Considerations for Interpreting Probabilistic Estimates of Uncertainty of Forest Carbon

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Introduction

Quantitative estimates of carbon inventories are needed as part of nationwide attempts to reduce net release of greenhouse gases and the associated climate forcing. Naturally, an appreciable amount of uncertainty is inherent in such large-scale assessments, especially since both science and policy issues are still evolving (Brown and Adger 1994; Klabbers et al. 1996; IPCC/OECD/IEA 1997a). Decision makers need an idea of the uncertainty in carbon estimates in order to consider tradeoffs between known effects, possible outcomes, and preferred consequences. While an ultimate goal of assessments is to minimize uncertainty, a more immediate concern is to adequately quantify existing uncertainty. The goal of this chapter is to present some useful considerations for the interpretation and subsequent use of information from probabilistic assessments of uncertainty.

Forests store a large portion of the carbon in terrestrial ecosystems; therefore the extensive and largely managed timberlands of the United States represent a potential for producing offsets to carbon dioxide emissions (Birdsey 1992; Heath et al. 1996; Sohngren and Haynes 1997). Carbon content is a function of the state of forests: size, age, composition, productivity, and area, for example. These, in turn, are dependent on histories of management, utilization, weather, disturbance, and land use. Finally, all of these variables can be manipulated in many ways to fit differing scientific modeling approaches, as demonstrated by other chapters in this volume and citations therein. Decision makers faced with such complexity are likely to want information about uncertainty.

Uncertainty is a natural element of scientific understanding and therefore also an element of simulation modeling. This is the case for many forest-system models where uncertainty is sometimes explicitly quantified, sometimes disregarded, but most often discussed in general qualitative terms. Uncertainty in models is sometimes poorly characterized because the primary purposes of many models are to present best estimates or evaluate cause-and-effect relationships, not emphasize what is unknown. Additionally, "uncertainty" itself is sometimes a poorly defined, or elusive, quantity (Morgan and Henrion 1990; Shackley and Wynne 1996). A complete quantitative estimate of total uncertainty in forest carbon budget projections is beyond the scope of this chapter. Fortu-nately, models of uncertainty are useful, even when they do not provide a "bottom line" (Morgan and Henrion 1990; Cullen and Frey 1999).

Decisionmakers, or anyone using quantitative assessments of uncertainty, will likely face the need for pooling, comparing, or otherwise synthesizing such assessments. Because such actions are essentially modeling, some understanding of the process may be beneficial. Here, we particularly emphasize the consequences of summarizing uncertainty, as well as how such summaries can affect the perception of uncertainty in subsequent use of the information. Our discussion is oriented toward providing decision makers with an overview of some links between the form assigned to uncertainty and the perception of that uncertainty. Examples are presented from our current forest carbon budget modeling efforts where we employ probabilistic definitions of uncertainty in Monte Carlo simulations. The method of summarizing model results can affect perceived uncertainty, and summing uncertainty without considering covariability among parts can create a false estimate of uncertainty. Details on methods of analysis are in Smith and Heath, (in press) and data are summarized from Heath and Smith (2000).

A Forest Carbon Budget Model: FORCARB

The model FORCARB was developed to estimate carbon budgets for U.S. forests (Heath and Birdsey 1993; Plant-inga and Birdsey 1993; Birdsey and Heath 1995; Heath et al. 1996). Carbon budgets, as used here, are essentially estimates of size for various pools of carbon inventory as well as net changes over time. Net change in carbon inventory is referred to as flux. FORCARB is linked to a system of models (Mills and Haynes 1995; Birdsey and Heath 1995) developed as part of the periodic Resources Planning Act timber assessments (Haynes et al. 1995). Inputs to FOR-CARB from other models include landscape-scale projections of age-structure, volume, and area (Mills and Kincaid 1992), and as such, they implicitly contain a wide array of uncertainties. The focus in these simulations was on uncertainty within the FORCARB model, thus all inputs from other models were assumed known with certainty.

Functional relationships are used to estimate carbon pool sizes for hardwood trees, softwood trees, understory,

