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Environmental Science & Policy 3 (2000) 73–82

Environmental Science & Policy

www.elsevier.com/locate/envsci

An assessment of uncertainty in forest carbon budget projections

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Abstract

Estimates of uncertainty are presented for projections of forest carbon inventory and average annual net carbon flux on private timberland in the US using the model FORCARB. Uncertainty in carbon inventory was approximately ±9% (2000 million metric tons) of the estimated median in the year 2000, rising to 11% (2800 million metric tons) in projection year 2040, with this range covering 95% of the distribution. Relative uncertainties about net flux were higher and more variable than relative uncertainty estimates of carbon inventory. Results indicated that relatively high correlations among projected carbon budgets for the regional forest types led to greater total uncertainty than under assumptions of independence among types, indicating that an accurate portrayal of correlations is important. Uncertainty in soil carbon, closely followed by uncertainty in tree carbon, were most influential in estimating uncertainty in carbon inventory, but uncertainties in projections of volume growth and volume removals were most important in estimating uncertainty in carbon flux. This implies the most effective ways of reducing uncertainty in carbon flux are different from those required to reduce uncertainties in carbon inventory. Analyses as presented here are necessary prerequisites to identify and reduce uncertainty in a systematic and iterative way. Published by Elsevier Science Ltd.

Keywords: Forest carbon model; FORCARB; United States; Uncertainty analysis; Carbon sequestration

1. Introduction

Issues of climate change are increasingly prompting nations to focus on accounting for and managing greenhouse gas emissions. Most strategies for limiting greenhouse gas emissions involve relatively expensive options, principally through reductions in energy consumption. Forests may offer a lower-cost way to remove atmospheric carbon dioxide (an important greenhouse gas) and sequester carbon — thus reducing net carbon dioxide emissions (US Environmental Protection Agency, 1995). Carbon assimilated by forests can be accumulated in forest ecosystems, used as a renewable energy source, or further stored as wood products (Birdsey and Heath, 1995; Heath et al., 1996).

Uncertainties associated with characterizing causes and effects of climate change, coupled with the possibly high opportunity costs of early response can make it difficult for decisionmakers to commit to actions (Morgan and Henrion, 1990; Smith et al., 1993). Appropriate descriptions of uncertainty are necessary to provide information for policy decisions pertaining to effects of forests on net carbon dioxide emissions at the national level. All estimates of current and future carbon sequestration by forests feature some amount of uncertainty. This holds true even when uncertainty is not explicitly mentioned in an assessment. Actual uncertainty depends partly on methods used to form estimates as well as scenarios for climate, management, and mitigation options. Sources of uncertainties include error in sampling inventories, estimating volumes at regional scales, identifying appropriate carbon pools, and limitations in understanding processes

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1462-9011/00/$ - see front matter Published by Elsevier Science Ltd.
PII: S1462-9011(00)00075-7

controlling pool sizes and fluxes (Birdsey and Heath, 1995). Identifying elements of the system that contribute most to overall uncertainties may help identify the value of alternate priorities for management and research. Limited resources can be used efficiently if research is directed toward those components that will have the greatest effect in reducing overall uncertainty. This study focuses on developing quantitative estimates of uncertainty using an uncertainty analysis approach (Brown and Adger, 1994; Morgan and Dowlatabadi, 1996; Peck and Teisberg, 1996) to project carbon budgets within forest ecosystems (Birdsey and Heath, 1995). We present uncertainty estimates of forest carbon inventory and flux on private timberland in the US and identify the components that contribute most to total uncertainty.

2. Modeling forest carbon budgets

Several studies have presented estimates of carbon in US forests (Plantinga and Birdsey, 1993; Birdsey and Heath, 1995; Turner et al., 1995); however, none have dealt with quantifying uncertainties of the estimates. Here, we apply an uncertainty analysis to the model FORCARB (Plantinga and Birdsey, 1993; Heath and Birdsey, 1993a; Heath and Smith, 2000), which projects carbon budgets for privately owned forests of the US. This version includes approximately 70% of productive US forests. The model is linked to the TAMM/NAPAP/ATLAS modeling system (Adams and Haynes, 1980; Ince, 1994; Mills and Kincaid, 1992; Alig et al., 1990), which provides estimates and projections of forest volumes and areas. Collectively, the models produce forest volume inventory projections at 10-year intervals. These projections of forest volumes are used by FORCARB to estimate four major carbon pools: soil carbon, forest floor carbon, carbon in understory vegetation, and carbon in living tree biomass (Heath and Birdsey, 1993a).

