Supporting Information. Dugan, A.J., J.W. Lichstein, A. Steele, J.M. Metsaranta, S. Bick, and D.Y. Hollinger. 2021. Opportunities for forest sector emissions reductions: a state-level analysis. Ecological Applications.

Appendix S1

Section S1. A systems-based approach to carbon accounting

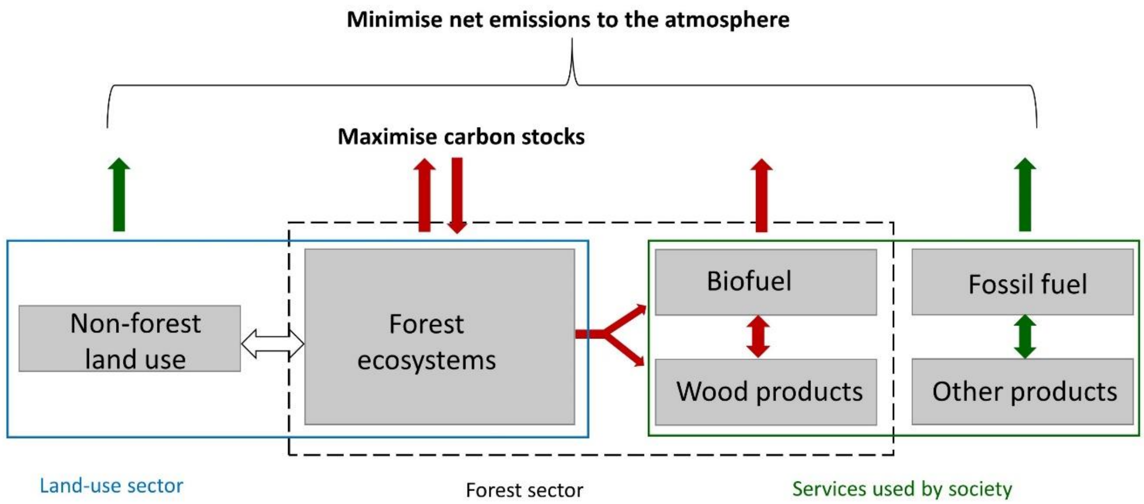

***Figure S1**. A complete accounting of net forest sector carbon emissions to the atmosphere and mitigation potential requires a systems-based approach which considers the relationships between the forest ecosystem, land use change, harvested wood products, and the substitution benefits associated of using bioenergy (biofuel) and wood products in place of fossil fuel energy and other more emission intensive materials (Graphic reproduced from Nabuurs et al. 2007, IPCC Assessment Report 4, Working Group 3, p. 549).*

Section S2. Study area

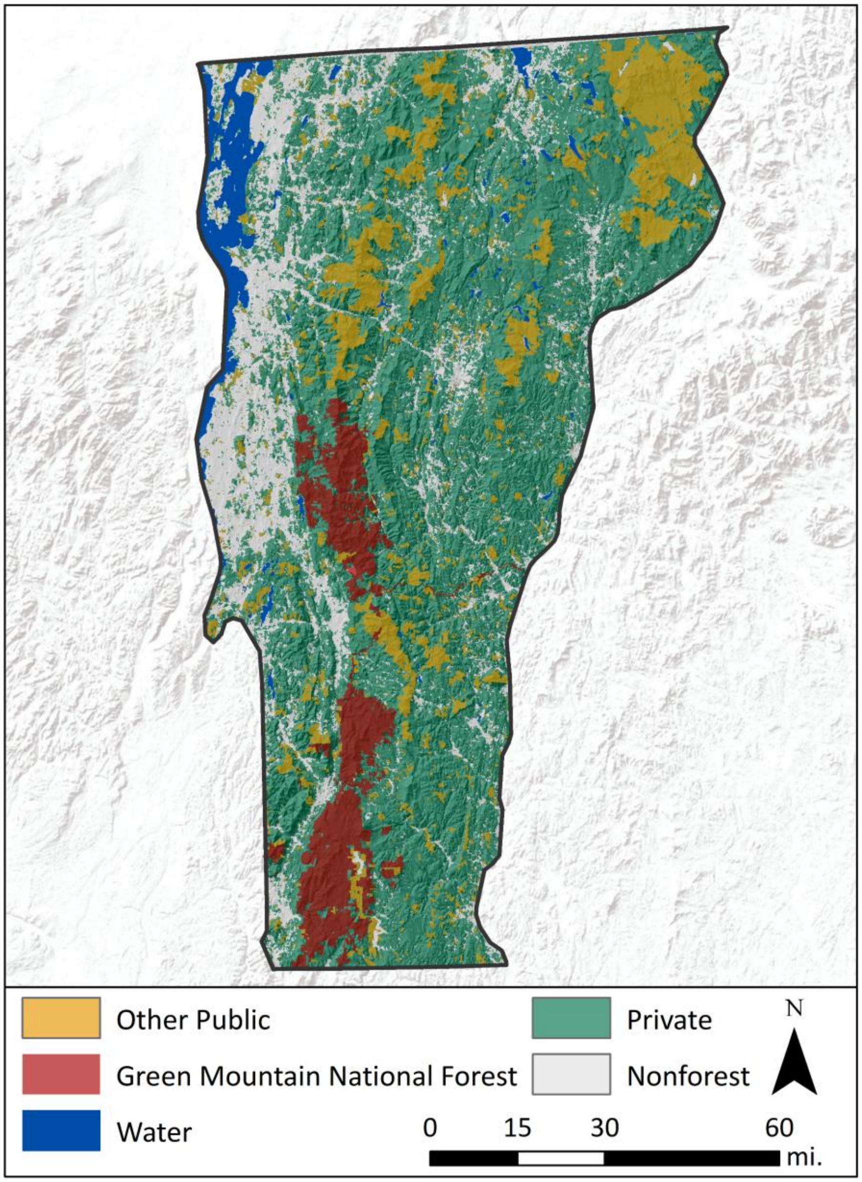

Figure S2. *Land ownership map of Vermont. Ownership data is provided by the USGS Protected Areas Database and the U.S. Forest Service Forest Inventory and Analysis database. Elevation base data are provided by the USGS National Atlas of the USA.*

Section S3. Description of mitigation scenarios:

Scenario 1 – Short rotation, bioenergy: Reduces harvest rotations which increases the amount of wood harvested and average growth rates by shifting more stands to younger age classes. To implement this scenario, we reduced the minimum age for harvesting from 80 years to 70 years for all forest types and increased the merchantable carbon harvested by 10% above baseline levels. All of the additional harvested wood was used for bioenergy.

Scenario 2 – Short rotation, all products: This scenario is identical to the scenario 1, except that all additional harvested wood was used for all products following baseline timber product proportions (Fig. 2, main text).

Scenario 3 – Extend rotation: This is the opposite of the short rotation scenarios in that it extends harvest rotations which results in a reduction in the merchantable carbon harvested and production of wood products. We increased the minimum harvest age from 80 years to 90 years for all forest types and reduced removals by 10% from baseline levels.

Scenario 4 – Reduce deforestation: Reduces the net loss of forest land by eliminating deforestation on public lands and cutting in half the annual area deforested on private lands.

Scenario 5 – No net loss: This scenario is also concerned with reducing the net area of forest loss by offsetting the area deforested with afforestation or reforestation. We maintain the baseline deforestation rates across ownerships, but increase the afforestation rate so that the annual rate of afforestation is equal to the annual rate of deforestation. Thus, the afforestation rate on private lands is increased from 87 ha per year to 745 ha per year, on public lands from 80 ha to 104 ha per year, and on national forest lands from 11 ha to 16 ha per year.

Scenario 6 – Increase residues: Increases the utilization of harvest residues (i.e., tops, stumps, branches) for bioenergy use. We assumed that typical cut-to-length or tree-length logging methods leave all residues behind, whereas whole-tree methods remove entire trees, leaving very little (<5%) residues on the forest floor to decay. Thus, we increased the proportion of harvests that use whole-tree removal methods in place of cut-to-length and tree-length removals. More specifically, for partial harvests and shelterwood harvests, we increased the percentage of whole tree removals from 30% to 60%. For overstory removals/clearcut treatments, we increased whole tree removals from 90% to 100%. All additional residues collected were utilized for bioenergy.

Scenario 7 – Increase productivity: Increases forest productivity through advanced silviculture, genetics, and site management. We do not propose specific silvicultural or land management practices, but rather assume that land managers may apply a range of practices that result in an average increase in productivity. This scenario targets 500 ha per year of forests on young (≤ 12 years old), private forest stands. To simulate this increased productivity, treated stands follow new volume curves generated by increasing the modeled volume curves by 15% for each forest type (Fig. 1b, main text) for the duration of the simulation period.

Scenario 8 – Insects: The extent and severity of insect outbreaks is projected to increase throughout the northeast (Janowiak *et al.* 2018). This scenario evaluates the potential effects on carbon of increased insect outbreaks followed by salvage harvesting of affected areas. We randomly affected an additional 500 ha a year with moderate to severe insect outbreaks, which result in 30% stand mortality. A year later, we simulated a salvage harvest of affected stands. Salvaged wood was used for all products following baseline timber product proportions.

Scenario 9 – Portfolio: This scenario combines the following scenarios: extend rotation (scenario 3), increase residues (scenario 6), and increase productivity (scenario 7). This represents an array of potential forest management activities that could be performed simultaneously. These activities interact with one another, thus their impacts are not additive and must be modeled together.

