporates the functional forms used exactly as they were in the analysis of FIA data. The behavior assesses tree survival as a function of climate and competition from neighbor trees. A tree has a maximum potential annual probability of survival that is reduced due to several possible factors.

For a tree, the annual probability of survival is calculated as:

*Survival Probability = Max Survival Probability * Size Effect * Precipitation Effect * Crowding Effect * Temperature Effect * Nitrogen Effect*

Max Survival Probability is the maximum possible annual survival probability. In the analyses, separate maxima are estimated for 3 different site class groupings based on FIA site class codes (see Canham and Murphy, *in prep* for details). The other effects are all factors which act to reduce the maximum survival probability and will vary depending on the conditions a tree is in. Each of these effects is a value between 0 and 1.

NOTE: The analyses of FIA data estimated 5-year (not annual) survival. The behavior has a parameter for the analysis period, and uses this to appropriately adjust to an annual survival rate.

The *Size Effect* is calculated with a compound exponential function, as follows:

$$SE = \left(1 - a * e^{(b*diam)}\right) * \left(e^{\left(c*diam^{d}\right)}\right)$$

Where *diam* is the DBH of the target tree, in meters, and *a*, *b*, *c*, and *d* are parameters.

NOTE: The analyses of FIA data included species-specific parameter estimates for the *Size Effect* terms, but most species had too few large stems to accurately estimate the uptick in mortality in larger size classes. Therefore, the species were grouped into 4 growth form/tolerance classes, and *Size Effect* term parameters were estimated from a model that also included competition effects to avoid biasing the size effect for smaller size classes. The fitted functions are illustrated in the figure below. The parameters of those 4 general *Size Effects* were then used instead of the species-specific parameters.

The species used to estimate the functions for the 4 groups were:
1. **Tolerant**: *Abies balsamea, Acer rubrum, Acer saccharum, Betula alleghaniensis, Fagus grandifolia, Nyssa sylvatica, Picea glabra, Picea rubens, Thuja occidentalis,* and *Tsuga canadensis*
2. **Intermediate**: *Betula lenta, Carya alba, Carya glabra, Carya ovata, Fraxinus americana, Fraxinus pennsylvanica, Liquidambar styraciflua, Liriodendron tulipfera, Pinus strobus, Prunus serotina, Quercus alba, Quercus coccinea, Quercus falcata, Quercus macrocarpa, Quercus nigra, Quercus prinus, Quercus rubra, Quercus stellata, Quercus velutina, Robinia pseudoaccacia, Tilia americana, Ulmus americana, Ulmus alata,* and *Ulmus rubra*
3. **Intolerant:** *Betula papyrifera, Fraxinus nigra, Juniperus virginiana, Pinus banksiana, Pinus echinata, Pinus resinosa, Pinus taeda, Pinus virginiana, Populus balsamea, Populus grandidentata,* and *Populus tremuloides*
4. **Subcanopy:** *Carpinus caroliniana, Cornus florida, Ostrya virginiana, Oxydenrum arborea,* and *Sassafras albidum*

The *Precipitation Effect* is calculated as:

$$PE = \left(a_l + \frac{1 - a_l}{1 + \left({}^{b_l}/_{ppt} \right)^{c_l}} \right) * \left(a_h + \frac{1 - a_h}{1 + \left({}^{ppt}/_{b_h} \right)^{c_h}} \right)$$

Where *ppt* is the plot's seasonal precipitation, in millimeters, for that timestep, and a_l, b_l, c_l, a_h, b_h, and c_h are parameters.

The *Temperature Effect* is calculated as:

$$TE = \left(a_l + \frac{1 - a_l}{1 + \left({}^{b_l}/_{T} \right)^{c_l}} \right) * \left(a_h + \frac{1 - a_h}{1 + \left({}^{T}/_{b_h} \right)^{c_h}} \right)$$

Where *T* is the plot's annual mean temperature, in degrees Celsius, for that timestep, and a_l, b_l, c_l, a_h, b_h, and c_h are parameters.

The *Crowding Effect* is calculated as:

$$CE = e^{-C*BA.RATIO^{Y}*TOT.BA^{D}}$$

Where:

- *TOT.BA* is the total basal area of adult and sapling neighbors with a DBH greater than the target tree's DBH, out to a maximum distance
    - For adults, the distance is 7.32 m, the size of the FIA plots (24')
    - For saplings, the distance is 2.073 m, the size of the FIA microplots (6.8')
- *BA.RATIO* is the ratio of the mean BA of neighbors (the same that went into *TOT.BA*) to the BA of the target tree
- *C*, *D*, and γ are parameters.

The *Nitrogen Effect* is calculated as:

$$NE = e^{-0.5\left(\frac{N-X_0}{X_b}\right)^2}$$

Where N is the nitrogen deposition as entered in the plot, and X_0 and X_b are parameters.

Size Dependent Logistic Mortality

Applied to

Adult trees of all species.

Description

This behavior applies a stochastic mortality function that is a logistic function of tree size. The behavior calculates a size-dependent probability of mortality (senescence) in very large trees (over and above mortality from other behaviors). This function is arbitrary, but is necessary because the FIA datasets include too few trees to provide reasonable estimates of the mortality rates for large trees. We use a very conservative functional form designed to prevent trees from reaching unrealistically large sizes.

For each tree to which this behavior is applied, the following function is evaluated:

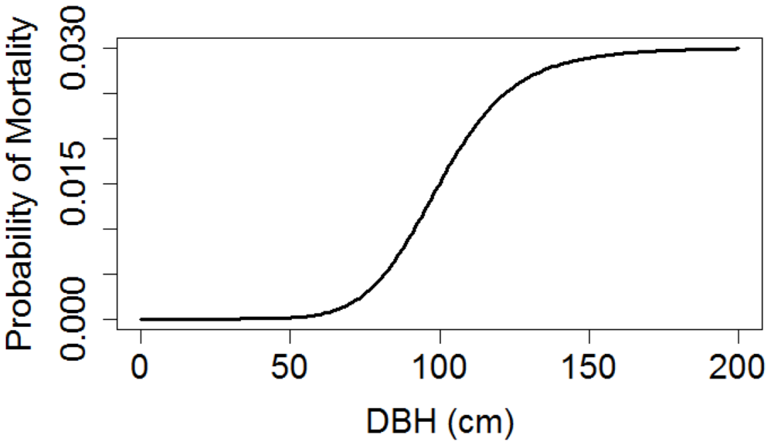
$$p = \frac{Max}{1 + \left(\frac{diam}{X_0}\right)^{X_b}}$$

where:

- p is the probability of mortality
- X_0 and X_b are parameters
- *diam* is DBH in cm

Parameters

Default parameters are max = 0.03, X_0 = 100, and X_b = -8, giving the functional form illustrated below:



Climate and Competition Dependent Neighborhood Survival

Applied to

Seedlings of all species.

Data source

FIA seedling count data from the eastern 31 states.

Analysis

The methods for estimating seedling survival as a function of climate and competition are reported in Canham and Murphy (2016b). The results of that analysis are incorporated directly in the behavior summarized below.

Description

This behavior assesses seedling survival as a function of:

- mean annual temperature (Gaussian)
- growing season water deficit (Gaussian)
- Total adult basal area in a 10 m radius circle around a seedling grid cell.

For efficiency, the behavior calculates survival rates for cells in a grid and assigns all seedlings the survival probability of the grid cell in which they are found.

The annual probability of survival for a given species and given grid cell is calculated as:

$$Surv = e^{-A*BAT^{B}} * e^{-0.5\left(\frac{T-M}{N}\right)^{2}} * e^{-0.5\left(\frac{WD-C}{D}\right)^{2}}$$

Where *Surv* is the annual probability of survival, *T* is the mean annual temperature in degrees Celsius for the current timestep, *BAT* is the adult total basal area within a 10 m radius, in square meters, *WD* is the plot water deficit, and *A*, *B*, *M*, *N*, *C,* and *D* are species-specific parameters.

Parameters

Species-specific parameters for the 30 tree species included in the simulations are contained in appendices in Canham and Murphy (2016b).