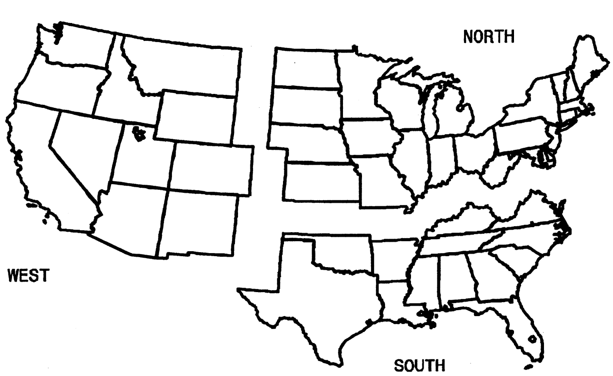

Fig. 1. Regions of the 48 contiguous states used for subtotals of carbon budget projections.

We apply uncertainty analysis to essentially the same data as previous assessments of private timberlands (Birdsey and Heath, 1995), yet updates in the model and the uncertainty analysis produce slight differences in median estimates of carbon. Our results are summarized by region (Fig. 1). The assumptions underlying the timber projection are described in Haynes et al. (1995). Although net flux of carbon in wood products and landfills are significant factors in carbon sequestration in the forest sector (Heath and Birdsey, 1993b; Heath et al., 1996), they are excluded from this study; we estimate median values plus uncertainties for forest ecosystems only.

2.1. Uncertainty and the simulation model

The term ‘uncertainty’ is used to describe phenomena such as statistical variability, lack of knowledge, or surprise (Morgan and Henrion, 1990; Hattis and Burmaster, 1994; Hoffman and Hammonds, 1994; Vose, 1996; Cullen and Frey, 1999). We adopt the simple definition that uncertainty is a lack of confidence in a single value. We represent uncertainty about a model variable as a range of potential values in the form of a probability density function (pdf). A consequence of explicit representation of uncertainty in model formulation is that results are probability densities, which reflect these uncertainties.

We used a Monte Carlo simulation, with Latin Hypercube sampling (Iman and Shortencarier, 1984; Morgan and Henrion, 1990; Vose, 1996; Cullen and Frey, 1999), to estimate uncertainties in projections of forest carbon. A Monte Carlo simulation is produced by choosing one value from each input probability distribution for each of a large number of iterations to successively form distributions of model results. Latin Hypercube sampling is simply a stratified sampling procedure in which distributions are sampled from equally probable intervals, without replacement. Siegel et al. (1995) and van der Voet and Mohren (1994) have used Latin Hypercube sampling in Monte Carlo simulations of process-based tree growth models. Uncertainty analysis involves identifying effects of uncertainties about inputs or model variables on overall model uncertainty. The relative influences of each uncertain value in a model can be identified by the correlation between the Latin Hypercube sampling and the probability density distribution of model results. Correlation coefficients are then used to identify a percentage influence of each part on the total (Conover, 1980; Morgan and Henrion, 1990; Vose, 1996).

Separate simulations were produced for different forest types, which were characterized by composition, ownership, region, and productivity. A total of 216 such forest types were included in these analyses. Input variables with uncertain values were conveniently classified in two groups: forest projections and carbon pool estimates. First, uncertainty in five variables contributed to projected forest volumes that were the starting point for FORCARB simulations. Uncertainty in initial forest volume inventory was successively modified for each 10-year period by summing uncertainty in volume changes due to growth, removals, thinning, and land area change. Second, estimates of the four major carbon pools in FORCARB — trees, understory, floor, and soil — were each based on two or more relationships parameterized for a given forest type. Estimates of carbon pools were summed to a total carbon inventory for each forest type; these were then summed for regional totals (Birdsey and Heath, 1995). Average annual carbon flux was calculated by dividing the difference between two inventory distributions by the intervening number of years (that is, 10 in this study).