Scenario 10 – Increase LLP: The proportion of roundwood used for long-lived wood products (sawlogs) are increased by 10% per year, while paper products (pulpwood) are decreased by 10% per year from average levels. In the baseline scenario, 66% of harvested roundwood is used for sawlogs and 19.5% is used for pulpwood (Fig. 2, main text). In this scenario 76% of roundwood goes to sawlogs and 9.5% is used for pulpwood. Total removals from the forest are not changed, only the product mix is altered as simulated by the harvested wood product model.

Scenario 11 – Increase bioenergy: The proportion of harvested wood used for bioenergy production is increased by 10% at the cost of pulp and paper products (Fig. 2, main text). Only the product mix is altered, but the total removals from the forest are not changed.

Section S4. Ecosystem Carbon Emissions

Figure S3 below shows carbon trends across each land use class making up the ecosystem. This includes emissions from forest remaining forest, nonforest (e.g., cropland) remaining nonforest, and transfers between forest and nonforest land. The UNFCCC distinguishes emissions and removals on lands subject to continuous land-use (> 20 years), such as forest remaining forest, from those that recently experienced a conversion (< 20 years). Consequently, in the CBM-CFS3, if a stand is deforested and converted to agriculture, it is tracked as "forest converted to cropland" for 20 years before converting to a cropland (Kurz *et al.* 2009).

When viewing the forest ecosystem in isolation of the other forest sector components, as in Figure S3, any harvest removals are considered to be instantaneously oxidized, and therefore are immediate emissions to the atmosphere. This is the approach applied by the IPCC, whereby harvested wood carbon is removed from the ecosystem (oxidized), but then taken up again by the HWP sector as a sink. Thus, in Figure S3 below, years of increased harvest removals, such as in 1996, correspond to an increase in emissions from the forest (FL-FL). This figure differs from Figure 5 in the main text, which shows harvest removals and associated end-of-life emissions tracked exclusively in the HWP sector, rather than as emissions from the ecosystem. This is done to avoid double counting of emissions associated with harvested wood, and the account for emissions where and when they occur.

When looking at the ecosystem alone, results indicate that if all net forest loss occurring between 1995 and 2015 had not occurred, cumulative sequestration by 2015 would have been approximately 11% higher. If forest loss did not occur in 2015 alone, sequestration by the forest would have been approximately 18% higher in that year.

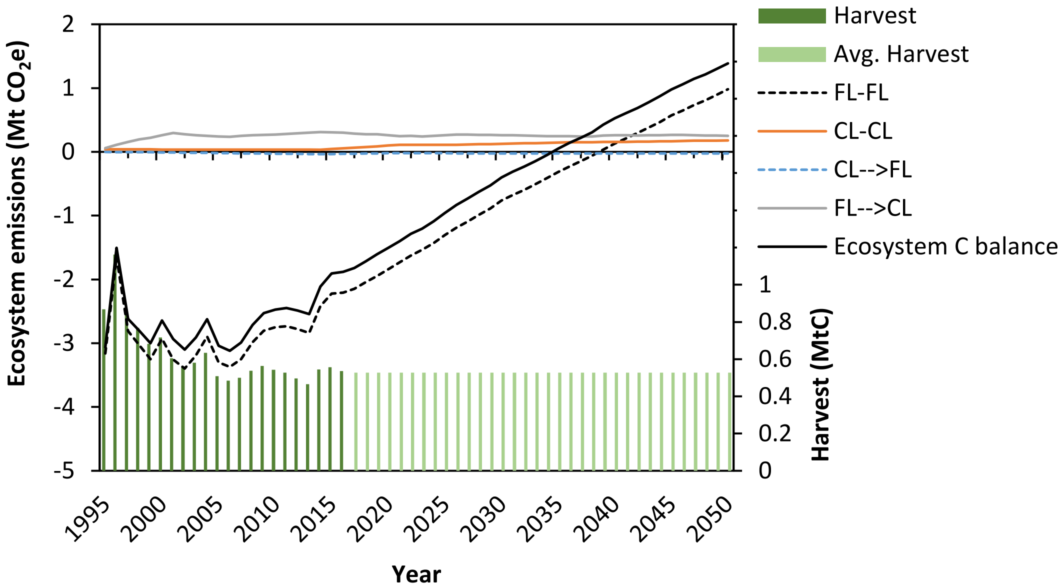

Figure S3. *Time series of the annual GHG emissions (left axis) from each land class within the forest ecosystem including: forest land remaining forest (FLFL), cropland (nonforest) land remaining other (CL-CL), forest converted to crop (FL → CL), crop converted to forest (CL → FL), and all land classes combined (Net CO2e) from 1995 to 2050 for Vermont. This assumes carbon leaving the forest is instantaneously oxidized.*

Section S5. Product sector Carbon Emissions & Storage

As noted in Supplementary Material section 1.4, harvest removals from the forest ecosystem are tracked in the HWP sector using the CBM-FHWP model. In this analysis of HWP carbon stocks and emissions (Figs. S4, S5), we assumed that the product sector started accumulating stocks in 1940 as part of a spin-up simulation. Thus, stocks and emissions contain inherited stocks from products in-use as well as products that have been retired to landfills prior to 1990.

Carbon storage in HWP, including retired products in landfills, has increased and is projected to continue to increase through 2050 (Fig. S4). At the beginning of the study period in 1995, about half of the carbon stored in HWP was in sawlogs (13.0 MtC). Forty-two percent of carbon was stored in landfills (11.0 MtC) and pulpwood and veneer logs each accounted for less than one percent of total storage. As more and more sawlog products were retired, the relative proportion of storage in landfills began to grow. By 2020 the amount of carbon stored in sawlogs and retired products is projected to be about equal. By 2050, carbon storage in landfills is projected to account for 51 percent of HWP carbon storage. Although pulpwood and fuelwood account for a large portion of products (Fig. 2, main text), they are short-lived products or immediately oxidized (bioenergy), thus do not account for long-term carbon storage.

Although total carbon storage in the product sector increased over the historical period, annual emissions from product use and retirement have declined from a peak of 3.4 Mt CO_2e in 1996 (Fig. S4). This decline in emissions tracks with a decline in harvest rates since the 1990s (Fig. 2, main text). In the mid-1990s, annual harvest rates reached over 1 million metric tonnes of carbon. The rate declined to a little over half a million metric tonnes by 2016 (Vermont Department of Forests Parks and Recreation 2019). The decline in emissions due to lower harvest rates offset an increase in emissions associated with the shift in wood product proportions from more sawlogs to more pulpwood (Fig. 2). If average harvest rates and product proportions over the past decade continue, HWP emissions are projected to start to increase slightly starting in the mid-2020s (Fig. S5). Also, the proportion of annual emissions coming from sawlogs is projected to increase as more and more sawlog products are retired overtime.

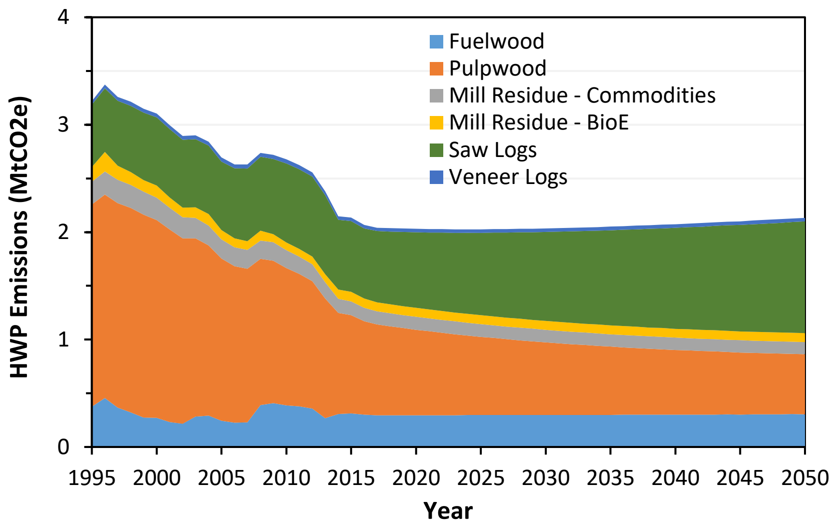

Figure S4*. Annual emissions by product type from harvested wood products in Vermont. Values beyond approximately 2012 are projected*.