Stochastic Double-Logistic Temperature Dependent Neighborhood Dispersal

Applied to

Creation of new seedling recruits of all species.

Overview

As in the original version of SORTIE, the model does not explicitly consider seeds and seed dispersal, germination and seedling "establishment". Rather, the approach used here models the input ("recruitment") of new seedlings of a minimum size. "Fecundity" is defined in this context as the # of new seedling recruits per year and per unit basal area of conspecific adult trees. Internally within SORTIE-ND, the new seedlings are created as a simple count, by species within a "seed grid". At the end of the time step an Establishment behavior converts each of the new recruits into an individual seedling (see below).

Analyses

Parameters were estimated from analyses reported in Canham and Murphy (2016b). Note that the behavior allows for temperature dependence of "fecundity", but there were parameter tradeoffs between fecundity and survival terms in the model when including the effects of temperature in both fecundity and survival, so the version used in Canham and Murphy (2016b) does not incorporate a temperature dependence of fecundity. Instead, fecundity (# of new seedling recruits/year) is a simple linear function of conspecific basal area (within a 10 m radius circle around the center of a seedling quadrat).

Description

The mean number of new seedlings per year in each cell of the Dispersed Seeds grid is calculated as:

$$\mathit{Seedling\ Recruits} = RA + RB * BAC$$

where:

- *Seedling recruits* is the mean number of new seedlings in the cell
- *RA* and *RB* are parameters
- *BAC* is the total basal area of neighborhood conspecific adults in square meters within a radius of **Max Search Distance for Conspecific Adults (m).** This distance is set to **10 m**, because adult basal area calculated for each FIA subplot was scaled to this area.

The mean value, above, is then scaled by grid cell size and number of years per timestep to specify the mean on a Poisson random draw. The actual number of new seedlings assigned to the grid is:

$$\mathit{Actual\ seedlings} = \mathit{Poisson}(\mathit{seedling\ recruits} * (CA/OA) * Y)$$

where:

- *Actual seedlings* is the result of the Poisson draw
- *CA* is the area of the grid cell, in square meters
- *OA* is the **Original Analysis Plot Size (m2)** parameter (set to 13.49577 m2 (i.e. a 6.8 ft radius))
- *Y* is the number of years per timestep

Note that this behavior works on a per-grid-cell basis, rather than calculating seed densities on a per-square-meter basis. This is because the Poisson function is influenced by seed grid cell size. The **Original Analysis Plot Size (m2)** parameter can be used to scale results to original analysis plot size, but for computational efficiency, the seed grid cell size is set to the same or slightly larger than the original analysis seed plot size.

Colonization

Note that the RA parameter in the mean seeds equation is an intercept, potentially allowing bath rain of seeds for species for which there are no parents present. To manage this, the behavior uses a colonization test. The **cumulative** probability of colonization is:

$$PC_c = pa * e^{-0.5\left(\frac{T-pm}{pb}\right)^2}$$

where:

- *PC* is the cumulative probability of colonization
- *pa* is the **Colonization PA** parameter
- *pb* is the **Colonization PB** parameter
- *pm* is the **Colonization PM** parameter
- *T* is the annual mean temperature, in degrees Celsius

PC_c is the cumulative probability of colonization over an arbitrary time period T. PC_c is used to calculate the annualized probability of colonization as:

$$PC_a = 1 - [(1 - PC_c)^{(1/t)}]$$

Where PC_a is the annualized probability of colonization, and *T* is the **Cumulative Colonization Probability Period (years)** parameter. Default value is 10 years.

The behavior compares PC_a to a random number to determine whether this species is allowed to colonize in this timestep. If so, it creates a new seedling cohort as described above.

Proportional Seed Survival

This behavior reduces the estimated number of new seedling recruits to 25% of numbers estimated in the FIA analyses reported in Canham and Murphy (2016b). The 25% value was arrived at through testing. The rationale is that in the analysis, for each cohort, the model assesses survival after seeds are dispersed (i.e. mortality happens after disperse each growing season). Recruitment of new seedlings in SORTIE-ND occurs after mortality each timestep (growing season), which would lead to an overproduction of seedlings of a magnitude proportional to survival rates. While the formal behavior name refers to seeds, the counts in the seed grid are actually of new seedling recruits, so the behavior acts on counts of seedlings, not seeds.

Establishment

As the final step in the creation of new seedlings, the counts in each seed grid for each species are used to create that many new seedlings, randomly dispersed within the seed grid, and assigned an initial seedling diameter slightly randomized around 0.2 cm basal diameter.

References

Canham, C. D., N. Rogers, and T. Buchholz. 2013. Regional variation in forest harvest regimes in the northeastern United States. Ecological Applications 23:515-522.

Canham, C. D., and L. Murphy. 2016a. The demography of tree species response to climate: seedling recruitment and survival. Ecosphere 7(8):e01424. 10.1002/ecs2.1424

Canham, C. D., and L. Murphy. 2016b. The demography of tree species response to climate: sapling and canopy tree growth. Ecosphere 7(10):e01474. 10.1002/ecs2.1474

Canham, C. D., and L. Murphy. 2017. The demography of tree species response to climate: sapling and canopy tree survival. Ecosphere 8(2):e01701. 10.1002/ecs2.1701.

Forsyth, D. M., D. J. Wilson, T. Easdale, G. Kunstler, C. D. Canham, W. A. Ruscoe, E. F. Wright, L. Murphy, A. M. Gormley, and D. A. Coomes. 2015. Century-scale effects of invasive deer and rodents on the dynamics of forests growing on soils of contrasting fertility. Ecological Monographs 85:157-180.

Kunstler, G., R. B. Allen, D. A. Coomes, C. D. Canham, and E. F. Wright. 2013. Sustainable management, earthquake disturbances, and transient dynamics: modelling timber harvesting impacts in mixed-species forests. Annals of Forest Science 70:287-298.

Pacala, S. W., C. D. Canham, J. Saponara, J. A. Silander, Jr., R. K. Kobe, and E. Ribbens. 1996. Forest models defined by field measurements: II. Estimation, error analysis and dynamics. Ecological Monographs 66:1-43.

Uriarte, M., C. D. Canham, J. Thompson, J. K. Zimmerman, L. Murphy, A. M. Sabat, N. Fetcher, and B. L. Haines. 2009. Natural disturbance and human land use as determinants of tropical forest dynamics: results from a forest simulator. Ecological Monographs **79**:423-443.

6.2. Appendix S2

APPENDIX S2. Effects of population density, legal protection status, and parcel size on the frequency and intensity of timber harvests in the northern forest.

POPULATION EFFECTS

We compiled 2010 US census data for the census tract in which an FIA plot was located, and converted the population data to population density (#/mi^2). Scatterplots of the fraction of basal area removed as a function of census tract population density showed a very weak negative relationship (Fig. S1). Histograms of the percent of plots logged showed no clear relationship to either census tract (Fig. S2)or county population density (data not shown).

We fitted models for the frequency and intensity of harvest as a function of census tract population density, using the basic approach outlined in the manuscript, with population density instead of stand basal area as the independent variable. Separate models were fit for northern hardwood – conifer forests (across all 4 states) and spruce – fir forests. Models were not fit for the other forest types because of small sample sizes and a poor distribution of the range of the population data. The predicted functional forms confirmed the very weak observed relationships between population density and either the frequency or intensity of timber harvests (Figs. S3 and S4).

Figure S1. The percent of basal area removed in timber harvest, for the 1,323 FIA plots with at least some degree of harvest during the most recent census interval (with second census dates ranging from 1999 – 2011, and an average remeasurement interval of 6.4 years). The red line is a least squares linear regression.