Simulations were based largely on previous deterministic analyses (Birdsey and Heath, 1995) and followed uncertainty analysis procedures developed for FORCARB. Additional details of the methods, applied to only one forest type including an analysis of sensitivity to pdf definitions, can be found in Smith and Heath (2000b). A discussion of interpretation of probabilistic estimates of uncertainty is featured in Smith and Heath (2000a). Carbon budget totals for the 216 forest types were based on summing pdfs in the Monte Carlo simulation (Smith and Heath, 2000a). This method explicitly accounted for any covariability input or developed in the model. Uncertainties about values of model variables were defined as modified two-parameter Beta distributions; both parameters were set equal to three and then the pdf was scaled to fit the appropriate variable and definition of uncertainty (Vose, 1996). Definitions of uncertainty used in these simulations are given in Table 1. Each Beta pdf was scaled so that the central 95% of the distribution spanned the range specified in Table 1. Uncertainty was summarized for model variables and results by expressing the range of the 2.5th–97.5th percentiles as plus or minus a percentage of the median.

Values for FORCARB parameter uncertainties (that is, the first four variables listed in Table 1) were adapted from preliminary uncertainty analyses (unpublished) and collectively produced a total carbon inventory uncertainty of slightly more than ±10% for most forest types for 2000. That is, the net effect of these four variables was that 95% of the resulting carbon inventory pdf was within ±10% of the median. Uncertainty generally ranged between 8 and 15%. USDA Forest Service estimates of sampling error for volume inventory are 5% per billion cubic feet for a 67% confidence interval (Hansen et al., 1992). Because uncertainty about forest type inventories are likely to covary, and most forest volumes exceed one billion cubic feet (Powell et al., 1993), we set a smaller value for initial uncertainty: 5% for the 95% confidence interval (that is, the fifth variable in Table 1). Uncertainties about volume changes for each 10-year interval (that is, the last four variables in Table 1) were not well-defined. Therefore, uncertainties about volume growth, removal, thinning, and that associated with area change were set to ±10%, a level comparable to the net effect of the FORCARB parameters.

The use of Beta distributions was consistent with the limited quantitative definitions of uncertainty — they produced a continuous symmetrical pdf with a slightly weaker central tendency than previous definitions of normal pdfs (Smith and Heath, 2000a). Adopting a better-defined central tendency would imply that we have more information about the variable than is available. No other significance is attached to the choice of Beta pdfs. Any other pdf would have worked as well from a strictly modeling standpoint. We applied the same uncertainty percentages across all for-

Table 1
Uncertainty defined for model parameters and projections of forest structure. Uncertainty about the precise value of a model variable was defined as a probability density function. The percentage of the median specified for each variable bounded the central 95% of the respective probability distribution

Model variable	Uncertainty as percentage of median
Tree volume to carbon conversion factor	±15%
Understory carbon per unit area	±25% for youngest stands, linearly adjusted to ±10% at 50 years, and constant at the 50-year value above 50
Forest floor carbon per unit area	±50% of value for youngest stands
Soil carbon per unit area	±15% for youngest stands, linearly adjusted to ±25% at age 15 years, linearly adjusted to ±10% at 50 years, and constant at the 50-year value above 50
Initial volume inventory	±5%
Volume growth over time interval	±10%
Volume removals over time interval	±10%
Volume thinning over time interval	±10%
Volume change from area change over time interval	±10%

est types for this analysis, and each Monte Carlo simulation included 200 iterations.

3. Results and discussion

3.1. Uncertainty in projected carbon budgets

Uncertainty in projections of carbon inventory for the years 2000, 2020, and 2040 are presented in Fig. 2 as pdfs. The distributions express the probability of values for carbon inventory based on the assumptions and uncertainties that went into the simulation. Clearly, the amount of uncertainty is large relative to the increase in carbon inventory over this period. Here, we summarize uncertainty as the lower and upper bounds of the central 95% of the pdf (Table 2). These 2.5 and 97.5 percentiles convey an absolute range but can provide essentially the same information as percent-error or variance measures (Smith and Heath, 2000a). Resulting sums are normally distributed, as expected from summing many pdfs.

Summary values for regional and national totals are presented for carbon inventory and average annual net flux for 10-year periods through 2040 in Table 2. A positive flux represents a net gain in forest carbon inventory. Median values correspond closely to previously published carbon budgets based on these data and the same modeling system (Birdsey and Heath, 1995). Uncertainty about carbon inventory and flux increased with time in each region as well as for the national total. Projections of growth and harvests made by forest sector models are generally sensitive to the time-span of the projection. As definitions for growth and harvest uncertainties are refined, projections of uncertainty may show greater sensitivity to time as well.

