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Uncertainty of inventory-based estimates of the carbon dynamics of Canada's managed forest (1990-2014)

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2   forest (1990-2014)

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Abstract

Canada's National Forest Carbon Monitoring Accounting and Reporting System (NFCMARS) quantifies the carbon (C) dynamics and greenhouse gas (GHG) emissions and removals of Canada's managed forest to fulfill reporting obligations under international climate conventions. Countries are also requested to assess the uncertainty associated with these estimates, which we report here. We used Monte Carlo simulation to quantify uncertainty of carbon stock and flux estimates from the Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3), the core ecosystem model of the NFCMARS. We evaluated the impacts of model algorithms, parameters, and of the input data used to describe forest characteristics and disturbance rates. Under our assumptions, 95% confidence interval widths averaged 16.2 Pg C (+8.3 and -7.9 Pg C, or $\pm 15\%$) for total ecosystem C stock and 32.2 Tg C yr⁻¹ (+16.6 and -15.6 Tg C yr⁻¹) for net biome production relative to an overall simulation median of -0.8 Tg C yr⁻¹ from 1990 to 2014. The largest sources of uncertainty were related to factors determining biomass increment, and the parameters used to model soil and dead organic matter C dynamics. Opportunities to reduce uncertainty and associated research challenges were identified.

Keywords: climate change, greenhouse gas inventory, boreal forest, mitigation, adaptation

1. Introduction

Canadian forests play an important role in the global biogeochemical cycling of carbon (C) because of their large area (310 million ha) and C stock (Pan et al. 2011; Stinson et al. 2011). Canada's National Forest Carbon Monitoring Accounting and Reporting System (NFCMARS; Kurz and Apps, 2006) was developed to quantify the C dynamics and greenhouse gas (GHG) sources and sinks of the managed portion (230 million ha) of these forests (Fig. 1). The NFCMARS has generated these estimates annually since 2006 to contribute to Canada's reporting obligations under the United Nations Framework Convention on Climate Change (UNFCCC) (e.g., Environment and Climate Change Canada, 2016). The NFCMARS follows an empirical approach based on forest management and forest inventory data and uses as its core model the Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3; Kurz et al. 2009). Over time, the NFCMARS and the CBM-CFS3 have been updated to incorporate new scientific and technological advances, but many uncertainties remain (Kurz et al. 2013).

Quantification of uncertainty has been required since GHG sources and sinks were first reported to the UNFCCC, and has been included in some form in Canada's annual reports since 2010. In this paper, we report on the scientific basis of the uncertainty estimates reported in NIR2016 (Environment and Climate Change Canada, 2016). GHG inventories consistent with guidance from the Intergovernmental Panel on Climate Change (IPCC) are "...those which contain neither over- nor underestimates, so far as can be judged, and in which uncertainties are reduced as far as is practicable", but few methodological suggestions for quantifying uncertainty are provided (IPCC 2000). In practice, model uncertainties are rarely quantified (Yanai et al. 2010, Xiao et al. 2014,

Gregor and Chan 2014). For example, a recent comprehensive model intercomparison for North America considered only uncertainty in the observations against which models were being evaluated, but not in the models themselves (Raczka et al. 2013). In this paper, we describe and quantify different sources of uncertainty in Canada's NFCMARS and use Monte Carlo approaches to obtain confidence interval estimates and to assess sensitivity to different categories of uncertainty. We also discuss challenges in interpreting and communicating the results of uncertainty analyses and approaches for reducing uncertainty in Canada's NFCMARS.

2. Methods

Conceptual considerations

We define "uncertainty" (U) as a confidence interval (CI; typically 95% CI) for a model output indicator, which represents a combination of uncertainties from different sources ($U_1, U_2, U_3, \dots, U_n$). The contribution of each source ($U_1, U_2, U_3, \dots, U_n$) to the total (U) is referred to as "sensitivity", which varies from the standard definition of sensitivity as the effect of alternative assumptions on an output variable. Conceptually, both "accuracy" (the difference between estimates and the true value) and "precision" (the distribution of estimates relative to each other, irrespective of the true value) contribute to uncertainty. Because we use only one model (CBM-CFS3) implemented in one system (the NFCMARS), we can only estimate precision. Assessing accuracy (or its counterpart "bias") requires comparison against known or assumed true values, which do not exist for the output indicators at spatial scales modelled by Canada's NFCMARS. When used, "bias" refers to differences between the central tendencies of the uncertainty simulations, relative to those derived under a set of default assumptions. Plot scale model accuracy

can be assessed by evaluation against independent ground data (Shaw et al. 2014). For landscapes, it can be examined indirectly through model inter-comparison (Wang et al. 2011; Raczka et al. 2013). Our estimates of uncertainty (u) are themselves potentially uncertain because of methodological disagreement. For example, probability distributions are often derived from judgement. There may also be disagreement about appropriate spatial and temporal scales or correlation structures for parameter variation, and different methods of calculating confidence intervals from Monte Carlo simulation results (Meyer et al. 1986). We term this “meta-uncertainty” (u_m), which accompanies each component of total uncertainty, ($u_{m1}, u_{m2}, u_{m3}, \dots, u_{mn}$) and which we assume to be zero. We know this is unlikely to be true, and explore the implications of meta-uncertainty further in the discussion.

System description

Canada’s NFCMARS and its core ecosystem model, the CBM-CFS3 (Kurz et al. 2009), provides estimates of the C and GHG balance of Canada’s managed forest (Fig. 1) by combining air-photo interpreted forest inventory maps, yield curves developed from sample plot data, process-based modelling of soil and dead organic matter (DOM) C dynamics, statistics on forest management activities, and remote sensing data to estimate area, type, and location of natural disturbance by wildfire and insects (Kurz and Apps, 2006; Kurz et al. 2009; Stinson et al. 2011; Kurz et al. 2013). Although the original inventory data and some disturbance data are spatially explicit, these are aggregated into ~600 spatial analysis units in NFCMARS, without retaining further geographic information. Uncertainty in these estimates, which can be broadly attributed to model inputs, parameters, and algorithms, was summarized into five related categories (Table 1)

that represent the components (u_1 , u_2 , u_3 , u_4 , and u_5) of total estimated uncertainty (u).

Further details are provided in the supplementary information.

Model Inputs

The first key inputs are forest inventories derived from air photo interpreted maps delineating homogeneous forest stands as polygons with attributes such as species composition, age, wood volume, site class, and stocking. The second are merchantable volume yield curves describing merchantable wood volume accumulation with age, which are linked to the inventory to enable landscape scale C stock estimation and conversion to biomass using allometric equations (Boudewyn et al. 2007, Li et al. 2003). The NFCMARS uses forest inventory data from provincial management agencies across Canada (Kurz and Apps 2006; Stinson et al. 2011), with methods and update frequencies that vary by jurisdiction (Leckie and Gillis 1995). Details on how these are used in the CBM-CFS3 are in Stinson et al. (2011). The error structures of these data are typically unknown, but they are known to be subject to boundary delineation and attribute misclassification error (20–30%; Leckie and Gillis 1995). This will vary by region, inventory age, forest characteristics, and data source. Yield curves are obtained from growth models used for wood supply analyses by jurisdictional forest management agencies. In theory, error estimates for yield curves are calculated as they are statistically fit to sample plot data, but in practice these are not available for most of the more than 100,000 such curves used by the NFCMARS to describe the wide range of species, site, and ecological conditions across Canada's forest. In the CBM-CFS3, net primary production (NPP) is modelled as the sum of net biomass increment and replacement of biomass turnover. Forest inventory, yield curves, and allometric equations primarily

influence estimates of the net growth portion of NPP, which represents about 16% of total NPP (21% of above-ground NPP, and 8% below-ground - Smyth et al. 2013), the rest being the replacement of biomass turnover. Due to a nearly complete lack of readily available estimates for error in these three factors, after consultation with forest inventory experts, we chose to estimate the combined uncertainty by applying a multiplier of $\pm 50\%$ to modelled net biomass increment.