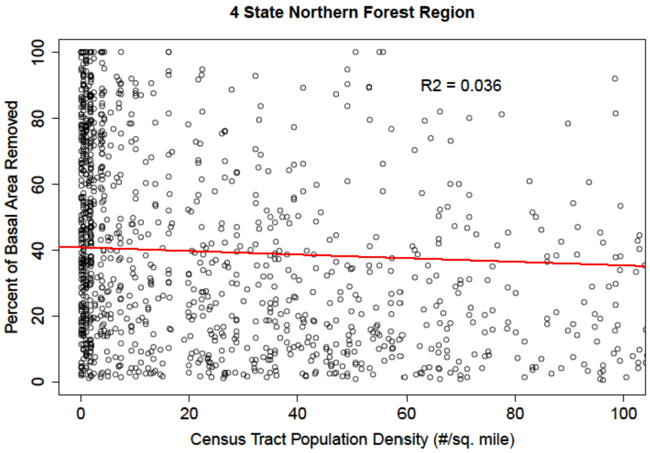


Figure S2. Histograms of the fraction of FIA plots logged as a function of census tract population density, during the most recent census intervals (mean = 6.4 years).

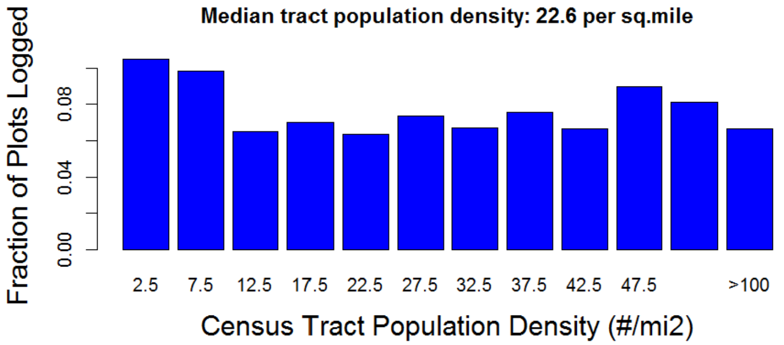


Figure S3. Predicted effect of census tract population density on the frequency and intensity of timber harvest for northern hardwood-conifer forests across the 4 northern forest states.

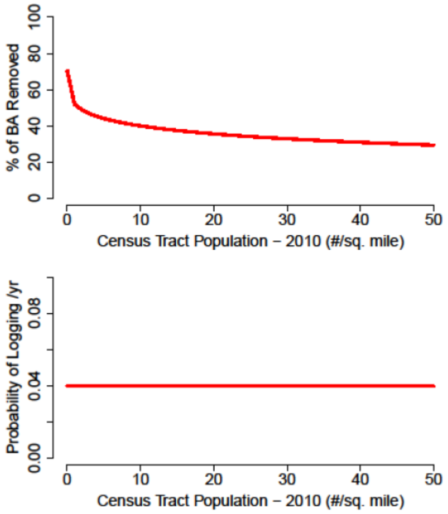
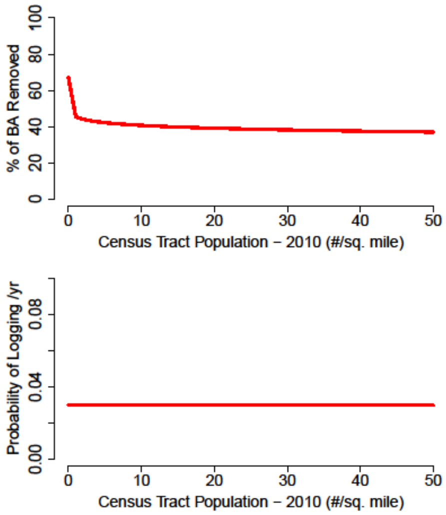


Figure S4. Predicted effect of census tract population density on the frequency and intensity of timber harvest for spruce-fir forests across the 4 northern forest states.



PROTECTION STATUS

A significant fraction of the working forests of the northern forest region have been placed under easements during the past 25 years, to limit development and help ensure the lands remain part of the working forest land base. In many cases, the easements include provisions that forests be managed sustainably under one or more of the existing forest certification schemes (FSC and SFI).

The Nature Conservancy has compiled datalayers recording the protection status of a significant fraction of the lands of the 4-state study region. For our purposes, we used those datalayers to record whether an FIA plot was on land for which there was an easement that limited development but allowed resource extraction, including timber harvest.

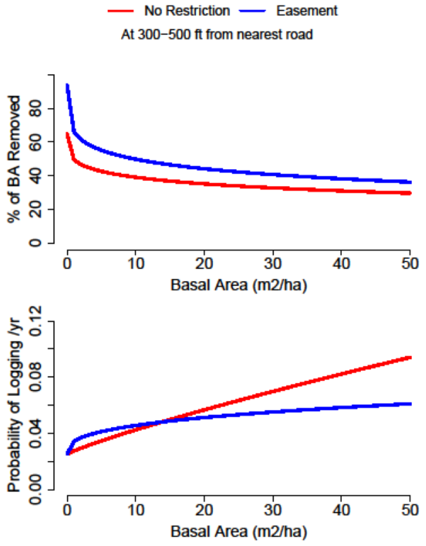
To test the effects of protection status we fitted the basic model in the manuscript for the frequency and intensity of timber harvest as a function of basal area with separate parameters for easement vs non-easement lands. That model was then compared to the null model in which the two groups were lumped together. There was sufficient sample size of the two protection categories to test models for just the northern hardwood – conifer forests (across all 4 states) and the spruce – fir forests.

For the northern hardwood – conifer forests, the model that estimated separate parameters for the two protection classes was marginally better than the null model ignoring protection status

(AIC = 11049 vs AIC = 11050 for the null model). The model predicted that forestland under easement had slightly lower probabilities of being harvested across most of the range of stand basal area, but had a slightly higher fraction of basal area removed when harvested (Fig. S5).

For the spruce – fir forests, the null model that did not distinguish between easement and non-easement lands was clearly superior (AIC = 3396 vs AIC = 3410 for the protection status model).

Figure S5. Predicted frequency and intensity of timber harvest on easement and non-easement working forests for northern hardwood – conifer forests across the northern forest region.



PARCEL SIZE

It is generally assumed that forest land in small parcel sizes is less likely to be harvested, and less intensively if harvested. The parcel datalayer compiled by The Nature Conservancy and used for our assessment of the effects of protection status (above) can also be used to test the effects of parcel size on timber harvesting. Examination of the raw data suggests that there is indeed an effect of parcel size on the intensity of harvest (Fig. S6), although with a great deal of variability. The data also suggest little effect of parcel size on frequency of harvest (Fig. S7). We tested a number of alternate models and different functional forms to assess the effects of parcel size on both frequency and intensity of harvest. Given the patterns visible in the empirical data, we settled on testing a logistic function form for the effect of parcel size on both frequency and intensity of harvest, since the empirical data suggested threshold effects of parcel size.

Figure S6. The mean and standard deviation of the percent of basal area removed from a plot in a timber harvest, as a function of parcel size.