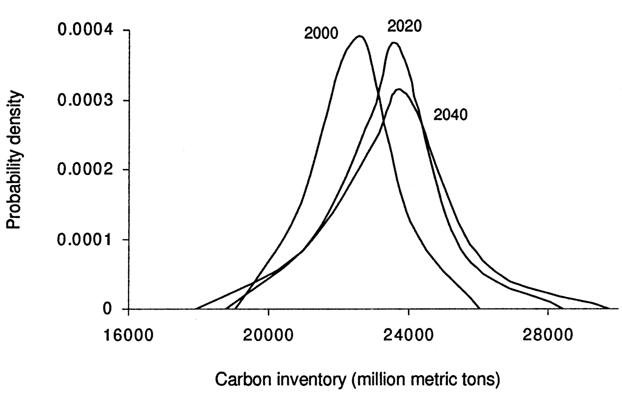

Fig. 2. Probability density functions representing uncertainty in projections of total carbon inventory for projection years 2000, 2020, and 2040. Note that the areas under the probability densities sum to one.

Relative uncertainty was lower and less variable in estimates of carbon inventory as compared with average annual net flux. These were generally between 5 and 6% for carbon inventory while relative uncertainty for average annual net flux was usually more than three-fold larger. This was partly related to the decrease in expected values of carbon flux throughout the period of the simulation. Estimates for the North contained greater absolute uncertainty in both inventory and flux, yet relative uncertainties about average annual net flux were generally greater in the South and West because median values were closer to zero.

Uncertainty in one time period affected uncertainty in subsequent times. However, effects in these results were limited to Monte Carlo sampling and did not incorporate any effects of uncertainty on median values. For example, harvests for a given forest type depend on both harvests of other forest types in a region as well as previous harvests. While these effects were included in the median projections provided by the TAMM/NAPAP/ATLAS modeling system, the same was not true for the Monte Carlo simulation. Uncertainty about a harvest at one time did not affect the expected value of subsequent harvests. To properly include such links in the current modeling system would require complete linked simulations of TAMM/NAPAP/ATLAS and FORCARB for the entire country for each iteration of the Monte Carlo simulation.

3.2. Influences on uncertainty

The simulations were developed to estimate likely levels of uncertainty in a large-scale forest carbon budget. Estimates of uncertainty and how they propagate through the model are subject to change as available data and our understanding of the system change. There are two principal reasons that these results are preliminary to a comprehensive description of uncertainty in the carbon budget projections. First, incomplete information about predicting total carbon from projections of forest volumes necessitate the subjective definitions of pdfs. Current research is focused on improving the quantitative descriptions of uncertainty of model parameters. Second, as in any complex system, there are multiple ways to model and analyze uncertainty. A detailed list of possible uncertainties can easily exceed the nine values defined for these simulations (Table 1). The process of identifying sources of uncertainty and appropriate levels of aggregation is useful because we can improve the model most effectively by focusing on reducing the most influential sources of uncertainty.

Carbon budget projections for each of the 216 forest types used in simulations can be described as a two-step process: first, estimating uncertainty in volume projections and second, converting volumes to total forest carbon. However, these were not independent steps. Uncertainty about volume projections for each year included estimates of uncertainty in initial inventory and cumulative effects of uncertainty in subsequent growth, removals, thinning, and area change. FORCARB estimates of total forest carbon were based on age and volume. Thus, cumulative forest projections influenced the distribution of volumes among age classes and, in turn, influenced the balance between age-based and volume-based carbon estimates made by FORCARB.