forest floor, and soil based principally on age and volume inputs. An example of such a relationship is shown as the solid line in figure 7.1. Here, forest floor carbon inventory is estimated from stand age. Subsequent reference to a "FORCARB parameter" refers to this type of functional relationship. Carbon pools are then expanded to total carbon for large areas of similar forest-type and productivity within a region. These large areas are termed "forest management units" (10^3 to 10^7 ha with a median of 180,000 ha for the 1990 inventory). Regional subtotals are formed and, finally, summed to a national total. Private timberlands in the 48 contiguous states are represented by results presented here, which include 216 forest management units. Carbon budget projections are presented in greater detail in Heath and Smith (2000). The basic sequence of a FORCARB simulation is illustrated in figure 7.2.
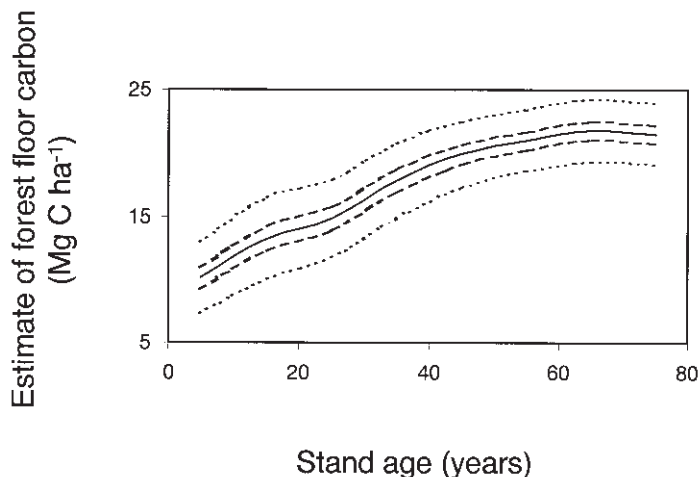
Figure 7.1—An example of a typical functional relationship (or FORCARB model parameter) used to project forest floor carbon inventory based on stand age (solid line). Probability bands illustrate our meaning and use of uncertainty in "FORCARB parameters" for this analysis. The bands indicate the 5th, 25th, 50th (expected value), 75th, and 95th percentiles (bottom to top respectively) of the probability distribution around the dependent variable. (Relationship is from a Douglas fir forest management unit.)
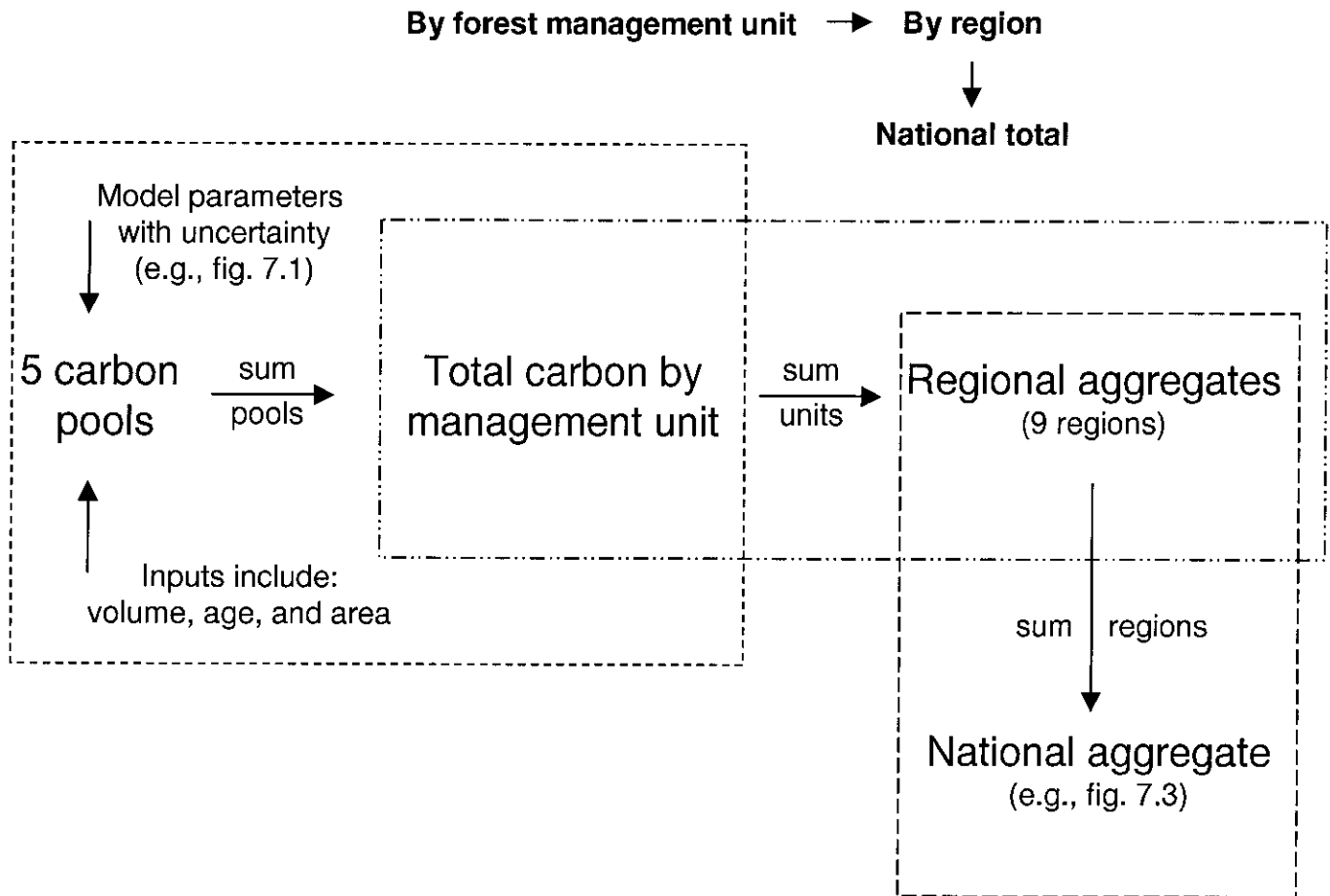
Uncertainty