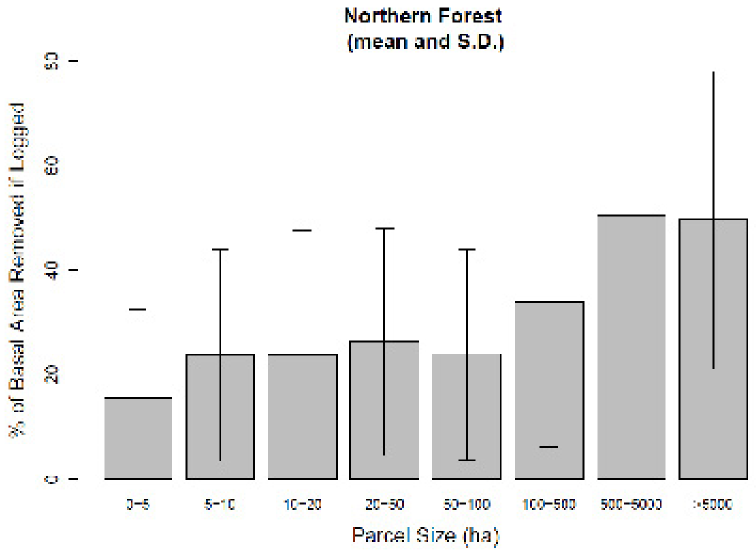
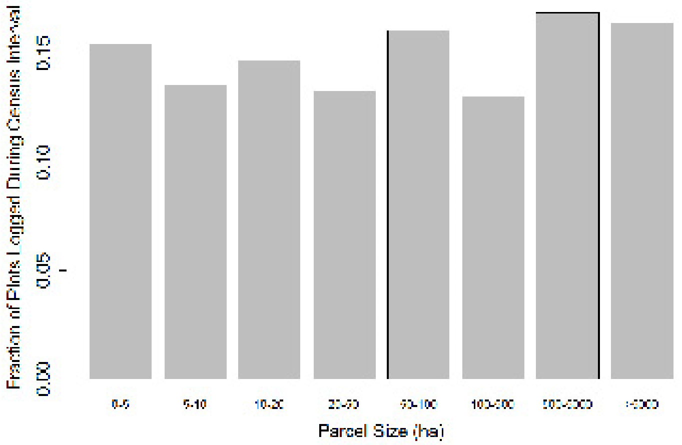
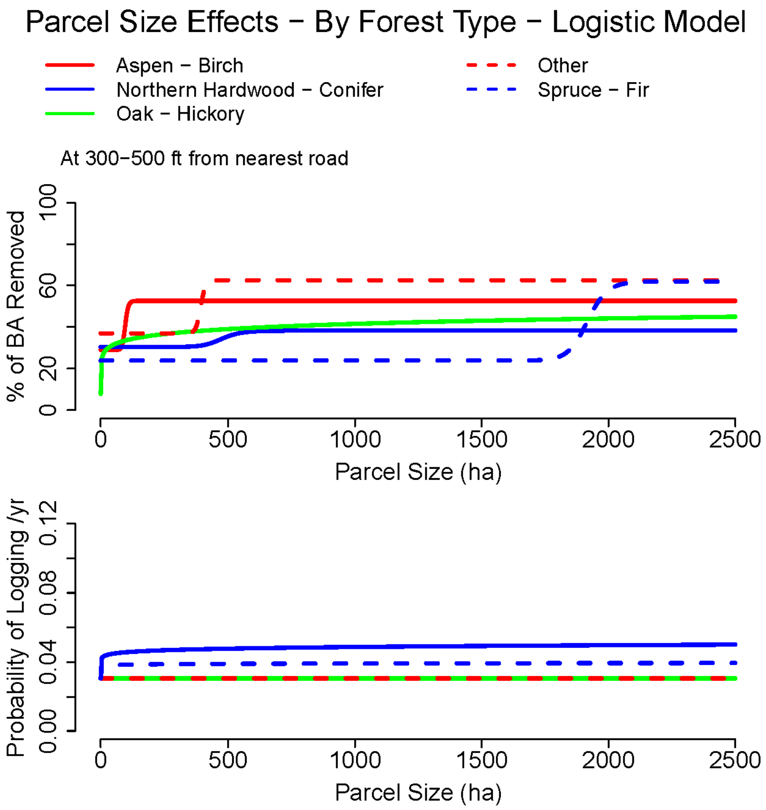


Fig. S7. The distribution of the fraction of plots logged during the most recent FIA census interval as a function of parcel size (n = 831 plots).



We fitted a model that used parcel size as the independent variable to predict both frequency and intensity of harvest, with separate parameters for the 5 main forest types. That model (Fig. S8) confirms the observation that there is a threshold effect of parcel size on intensity of harvests, and that the threshold varies substantially among the 5 forest types. But as was observed in the raw data Fig. S7), there is no real effect of parcel size on the probability that a plot will be logged (Fig. S8). This model, however, was not superior to a null model that lumped all forest types and estimated a single set of parameters regardless of forest type (AIC = 12118 vs. AIC = 12097 for the simpler model).

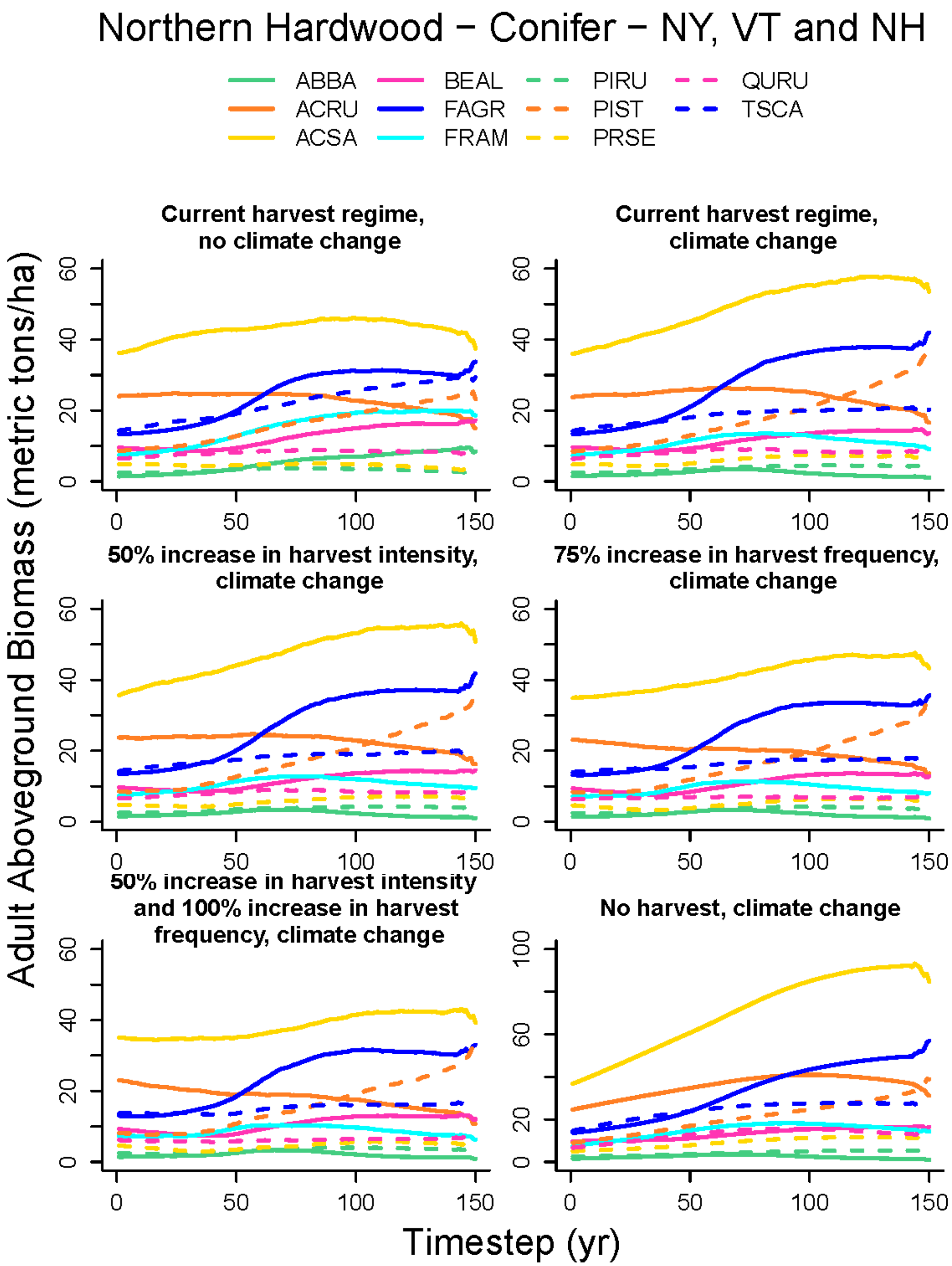
Figure S8. The predicted effects of parcel size on the frequency and intensity of timber harvest, by forest type, in the 4-state study region. The "other" forest type category are primarily bottomland forests.