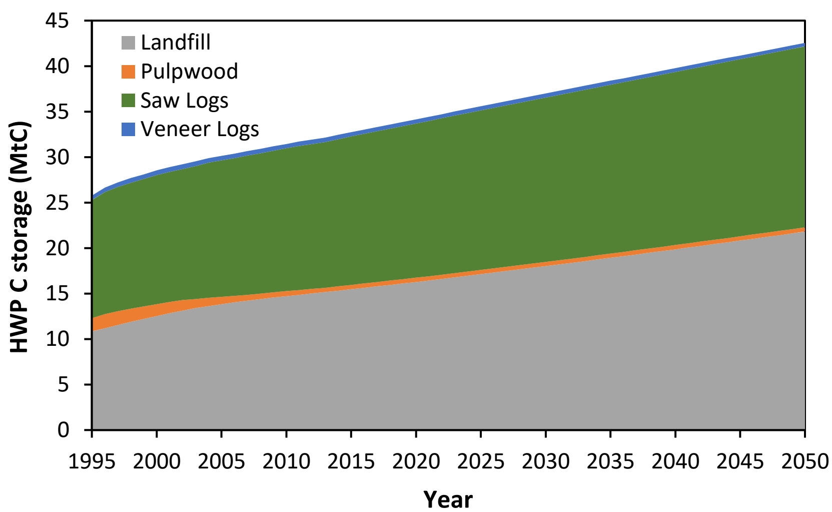

Figure S5. *Carbon storage in harvested wood products in–use and retired products in landfills for the state of Vermont. Values beyond approximately 2016 are projected.*

Section S6. Stand-age Time Series

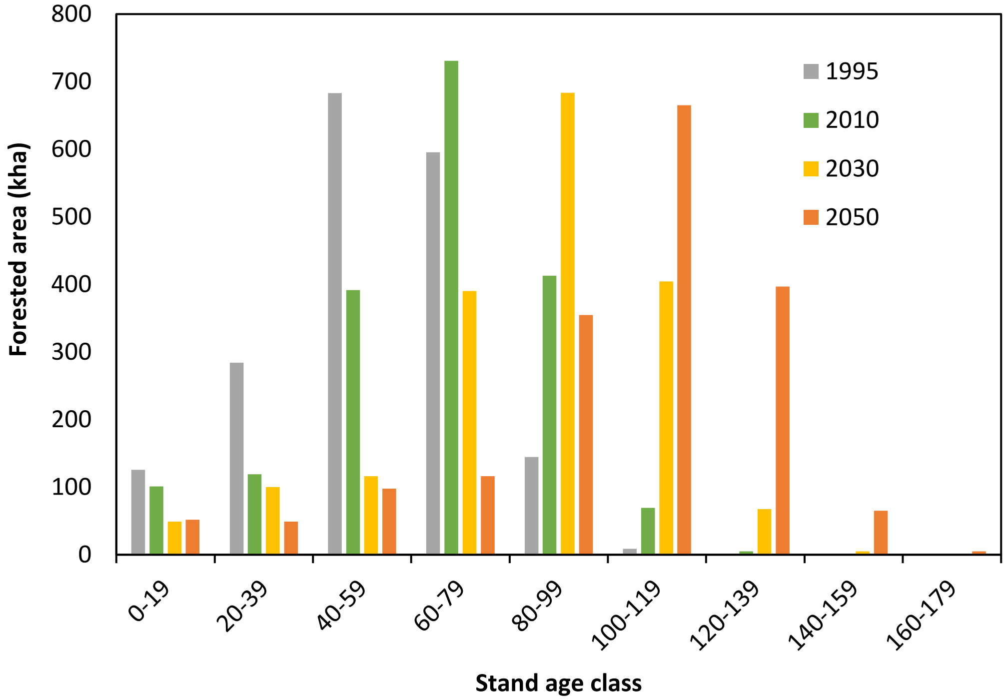

Figure S6. *Modeled age-structure time series under the baseline scenario from 1995 to 2050 for forestland, Vermont. Derived from CBM-CFS3.*

Section S7. Uncertainty Analysis

Overview of uncertainty analysis and error correlation assumptions

We estimated uncertainty in mitigation (scenario emissions minus baseline emissions) for each component of the forest sector: the forest ecosystem, the harvested wood products (HWP) sector, energy displacement, and product displacement. Uncertainty analysis for each these four components is described below. We used a simple Monte Carlo approach to combine the four component uncertainties to estimate the distribution of cumulative (year 2050) total mitigation for each scenario relative to baseline. Specifically, we drew a random sample from the estimated distribution of each cumulative mitigation component, summed the four values to yield one sample of total mitigation, and repeated this process 10,000 times to estimate the probability distribution of total mitigation (black symbols and error bars in Fig. 6).

For all four components, we assumed that the parameter values affecting emissions were unknown, but that the same true (unknown) parameter values applied across time and space. This implies an error correlation across years and scenarios of $r = 1$. For example, if a litter decay rate in the forest ecosystem model (CBM-CFS3) is increased relative to its default value in the baseline scenario, then we assume that the rate is identically increased in all years and all mitigation scenarios. Similarly, when estimating emissions effects due to energy or product displacement, if a displacement factor is increased in the baseline scenario, then the displacement factor is assumed to identically increased in all years and all mitigation scenarios. This $r = 1$ assumption is appropriate for our study, because our goal is to estimate the emissions consequences of different potential mitigation activities, while controlling for the many sources of variation that are unknown or difficult to quantify. For example, a land manager could increase rotation lengths with the goal of increasing ecosystem C stocks, but this would not guarantee increased C stocks relative to the baseline scenario due to the stochastic nature of disturbances. Accounting for this type of variation among scenarios (which implies an error correlation across scenarios of $r < 1$) would be important when forecasting potential outcomes for specific parcels of land. However, this variation is orthogonal to our goal of evaluating scenario effects per se. Therefore, we assume $r = 1$ in the main results presented in Fig. 6 and Fig. S7.

To explore the implications of the $r = 1$ error correlation assumption, and to illustrate why this assumption is appropriate for our analysis goals, we consider an alternative error correlation assumption ($r = 0$) in Appendix 1.9. We now describe the uncertainty analysis approach for each of the four mitigation components.

Forest ecosystem

We developed an analytical framework to quantify uncertainty in the CBM-CFS3 forest ecosystem model based on uncertainty estimates for Canada's National Forest Carbon Monitoring, Accounting, and Reporting System (NFCMARS, Kurz and Apps 2005, Stinson *et al.* 2011). In brief, Monte Carlo simulation is used to propagate errors in input data (forest inventory, growth and yield curves, and disturbances), model parameters (turnover rates of soil and dead organic matter (DOM) C and biomass turnover), and model algorithms (soil and DOM C initialization and selection of disturbed stands) to estimates of any C stock or flux indicators that can be derived from the model output. Further details on these analyses are provided in Metsaranta *et al.* (2017). To estimate CBM-CFS3 uncertainties for the state of Vermont, we analyzed available Monte Carlo simulation output for floristically similar nearby areas in Canada. We assume that these uncertainties, after appropriate area-based scaling, would be similar for our Vermont study area. Therefore, we used the output of these analyses to estimate the standard deviation (SD) of forest ecosystem emissions and the SD of harvested wood that flows out of the forest ecosystem and into other mitigation components (HWP sector, product displacement, and energy displacement). The estimated SD of forest ecosystem emissions is:

(Equation S1) $$SD(F_t) = (9.19325 - 0.03435 \times F_t) \times Area_{CF}$$

where F_t is forest ecosystem emissions in year t (negative values indicate a net C sink), and $Area_{CF}$ is a correction factor equal to the ratio of the area where Equation 1 is applied in our study (Vermont forest area: 1.8 Mha) to the area where it was derived (floristically similar nearby area in Canada; 37.9 Mha); i.e., $Area_{CF} = 1.8/37.9$.

The estimated SD of harvested wood products is:

(Equation S2) $$SD(HW_t) = 0.0336 \times HW_t$$

where HW_t is the flux of harvested wood out of the forest ecosystem in year t. Equation S2 describes uncertainty in the flux of harvested wood flowing to other mitigation components (HWP and displacement). The sub-sections below describe our uncertainty analysis for these mitigation components, which incorporates Equation S2.

We now describe our uncertainty analysis for forest ecosystem emissions (F). Equation S1 provides an estimate of $SD(F_t)$ for each year t in the evaluation period (2020-2050). Given these SD estimates, and given the assumed $r = 1$ correlation in errors across years, we can estimate the cumulative variance for a given scenario over the years 2020-2050 based on the fact that the variance of the sum of n correlated variables is the sum of their covariances:

(Equation S3) $$\mathrm{Var}\left(\sum_i^n X_i\right) = \sum_i^n \sum_j^n \mathrm{Cov}(X_i, X_j).$$

To estimate the cumulative variance in forest ecosystem emissions (F) for a given scenario from 2020 through year t (up to year 2050), this expression becomes:

(Equation S4) $$\mathrm{Var}\left(\sum_{i=2020}^t F_i\right) = \sum_{i=2020}^t \sum_j^t \mathrm{Cov}(F_i, F_j),$$

where $\mathrm{Cov}(F_i, F_i) = \mathrm{Var}(F_i)$; $\mathrm{Cov}\left(F_i, F_j\right) = \mathrm{Var}(F_i) + \mathrm{Var}(F_i) + 2r\mathrm{SD}(F_i)\mathrm{SD}(F_j)$ for all $i \neq j$; $\mathrm{Var}(F_i) = [\mathrm{SD}(F_i)]^2$; and $\mathrm{SD}(F_i)$ is given by Equation S1. As noted above, we assumed $r = 1$ for the results presented in Fig. 6 and Fig. S7a, and we consider $r = 0$ in Appendix 1.9.