Data describing the location and quantity of forest harvest and natural disturbance by fire and insects are also a key input. Area burned data for 1990 to 2003 are obtained from the Canadian large fires database (Amiro et al. 2001; Stocks et al. 2002) and for 2004 to present from the Canadian National Burn Area Composite (NBAC) (Fraser et al. 2000, de Groot et al. 2007, Stinson et al. 2011). Errors have not formally been estimated for these data, so after consultation with fire monitoring experts we assumed an uncertainty of $\pm 10\%$ for area burned. Data on area subject to moderate or severe insect damage are obtained from jurisdictional data sources for mountain pine beetle in British Columbia (e.g., Westfall and Ebata, 2014) and for aspen defoliators in Alberta (e.g., Forest Health and Adaptation Program 2014). Additional outbreaks of aspen defoliators in Saskatchewan and Manitoba, hemlock looper in Newfoundland, and spruce beetle in Yukon use historical data from Canada's Forest Insect and Disease Survey (Simpson and Coy 1999), obtained from the national forestry database program (NFDP). These data are formatted as model input instructions describing annual area affected by insect, region, and severity class and applied to stands containing host species. Further details are provided in Kurz et al. (2008) for mountain pine beetle and Stinson et al. (2011) for other insects. No published estimates of error exist for these data but, it would clearly be higher

than more sharply delineated burn areas, so we assumed an area uncertainty of $\pm 25\%$. For harvest, volume and area statistics from the NFDP are translated to annual targets of C mass to be harvested using a procedure that accounts for the volume, density, C proportion, and bark fraction of harvested wood. Resulting minimum and maximum values for harvest target uncertainty range from ± 4 to 16% and vary by jurisdiction due to variation in species composition and wood density (Gonzales 1990). Further details are in Stinson et al. (2011) and the supplement (Table S1).

Model Parameters

Parameter ranges were obtained for 32 biomass turnover and DOM C modelling parameters from a comprehensive literature review, and used as minimum and maximum values of a triangular distribution (with mode set to the CBM-CFS3 default value) in the Monte Carlo simulations. Parameter values were varied independently, because the correlation structure among parameters could not yet be estimated, which contributes to meta-uncertainty. Further details, literature references, and a description of CBM-CFS3 biomass, dead organic matter and soil C pools are in the supplement (Table S2 and S3). The allometric equations used to estimate above-ground biomass from merchantable volume (Boudewyn et al. 2007) and below-ground from above-ground biomass (Li et al. 2003) also contribute to uncertainty, primarily in the net biomass increment portion of NPP, which we combined with forest inventory and yield curves into the $\pm 50\%$ error applied to net biomass increment. The disturbance matrices used to model the transfer of C between pools, to forest products, or to the atmosphere at the time of a disturbance event (Kurz et al. 1992) were not varied in the current analysis, also an important factor contributing to meta-uncertainty.

174 *Model algorithms*

175 Some uncertainty is also attributable to the selection of stands for disturbance. Natural
176 disturbance and management activity data are referenced to spatial unit boundaries, but
177 within these units the specific stands affected are not known and therefore modelling
178 rules are used to select records to which these events are applied (Kurz et al. 2009).
179 Biological knowledge informs target forest types for insects, and wood supply analyses
180 inform stands targeted for harvest. For fire, however, records are selected randomly from
181 all stands within the spatial unit boundaries with at least 1 Mg of above-ground biomass
182 C. Thus, unless a constant random seed value is specified, each execution of a CBM-
183 CFS3 simulation will differ. Selecting stands with higher biomass or DOM C pools will
184 result in higher C emissions, contributing to uncertainty in regions or years with
185 significant levels of fire disturbance and where fire exhibits selective behaviour (Bernier
186 et al. 2016). We quantified this source of uncertainty by allowing the random seed value
187 to vary for each simulation and in doing so altered the stands affected by disturbance
188 types with random selection rules.

189 The initialization procedure used to populate soil and DOM C pools in the CBM-
190 CFS3 also contributes to uncertainty. These pools are initialized by simulating repeated
191 iterations of growth and stand-replacing disturbance until the difference between the sum
192 of the slow soil C pools in successive iterations is less than 1%. Subsequently the last
193 known stand-replacing disturbance (fire, clearcut) is simulated and the stand grown to the
194 age specified in the inventory, yielding dead organic matter and soil conditions at the end
195 of the initialization that are consistent with the disturbance history of the stand (Kurz et
196 al. 2009). The default assumption for the historical disturbance regime is stand-replacing

fire on a constant return interval ranging from 75 to 300 years depending on terrestrial ecozone (Kurz et al. 2009). The results from the CBM-CFS3 are sensitive to assumptions made about the long-term disturbance return interval (White et al. 2008), which is in reality highly uncertain because of interannual variability in area burned (Armstrong 1999; Metsaranta 2010). We assessed this source of uncertainty by using random disturbance intervals during initialization. Each record was simulated for up to 30 repeated cycles of growth and disturbance of random length, resulting in soil and DOM C stocks that vary at the start of each simulation. Probability distributions of fire return intervals for each ecozone were developed using data from the Canadian Large Fire Database (Amiro et al. 2001; Stocks et al. 2002) using a procedure outlined in Metsaranta (2010), and scaled so the mean matched the default historical average return intervals (Kurz et al. 2009). Further details are in the supplement (Table S4).

Summary of analysis

We used the NFCMARS databases to develop the estimates for the 2016 National Inventory Report (NIR2016; Environment and Climate Change Canada, 2016), spanning 1990 to 2014. All uncertain parameters and input quantities were simulated independently using triangular distributions. Input data for Canada's 230 million ha of managed forest are contained in 20 CBM-CFS3 data bases, each representing province and territories or regions within them. We conducted 100 Monte Carlo simulations for each of these 20 databases. Additional runs were prohibitive due to computational and data storage limitations. However, because the 100 simulations for each of the 20 projects were conducted independently, we could increase the sample size for national totals by summing random combinations of the 100 Monte Carlo runs. We generated $n = 1000$

randomly recombined estimates of national totals, and approximated a 95% confidence interval (CI) from the 2.5th and 97.5th percentiles of these national estimates. Our examination mainly focussed on two model indicators: total ecosystem C (a stock) and net biome production (NBP, a flux). Although harvested wood product C stocks and fluxes are also reported in NIR2016, our analysis does not address the uncertainty analysis of this independent model, the Carbon Budget Modelling Framework for Harvest Wood Products (CBM-FHWP). Instead, we used the assumption of instant oxidation of all C transferred from the ecosystem to the forest product sector and report NBP accordingly. The estimated total C transferred to harvested wood products (with uncertainty) is provided in the supplement (Fig. S1).

Sensitivity Analysis

We conducted two sensitivity analyses. First, we estimated the contribution of each uncertainty component (u_1 , u_2 , u_3 , u_4 , and u_5 ; Table 1) to total estimated uncertainty (u) by repeating the full national analysis five times, varying one component at a time. The exception to this was that uncertainty due to random selection of stands for disturbance (u_1) was also implicitly accounted for in the analysis of the other four components (u_2 , u_3 , u_4 , and u_5). We also assessed sensitivity to each of the individual soil and DOM C modelling parameters that varied in our analysis (Table S2) and contributed to the estimate of uncertainty due to that component (u_5). We did this for an example region, repeating the analysis once for each of the 32 soil and DOM C modelling parameters, varying one parameter at a time. We grouped these into three categories, (1) base decay rates, (2), proportion of C respired, and, (3) turnover, and we then examined three fluxes, NPP, heterotrophic respiration (Rh), and net ecosystem production (NEP),

as well as total ecosystem C. This differed from a previous similar analysis that examined identical variation ($\pm 5\%$) for a set of ground plots with available soil C data (Smyth et al. 2013).