Overall uncertainty as shown in Fig. 2 and Table 2 can be apportioned to each of the model uncertainties described in Table 1. Collectively, FORCARB parameters — estimating the four carbon pools — accounted for a major portion of uncertainty, but the relative contribution generally decreased with time. The relative contribution of FORCARB parameters to carbon inventory uncertainty decreased from 79 to 64% from 2000 to 2040, and the contribution to flux uncertainty decreased from 45 to 40% over the same period. The percentage contribution of each input uncertainty on total carbon budget uncertainty projected for 2010 and 2040 is shown in Fig. 3. In general, uncertainty in estimates of tree and soil carbon and projections of volume growth and volume removals were most important in contributing to uncertainty about the whole. Uncertainty about initial forest volume inventory had little influence at the levels of uncertainty set in Table 1. The influence of uncertainty about growth and removals usually increased with time. Influences of individual uncertain values can depend on the amount of uncertainty associated with each as well as how each part contributes to the whole (Smith and Heath, 2000b). Identifying such trends in a linear model will usually depend more on relative values for uncertainty than precise definitions of absolute uncertainty. For example, a moderate (10–20%) increase in all definitions of uncertainty listed in Table 1 would produce the same general trend as found in Fig. 3 (data not shown).

Influences on uncertainty can vary with time and forest type, but such details are generally obscured in aggregate results such as in Fig. 3. An example of details for an individual forest type is given in Fig. 4,

Table 2
Projected carbon inventories and average annual net carbon flux, by region and as a national total. Each group of three numbers represents uncertainty in each estimate: the median value of the pdf bounded by the 2.5 percentile (below) and the 97.5 percentile (above)

Region	C estimate	2000	2010	2020	2030	2040
North	Inventory	11200	11600	11900	12300	12600
	(Million metric tons)	10200	10600	10900	11100	11300
		9200	9450	9550	9630	9750
	Flux		54	40	38	37
	(Million metric tons per year)		40	26	24	22
			23	11	8	6
South	Inventory	10100	10300	10400	10300	10200
	(Million metric tons)	9350	9480	9500	9360	9130
		8550	8610	8560	8340	8020
	Flux		24	15	−6	−16
	(Million metric tons per year)		13	2	−15	−23
			4	−8	−23	−32
West	Inventory	3090	3120	3180	3260	3310
	(Million metric tons)	2810	2860	2920	2970	2980
		2540	2560	2570	2570	2570
	Flux		10	10	9	5
	(Million metric tons per year)		5	5	4	1
			1	1	0	−3
Total	Inventory	24400	25100	25600	26000	26300
	(Million metric tons)	22400	23000	23400	23500	23500
		20400	20700	20800	20700	20500
	Flux		86	63	39	23
	(Million metric tons per year)		58	33	13	0
			29	4	−14	−26

which shows results from simulations of high productivity planted pine in the eight western states of the Southern region. FORCARB parameters remain most influential for carbon inventory uncertainty (Fig. 4, upper graph), yet uncertainty in carbon flux is eventually most influenced by growth and removals (Fig. 4, lower graph). Note that the sum of the percentage influences of the Tree C and Soil C lines is slightly less than the percentage for the FORCARB line. This is because the total influence of FORCARB parameters also includes the effects of uncertainty about understory and forest floor carbon. The balance between influences of FORCARB vs projections of growth and removals can vary with type, productivity, and use (ownership) of forests; some examples of relative influences on uncertainty are given in Table 3. The different influences among forest types suggest that efforts to better define or reduce projected uncertainty should be forest specific.

Effects of setting uncertainty at the levels described in Table 1 were investigated with sensitivity analyses. We applied two scenarios to the high productivity, planted pine example from Fig. 4. In the first scenario, doubling the level of uncertainty in initial forest volume inventory had little effect on overall uncertainty. The influence of initial volume inventory on total uncertainty (analogous to results of Fig. 4) never exceeded 10% for any time between 2000 and 2040. In the second scenario, doubling the uncertainty about growth and removals did affect model uncertainty. Uncertainty about carbon inventory increased over 50% by 2040, while absolute uncertainty about projected flux doubled. The different responses of inventory and flux could be foreseen from the information in Fig. 4, which indicated that volume removals were more influential for flux than for volume in 2030 and 2040. These results suggested that careful definitions of growth and removals are important in future model development, but refinement of uncertainty about forest inventory becomes less important with time.