We then quantified uncertainty in forest ecosystem mitigation in year t for each scenario as the variance of the difference in emissions between each scenario and baseline using the formula for the variance of the difference of correlated variables:

(Equation S5) $\mathrm{Var}(X-Y)=\mathrm{Var}(X)+\mathrm{Var}(Y)-2\mathrm{Cov}(X,Y)=\mathrm{Var}(X)+\mathrm{Var}(Y)-2r\mathrm{SD}(X)\mathrm{SD}(Y)$

where *X* and *Y*, respectively, are cumulative scenario and baseline emissions in the forest ecosystem in year t; and $r=1$ as before. We assumed normally distributed errors in cumulative mitigation, with the SD of this distribution given by the square root of Equation S5. Thus, the 95% confidence intervals shown in Fig. S7a have width ±1.96SD_t for each year t, and we drew samples from a normal distribution with the year 2050 SD to account for forest ecosystem mitigation uncertainty when estimating total uncertainty in Fig. 6.

Harvested wood products sector

We evaluated how uncertainty in harvested wood product (HWP) lifetimes (half-lives) translated to uncertainty in emissions from the HWP sector. To isolate the effects of mitigation activities (and consistent with the *r* = 1 error correlation assumption discussed above), we assumed that all years and scenarios shared the same (unknown) product half-lives. Thus, in our analysis, the only differences among scenarios in the HWP sector are (1) the amount of harvested wood entering the HWP sector and (2) the relative proportions of harvested material used to produce each commodity. A third potential HWP sector uncertainty is post-use treatment of wood—whether wood is landfilled, recycled, and/or burned for energy. Thus, for simplicity, we assumed that all HWP carbon is emitted to the atmosphere when a product is retired.

The amount of wood harvested and entering the HWP sector is tracked in the forest ecosystem through CBM-CFS3 and its associated uncertainty is described Equation S2 above. The fate of the harvested wood is then tracked in the CBMF-HWP modeling framework described in Methods. In CBMF-HWP, the only difference among commodities (in terms of C emissions) is the product retention times; i.e., how long C remains stored in the product. Retention times are determined by the product half-lives applied for each commodity. Therefore, to quantify the uncertainty HWP sector mitigation, we assessed the sensitivity of HWP sector mitigation to uncertainty in product half-lives.

Based on a literature review (Dymond 2012, Skog 2008, IPCC 2006), we derived three plausible product half-life scenarios: low, medium, and high half-lives for the product classes in Vermont (sawlogs, veneer logs, pulp and paper) (Figure 2 in main text). For instance, the IPCC (2006) reports a default half-life of 2 years for pulp and paper, while Dymond 2012 and Skog 2008 both report 2.5 years. Therefore, we applied 2 years to the low scenario, 2.5 years to the medium and assumed 3 years at the high end. The medium half-lives (Table S1) were used to generate the HWP emissions reported in our main results (e.g., main text figures). These HWP emissions are the most likely emissions (or mode) of the probability distribution described below.

We then used the CBMF-HWP modeling framework described in Methods to simulate the three separate cases (low, medium, and high half-lives) for HWP sector emissions for each scenario and baseline. For each scenario, we assumed a triangular error distribution for HWP mitigation (scenario emissions minus baseline emissions), with the mode, minimum, and maximum (curve and error bars in Fig. S7b) based on the three sets of CBMF-HWP simulations (Table S1). To account for HWP sector mitigation uncertainty in Fig. 6 (main text), we drew random samples from this triangular distribution, and we multiplied each of these values by a random sample from a normal distribution with mean = 1 and SD given by Equation S2 to account for uncertainty in the flux of harvested wood flowing into the HWP sector. The product of these two random draws accounts for uncertainty in both the quantity and residence time of harvested wood products.

Table S1. Product half-life values for wood commodities in Vermont used to evaluate uncertainty in mitigation from the harvested wood products sector.

	Product Half-lives (years)		
	Low	**Medium**	**High**
Saw logs	30[a, c]	53[a, b]	90[a]
Veneer logs	27	38[a,b]	50[a, b]
Pulp & paper	2[c]	2.5[a,b]	3

[a] Source: Dymond 2012, Table 8
[b] Source: Skog 2008, Table 8
[c] Source: IPCC 2006, Table 12.2

Substitution effects

To assess the uncertainty associated with the substitution effects, we evaluated mitigation outcomes based on a range of plausible energy and product displacement factor (DF) values using a similar approach as described above for the HWP sector. Based on a literature review we estimated low, most likely, and high values for energy and product displacement factors (Table S2).

Product DFs can vary widely based on the many non-wood materials for which wood can substitute, variability in production technology, and the life-cycle stages considered. A meta-analysis by Sathre & O'Connor (2010) calculated product DFs ranging from -2.3 to as high as 15.0 t C/t C, with an average value of 2.1. A more recent and larger meta-analysis by Leskinen *et al.* (2018) found a smaller range of product DFs from -0.7 to 5.1 t C/t C, with an average value of 1.2 t C/t C considering all product categories and post-use energy recovery and an average of 0.8 t C/t C of all reported substitution factors for the production stage (omitting post-use energy recovery).

For our uncertainty analysis, we evaluated a conservative range of product DFs based on the average values from Leskinen *et al. (*2018), and variability in assumptions of end-of-life uses and product categories included. The Leskinen *et al.* meta-analysis reported an average DF of 1.2 t C/t C, which assumes an average mix of product categories including higher displacement structural and non-structural construction materials and textiles, and lower displacement categories (furniture, packaging, chemicals), and accounts for energy recovery at the end-of life stage (i.e., energy displacement from burning retired products). Although Leskinen *et al.* (2018) reports higher DFs when considering only structural materials, we sought a more conservative range of values, thus we used this DF value of 1.2 t C/t C as our high estimate for product DF. Leskinen *et al.* (2018) reported that the end-of-life-stage energy displacement component accounts of 0.4 t C/t C. Thus, we assumed a medium product DF of 0.8 t C/t C (1.2 minus 0.4), which assumes the average mix of products and no end-of life energy recovery. Leskinen *et al.* (2018) also reported a lower DF of 1.0 t C/t C when considering only a mix of low displacement products (i.e. furniture, packaging, chemicals). Therefore, we applied a low product DF of 0.6 t C/t C, which assumes the low displacement products only and omits end-of-life energy recovery, (i.e., 1.0 minus 0.4).

Like product DFs, energy DFs can also vary widely depending on region-specific factors such as energy demand, energy source being displaced, efficiency of bioenergy facilities, road networks and accessibility to forests, and consumption patterns (Smyth *et al*. 2017, Köhl *et al.* 2020). We used an average bioenergy DF of 0.89 t C displaced per t C of bioenergy (Table S2), estimated at the national-level for Canada (Smyth *et al.*, 2017), as there is no similar estimate available for the U.S. Smyth *et al.* 2017 assumed that bioenergy would substitute for the most emission-intensive energy source first and then proceed to successively less emission intensive sources. This value also assumed a constrained supply, meaning if bioenergy produced exceeds local demand, the excess would be converted to electricity and transferred to the grid for later use. Smyth *et al.* 2017 reported an energy DF of 0.47 t C/t C for a constant supply. Soimakallio *et al.* 2016 indicated that DFs for bioenergy are likely to range from 0.5 t C/ t C when bioenergy substitutes for less emission intensive natural gas power generation, to as high as 1.0 t C/ t C when substituting for high emitting coal-fired power and heat systems. Thus, based on this literature review, we evaluated low (0.5), medium (0.89) and high (1.0) energy DFs for this uncertainty analysis.

We considered three separate cases (low, medium, and high DFs) for energy and product displacement emissions for each scenario. As with HWP sector mitigation uncertainty, we assumed a triangular error distribution for displacement mitigation (scenario minus baseline), with the mode, minimum, and maximum (curve and error bars in Fig. S7c-d) given by the three cases (Table S2). We accounted for uncertainty in energy and product displacement emissions in Fig. 6 as explained above for HWP sector emissions; i.e., we sampled from the triangular distributions of energy and product displacement mitigation, and we multiplied these values by a random sample from a normal distribution with mean = 1 and SD given by Equation S2 to account for uncertainty in the flux of harvested wood available for displacement.

Table S2. The range of product and energy displacement factors applied to evaluate uncertainty in the substitution component.

	Displacement Factors (t C/ t C)		
	Low	**Medium**	**High**
Energy	0.5[a, c]	0.89[b]	1.0[a]
Product	0.6[c]	0.8[c]	1.2[c]

[a] Source: Soimakallio *et al.* 2016
[b] Source: Smyth *et al.* 2017
[c] Source: Leskinen *et al.* 2018

Section S8. Cumulative Mitigation by Component with Uncertainty

In this section, we present cumulative mitigation (with uncertainties) for separate forest sector components for each scenario. For each component (forest ecosystem, harvested wood products, energy displacement, and product displacement), cumulative mitigation is quantified as scenario emissions minus baseline emissions, with negative values denoting reduced GHG emissions relative to the baseline (BAU) scenario. Uncertainty analysis methods are described in Section S7. Here, we present forest ecosystem mitigation uncertainty based on an assumed error correlation of $r = 1$ across years and scenarios. As explained in Section S7, this assumption is most relevant for quantifying the effects of mitigation strategies per se, and is therefore the preferred assumption for the goals of our analysis. An alternative forest ecosystem uncertainty analysis, based on an alternative error correlation assumption, is presented in Section S9.