3. Results

Carbon stocks

Total ecosystem C stock (1990–2014) for the NFCMARS default values and the 2.5th, 50th (median) and 97.5th percentiles for the uncertainty simulations are shown in Fig. 2a. On average, the width of the 95% CI spanned 16.2 Pg C (+8.3 and -7.9 Pg C, or $\pm 15\%$ in relative terms, compared to the simulation median), with little interannual variation (Fig. 2b). Annual results for the CBM-CFS3 default values averaged the 8th percentile of the range of simulated values and were about 12% or 5.9 Pg C lower than the simulation median values. For individual C pools (Table 2), the simulation default values were lower than the 2.5th percentile of the simulations or higher than the 97.5th percentile of the simulations in 5 of 21 cases. The largest differences were for the Slow Below Ground (median simulation result was 25% or 5.0 Pg C higher than the default simulation result), Fast Above Ground (median simulation result was 42% or 1.1 Pg C higher than the default simulation result), and Slow Above Ground (median simulation result was 9% or 0.7 Pg C higher than the default simulations) DOM C pools. Relative differences were also large for the Softwood and Hardwood Stem Snag pools (the median of the simulations were 48 and 49% less than the default simulation, respectively) and the Very Fast Below Ground soil C pool (the median of the simulations was 37% higher than the default simulation), but these contributed little to the total absolute difference because they are small pools (0.5 Pg C or less; Table 2). In general, the slowly decaying soil C

pools (both Above and Below Ground), which together represent 72% of the total DOM C and 53% of total ecosystem C, also accounted for the largest portion of the difference between the simulation median and default simulation estimate of total ecosystem C.

Carbon fluxes

Time series of NBP (1990–2014) for NFCMARS default values along with the 2.5th, 50th (median), and 97.5th percentiles for the uncertainty simulations are plotted in Fig. 2c. On average, the width of the 95% CIs spanned 32.2 Tg C yr⁻¹ (+16.6 and -15.6 Tg C yr⁻¹), relative to an overall simulation median of -0.8 Tg C yr⁻¹ over the time series, with some interannual variation related to variation in annual area burned (Fig. 2d). The CI for NBP cannot be meaningfully expressed in percentage terms because its range of possible values contains zero. Similar to the results for total ecosystem C, the NBP results for the CBM-CFS3 default values averaged around the 32nd percentile of the simulation distribution and were, on average, 4 Tg C yr⁻¹ lower than the simulation median values. An examination of the results by ecosystem C flux components (Table 3) shows that the largest absolute differences between simulation median and default values for the C fluxes was for the litterfall component of NPP (the median flux was 32 Tg C yr⁻¹ higher than the default flux), which also contributed most of the observed difference for total NPP (calculated as the sum of biomass production to replace litterfall and net growth), because the difference in net growth was negligible. The largest relative difference was for NEP (9%; the median of the simulations were high relative to the default simulation). Default simulation values for all flux components fell within the 95% CI for the simulations and were in all cases within 10% of the median value (Table 3).

Sensitivity analysis

Uncertainty components

Average CI widths over the time series for total ecosystem C and NBP for each of the five uncertainty categories (Table 1) are plotted in Fig. 3, scaled relative to the CI for all factors combined. The relative rankings of the five categories for total ecosystem C and NBP are identical. The largest contributors to uncertainty are biomass increment (u_4) (56% of the total CI width for total ecosystem C, 59% for NBP) and biomass turnover and DOM C modelling parameters (u_5) (56% of the total CI width for stocks, 52% for fluxes). Disturbance targets (u_3) are intermediate and much lower (2% for total ecosystem C, 10% for NBP), while both random initialization (u_2) and random selection of stands (u_1) contribute relatively little (together less than 1% of the total CI width for total ecosystem C and ~5% for NBP). The sum of the individual uncertainty components is greater than total uncertainty (individual factors sum to 114% for total ecosystem C and 131% for NBP), indicating that the contribution of each uncertain component (u_1 , u_2 , u_3 , u_4 , and u_5) to total uncertainty was not additive.

Biomass turnover and DOM C modelling parameters

Of the 32 biomass turnover and DOM C modelling parameters that varied in our analysis, total ecosystem C stock was the most sensitive to base decay rates for Slow Above and Slow Below Ground pools, the proportion of decayed C transferred to the atmosphere from the Very Fast Above and Below Ground pools, the Fast Above Ground pool, and the turnover of fine roots (Fig. 4). All of these pools are component of the soil organic layer, mineral soil, or are located in the soil as is the case for the fine roots. The pattern of sensitivity to parameters controlling biomass turnover were the same for NPP (Fig. 5c) and Rh (Fig. 5f). The NEP was most sensitive to the base decay rates for the small and

fine (Fast Above Ground), and coarse (Medium) downed dead wood (Fig. 5g), as well as to all of the remaining parameters to varying and relatively small degrees (Fig. 5g,h,i). In general, the importance of turnover parameters to NEP was diminished relative to their importance to Rh and NPP because Rh and NPP are highly correlated and cancel one another once NEP is calculated by subtracting Rh from NPP. Because the significance of turnover parameters is diminished for NEP, the deadwood decay parameters became relatively more important to NEP than to Rh, for which they were somewhat relevant, and much more important to NEP than to NPP, which is not affected by decay parameter estimates (Fig. 5a).

4. Discussion

Our study is important because it is one of the first published demonstrations of a formal uncertainty analysis of a modelling system used to generate national-scale estimates of forest sector GHG emissions and removals for reporting to the UNFCCC. While the IPCC Guidelines describe the need for such analyses, and suggest methods such as the one implemented here, actual quantifications of uncertainty in national-scale estimates of GHG balances, and attribution of this to different potential uncertainty sources, have only been previously available for a few countries (e.g. Finland, Peltoniemi et al. 2006; Monni et al. 2007). It is also important because science investments are often justified on the basis of their ability to reduce uncertainty by improving national scale estimates of C and GHG estimates for forests in Canada (Bernier et al. 2013) and elsewhere. A quantified assessments of uncertainty, both before and after such improvements are made, is critical information required for determining how much uncertainty reduction was achieved by such investments.

335 *Comparison to other assessments*

336 Directly comparing our analysis with other uncertainty assessments for ecosystem models
337 or budget calculations is challenging because each model and modelling system has a
338 unique configuration and uncertainty profile, and the details of how uncertainty is
339 estimated vary depending upon individual circumstances. For example, variables in
340 models may be grouped differently and assigned one uncertainty value, or assessments
341 may reflect elements of both precision and accuracy, whereas this assessment is for
342 precision only. However, our results are consistent with other regional (Richardson et al.
343 2010; Xiao et al. 2014), national (Peltoniemi et al. 2006), and global (Todd-Brown et al.
344 2013) assessments which conclude that the largest contributors to model uncertainty are
345 those which are the main model determinants of the largest fluxes, NPP and Rh. In our
346 case, these are biomass turnover, net biomass increment, and DOM C modelling
347 parameters. Although disturbance is known to affect model estimates of forest C
348 dynamics (Stinson et al. 2011; Weng et al. 2012), uncertainty about levels of disturbance
349 is not commonly assessed. We found that uncertainty about disturbance targets was
350 significant, but contributed less than uncertainties related to NPP and Rh. The
351 contribution of random selection of stands for disturbance, a source of uncertainty
352 relatively unique to Canada's NFCMARS, was also relatively small but one that may
353 significantly affect how model results are interpreted in regions with significant fire
354 disturbance.

355 In contrast to other assessments (Heath and Smith 2000, Peltoniemi et al. 2006),
356 the relative ranking of the five broad sources of uncertainty (Table 1) was the same for
357 the stock (total ecosystem C) and flux (NBP) indicators analyzed. However, our broad

categories account for sources of uncertainty that were not considered in the other assessments, primarily those related to disturbance effects. The three categories related to disturbance implementation were not as influential on C stock and flux uncertainty as those related to biomass turnover, DOM parameters, and biomass increment. A detailed investigation of the two more influential categories did reveal that C stock or flux indicators are sensitive to different individual parameters within these categories. The decay of small woody debris pools, and the turnover of biomass components contributing to these pools, emerged as very influential on uncertainty estimates of fluxes. Both NPP and Rh were most sensitive to parameters simulating fine root turnover and the turnover of woody biomass contributing to small woody debris pools. Heterotrophic respiration was somewhat sensitive and NEP very sensitive to woody debris decay rates. Total ecosystem C stock was mainly sensitive to the base decay rate of the slowly decaying DOM C pools that represent humified organic matter in the soil organic layer and in the mineral soil. Total ecosystem C was also sensitive to fine root turnover, which was influential for both stocks and fluxes.