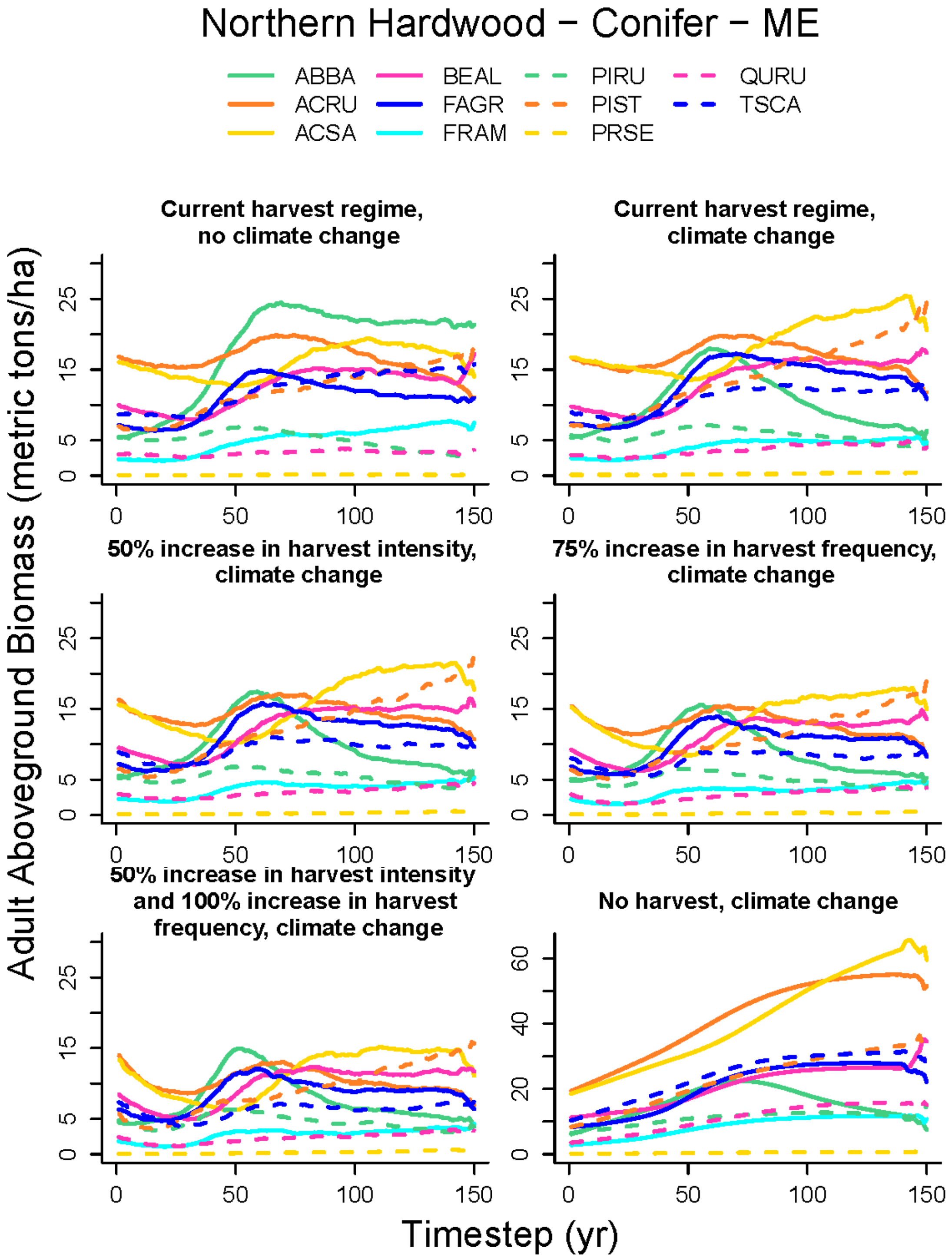
6.3. Appendix S3

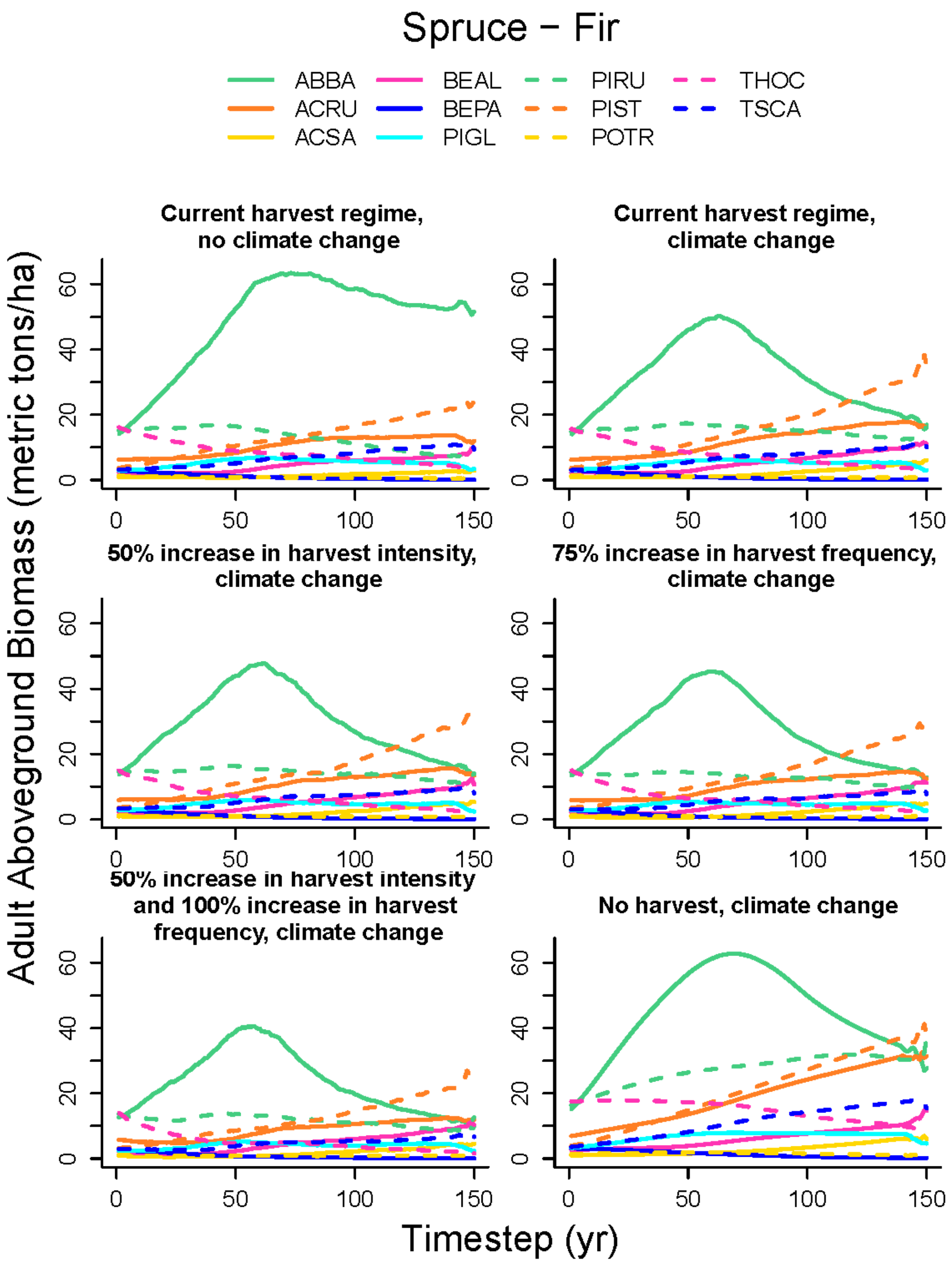
Appendix S3. Predicted changes from 2011 (Timestep 1) to the year 2160 in the biomass of the dominant species of the 6 forest type/regions, under the 6 different harvest scenarios. Species are identified by 4-letter acronyms corresponding to the first two letters of the genus and the first two letters of the specific epithet. Only the most common species in each forest type are plotted.