Given the assumption of correlated errors ($r = 1$), there is very little uncertainty in forest ecosystem mitigation (error bars in Fig. S7a). The negligible uncertainty in forest ecosystem mitigation results from a combination of two factors. Firstly, a generic property of uncertainty in differences (in this case differences in emissions between each mitigation scenario and the baseline scenario) is that the uncertainty diminishes as covariance between the two uncertainty quantities increases (see Equation S5). The $r = 1$ assumption leads to high covariance between each scenario and baseline, and thus smaller uncertainty in the difference than would occur for $r < 1$ (see analysis of alternative assumptions in Section S9). Secondly, a specific property of uncertainty in CBM-CFS3 is that uncertainty in forest ecosystem emissions is insensitive to the emissions estimate. In fact, the standard deviation of CBM-CFS3 emissions decreases (but only slightly) with an increase in predicted emissions (see Equation S1 in Section S7). This insensitivity, combined with the $r = 1$ assumption, ensures that the variance of the difference in forest ecosystem emissions between each scenario and baseline is approximately 0. This result does not imply low uncertainty in CBM-CFS3 output (Metsaranta *et al.*, 2011, 2017). Rather this result shows that if a single set of CBM-CFS3 parameters is applied to different scenarios, then there is little uncertainty in forest ecosystem emissions differences among scenarios, even if the estimated emissions difference is large (Fig. S7a).

In contrast to the forest ecosystem (Fig. S7a), the $r = 1$ assumption does not diminish uncertainty in other mitigation components (harvested wood products, energy displacement, and product displacement) to negligible levels (Fig. S7b-d). Particularly for energy and product displacement (Fig. S7c-d), cumulative uncertainty is large by the year 2050. Although the first factor described in the preceding paragraph (effects of $r = 1$ assumption on the variance of differences) applies to all mitigation components, the second factor (decoupling of emissions uncertainty from emissions estimate in CBM-CFS3) does not. Therefore, although assuming $r = 1$ yields smaller error bars in Fig. S7b-d than would result from assuming $r < 1$, the $r = 1$

assumption still allows for considerable uncertainty in mitigation estimates for the wood products sector and displacement.

The results of the HWP uncertainty analysis (Fig. S7b) indicate that the sensitivity of mitigation effect to changes in half-lives is much smaller than the displacement uncertainty (Fig S7c-d) but somewhat larger than the forest ecosystem uncertainty (Fig. S7a). The range of HWP mitigation effect varies among scenarios, whereby scenarios that result in the greatest differences from the baseline in terms of emissions (higher or lower), generally have larger HWP uncertainties. The LLP scenario which had the highest mitigation potential also had the largest uncertainty. On the other hand, the mitigation effect of scenarios that only entail an increase in the amount of wood used for bioenergy, such as the *residues* scenario or *short rotation – bioE* scenario, are mostly unaffected by a change in product half-lives. This was expected given that we assumed bioenergy was always burned immediately (half-life of zero).

The energy and product displacement factors (DFs) are the largest source of uncertainty in estimating the mitigation potential of each scenario. Lower DFs lead to lower estimated displacement and, therefore, lower emissions. The opposite is true when applying higher DFs. These effects of DFs on emissions do not affect all scenarios equally. In terms of mitigation (scenario emissions minus baseline emissions), uncertainty in DFs leads to the largest mitigation uncertainty for scenarios that differ strongly from baseline in terms of displacement. For scenarios with more energy or product displacement than baseline, lower DFs lead to reduced mitigation, and higher DFs lead to increased mitigation. Scenarios in this category have a bold mitigation value in the right column of Table S3 (highest mitigation with high DFs). In contrast, for scenarios with less energy or product displacement than baseline, lower DFs lead to increased mitigation (relative to baseline), and lower DFs lead to reduced mitigation. Scenarios in this category have a bold mitigation value in the left column of Table S3 (highest mitigation with low DFs). Due to the unequal effects of DFs on different scenarios, DF uncertainty leads to uncertainty when ranking scenarios by mitigation potential. For example, with medium DFs, the *extend rotation* scenario has the sixth highest mitigation potential; whereas with low DFs, the *extend rotation* scenario has the third highest mitigation potential (Table S3). When averaging across the three DF cases (low, medium, and high DFs), the *increase LLP* scenario has the greatest estimated mitigation potential, followed by the *portfolio* scenario Table S3).

(a) Forest Ecosystem

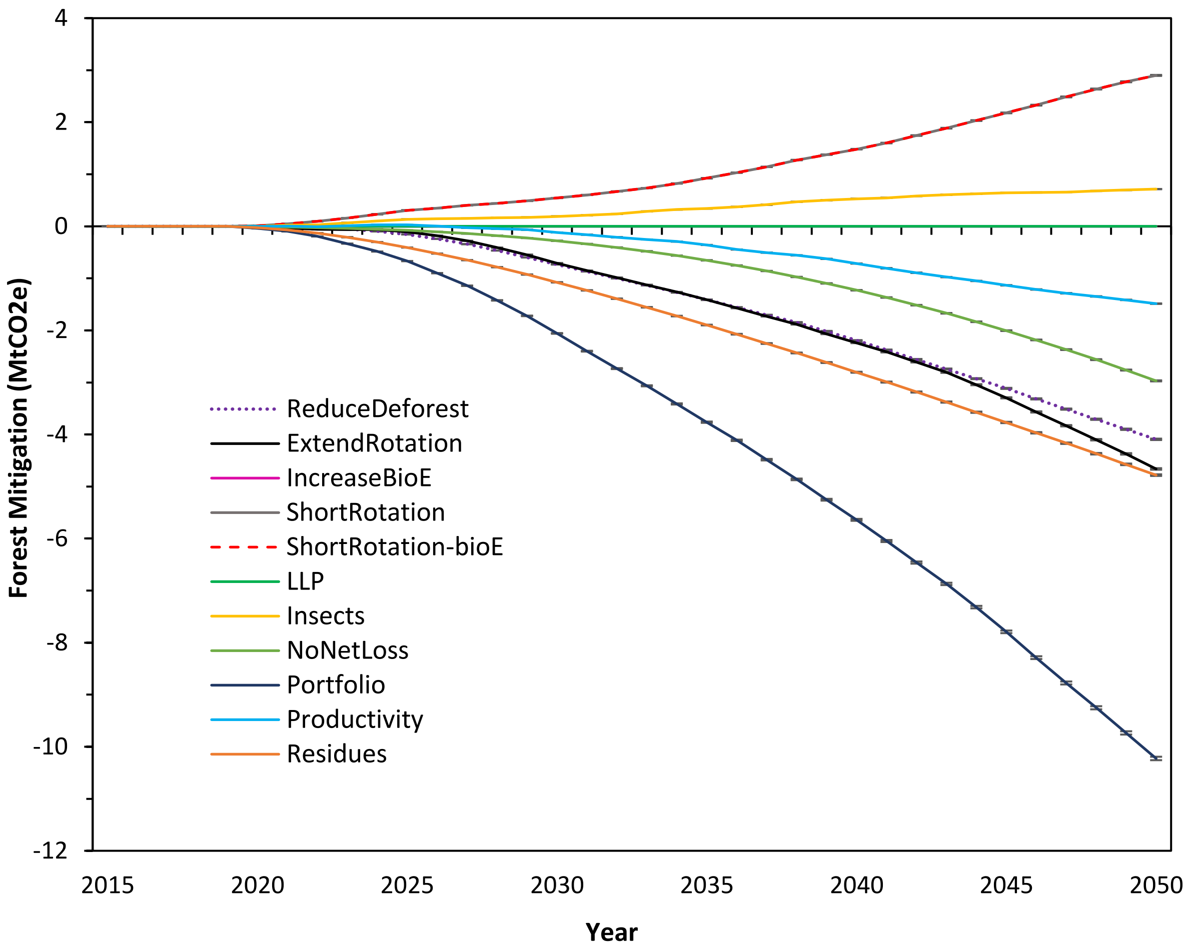

***Figure S7a**. Modeled cumulative mitigation for the forest ecosystem sector, from 2020 to 2050 for all ownership classes in Vermont. Negative values denote a reduction in GHG emissions relative to the baseline (BAU) scenario. Solid lines show mean (expected) cumulative mitigation, and errors bars indicate 95% confidence intervals assuming an error correlation of r = 1 across years and scenarios.*