Sensitivity rankings for stocks were congruent with a similar analysis for the CBM-CFS3 that used a consistent $\pm 5\%$ variation in these same parameters at a set of ground plots with soil C measurements (Smyth et al. 2013). In addition, there are some similarities between our results and those of another national-scale assessment in Finland (Peltoniemi et al. 2006). The Finnish assessment looked at parameters influential on sinks and stocks for vegetation, soil, and the forest. Their soil pool is similar to our DOM pool and their growing stock and growth indexes variables approximate our biomass increment category. They concluded that soil parameters were most influential on stocks

uncertainty and that once soil parameters were fixed the transfer rate from live to dead vegetation and fine root biomass emerged as the important variables affecting uncertainty of stocks. We also concluded that biomass turnover and DOM parameters were very influential on C stock uncertainty and because we examined them in detail we were able to identify that the most important of these were the base decay rates of the slow turnover pools (in the mineral soil and soil organic layer), the proportion of C respired from the very fast (foliar litter and dead fine roots) and fast aboveground (small and fine woody debris) pools, and fine root turnover. The Finnish analysis concluded that soil initial state was the most important variable contributing to the average flux uncertainty and when this variable was fixed growing stock emerged as the most important variable contributing somewhere between 55% to 60% to the total variance of the average sink. Because it is universally understood that initial soil C stock values are critical to accurate soil C modelling, we treated this topic in a separate evaluation (Shaw et al. 2015) where it was concluded that it will be necessary to include variables, such as leading tree species, soil taxa, and mosses, that are typically absent in soil C models to improve their accuracy. The uncertainty contribution from the growing stock in the Finnish analysis is similar to our estimate of biomass increment accounting for 59% of uncertainty in NBP. For both stocks and fluxes the observed position of the estimate for default values below the median of the uncertainty simulations (32nd percentile for NBP and the 8th percentile for total ecosystem C) was mainly attributable to larger estimates of total C in the Slow Below Ground pool (mineral soil C) in the uncertainty simulations, the single largest ecosystem C pool, in addition to asymmetry in the probability distribution for many DOM C modelling parameters (Table S2). The larger estimates for mineral soil C may

also be attributed to important, but as yet universally unresolved, issues surrounding accuracy in initial soil C stocks.

Opportunities for reducing uncertainty and meta-uncertainty

Productivity

We applied a $\pm 50\%$ multiplier on net biomass increment independently to each of the 20 CBM-CFS3 data bases required to simulate all of Canada, which was meant to collectively quantify uncertainty in yield curves, forest inventory, and allometric equations. The assumption of independence, even if the same multiplier is applied nationally, was justified on the basis that these data bases typically represent provinces or territories (or portions therein), where administrative, ecological, and management differences exist. Error among jurisdiction is, in reality, likely to be independent because forest inventories, yield curves, and allometric equations are to a large degree derived from jurisdiction-specific data and models. A single broad multiplier was used because key error statistics needed for these factors are often not provided (Wayson et al. 2015; Magnussen and Negrete, 2015). However, the choice of this multiplier contributes significantly to meta-uncertainty. Smaller or larger multipliers would have resulted in narrower or wider confidence intervals, respectively. Further analysis is required to inform judgements around the true magnitude of this uncertainty. Forest inventories and yield curves vary in their vintage, and jurisdictions with updated data or rigorous and readily available error assessments should potentially have a lower error estimate. In the case of forest inventories, species misclassification and age determination are known to be the largest sources of uncertainty (Magnussen and Russo, 2012). Ultimately, estimates based on remote sensing of forest characteristics may be needed (e.g., Beaudoin et al.

2014; White et al. 2014). In the case of allometric equations, no alternatives to those currently used by the CBM-CFS3 (Li et al. 2003; Boudewyn et al. 2007) exist. The most recent efforts to create new tree level biomass equations in Canada are all still based on source data collected in the 1980s (Lambert et al. 2005; Ung et al. 2008). Above-ground biomass estimates can be evaluated by comparison against alternative methods, which experience in other countries shows can result in very different estimates of forest biomass regionally and nationally (Temesgen et al. 2015; Weiskittel et al. 2015). Evaluating below-ground biomass estimates is even more difficult because of the elusive nature of roots and few suitable data (Finer et al. 2011), with the result that the representation of belowground biomass in ecosystem models remains simplistic with little ability to develop or evaluate more sophisticated alternatives (Smyth et al. 2013). Recent work suggests that an improved functional classification of fine roots may provide a useful path forward (McCormack et al. 2015).

As with all models, the CBM-CFS3 does not account for all ecosystem processes (Kurz et al. 2013). This type of uncertainty contributes to model bias, which we could not assess in our analysis because only precision can be estimated when a single model is analyzed. However, uncertainty in productivity estimates may also be reduced through structural changes in the model to account for processes that are known to influence productivity but are not currently included in the model. Neither interannual variation in growing conditions nor trends resulting from global change factors (e.g., CO₂ fertilization, nitrogen deposition, and drought) are accounted for in estimated NPP, resulting in possible over- or underestimates of growth and mortality rates depending on

species and region (e.g., Hember et al. 2012; Girardin et al. 2016; Hember et al. 2016, 2017).

DOM C modelling parameters

Modelling DOM C, including soil, in forest ecosystems remains a significant challenge (Lehtonen and Heikkinen 2016). The CBM-CFS3 also does not account for all possible processes influencing soil and DOM C dynamics, and generates much less variable estimates of C stocks than observed in reality (Shaw et al. 2015). A parameter stratification that accounts for effects related to tree species and soil taxonomy may be a potentially useful approach (Shaw et al. 2008, 2015). Such parameters exist for the transfer of standing dead trees to coarse woody debris (Hilger et al. 2012), but are not yet implemented in a national-scale analysis. Decomposition rates simulated here are not sensitive to water stress although several potential modifiers have been tested, and a modified parameterization is available (Smyth et al. 2011). Also, all forests are simulated as upland stands; thus, the DOM dynamics of peatlands and other forested wetlands are not represented, and the NFCMARS does not account for shrubs, herbs, or moss productivity (Bona et al. 2013; Kurz et al. 2013). In some ecosystems, this can underestimate both total ecosystem productivity and litterfall transfers to DOM; therefore, the implication for NEP is less clear. An upland moss module for the CBM-CFS3 has recently been developed (Bona et al. 2016) and is currently being tested for future implementation. Finally, although measuring changes in soil C stock and stock change is difficult (Schrumpf et al. 2011), data-based approaches to improving DOM C modelling parameters have shown promise (e.g., Hararuk et al. 2014). Efforts to apply these methods to the CBM-CFS3 are ongoing.

Our assumption that all parameters used to model the replacement of biomass turnover and DOM C dynamics varied independently could result in a biased estimate of uncertainty if these parameters are actually correlated (Smith and Heath 2001, Smyth and Kurz, 2013). Model results are known to be sensitive to these parameters, but with varying influence depending on landscape characteristics such as species composition and simulation time horizon (White et al. 2008). Further data-based work (e.g., Hararuk et al. 2014) on examining potential correlations between model parameters is ongoing but is complicated by the multivariate nature of the problem (Magnussen et al. 2014). In an additional sensitivity analysis (results not shown), we assessed the contribution of individual components of NPP and Rh to their total variance. We found that it would be necessary need to assume positive correlations to obtain CIs approximating the results from the uncertainty simulations, whereas the parameters for the uncertainty analysis were drawn independently. The positive correlations inherent in the structure of models can cause the error in the size of a pool originating in an upstream pool to be transferred to a downstream pool regardless of the dependence between the parameters controlling input or output rates from those pools (Shaw et al. 2014). Estimated uncertainty could also have been influenced by the spatial stratification of model parameters, relative to how they vary in the real world. In the CBM-CFS3, default values for these parameters are typically constant across all spatial strata (Kurz et al. 2009) but are known to be influenced by factors that vary across these strata, including tree species and soil type (Shaw et al. 2008; Hilger et al. 2012; Shaw et al. 2014, 2015). In addition, the degree of agreement between model-predicted C stocks and C stock measured at ground plots of Canada's National Forest Inventory (NFI) varies greatly by species and modelling pool

(Shaw et al. 2014). Thus, our assumption of independence across spatial strata, even though the default parameter values and their uncertainties were the same across all strata, was likely justified because parameter errors are unlikely to be correlated across all of Canada due to variability related to tree species and soil type (Shaw et al. 2008; Hilger et al. 2012; Shaw et al. 2014, 2015).