Some level of uncertainty is usually a part of any model, assessment, or decisionmaking whether or not it is an explicitly considered part of the process. A widely used and potentially general term such as "uncertainty" can be confusing or misleading unless it is adequately defined (Hattis and Burmaster 1994; Shackley and Wynne 1996). At its simplest level, uncertainty can be the state of not knowing, or the inability to quantify something with a single discrete value. Sources of uncertainty can vary widely, and as a consequence, attempts to narrow the definition can require reference to variability, ignorance, systematic error, unknowns, expert opinion, semantics, or misapplication of a model (Morgan and Henrion 1990; Hattis and Burmaster 1994; Rowe 1994; Ferson and Ginzburg 1996; Cullen and Frey 1999). In earlier literature (largely stemming from Knight 1921), scientists were careful to define the risk of an event by a probability based on documented frequencies of occurrence. Risk was contrasted with uncertainty where such probabilities could not be assigned. However, current applications employ a range of definitions for uncertainty, including probability; furthermore, valid definitions of probabilities can include observed frequency or even subjective expectation (Hoffman and Hammonds 1994; Reckhow 1994; Dakins et al. 1996; Schimmelpfennig 1996; Paoli and Bass 1997; Haynes and Cleaves 1999). We use a probabilistic definition of uncertainty.

An unknown, but unique, inventory of carbon exists within a given forest management unit for a particular year. Our inability to precisely specify that value is the general definition of uncertainty we employ here. This concept of uncertainty implies that we can specify a range of possible values and an associated likelihood for values within that range. This describes a probability distribution, or more properly, a probability density function (PDF). Thus, we use PDFs as convenient quantitative and graphical representations of uncertainty (Vose 1996; Cullen and Frey 1999).

The effect of this definition of uncertainty, applied to estimating carbon for a given subset of a forest management unit, is illustrated in figure 7.1. The broken lines are probability bands indicating specific points on dependent variable PDFs–or uncertainties–about exact values of carbon per unit area. These probabilities reflect uncertainty in predicting carbon from stand age. Normally distributed PDFs were assumed to describe uncertainty about FORCARB parameters (details in Heath and Smith, 2000). No assumption of normality was required for this model: its use was simply a convenience for describing assumed expected values with symmetrical distributions. Analyses would ideally address all sources of uncertainty relevant to policymakers' questions about forest carbon inventory and flux. However, as mentioned above, a pragmatic first step is to focus on uncertainty internal to FORCARB. Therefore, uncertainties presented here are limited to this portion of the potentially much larger system of models that describe forests.

FORCARB simulations:

By forest management unit → By region

↓

National total

Model parameters
with uncertainty
(e.g., fig. 7.1)

↓

5 carbon
pools

sum
pools
→

Total carbon by
management unit

sum
units
→

Regional aggregates
(9 regions)

↑

Inputs include:
volume, age, and area

↓

sum | regions

↓

National aggregate
(e.g., fig. 7.3)

Figure 7.2—Graphic depicting organization of FORCARB simulations to estimate carbon inventory for individual forest management units (leftmost box), regional subtotals (upper right), and the national total (lower right). FORCARB estimated five carbon pools that were summed for total carbon inventory per forest management unit. A total of 216 such simulations were made for the national total.
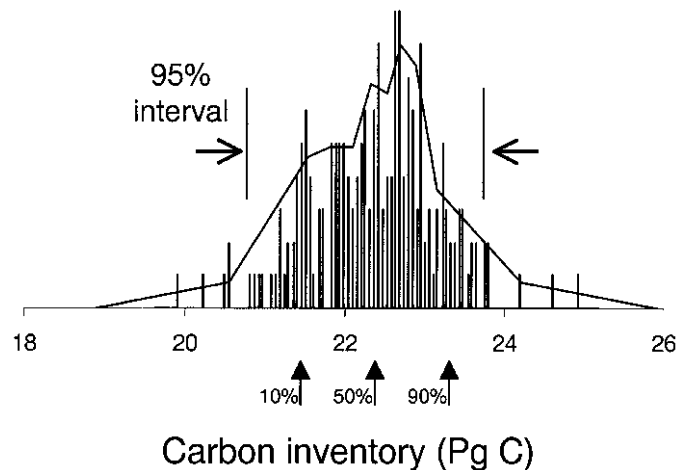
Method of Simulating Uncertainty