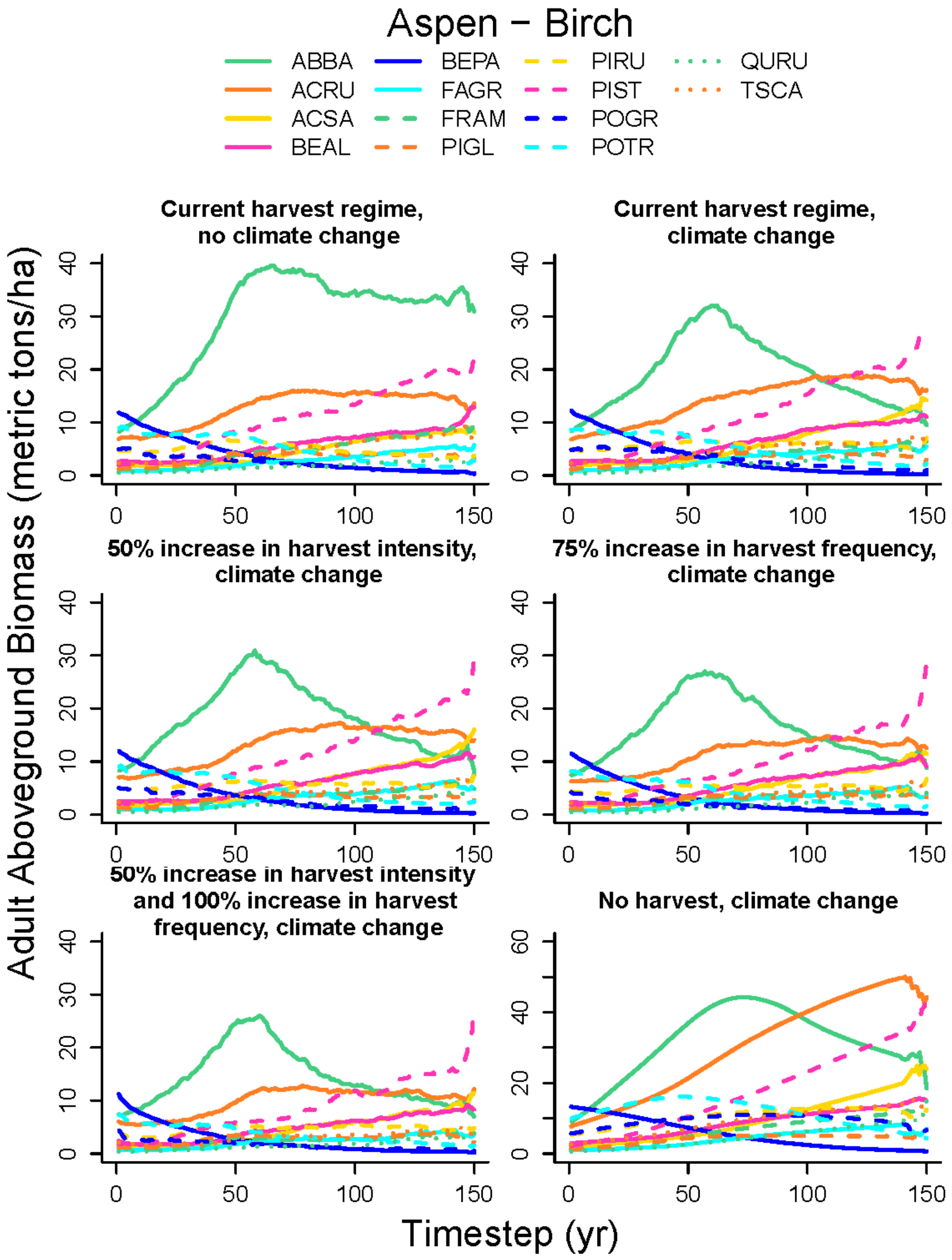
Species	Acronym
Abies balsamea	ABBA
Acer rubrum	ACRU
Acer saccharum	ACSA
Betula alleghaniensis	BEAL
Betula lenta	BELE
Betula papyrifera	BEPA
Carya alba	CAAL
Carya glabra	CAGL
Carya ovata	CAOV
Fagus grandifolia	FAGR
Fraxinus americana	FRAM
Liriodendron tulipifera	LITU
Ostrya virginiana	OSVI
Picea glauca	PIGL
Picea rubens	PIRU
Pinus resinosa	PIRE
Pinus strobus	PIST
Populus balsamifera	POBA
Populus grandidentata	POGR
Populus tremuloides	POTR
Prunus serotina	PRSE
Quercus alba	QUAL
Quercus coccinea	QUCO
Quercus prinus	QUPR
Quercus rubra	QURU
Quercus velutina	QUVE
Thuja occidentalis	THOC
Tilia americana	TIAM
Tsuga canadensis	TSCA
Ulmus americana	ULAM