Fire disturbance data and impacts

Fires exhibit selective behavior in many parts of Canada (Bernier et al. 2016, but see also Podur and Martell 2009), thus the procedure of randomly selecting stands for burning could be improved. While random selection of burned stands (u_i) makes only a small contribution to total uncertainty, it can disproportionately affect how scenario analyses are interpreted. In regions with significant fire disturbance, the effect of a scenario cannot always be distinguished from variation resulting from random selection of burned stands. Remote sensing data could be used to infer pre-disturbance characteristics, but equally plausible algorithms and data sources vary in the fire emission estimates produced (Anderson et al. 2015). A complete resolution requires spatially-explicit modelling, as implemented for a test region of Canada (Boisvenue et al. 2016). In addition, fire impacts were not varied in our analysis. The present procedure used to calibrate fire impacts using the Canadian Fire Effects Model (CanFIRE; de Groot et al. 2003) gives fuel consumption estimates that assume the same proportional impact for all types, reflecting average fire season weather conditions for a given year and region. A research version of the CBM-CFS3 implements the CanFIRE algorithms. Once operational, this would enable specific values of the Canadian Fire Weather Index to

estimate burn conditions and fuel consumption for every fire event, reducing uncertainty originating from static disturbance effects but with large incremental data requirements.

Finally, our error estimate for area burned was based on expert judgement. The NBAC is structured in a way that could allow error to formally be estimated. It is a compilation of burned areas (ranked in order from lowest to highest assumed uncertainty) from (1) fine-resolution spatial satellite mapping (Landsat-TM), (2) provincial and territorial government agency fire mapping, and (3) coarse-resolution satellite mapping (SPOT-VGT) with statistical calibration (Fraser et al. 2000). The final data product compiles data from the available source with the lowest uncertainty to generate a national geospatial burn area product with the best available information for every fire. However, each fire may have been mapped by up to three methods, and the difference in area estimated by different methods could be used to estimate an overall error. The expectation is that as more high-resolution satellite data are used in the compilation of the annual NBAC statistics, the uncertainty of area burned can be reduced. Analyses designed to provide formal error estimates for area burned statistics derived from the NBAC, including comparisons against alternative data sources that have recently become available (Guindon et al. 2013; Hermosilla et al. 2015), are ongoing.

Forest management data and impacts

Forest management activity data are obtained from NFDP statistics, which also represent the compilation of data from many jurisdictional sources and do not report errors. Therefore, our estimates of error for harvest targets also contained elements of judgement that could be refined by a more comprehensive analysis. Logical rules derived from wood supply analysis govern the selection of stands to be disturbed by harvesting,

but the translation of this to model instructions is an approximation because the precise identity and characteristics of harvested stands are not known. In addition, the NFDLP only reports provincial level data. Thus, harvest targets are assigned to provincial spatial units (either ecozones or forest management units) using rule-based approaches that contribute to uncertainty. As a result of this and other factors, the modelled harvest area resulting from a simulation of harvest as a C (derived from volume) target may not necessarily match the reported harvest area statistics from the NFDLP. Similar to the situation for wildfire, spatial data on the true distribution of harvest and associated pre-harvest stand characteristics are needed before this uncertainty can be reduced. New systems for obtaining these data should, as part of their design, include methods for calculating errors for their reported statistics. Work to develop the modelling and computing capacity to process new data on the spatial distribution of harvest (Guindon et al. 2013; Hermosilla et al. 2015) and to compare them to existing alternative approaches is ongoing. An additional point contributing to uncertainty in the representation of forest management is that not all silvicultural activities are explicitly modelled, and harvest is represented using generalized disturbance impacts that may not adequately account for all possible harvesting methods or silvicultural systems.

Insect disturbance data and impacts

Insect outbreaks in Canada are typically monitored using aerial sketch mapping onto large-scale base maps during fixed-wing aircraft surveys that can classify moderate and severe damage with relatively high accuracy (MacLean and MacKinnon, 1996). The extent of growth loss and mortality resulting from this disturbance varies. Successive years of damage are usually required to cause mortality, which varies by tree species,

insect species, and other factors. The translation of these observations into modelled disturbance effects, although based on the best available knowledge, may not be accurate. Insect disturbance data shifted from federal to jurisdictional responsibility after 1996 (Simpson and Coy, 1999) and since that time have only been consistently reported nationally as tabular data by Canada's NFD. A nationally consistent spatial insect damage data product would reduce some of these uncertainties. A number of ongoing initiatives aim to develop such a data product.

Interpreting and communicating uncertainty

Quantifications of uncertainty are interpreted as statements about the probability of a given model indicator being within stated ranges. Psychological research has repeatedly demonstrated the difficulty of reasoning correctly about probability-based statements because humans frequently make errors due to cognitive biases (Tversky and Kahneman, 1974). The most potentially pernicious of these is the overconfidence bias. This occurs when individuals, acting as experts, tend to exhibit more confidence in their statements or predictions than justified by the circumstances or evidence because societal rewards tend to accrue to the confident rather than to the accurate (Johnson and Fowler, 2011). Because there is not yet a consistently accepted method for calculating CIs for ecosystem models, it is likely that in any set of models (e.g., in an intercomparison study), some will underestimate uncertainty (alternatively, exhibit overconfidence in model results) compared with others, complicating the interpretation of such comparisons (Xiao et al. 2014). It can be advantageous in some circumstances to overstate certainty in models or model-based data products in a competitive marketplace, but it is societally disadvantageous if our goals are to use models to produce the best possible assessments

resulting in optimal policy choices (Johnson and Fowler 2011), and correct valuations of GHG emission reductions (Marland et al. 2014). It is possible to calibrate our judgement when information is provided for which accuracy can be assessed (Tenney et al. 2008), but our recent comprehensive evaluation of the CBM-CFS3 results using independent C stock measurements (Shaw et al. 2014) showed that few similarly comprehensive exercises have ever been conducted.

The IPCC states that the purpose of uncertainty estimates is to provide guidance on where best to invest resources to reduce uncertainty (IPCC 2000) because the overconfidence bias could cause estimates with wider CIs to be erroneously judged as less valid, when this is in fact not the case (Shvidenko et al. 2010). For example, when forest C balance estimates are included in total national GHG inventories they may reduce the precision of the inventories but increase their accuracy because the inventory is more complete (Monni et al. 2007). Unfortunately, it is easy to confuse a reduction in precision with an increase in uncertainty (Johnson and Fowler 2011), an interpretation that should be avoided because both precision and accuracy contribute to total uncertainty. Our initially stated assumption about meta-uncertainty ($u_{m1}, u_{m2}, u_{m3}, \dots, u_{mn} = 0$) is unlikely to be true. One or more values are certain to be greater than zero; thus, our CIs are probably too narrow (overconfident) rather than too wide. We believe this is a problem common in reported uncertainties for all ecosystem models, and possibly in other situations for which multiple models or data products are available for use, and there are no rational decision criteria for selecting among alternatives (Schofield et al. 2016). Consequently, care must be taken to ensure that uncertainty estimates are correctly

interpreted and carefully evaluated, particularly if reductions in uncertainty are incentivized (Stephens, 2011; Marland et al. 2014).

We attempted to vary as many uncertain model components as possible, but some were still held constant. Incomplete accounting of all sources of uncertainty is common, even in the simple situation of above-ground biomass change for an area with a well-designed forest inventory (Magnussen et al. 2014). For example, we did not vary the disturbance effects used to model harvest, insect, and fire impacts. Although we describe methods that could be used to improve the modelling of disturbance effects, and believe that implementing such improvements would reduce uncertainty, we cannot, on the basis of the results that we report here, estimate the magnitude of that reduction or whether the reductions would be reflected in greater accuracy or higher precision. We also did not vary the mean annual temperature by year, which in the model influences the climate response of DOM C decay but not the growth dynamics. Introducing this climate response would further increase uncertainties, given the ongoing debate about the magnitude, and at times direction, of ecosystem responses to environmental variation and trends (Kurz et al. 2013). Increasing the number of types of uncertain quantities allowed to vary may or may not affect the estimated CIs, depending on the degree to which the additional factors are additive to factors already considered. Some factors already assessed had compensating errors because the sum of total CIs from the scenarios in which factors vary individually is greater than when all varied together (Fig. 3). Allowing additional factors to vary would not likely result in narrower CIs, although the contribution of each additional factor to the total when all vary together would likely be less than its contribution assessed alone. Improved estimates of uncertainty (i.e., reduced

meta-uncertainty) will require better estimates of the error for individual model components as well as the interactions amongst those errors (Larocque et al. 2008).