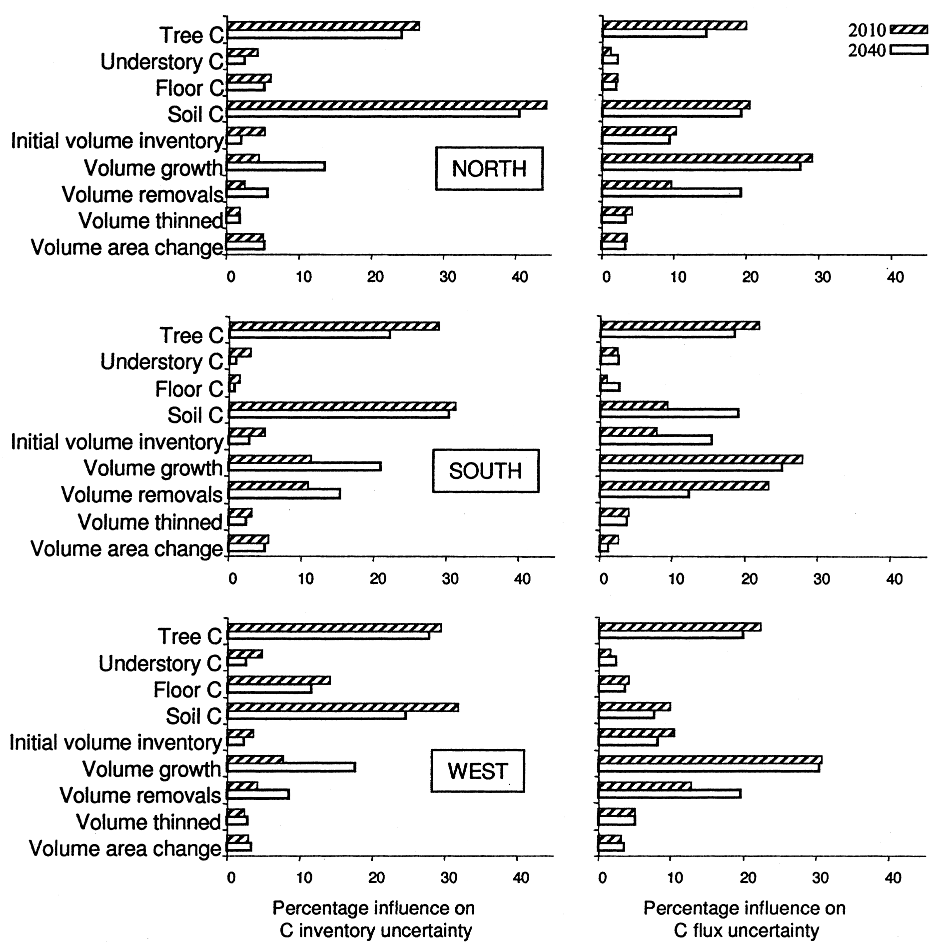

Fig. 3. Percentage of total uncertainty attributable to each of the nine variables whose values were defined as uncertain. Results are by region for carbon inventory (left column) and average annual net flux (right column) for projection years 2010 and 2040.