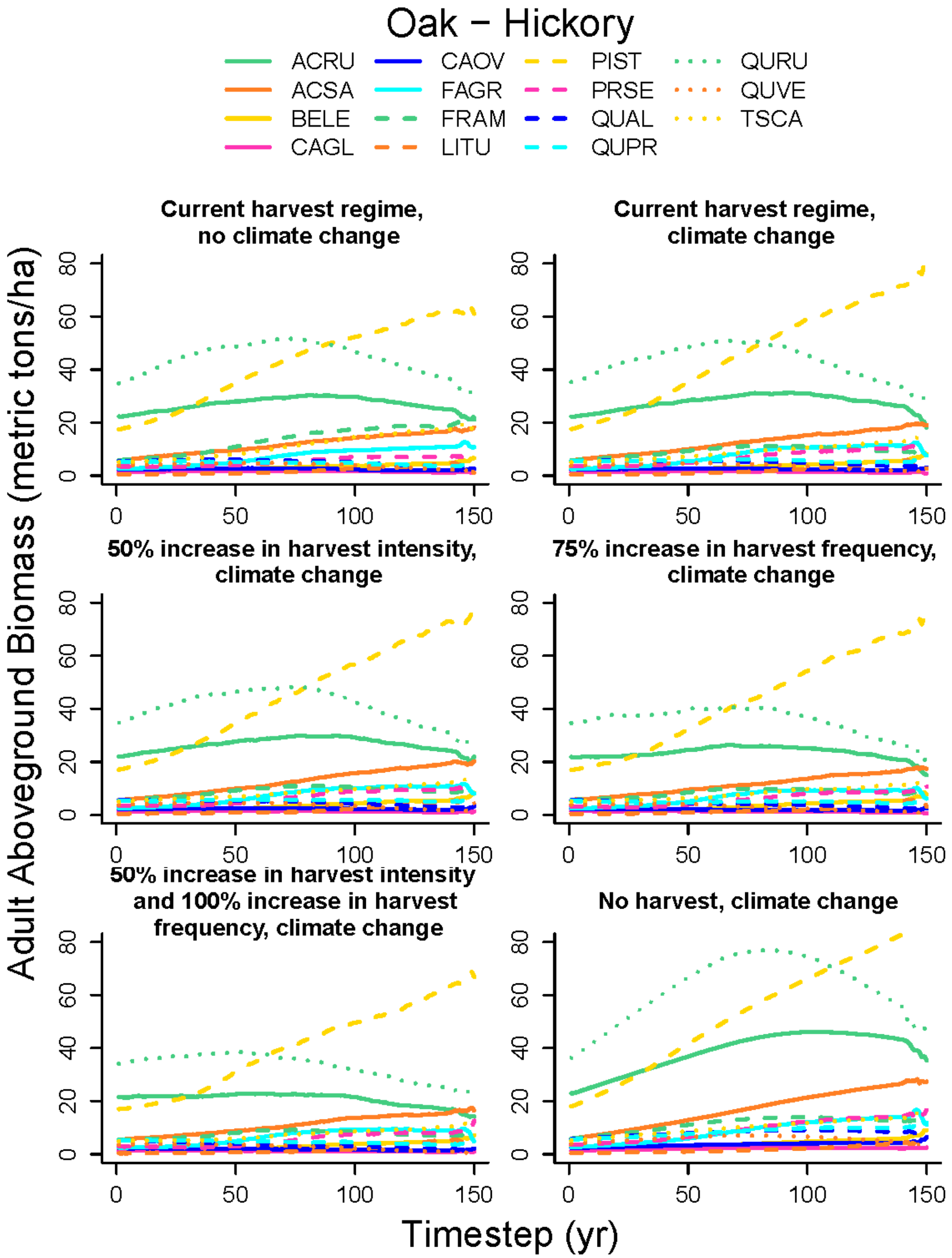


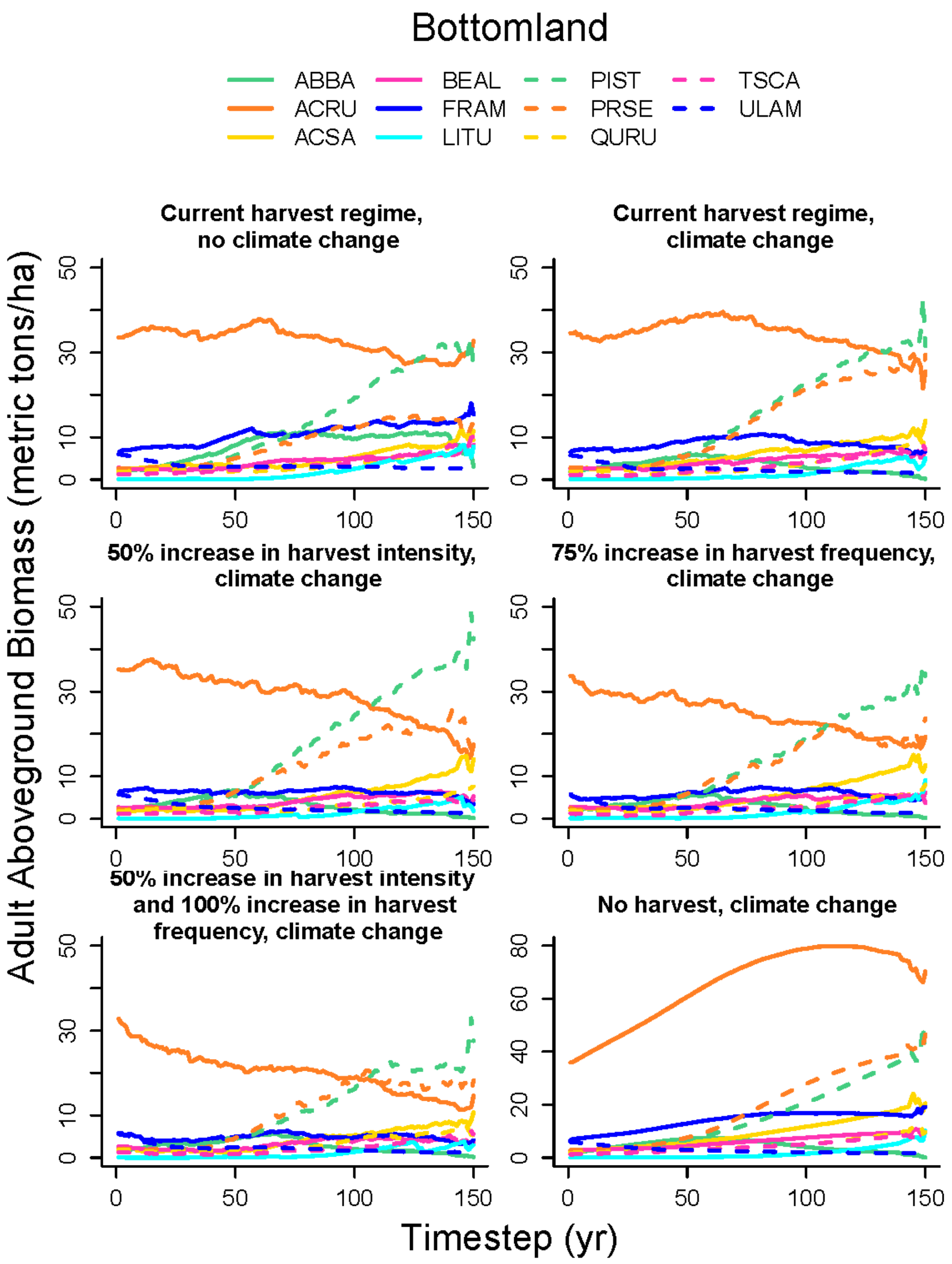
Northern Hardwood − Conifer − NY, VT and NH
ABBA
ACRU
ACSA
BEAL
FAGR
FRAM
PIRU
PIST
PRSE
QURU
TSCA
Current harvest regime, no climate change
Current harvest regime, climate change
50% increase in harvest intensity, climate change
75% increase in harvest frequency, climate change
50% increase in harvest intensity and 100% increase in harvest frequency, climate change
No harvest, climate change
Adult Aboveground Biomass (metric tons/ha)
Timestep (yr)
0
20
40
60
100
0
50
100
150


Northern Hardwood − Conifer − ME
ABBA
ACRU
ACSA
BEAL
FAGR
FRAM
PIRU
PIST
PRSE
QURU
TSCA
Current harvest regime, no climate change
Current harvest regime, climate change
50% increase in harvest intensity, climate change
75% increase in harvest frequency, climate change
50% increase in harvest intensity and 100% increase in harvest frequency, climate change
No harvest, climate change
Adult Aboveground Biomass (metric tons/ha)
Timestep (yr)
0
5
15
25
20
40
60
0
50
100
150


Spruce − Fir
ABBA
ACRU
ACSA
BEAL
BEPA
PIGL
PIRU
PIST
POTR
THOC
TSCA
Current harvest regime, no climate change
Current harvest regime, climate change
50% increase in harvest intensity, climate change
75% increase in harvest frequency, climate change
50% increase in harvest intensity and 100% increase in harvest frequency, climate change
No harvest, climate change
Adult Aboveground Biomass (metric tons/ha)
0
20
40
60
0
50
100
150
Timestep (yr)


Aspen − Birch
ABBA
ACRU
ACSA
BEAL
BEPA
FAGR
FRAM
PIGL
PIRU
PIST
POGR
POTR
QURU
TSCA
Current harvest regime, no climate change
Current harvest regime, climate change
50% increase in harvest intensity, climate change
75% increase in harvest frequency, climate change
50% increase in harvest intensity and 100% increase in harvest frequency, climate change
No harvest, climate change
Adult Aboveground Biomass (metric tons/ha)
Timestep (yr)
0
10
20
30
40
60
50
100
150


Oak − Hickory
ACRU
ACSA
BELE
CAGL
CAOV
FAGR
FRAM
LITU
PIST
PRSE
QUAL
QUPR
QURU
QUVE
TSCA
Current harvest regime, no climate change
Current harvest regime, climate change
50% increase in harvest intensity, climate change
75% increase in harvest frequency, climate change
50% increase in harvest intensity and 100% increase in harvest frequency, climate change
No harvest, climate change
Adult Aboveground Biomass (metric tons/ha)
Timestep (yr)
0
20
40
60
80
0
50
100
150


Bottomland
ABBA
ACRU
ACSA
BEAL
FRAM
LITU
PIST
PRSE
QURU
TSCA
ULAM
Current harvest regime, no climate change
Current harvest regime, climate change
50% increase in harvest intensity, climate change
75% increase in harvest frequency, climate change
50% increase in harvest intensity and 100% increase in harvest frequency, climate change
No harvest, climate change
Adult Aboveground Biomass (metric tons/ha)
Timestep (yr)
0
10
30
50
20
40
60
80
0
50
100
150

6.4. Appendix S4

Appendix S4. Consequence table derived during Multi-Criteria Decision Analysis process for all combinations of forest management alternatives (n=5), years (n=2), and geographies (n=5).