5. Conclusions

We conducted an analysis to quantify the uncertainty of the C dynamics of Canada's managed forest estimated by Canada's NFCMARS (Kurz and Apps, 2006; Stinson et al. 2011). The sources of uncertainty considered were related to the parameters and algorithms of CBM-CFS3 (Kurz et al. 2009), the core ecosystem model of NFCMARS, as well as input data used by the system to determine forest characteristics and the amount and type of disturbance. Under the assumptions made, 95% CI widths averaged 32.2 Pg C (+16.6 and -15.6 Tg C or $\pm 15\%$, relative to the simulation median) for NBP and 16.2 Tg C yr⁻¹ (+8.3 and -7.9 Tg C yr⁻¹, relative to the overall simulation median of -0.8 Tg C yr⁻¹) for total ecosystem C stock. Improved understanding of continuous processes determining NPP and Rh, in addition to disturbance-related processes, and their interactions, are required to further reduce uncertainties in the estimates of current and future C balances of Canada's managed forest from the NFCMARS (Kurz et al. 2013). However, some these processes also vary in their intrinsic degree of predictability (Luo et al. 2015), meaning that some factors causing large contributions to uncertainty may prove difficult to reduce (e.g., fine root turnover and its spatial and temporal variation). Despite all these sources of uncertainty, models are useful for quantifying and ranking policy alternatives (Smyth et al. 2014, Xu et al. 2017), and their utility for such applications is increased when uncertainties are explicitly stated and quantified (GREGG and Chan 2014). They also continue to be required to meet obligations for GHG reporting under international climate conventions. An additional benefit of uncertainty quantification is

that it provides a basis against which investments in research and development activities related to C cycle science and models can be formally evaluated. These investments are often justified on the basis that they will reduce uncertainty (Bernier et al. 2013).

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Table 1. Summary of factors affecting uncertainty in the Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3), as implemented in Canada’s National Forest Carbon Monitoring, Accounting and Reporting System (NFCMARS), and how these are categorized into related uncertainty components for this uncertainty analysis. DOM stands for dead organic matter.

Component Name	Description	Additional Methodological Detail
Random stand selection (u_1)	The random seed value for sorting records prior to selecting stands for disturbance was allowed to vary for each simulation.	Material and methods describe uncertainty resulting from the model algorithms used to select stands for disturbance.
DOM C stock initialization (u_2)	Fire return intervals during model initialization were varied randomly.	Material and methods describes uncertainty arising from the initialization of DOM C stocks. Supplement Table S4 gives probability distribution for each ecozone used to model fire return intervals during initialization.
Disturbance targets (u_3)	Multipliers were applied to the targets used to simulate forest management activities and natural disturbances. These varied by disturbance type: wildfire ($\pm 10\%$), insects ($\pm 25\%$), and harvest (varies by jurisdiction).	Material and methods describe uncertainty in areas disturbed. Supplement Table S1 gives harvest uncertainty ranges for each jurisdiction.
Biomass increment (u_4)	A multiplier with a range of $\pm 50\%$ was applied to net biomass increment. This was assumed to simulate uncertainty due to forest inventory, yield curves, and allometric equations used to estimate above- and below-ground biomass.	Material and methods describe uncertainty in forest inventory, yield curves, and allometric equations.
Biomass turnover DOM C modelling parameters (u_5)	Parameters used to simulate biomass turnover and DOM C dynamics were varied. Parameter ranges were derived from a combination of literature review and expert judgement.	Material and methods describe uncertainty in biomass turnover and DOM C modelling parameters in general. Table S2 shows the probability distribution for each of 32 parameters varied in the analysis and how these were derived. Table S3 describes the CBM-CFS3 pools structure (more information can be found in Kurz et al. (2009) and Shaw et al. (2014)).

Table 2. Average carbon stocks (1990–2014) by pool (Pg) from the Monte Carlo simulations (97.5th, 50th, and 2.5th percentiles) and for default parameter values. The default percentile is the percentile at which the default value lies in the Monte Carlo simulations and the difference between the default estimate and the simulation median is shown as a percentage relative to the default value, and in absolute (Pg C) terms. Pool definitions can be found in the supplement (Table S3) and Kurz *et al.* (2009). HW stands for hardwood and SW stands for softwood.

Pool	97.5th	50th	2.5th	Default	Default Percentile (%)	Relative Difference (%)	Absolute Difference (Pg C)
Very Fast Above Ground	2.1	1.8	1.6	1.9	53	1	0
Very Fast Below Ground	0.7	0.5	0.4	0.4	0	-37	-0.1
Fast Above Ground	6	3.6	2.6	2.5	1	-42	-1.1
Fast Below Ground	0.5	0.4	0.3	0.4	89	19	0.1
Medium	4.1	2.4	1.7	2.8	73	14	0.4
Slow Above Ground	9.8	8	6.5	7.3	20	-9	-0.7
Slow Below Ground	29.6	24.4	19.8	19.5	1	-25	-5.0
SW Stem Snag	0.6	0.5	0.4	1	100	48	0.5
SW Branch Snag	0.3	0.2	0.2	0.3	83	11	0
HW Stem Snag	0.2	0.1	0.1	0.3	100	49	0.1
HW Branch Snag	0.1	0.1	0.1	0.1	78	10	0
SW Merchantable	5.7	4.9	4.2	4.9	50	0	0
SW Foliage	1	0.9	0.8	0.9	52	0	0
SW Other	3.7	3.2	2.7	3.2	55	1	0
SW Coarse Roots	2	1.7	1.5	1.7	51	0	0
SW Fine Roots	0.3	0.3	0.2	0.3	64	1	0
HW Merchantable	1.8	1.5	1.3	1.5	49	0	0
HW Foliage	0.1	0.1	0.1	0.1	47	0	0
HW Other	1	0.9	0.8	0.9	53	1	0
HW Coarse Roots	0.8	0.7	0.6	0.7	54	1	0
HW Fine Roots	0.1	0.1	0.1	0.1	65	0	0
Grand Total	65	56.7	48.8	50.8	8	-12	-5.9

Table 3. Average values (1990–2014) for ecosystem carbon flux components in the simulations (97.5th, 50th, and 2.5th percentiles) and for default parameter values, as well as the percentile at which the default value lies in the simulations and the difference between the simulation median and the default estimate, in both relative (%) and absolute (Tg C yr⁻¹) terms

Carbon Flux Component	97.5th	50th	2.5th	Default	Default Percentile (%)	Relative Difference (%)	Absolute Difference (Tg C yr ⁻¹)
Net Primary Production (NPP)	941	845	750	812	27	4	33
Litterfall	796	714	628	682	24	5	32
Net Growth	145	128	114	130	55	-1	-1
Heterotrophic Respiration (Rh)	853	764	686	742	29	3	22
Net Ecosystem Production (NEP)	95	76	59	70	23	9	6
Disturbance Releases	88	77	70	75	32	2	2
Net Biome Production	15	-1	-17	-5	32	n/a ¹	4
Disturbance Transfers	108	95	84	94	39	1	1

¹Relative difference not meaningful for Net Biome Production because it may be either above or below zero

Fig. 1. Managed forests of Canada cover $2.3 \times 10^6 \text{ km}^2$ in the $4.4 \times 10^6 \text{ km}^2$ geographic area that contains all Canadian forests. For reporting purposes, the managed forest is subdivided into ecozones (black lines, coloured). These are further subdivided into spatial analysis units (thin grey lines) for modelling, which are implemented as 20 CBM-CFS3 projects in the NFCMARS. Provincial and territorial boundaries are shown with thick grey lines, and the unmanaged forest is shown in light green. Only very small portions of the Hudson Plains, Taiga Shield East, and Taiga Shield West are in the managed forest.

Fig. 2. Uncertainty estimates for (a) Total ecosystem C stock and (c) net biome production in Canada's managed forest (1990–2014). The lines in (a) and (c) represent the 2.5th, 50th, and 97.5th percentiles of 1,000 bootstrapped national totals, and the filled circles represent the result obtained using default parameter values. The width of the annual 95% CI (97.5th–2.5th percentile) is also plotted for (b) total ecosystem C and (d) net biome production.