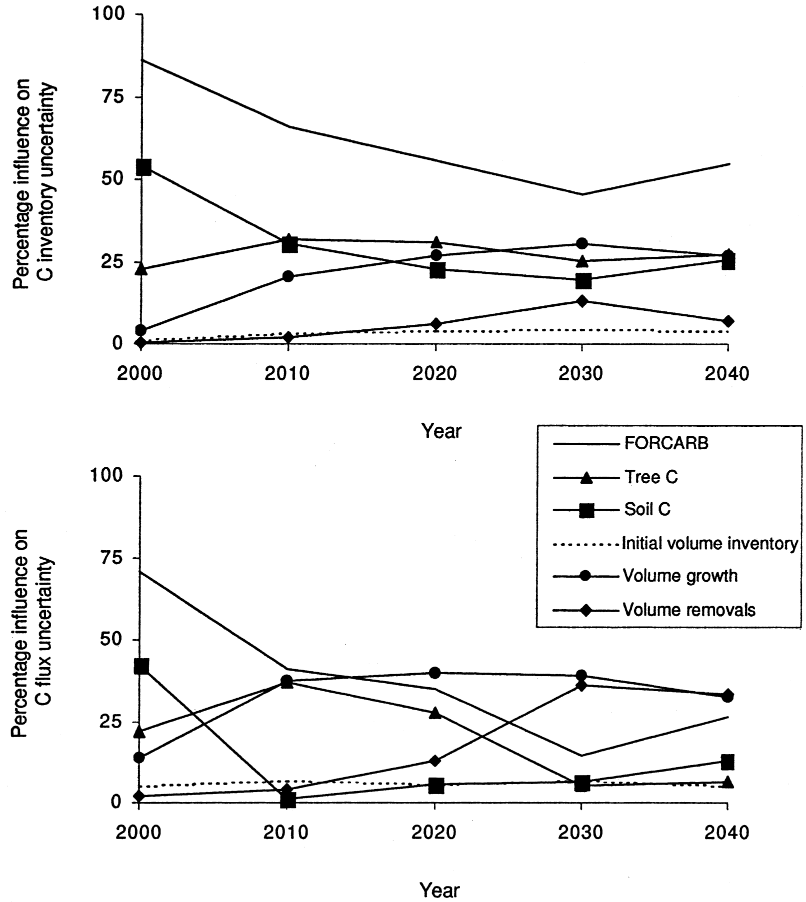

Fig. 4. Percentage of total uncertainty attributable to selected variables whose values were defined as uncertain. Results are for forest industry high productivity planted pine forest type in the eight western states of the South. Influence on uncertainty in projected carbon inventory is in the top panel, and influence on uncertainty in projected average annual net flux is in the bottom panel. Note that the FORCARB line represents the sum effect of all FORCARB parameters.

3.3. National total as a sum

At the level of individual forest types, sensitivities to uncertainties can vary according to such factors as productivity, land use, and age structure. The national totals presented here involve aggregating carbon budgets and uncertainty for all 216 forest types. Such sums are more sensitive to assumptions about relatedness among the parts than to the magnitude of uncertainty in an individual variable. Results are based on

Table 3
Percent contribution to average annual net carbon flux uncertainty in 2040 for six of the 216 forest types. Values specify the percentage of flux uncertainty attributable to the respective model variables

Forest type	FORCARB	Initial inventory	Volume growth	Volume removals
Maple beech birch, northeast, forest industry	43	15	13	23
Spruce fir, northeast, forest industry	23	17	52	0
North total	38	9	27	19
High productivity planted pine, south central, forest industry	26	5	32	33
Upland hardwoods, south central, farm	40	27	25	6
South total	42	15	25	12
High productivity Douglas fir, Pacific northwest, forest industry	31	7	42	10
Ponderosa pine, northern Rocky Mountains, forest industry	22	8	37	28
West total	33	8	30	19

the assumption that information leading to uncertainty in the given variables was highly correlated. In reality, this is somewhat true: uncertainties are based on our ability to accurately simulate forest-specific characteristics, and positive correlations are likely where regional or forest-specific characteristics are similar. Negative correlations are also possible: overestimates of timber harvests in one area are likely to correspond to underestimates in a second area if overall median projections are considered accurate. The degree of correlation will depend on data and how processes are modeled. While assumptions leading to high covariability in uncertainty among forest types are admittedly somewhat speculative, at worst the result of positive covariability is a tendency to inflate uncertainty when 216 inventory or flux pdfs are summed.

Starting uncertainties (Table 1) were all perfectly correlated among forest types at the start of each simulation, that is, the sampling distribution for a given variable was the same for each simulation. Differences in initial volume inventory and the patterns of growth and removals produced different distributions of volume and age. Thus, although the final carbon inventories were highly correlated, they were not perfectly correlated. Coefficients of correlation for carbon inventories of all possible paired combinations of forest types ranged from about 0.2 to over 0.99 with the median at about 0.8.

Latin Hypercube sampling facilitates resampling at specified levels of covariability. This allows for 'what if' experiments to examine the sensitivity of the results to modeled uncertainty (Smith and Heath, 2000b). Uncertainty about total carbon inventory projected for the year 2040 under different assumptions of relatedness is shown in Fig. 5. The solid line represents the pdf produced by the basic simulation (that is, the pdf for 2040 in Fig. 2). Clearly, correlations among forest types had an effect on the aggregate distribution, which was very similar to one based on perfect correlation among forest types (that is, the pdf represented by the dotted line in Fig. 5). The assumption of independence (that is, the pdf represented by the dashed line in Fig. 5) had a five-fold effect on total uncertainty: that is, uncertainty is apparently reduced by more than 80%. This effect extended to estimates of average annual flux, which were based on differences between successive inventories followed by summing the 216 forest types. Flux estimates summed for 2040 were reduced by 68% under the assumption that simulated carbon inventories among forest types were independent (data not shown). Factors affecting year-to-year covariability also strongly affected apparent levels of uncertainty. Assumptions of relatedness among forest types in these simulations formed high year-to-year correlations.