Scenario	Year	State	Biodiveristy (probability of occurrence)												Net sequestration (metric tons CO2e/ha)	Harvested wood products (metric tons HWP/ha)	Bioenergy feedstocks (metric tons bioenergy feedstocks/ha)
			AMRE	BTBW	BTNW	BLBW	CAWA	CSWA	MOWA	OVEN	SCTA	VEER	WOTH	WTSP			
0	2070	ME	0.66	0.57	0.64	0.52	0.28	0.58	0.28	0.82	0.58	0.55	0.40	0.60	314.8	0.0	0.0
0	2070	NE	0.66	0.59	0.60	0.48	0.23	0.51	0.25	0.84	0.67	0.56	0.44	0.53	289.8	0.0	0.0
0	2070	NH	0.68	0.62	0.63	0.53	0.19	0.53	0.25	0.88	0.74	0.59	0.50	0.45	327.7	0.0	0.0
0	2070	NY	0.67	0.56	0.52	0.40	0.17	0.43	0.21	0.84	0.75	0.56	0.47	0.46	251.6	0.0	0.0
0	2070	VT	0.66	0.69	0.63	0.47	0.19	0.39	0.19	0.91	0.84	0.57	0.53	0.44	249.7	0.0	0.0
0	2120	ME	0.69	0.59	0.67	0.54	0.26	0.57	0.29	0.85	0.61	0.54	0.43	0.53	469.2	0.0	0.0
0	2120	NE	0.69	0.61	0.65	0.51	0.22	0.50	0.26	0.88	0.70	0.56	0.46	0.48	473.7	0.0	0.0
0	2120	NH	0.71	0.65	0.70	0.58	0.18	0.52	0.25	0.91	0.76	0.59	0.52	0.41	555.0	0.0	0.0
0	2120	NY	0.71	0.59	0.60	0.45	0.17	0.42	0.22	0.89	0.79	0.57	0.47	0.43	466.4	0.0	0.0
0	2120	VT	0.70	0.72	0.71	0.52	0.19	0.38	0.19	0.94	0.86	0.59	0.55	0.40	454.4	0.0	0.0
1	2070	ME	0.61	0.53	0.51	0.43	0.30	0.60	0.26	0.71	0.52	0.55	0.37	0.66	244.5	12.0	0.8
1	2070	NE	0.62	0.55	0.50	0.41	0.25	0.53	0.23	0.76	0.63	0.55	0.42	0.58	209.3	9.5	0.5
1	2070	NH	0.64	0.59	0.54	0.46	0.21	0.54	0.23	0.82	0.69	0.58	0.48	0.50	226.0	9.1	0.3
1	2070	NY	0.63	0.53	0.45	0.35	0.18	0.44	0.20	0.79	0.72	0.55	0.45	0.50	159.6	6.1	0.2
1	2070	VT	0.62	0.67	0.56	0.42	0.21	0.40	0.18	0.87	0.81	0.56	0.51	0.48	169.3	7.4	0.3
1	2120	ME	0.60	0.52	0.48	0.40	0.30	0.60	0.29	0.70	0.52	0.52	0.39	0.64	213.8	21.7	0.6
1	2120	NE	0.63	0.55	0.51	0.41	0.25	0.52	0.25	0.77	0.64	0.55	0.43	0.56	239.7	17.5	0.5
1	2120	NH	0.66	0.61	0.60	0.51	0.20	0.53	0.24	0.85	0.71	0.59	0.49	0.48	312.7	16.3	0.3
1	2120	NY	0.66	0.56	0.51	0.40	0.18	0.43	0.20	0.83	0.74	0.57	0.45	0.49	260.3	11.9	0.3
1	2120	VT	0.65	0.69	0.61	0.45	0.21	0.39	0.18	0.89	0.83	0.58	0.52	0.46	251.6	14.4	0.9
2	2070	ME	0.60	0.52	0.49	0.41	0.30	0.60	0.26	0.70	0.52	0.55	0.37	0.67	238.4	13.3	0.8
2	2070	NE	0.61	0.54	0.49	0.40	0.25	0.53	0.23	0.75	0.62	0.55	0.42	0.58	202.7	10.6	0.5
2	2070	NH	0.63	0.58	0.54	0.46	0.21	0.54	0.23	0.82	0.69	0.59	0.48	0.50	222.2	9.8	0.2
2	2070	NY	0.63	0.53	0.44	0.35	0.19	0.44	0.20	0.78	0.71	0.55	0.45	0.50	153.2	7.4	0.2
2	2070	VT	0.62	0.67	0.56	0.42	0.21	0.40	0.18	0.87	0.81	0.56	0.51	0.48	156.6	7.8	0.2
2	2120	ME	0.59	0.51	0.46	0.39	0.31	0.61	0.30	0.67	0.51	0.51	0.38	0.66	190.4	23.0	0.5
2	2120	NE	0.62	0.55	0.50	0.40	0.25	0.53	0.25	0.75	0.63	0.54	0.42	0.58	218.4	18.7	0.5
2	2120	NH	0.65	0.60	0.57	0.49	0.21	0.54	0.23	0.84	0.70	0.59	0.49	0.49	281.1	18.8	0.5
2	2120	NY	0.66	0.55	0.51	0.39	0.19	0.43	0.20	0.82	0.74	0.57	0.45	0.50	244.5	12.9	0.4
2	2120	VT	0.65	0.68	0.60	0.45	0.21	0.39	0.18	0.88	0.82	0.58	0.51	0.46	231.8	14.8	0.5
3	2070	ME	0.59	0.51	0.47	0.40	0.31	0.61	0.25	0.67	0.51	0.54	0.36	0.67	234.2	14.3	0.8
3	2070	NE	0.60	0.53	0.46	0.38	0.25	0.53	0.22	0.73	0.61	0.55	0.41	0.60	187.5	12.2	0.6
3	2070	NH	0.62	0.57	0.50	0.44	0.22	0.55	0.22	0.80	0.67	0.58	0.48	0.52	185.3	13.6	0.6
3	2070	NY	0.62	0.52	0.42	0.34	0.19	0.44	0.19	0.77	0.70	0.55	0.44	0.51	127.1	8.9	0.4
3	2070	VT	0.61	0.66	0.52	0.40	0.21	0.40	0.17	0.85	0.80	0.56	0.50	0.50	136.0	10.5	0.6
3	2120	ME	0.58	0.50	0.44	0.37	0.31	0.61	0.28	0.65	0.50	0.51	0.37	0.68	171.7	24.6	0.7
3	2120	NE	0.61	0.54	0.47	0.39	0.26	0.53	0.24	0.73	0.62	0.54	0.41	0.59	185.7	20.8	0.6
3	2120	NH	0.63	0.58	0.54	0.47	0.21	0.54	0.22	0.82	0.68	0.58	0.48	0.51	208.4	23.0	0.6
3	2120	NY	0.65	0.54	0.48	0.38	0.19	0.44	0.20	0.81	0.73	0.57	0.44	0.51	200.3	15.1	0.4
3	2120	VT	0.63	0.68	0.58	0.44	0.21	0.40	0.18	0.88	0.82	0.58	0.51	0.48	194.0	17.2	0.5
4	2070	ME	0.58	0.50	0.44	0.38	0.31	0.61	0.25	0.65	0.50	0.54	0.36	0.69	236.6	15.3	1.0
4	2070	NE	0.59	0.53	0.44	0.37	0.26	0.53	0.22	0.71	0.60	0.55	0.41	0.61	181.1	13.1	0.7
4	2070	NH	0.61	0.56	0.48	0.42	0.22	0.55	0.22	0.79	0.67	0.58	0.47	0.53	165.1	14.2	0.4
4	2070	NY	0.61	0.51	0.41	0.33	0.19	0.45	0.19	0.75	0.69	0.55	0.44	0.52	110.4	9.8	0.4
4	2070	VT	0.60	0.65	0.51	0.39	0.21	0.41	0.17	0.84	0.79	0.56	0.49	0.51	127.3	11.1	0.6
4	2120	ME	0.57	0.50	0.41	0.35	0.32	0.62	0.29	0.61	0.49	0.50	0.36	0.70	155.0	25.2	0.7
4	2120	NE	0.60	0.53	0.45	0.37	0.26	0.54	0.25	0.71	0.61	0.53	0.40	0.61	164.5	22.4	0.7
4	2120	NH	0.62	0.58	0.52	0.45	0.22	0.54	0.22	0.80	0.68	0.58	0.47	0.52	176.5	24.6	0.7
4	2120	NY	0.64	0.54	0.47	0.37	0.20	0.44	0.20	0.79	0.72	0.57	0.44	0.53	175.6	17.6	0.6
4	2120	VT	0.62	0.67	0.55	0.42	0.22	0.40	0.17	0.86	0.81	0.58	0.50	0.49	169.8	20.5	0.8