Fig. 3. Mean width of the 95% confidence interval for total ecosystem carbon stock and net biome production in Canada's managed forest for five categories of uncertainty, when only one category of uncertain values is varied at a time (Table 1), relative to the mean width when all uncertain factors vary together. The bar labelled model parameters refers to biomass turnover and DOM C modelling parameters.

Fig. 4. Sensitivity of total ecosystem C stock to variation in parameters controlling (a) base decay rates, (b) proportion of C respired, and (c) turnover when each parameter is varied one at a time. The bars represent the mean annual width of the 95% confidence interval over the simulation period when each parameter varies, scaled relative to the mean width when all parameters vary simultaneously.

Fig. 5. Sensitivity of (a), (b), and (c) net primary production, (d), (e), and (f) heterotrophic respiration, and (g), (h), and (i) net ecosystem production to variation in parameters controlling (a), (d), and (g) base decay rates, (b), (e), and (h) proportion of C respired, and (c), (f), and (i) turnover when each parameter is varied one at a time. The bars represent the mean annual width of the 95% confidence interval over the simulation period when each parameter varies, scaled relative to the mean width when all parameters vary simultaneously.

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Fig. 1. Managed forests of Canada cover $2.3 \times 10^6 \text{ km}^2$ in the $4.4 \times 10^6 \text{ km}^2$ geographic area that contains all Canadian forests. For reporting purposes, the managed forest is subdivided into ecozones (black lines, coloured). These are further subdivided into spatial analysis units (thin grey lines) for modelling, which are implemented as 20 CBM-CFS3 projects in the NFCMARS. Provincial and territorial boundaries are shown with thick grey lines, and the unmanaged forest is shown in light green. Only very small portions of the Hudson Plains, Taiga Shield East, and Taiga Shield West are in the managed forest.

215x166mm (300 x 300 DPI)

Fig. 2. Uncertainty estimates for (a) Total ecosystem C stock and (c) net biome production in Canada’s managed forest (1990–2014). The lines in (a) and (c) represent the 2.5th, 50th, and 97.5th percentiles of 1,000 bootstrapped national totals, and the filled circles represent the result obtained using default parameter values. The width of the annual 95% CI (97.5th–2.5th percentile) is also plotted for (b) total ecosystem C and (d) net biome production.

141x97mm (300 x 300 DPI)

Fig. 3. Mean width of the 95% confidence interval for total ecosystem carbon stock and net biome production in Canada's managed forest for five categories of uncertainty, when only one category of uncertain values is varied at a time (Table 1), relative to the mean width when all uncertain factors vary together. The bar labelled model parameters refers to biomass turnover and DOM C modelling parameters.

142x135mm (300 x 300 DPI)

Fig. 4. Sensitivity of total ecosystem C stock to variation in parameters controlling (a) base decay rates, (b) proportion of C respired, and (c) turnover when each parameter is varied one at a time. The bars represent the mean annual width of the 95% confidence interval over the simulation period when each parameter varies, scaled relative to the mean width when all parameters vary simultaneously.

142x120mm (300 x 300 DPI)

Fig. 5. Sensitivity of (a), (b), and (c) net primary production, (d), (e), and (f) heterotrophic respiration, and (g), (h), and (i) net ecosystem production to variation in parameters controlling (a), (d), and (g) base decay rates, (b), (e), and (h) proportion of C respired, and (c), (f), and (i) turnover when each parameter is varied one at a time. The bars represent the mean annual width of the 95% confidence interval over the simulation period when each parameter varies, scaled relative to the mean width when all parameters vary simultaneously.

206x250mm (300 x 300 DPI)

Uncertainty in inventory-based estimates of the carbon dynamics of Canada's managed forest (1990-2014): Supporting Material—Methods and Results

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In this supplement, we describe further detail on methods and assumptions used to estimate the contribution of various sources of uncertainty to total estimated uncertainty in the CBM-CFS3 (Kurz et al. 2009), as implemented in Canada's National Forest Carbon Monitoring Accounting and Reporting System (NFCMARS; Kurz and Apps 2006; Stinson et al. 2011). We also provide some additional details for results on transfers of carbon to harvested wood products (Figure S1).

S1 Additional details on sources of uncertainty

S1.1 Input data - Forest harvesting

Canada's National Forestry Database Program (NFD, <http://nfdp.ccfm.org/>) also compiles net merchantable roundwood volume and area harvested statistics by jurisdiction. These data are translated to annual targets of C mass to be harvested in each jurisdiction; further details can be found in Stinson *et al.* (2011). Briefly, merchantable C targets are estimated from harvest volume statistics using:

$$M = VGPB, \quad (1)$$

where M is mass of merchantable tree bole C to be harvested; V is the reported volume harvested; G is the density of the biomass to be harvested; P is the proportion of biomass that is C; and B is a bark adjustment factor, necessary because NFD data report wood volume (inside bark) whereas the CBM-CFS3 merchantable biomass C pool from which C is harvested includes both wood and bark of the merchantable portion of the tree bole. For this analysis, we first estimated error in each component of Eqn. (1). Error estimates for wood density (G) by province and species were obtained from Gonzales (1990) and combined to give a species composition-weighted average for each jurisdiction. Error in the bark adjustment factor (B) was assumed to be proportional to error in density. The proportion (P) of dry weight biomass was assumed to be C and was held constant at 50%, whereas this value is known to vary (Lamlom and Savidge 2003; Thomas and Martin 2012). We know of no formal published error assessment for the NFD harvest statistics but assume that they were relatively accurate and so used an error of $\pm 1\%$ in the calculation. We combined errors in each component of Eqn. (1) to an overall error estimate for the mass of merchantable C to be harvested (M) using standard error propagation arithmetic. We used minimum and maximum bounds that approximate the 95% limits of a normal distribution with a triangular distribution centered on one to simulate error in harvest targets (Table S1). Ranges vary by jurisdiction because of the variation in species composition and wood density estimates for different species.

S1.2 Biomass turnover and DOM C modelling parameters

Parameters used to model the replacement of biomass turnover and dead organic matter (DOM) C dynamics contribute to uncertainty, with varying influence depending on landscape characteristics such as species composition and simulation time horizon (White et al. 2008). Parameter ranges were obtained for 32 biomass turnover and DOM C modelling parameters from a comprehensive literature review and used as minimum and maximum values of a triangular distribution, with the mode set to the CBM-CFS3 default value, in the Monte Carlo simulations. Further details and literature references are in Table S2. Parameter values were varied independently, because the correlation structure could not be reasonably estimated.

S1.3 Disturbance effect on DOM C initialization

DOM C pools in the CBM-CFS3 are initialized by simulating repeated iterations of growth followed by stand-replacing disturbance until the difference between the sum of the slow DOM C pools in successive iterations is less than 1%. The default assumption for the historical disturbance regime is stand-replacing fire on a constant return interval ranging from 75 to 300 years by terrestrial ecozone (Kurz et al. 2009). However, historical average disturbance rates are highly uncertain because of interannual variability in area burned (Armstrong 1999). We assessed this source of uncertainty by using random disturbance intervals during initialization. Parameters for the return interval probability distributions for each ecozone are in Table S3.