(b) HWP Sector

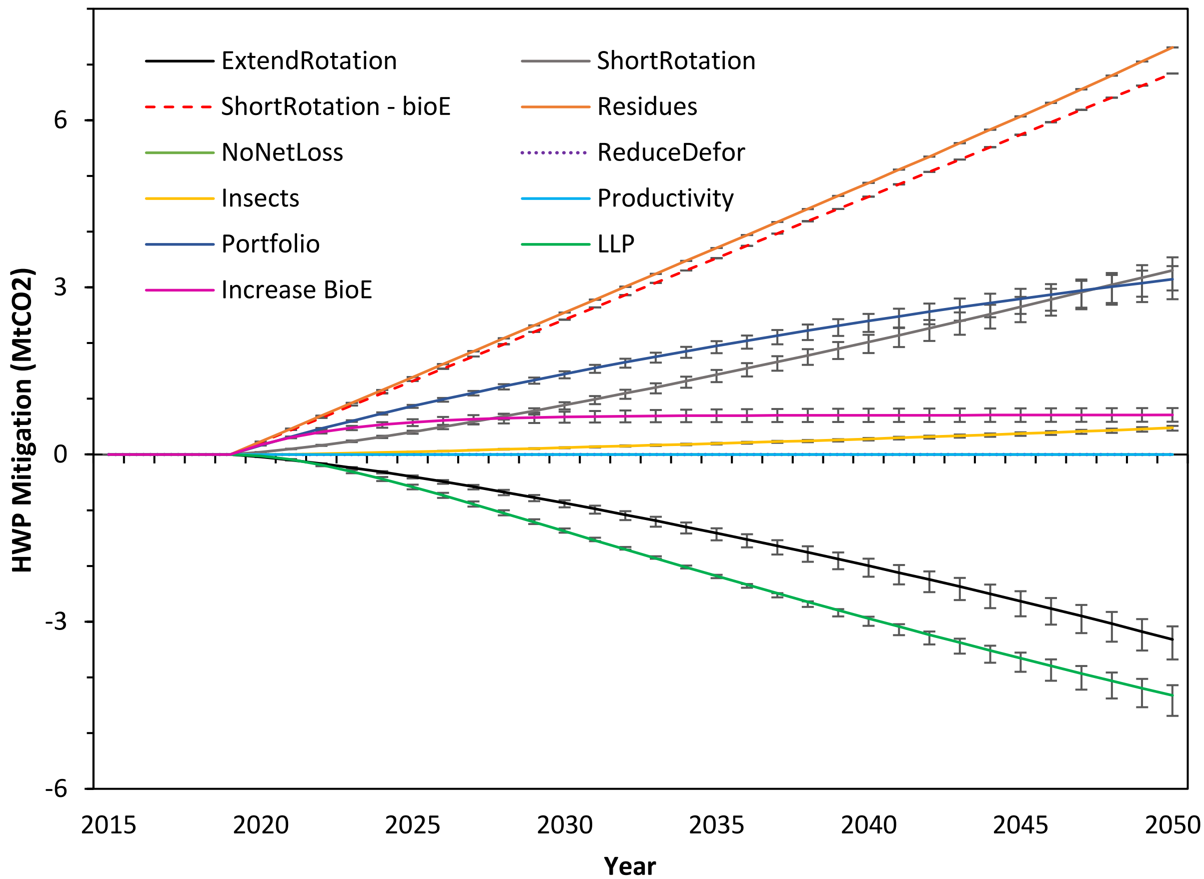

Figure S7b. *Modeled cumulative mitigation for the harvested wood products (HWP) sector, from 2020 to 2050 for all ownership classes in Vermont. Negative values denote a reduction in GHG emissions relative to the baseline (BAU) scenario. Solid lines indicate cumulative mitigation based on the mostly likely product retention times (half-lives) for saw logs, veneer logs, and pulpwood (see Table S1 in Appendix 1.7). Error bars show cumulative mitigation for scenarios based on minimum and maximum plausible half-lives (see Table S1 in Appendix 1.7). Error bars reflect uncertainty in mitigation due to uncertainty in half-lives, assuming a known input to the HWP sector each year. Thus, uncertainty in HWP input fluxes is ignored here but is accounted for in the total uncertainty shown in Fig. 6.*

(c) Energy Displacement

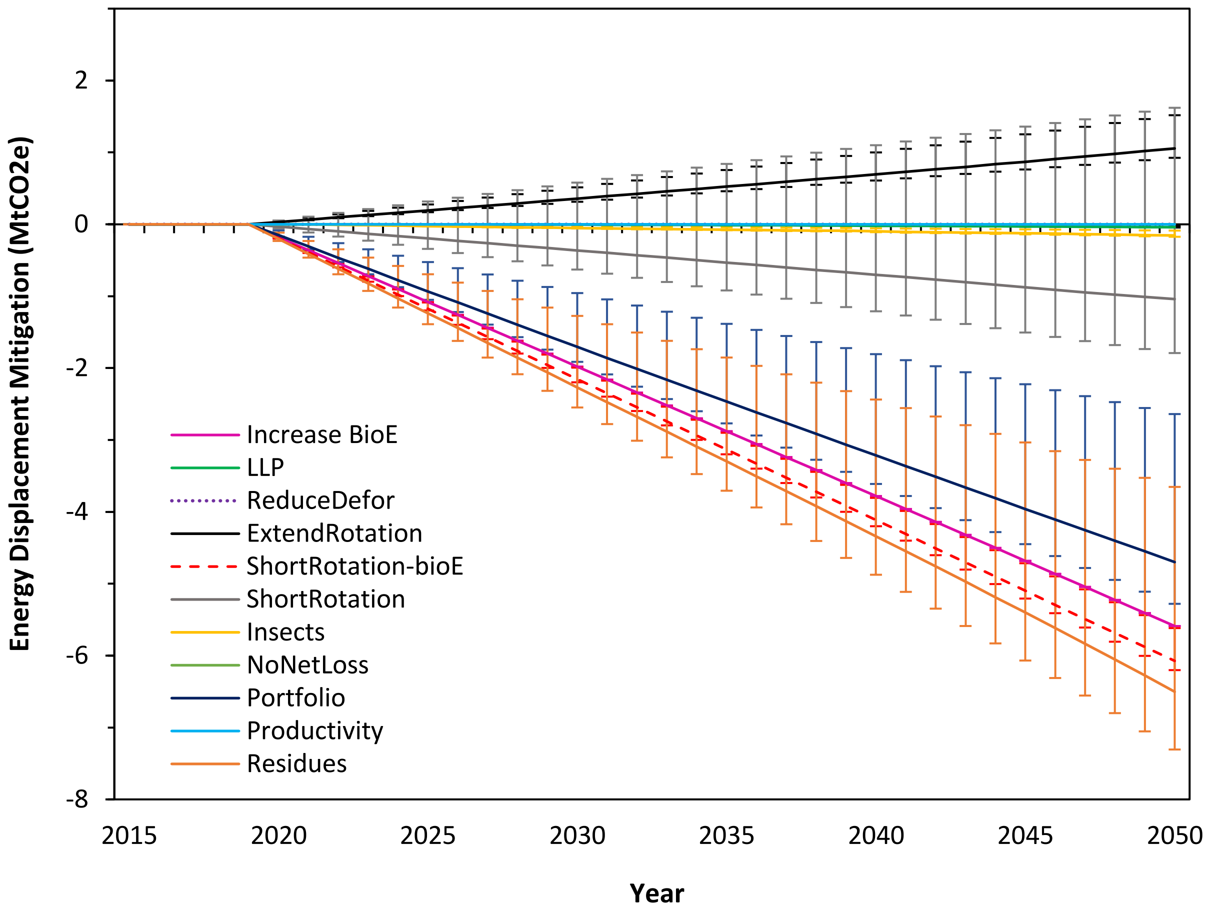

***Figure S7c**. Modeled cumulative mitigation due to energy displacement, from 2020 to 2050 for all ownership classes in Vermont. Negative values denote a reduction in GHG emissions relative to the baseline (BAU) scenario. Solid lines indicate cumulative mitigation based on the mostly likely energy displacement factors (see Table S2 in Appendix 1.7). Error bars show cumulative mitigation for scenarios based on minimum and maximum plausible energy displacement factors (see Table S2 in Appendix 1.7). Error bars reflect uncertainty in mitigation due to uncertainty in energy displacement factors, assuming known harvested wood product (HWP) availability for energy displacement each year. Thus, uncertainty in HWP quantities are ignored here but are accounted for in the total uncertainty shown in Fig. 6.*