The net effect of these general observations about sums and differences of pdfs underscores the importance of covariability in quantifying uncertainty (Vose, 1996; Cullen and Frey, 1999; Smith and Heath, 2000a). The Latin Hypercube sampling of pdfs representing the four FORCARB parameters and the five variables used to estimate volume were independent of each other. However, separate sampling sequences were not used for different years or forest types. The net effects were high, but not perfect, correlations among years and among forest types. As a consequence of this modeling procedure alone, carbon budget uncertainty was reduced at the forest-type level and increased when represented at the national level. Specifically, reductions at the level of forest type were from a sum of four independent carbon pools to determine the pdfs to represent inventory, and a difference between two highly correlated distributions to determine the pdfs to represent flux. As these forest-type

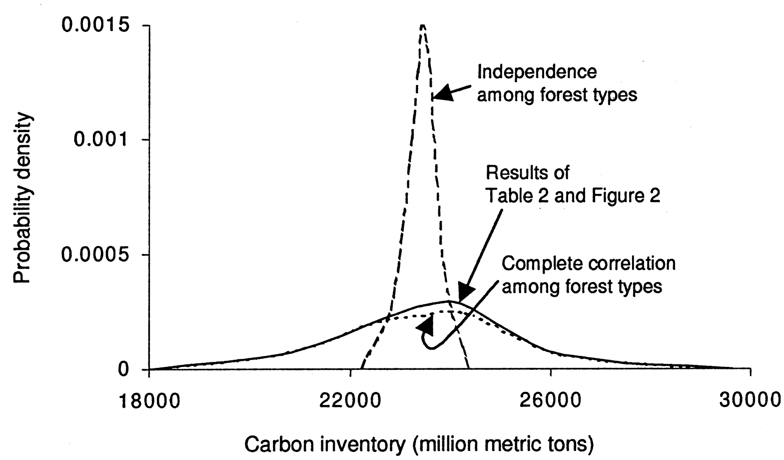

Fig. 5. Effect of covariability among projections on apparent uncertainty of summed carbon inventory for 2040. Note that the areas under the probability densities sum to one.

level pdfs — inventory and flux — were summed for national estimates, the generally positive correlations among the individual forest types inflated uncertainty relative to an assumption of independence. Ostensibly, such results may be viewed as mere modeling considerations, however, they are perhaps more important as considerations for evaluating information provided by models. Knowing the consequences of how the numbers are put together are an early step toward applying model results in assessments or policy.

4. Conclusions

We estimated the uncertainty in carbon inventory of privately owned forests in the US as approximately $\pm 9\%$ (2000 million metric tons) of the estimated median in the year 2000, with this range covering the central 95% of the distribution. Uncertainty in flux ranged from approximately ± 28 million metric tons over the period 2001–2010 on an annual average basis, to ± 24 million metric tons annually over the period 2031–2040. (Note the difficulty in interpreting relative uncertainty as a percentage as the median approaches zero.) The soil carbon component contributed most to the overall uncertainty of carbon inventory, followed by the tree carbon component. Uncertainties in volume growth and removals were most influential in estimating uncertainties in carbon flux.

Our results are best considered an iterative step in a process to identify uncertainties and improve model estimates. All projections are a result of model assumptions, and our results are no exception. Uncertainties defined for these simulations were a subset of the many uncertainties inherent in such a comprehensive projection. Uncertainties in issues such as land use, management, economics, and climate, as well as the uncertainties defined here all necessitate continuous improvements. Expected values and uncertainty in projected forest carbon budgets are likely to continue to change as uncertainties in assumptions and underlying data are better described. However, our results do suggest that differentiating between 10 or 20% error in some empirical relationships or model projections may have less effect on results than clearly understanding how model parts are related. In addition, results indicated that the most effective ways of reducing uncertainty in carbon flux would differ from those required to reduce uncertainties in carbon inventory.

Acknowledgements

This study was made possible by the financial support of the USDA Forest Service Northern Global Change Research Program. We thank Richard Birdsey, Jari Liski, David Williams, and two anonymous reviewers for helpful comments on the manuscript.

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