Table S1. Uncertainty multiplier ranges by jurisdiction applied to harvest carbon targets. Minimum and maximum values were used in a triangular distribution (with mode = 1) to vary the harvest carbon target for each simulation

Jursidiction	Mean Wood Density (<i>G</i> (SD))	Bark Fraction (<i>B</i> (SD)) ¹	Carbon proportion (<i>C</i>) ²	Volume (<i>V</i>) ³	Minimum Multiplier ⁴	Maximum Multipliers ⁴
Alberta	433.9 (15.3)	1.17 (0.04)	0.5	—	0.90	1.10
British Columbia	432.7 (12.9)	1.15 (0.03)	0.5	—	0.92	1.08
Newfoundland	432.8 (19.8)	1.2 (0.06)	0.5	—	0.96	1.04
Manitoba	472.8 (11.4)	1.15 (0.03)	0.5	—	0.86	1.14
New Brunswick	408.5 (6.4)	1.15 (0.02)	0.5	—	0.92	1.08
NWT	487.1 (16.4)	1.15 (0.04)	0.5	—	0.74	1.26
Nova Scotia	424.4 (45)	1.14 (0.12)	0.5	—	0.88	1.12
Ontario	459.5 (12.5)	1.15 (0.03)	0.5	—	0.92	1.08
PEI	541.9 (23.2)	1.15 (0.05)	0.5	—	0.88	1.12
Quebec	444.5 (22.4)	1.14 (0.06)	0.5	—	0.86	1.14
Saskatchewan	433.8 (13.3)	1.19 (0.04)	0.5	—	0.92	1.08
Yukon	427.7 (24.5)	1.13 (0.06)	0.5	—	0.84	1.16

¹ Standard Devation (SD) or bark fraction assumed proportional to SD for wood density

² no error for carbon proportion

³ Value varies annually, as reported in the statistics. Assumed an error of ±1% of the reported value

⁴ Annual coefficient of variation was multiplied by two to approximate a normal distribution with a triangular distribution

Table S2. Parameter ranges used to simulate uncertainty in biomass turnover and DOM C modelling parameters

	Default	Minimum	Maximum	References and Notes
<i>Base Decay rates</i>				
Very Fast Above Ground	0.355	0.284	0.426	White <i>et al.</i> (2008)
Very Fast Below Ground	0.5	0.16	0.56	Harmon <i>et al.</i> (2009); Hobbie <i>et al.</i> (2010)
Fast Above Ground	0.1435	0.01	0.27	30 measured values (Erickson <i>et al.</i> 1985; Edmonds <i>et al.</i> 1986; Edmonds, 1987; Taylor <i>et al.</i> 1991; Tarasov and Birdsey, 2001)
Fast Below Ground	0.1435	0.045	0.41	Silver and Miya (2001); Melin <i>et al.</i> (2009)
Medium	0.0374	0.007	0.11	99 measured values (Lambert <i>et al.</i> 1980; Erickson <i>et al.</i> 1985; Harmon <i>et al.</i> 1986; Krankina and Harmon, 1995; Alban and Pastor, 1993; Wei and Kimmins 1997; Bond-Lamberty <i>et al.</i> 2002; Yatskov <i>et al.</i> 2003; Laiho and Prescott, 2004; Janisch <i>et al.</i> 2005; Boulaner and Sirois, 2006; Brais <i>et al.</i> 2006; Gough <i>et al.</i> 2007)
Slow Above Ground	0.015	0.002	0.03	White <i>et al.</i> 2008; Smyth <i>et al.</i> 2010); Smyth and Kurz, 2013
Slow Below Ground	0.0033	0.0017	0.0049	White <i>et al.</i> 2008; Smyth and Kurz, 2013. , With range re-centered on default;
Softwood Snag Stem	0.0187	0.005	0.078	70% of medium pool range, based on average difference between snag and log decay rates; Yatskov <i>et al.</i> (2003)
Softwood Snag Branches	0.07175	0.036	0.11	±50%
Hardwood Snag Stem	0.0187	0.005	0.078	70% of medium pool range, based on average difference between snag and log decay rates; Yatskov <i>et al.</i> (2003)
Hardwood Snag Branches	0.07175	0.036	0.11	±50%
<i>Proportion C respired</i>				
Very Fast Above Ground	0.815	0.72	0.888	Smyth <i>et al.</i> (2010)
Very Fast Below Ground	0.83	0.445	0.999	Currie <i>at al.</i> (2010)
Fast Above Ground	0.83	0.65	0.999	Smyth <i>et al.</i> (2010)
Fast Below Ground	0.83	0.7	0.9	White <i>et al.</i> (2008)
Medium	0.83	0.7	0.9	White <i>et al.</i> (2008)

<i>Turnover and Litterfall</i>				
Softwood Foliage	0.05 to 0.15	Varies by ecozone	Varies by ecozone	$\pm 50\%$; Kurz <i>et al.</i> (2009) for ecozone default values
Hardwood Foliage	0.95	0.855	0.999	$\pm 10\%$; used a lower range than softwood because most hardwood foliage turns over annually
Merchantable Stemwood	0.0045 to 0.0067	Varies by ecozone	Varies by ecozone	$\pm 50\%$; Kurz <i>et al.</i> (2009) for ecozone default values
Softwood Other	0.03 to 0.04	0.012	0.1	White <i>et al.</i> (2008); Bernier <i>et al.</i> (2007); values 25% lower in the Taiga Shield and Taiga Plains
Hardwood Other	0.03 to 0.04	0.012	0.1	White <i>et al.</i> (2008); Bernier <i>et al.</i> (2007); values 25% lower in the Taiga Shield and Taiga Plains
Coarse Roots	0.02	0.01	0.03	$\pm 50\%$; Li <i>et al.</i> (2003); Gill and Jackson (2000)
Fine Roots	0.641	0.32	0.96	$\pm 50\%$; Li <i>et al.</i> (2003); Gill and Jackson (2000)
Softwood Snag to DOM	0.032	0.008	0.2	71 measured values, Hilger <i>et al.</i> (2012)
Hardwood Snag to DOM	0.032	0.008	0.2	71 measured values, Hilger <i>et al.</i> (2012)
Softwood Branch Snag to DOM	0.1	0.074	0.31	6 measured values, Hilger <i>et al.</i> (2012)
Hardwood Branch Snag to DOM	0.1	0.074	0.31	6 measured values, Hilger <i>et al.</i> (2012)
Other to Branch Snag	0.25	0.125	0.375	$\pm 50\%$

Table S3. Ecosystem carbon pools represented by the Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3) and a brief description of the biomass, dead organic matter (DOM), or soil C contained in these pools. HW refers to hardwood, and SW to softwood.

CBM-CFS3 pool	Description
Merchantable Biomass (HW and SW)	Live stemwood of merchantable size trees ¹ , including bark
Other Biomass (HW and SW)	Live branches, stumps and tops of merchantable size trees, and non-merchantable trees, including bark
Foliage Biomass (HW and SW)	Live foliage
Fine Root Biomass	Live roots, <5mm in diameter
Coarse Root Biomass	Live roots, ≥5mm in diameter
Stem Snag (HW and SW)	Dead standing stemwood of merchantable size trees, including bark
Other Snag (HW and SW)	Dead standing branches, dead tops and stumps of merchantable size trees, and dead non-merchantable size trees, including bark
Very Fast Above Ground	The L horizon ² , consisting of foliar litter and dead fine roots <5 mm in diameter
Very Fast Below Ground	Dead fine roots in the mineral soil, <5 mm in diameter
Fast Above Ground	Fine and small woody debris and dead coarse roots in the forest floor, approximately ≥5 and ≤75 mm diameter
Fast Below Ground	Dead coarse roots in the mineral soil, ≥5 mm in diameter
Medium	Coarse woody debris on the ground
Slow Above Ground	The F, H, and O horizons ²
Slow Below Ground	Humified organic matter in the mineral soil

¹ Definition of merchantable sized trees varies by province (Kurz et al. 2009)

² Soil Classification Working Group (1998)

Table S4 Parameters of the gamma distribution¹ (*a* and *b*) used to model random fire return intervals during model initialization, by ecozone

Ecozone	Average Return Interval (years)	Parameter <i>a</i>	Parameter <i>b</i>
Taiga Plains	125	0.5833	0.6283
Taiga Shield West	100	0.5078	0.6254
Boreal Shield West	75	0.4753	0.9512
Atlantic Maritime	125	0.1689	0.6991
Mixedwood Plains	125	0.1689	0.6991
Boreal Plains	125	0.3393	0.8039
Subhumid Prairies	75	0.5372	0.3521
Taiga Cordillera	83	0.8321	0.2180
Boreal Cordillera	175	0.4185	0.6426
Pacific Maritime	300	0.2936	0.4007
Montane Cordillera	150	0.2589	0.6115
Hudson Plains	75	0.7331	0.2247
Taiga Shield East	100	0.5078	0.6254
Boreal Shield East	125	0.4753	0.9512
Semiarid Prairies	75	0.5372	0.3521

¹ $f(x;a,b)=\frac{b^a}{\Gamma(a)}x^{a-1}e^{-bx}$

Fig. S1 Median and 95% CI (2.5th and 97.5th percentiles) of annual transfers to harvested wood products in the Monte Carlo simulations relative to the default simulation.

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