(d) Product Displacement

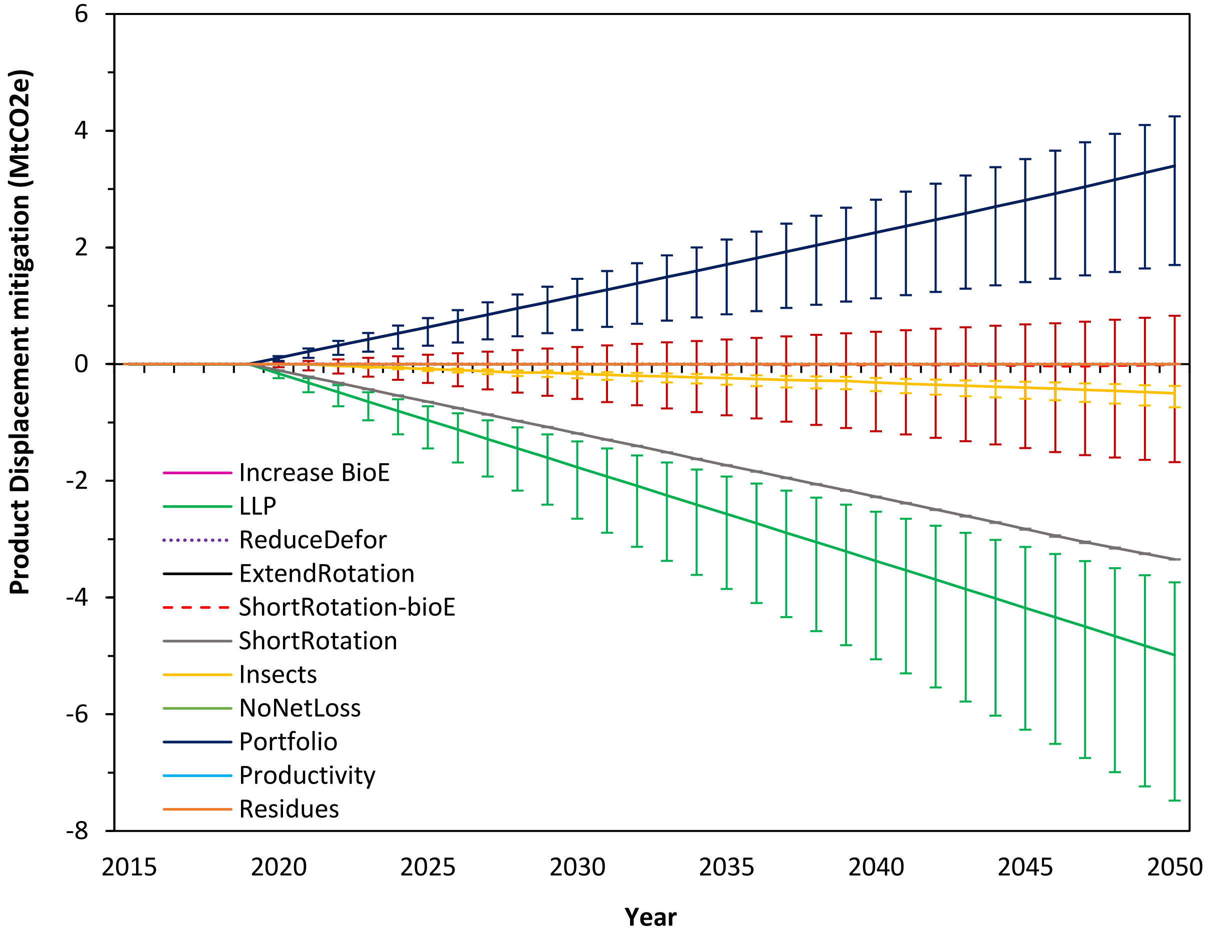

Figure S7d. *Modeled cumulative mitigation due to product displacement, from 2020 to 2050 for all ownership classes in Vermont. Negative values denote a reduction in GHG emissions relative to the baseline (BAU) scenario. Solid lines indicate cumulative mitigation based on the mostly likely energy displacement factors (see Table S2 in Appendix 1.7). Error bars show cumulative mitigation for scenarios based on minimum and maximum plausible energy displacement factors (see Table S2 in Appendix 1.7). Error bars reflect uncertainty in mitigation due to uncertainty in product displacement factors, assuming known harvested wood product (HWP) availability for product displacement each year. Thus, uncertainty in HWP quantities are ignored here but are accounted for in the total uncertainty shown in Fig. 6.*

Table S3. Uncertainty in cumulative mitigation potential (Mt CO_2e) due to uncertainty in product and energy displacement factors (DFs). The table shows cumulative (year 2050) mitigation (scenario emissions minus baseline emissions; negative emissions indicate carbon sinks) resulting from low, medium, and high DFs (Table S2), while controlling for uncertainty in other sectors (forest ecosystem parameters fixed at their default values and HWP half-lives fixed at their medium values; Table S1). Scenarios are ranked from highest to lowest mitigation potential under the medium DF case; rankings differ under low or high DF assumptions. Bold values indicate the highest mitigation potential.

Cumulative mitigation in (2050) Mt CO_2e			
	Low DFs	*Medium DFs*	*High DFs*
Increase LLP	-8.1	-9.3	**-11.8**
Portfolio	-7.2	**-8.4**	-7.3
Increase Bioenergy	-2.4	-4.9	**-5.6**
Residues	-1.1	-4.0	**-4.8**
Reduce Deforestation	-3.6	-3.6	-3.6
Extend Rotation	**-4.8**	-3.5	-1.7
No Net Loss	-3.0	-3.0	-3.0
Productivity	-1.5	-1.5	-1.5
Insects	**0.2**	0.5	0.3
Short Rotation	3.1	1.8	**0.0**
Short Rotation BioE	6.3	3.7	**2.9**

Section S9. Forest Ecosystem Mitigation Uncertainty: Correlation Assumptions

In Fig. 6 and Fig. S7, we assumed an error correlation of $r = 1$ across years and scenarios when quantifying uncertainty in all forest sector components (forest ecosystem, harvested wood products, energy displacement, and product displacement). To explore the implications of this assumption, and to illustrate its rationale, we explored the opposite extreme assumption of $r = 0$ for forest ecosystem mitigation. We restricted this analysis to forest ecosystem emissions because an analytical framework was available for the CBM-CFS3 forest ecosystem model (see Appendix 1.7) that facilitated exploration of alternative assumptions.

In contrast to the $r = 1$ assumption (which corresponds to applying a single set of uncertain parameter values to each year and scenario in CBM-CFS3), the $r = 0$ assumption corresponds to assuming independent errors in parameter values across years and scenarios. As explained in Appendix 1.7, assuming $r = 1$ across scenarios is appropriate for our study, because our goal is to quantify the effects of mitigation activities per se, while controlling for sources of variation that are unrelated to mitigation activities. In contrast, assuming $r < 1$ across scenarios would be more realistic if the goal were to forecast emissions differences on specific parcels of land, allowing for the possibility that disturbance or other ecosystem processes unrelated to mitigation activities may differentially affect different land units. The $r = 0$ case considered here is the extreme case of independent errors. Note that a range of assumed correlation values across years could be combined with any assumed correlation across scenarios. Thus, there is no requirement that correlations across years and scenarios be assumed equal. As we show here, assuming $r = 0$ across years and scenarios leads to much greater mitigation uncertainty than assuming $r = 1$. The uncertainty would be even greater if we assumed $r > 0$ across years and $r = 0$ across scenarios. In general, higher values of r across years will tend to increase mitigation uncertainty (due to the compounding of variance when summing over years; see Equations S3-S4), whereas higher values of r across scenarios will tend to decrease mitigation uncertainty (due to the decreasing variance of differences with increasing correlation among variables; Equation S5).

Uncertainty in mitigation (scenario emissions minus baseline emissions) is shown for the 11 mitigation scenarios in Fig. S8. The expected mitigation (curves in Fig. S8) are the same as those in Fig. S7a, but the confidence intervals are much wider. The large uncertainty shown here illustrates why assuming correlated errors is more appropriate for evaluating the effects of mitigation activities per se. Consider, for example, the “Increase LLP” and “Increase Bioenergy” (bottom row of Fig. S8). In terms of the forest ecosystem, these scenarios are identical to the baseline scenario; they differ only in the fate of harvested wood. Therefore, the expected mitigation (relative to baseline) of these scenarios is zero. However, under the $r = 0$ assumption, there is large uncertainty in emissions differences between these scenarios and baseline, even though these scenarios involve no differences from baseline in terms management, disturbance, or other ecosystem processes. In other words, the uncertainty for these scenarios (as well as for the other nine scenarios in Fig. S8) has nothing to do with mitigation activities, and is solely due to sources of variation that land managers cannot control.

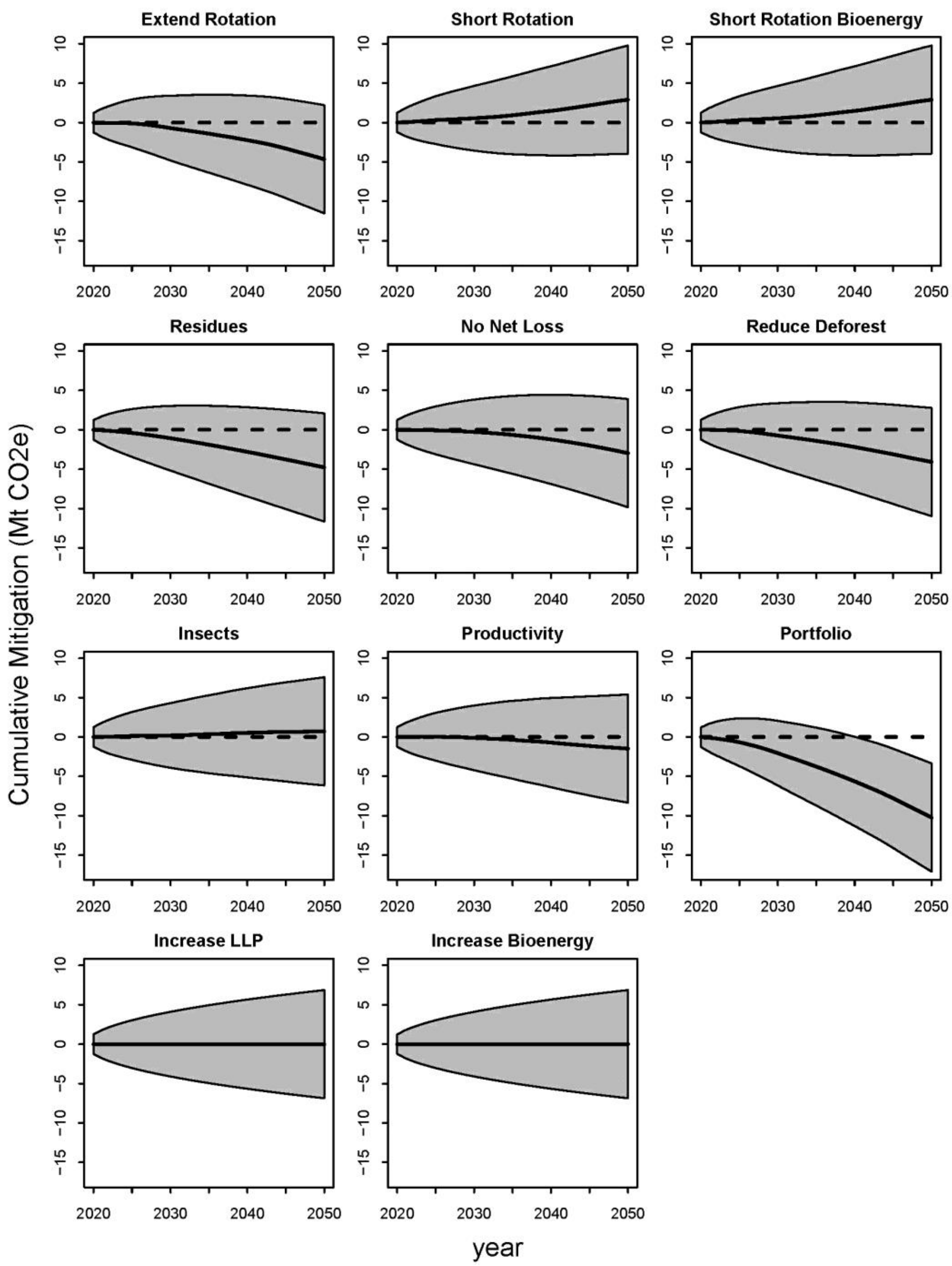

Figure S8. *Modeled cumulative mitigation with alternative uncertainty analysis assumptions for the forest ecosystem sector, from 2020 to 2050 for all ownership classes in Vermont. Negative values denote a reduction in GHG emissions relative to the baseline (BAU) scenario. Baseline is represented by the dashed horizontal line. Solid lines show mean (expected) cumulative mitigation for each scenario, and gray shading indicates 95% confidence intervals assuming an error correlation of r = 0 across years and scenarios. Uncertainty in mitigation (i.e., emissions differences between each scenario and baseline) is much larger under the alternative error correlation assumption here (r = 0) compared to our primary uncertainty analysis (r = 1; see Fig. S8).*

Section S10. Cumulative emissions for each scenario

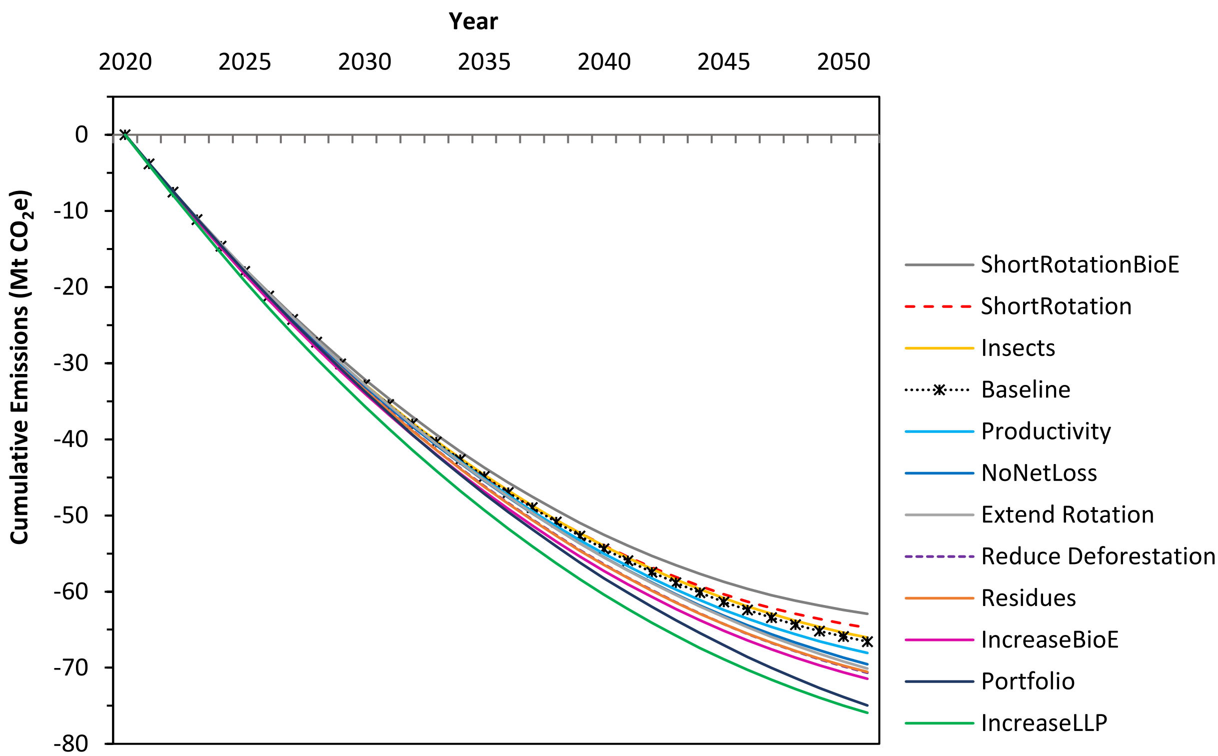

Figure S9 *Cumulative emissions from 2020 through 2050 for the baseline business as usual scenario and each of the 11 mitigation scenarios (assumes zero emissions prior to 2020). The legend lists scenarios in order from greatest emissions (top) to lowest emissions (bottom).*

Section S11. Appendix S1 References

Dymond, C.C., 2012. Forest carbon in North America: annual storage and emissions from British Columbia's harvest, 1965-2065. Carbon balance and management 7, 8-8.

IPCC, 2006. Generic methodologies applicable to multiple land-use categories. 2006 IPCC Guidelines for National Greenhouse Gas Inventories. In: Eggleston, S., Buendia, L., Ngara, T., Tanabe, K. (Eds.). Intergovernmental Panel on Climate Change Hayama, Japan, p. 59.

Janowiak, M.K., D'Amato, A.W., Swanston, C.W., Iverson, L., Thompson, F.R., Dijak, W.D.; Matthews, S., Peters, M.P., Prasad, A., Fraser, J.S., Brandt, L.A., Butler-Leopold, P., Handler, S.D., Shannon, P.D., Burbank, D., Campbell, J., Cogbill, C., Duveneck, M.J., Emery, M.R.,…Templer, Pamela H. 2018. New England and northern New York forest ecosystem vulnerability assessment and synthesis: a report from the New England Climate Change Response Framework project. Gen. Tech. Rep. NRS-173. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. 234 p.

Köhl, M., Ehrhart, H-P, Knauf, M., Neupane, P.R. 2020. A viable indicator approach for assessing sustainable forest management in terms of carbon emissions and removals. Ecological Indicatiors. 111: 106057.

Kurz, W.A., and Apps, M.J. 2006. Developing Canada's National Forest Carbon Monitoring, Accounting and Reporting System to meet the reporting requirements of the Kyoto Protocol. Mit. Adapt. Strat. Glob. Change 11, 33–43.

Kurz, W.A., Dymond, C.C., White, T.M., Stinson, G., Shaw, C.H., Rampley, G.J., Smyth, C., Simpson, B.N., Neilson, E.T., Trofymow, J.A., Metsaranta, J., Apps, M.J., 2009. CBM-CFS3: A model of carbon-dynamics in forestry and land-use change implementing IPCC standards. Ecological Modelling 220, 480-504.

Leskinen, P., Cardellini, G., González-García, S., Hurmekoski, E., Sathre, R., Seppälä, J., Smyth, C., Stern, T., Verkerk, P.J., 2018. Substitution effects of wood-based products in climate change mitigation. In. European Forest Institute.

Metsaranta, J.M., Shaw, C.H., Kurz, W.A., Boisvenue, C., Morken, S. 2017. Uncertainty of inventory-based estimates of the carbon dynamics of Canada's managed forest (1990–2014). Canadian Journal of Forest Research 47, 1082-1094.

Nabuurs, G.J., Masera, O., Andrasko, K., Benitez-Ponce, P., Boer, R., Dutschke, M., Elsiddig, E.A., Ford-Robertson, J., Frumhoff, P., Karjalainen, T., Krankina, O., Kurz, W.A., Matsumoto, M., Oyhantcabal, W., Ravindranath, N.H., Sanchez, M.S., Zhang, X., 2007. Forestry. In Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. In: Metz, B., Davidson, O.R., Bosch, P.R., Dave, R., Meyer, L.A. (Eds.). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Sathre, R., O'Connor, J., 2010. Meta-analysis of greenhouse gas displacement factors of wood product substitution. Environmental Science & Policy 13, 104-114.

Skog, K.E., 2008. Sequestration of carbon in harvested wood products for the United States. Forest Products Journal 58, 56-72.

Soimakallio, S., Saikku, L., Valsta, L., Pingoud, K. 2016. Climate Change Mitigation Challenge for Wood Utilization—The Case of Finland. Environmental Science & Technology 50, 5127-5134.

Smyth, C., Rampley, G., Lemprière, T.C., Schwab, O., Kurz, W.A., 2017. Estimating product and energy substitution benefits in national-scale mitigation analyses for Canada. Gcb Bioenergy 9, 1071-1084.

Stinson G., Kurz, W.A., Smyth, C.E., Neilson, E.T., Dymond, C.C., Metsaranta, J.M., Boisvenue, C., Rampley, G.J., Li, Q., White, T.M., Blain, D. 2011. An inventory-based analysis of Canada's managed forest carbon dynamics, 1990 to 2008. Global Change Biology 17, 2227-2244.