An uncertainty analysis is a modeling process that is implemented for two related purposes–estimating uncertainty and identifying influences on that uncertainty (Morgan and Henrion 1990; Cullen and Frey 1999). We estimate uncertainty in the FORCARB model by employing Monte Carlo simulations with Latin Hypercube sampling (Morgan and Henrion 1990; Vose 1996; Cullen and Frey 1999). This is but one of a number of approaches to uncertainty analysis, and we apply the method here to estimate uncertainty in forest carbon budgets.

A Monte Carlo simulation is produced through repeating a basic model simulation for a large number of iterations. One value is randomly selected from each input PDF for each iteration. For example, random selection from a PDF describing the parameterized relationship shown in figure 7.1 would produce estimates of forest floor carbon inventories ranging between approximately 10 and 16 Mg C per ha for 15-year-old stands. A different single value would be randomly selected for each iteration of the Monte Carlo simulation with most selections being near 13 Mg C per ha. Each iteration produces a single-valued model result. An accumulation of many such individual results produces a distribution representing the results of the Monte Carlo simulation. Latin Hypercube sampling is simply a stratified sampling procedure in which distributions are sampled from equal-probable

intervals, without replacement, thus reducing the sampling required to fully represent PDFs. The number of iterations included in a simulation affects precision of resulting distributions. Results provided here were from 100 iterations, which were adequate to define the shape of distributions for the quantities we examined.

We employ Monte Carlo simulation for uncertainty analysis because it features four principal advantages: 1) expressions of likelihood; 2) analysis of influences; 3) flexibility; and 4) explicit representation of covariability among parts (Morgan and Henrion 1990; Joint Climate Project 1992; Dakins et al. 1996; Morgan and Dowlatabadi 1996; Vose 1996; Cullen and Frey 1999). Although a first question often asked about uncertainty concerns identification of possible extreme events, this can quickly lead to a need to identify the likelihood of specific events between the extremes. Results as PDFs specify the range of possible outcomes together with their respective probabilities—both central tendencies and extreme events. The second factor is an advantage because influences on results are usually not evenly distributed among the components of a model. Identifying most-influential components as they affect overall uncertainty or even a tendency toward extreme results has utility for both model developers and policy analysts. Third, questions asked of an analysis are likely to change, and the same is true for information going into an analysis. This is a simple and flexible approach relatively free of restrictive assumptions. For example, although normal distributions were input for model parameters as a convenience, there were no required assumptions about distributions nor any need to know central moments. Finally, Monte Carlo simulation explicitly accounts for covariability among all derived PDFs. The third and fourth characteristics are of most interest here: minimal assumptions and explicit representation of relatedness among parts of the model.

Results and Discussion

Values for carbon budgets and uncertainty presented here are based on results of Heath and Smith (2000) and represent preliminary estimates for private timberlands. This chapter is intended to illustrate links between summary values extracted from PDFs and the perception of uncertainty associated with use of the summaries. Results are presented in three parts. First, we discuss considerations for avoiding the loss of important information when forming tabular summaries of PDFs. These results underscore the usefulness of need-specific summaries and careful definition of terms so that summaries reflect the interests of users. Second, we discuss additional con-

Figure 7.3—Estimate of carbon inventory (billion metric tons) of private timberlands for 2000. Model results presented as a histogram and smoothed probability density produced by Monte Carlo simulation. The central 95 percent of the distribution may be considered analogous to a 95 percent confidence interval. Arrows indicate carbon levels for the 10th, 50th, and 90th percentiles, commonly used to summarize low, median, and high simulation results, respectively.

siderations necessary when combining a number of PDFs. Here, disparity in size and dependencies (or covariability) among PDFs become important. Finally, we discuss some implications of these results for expanding the uncertainty analysis to the larger system of models.

Tabular Summaries from Continuous Distributions

Frequency distributions of model results are initial products of Monte Carlo simulations. A result of uncertainty in FORCARB projections of carbon on private timberlands for the year 2000 is shown in figure 7.3. The figure shows both a histogram of individual results from the many iterations of the Monte Carlo simulation and the smoothed distribution fit to the histogram. PDFs are formed from frequency distributions by normalizing the distribution, or setting the total area under the smoothed histogram to equal one (the cumulative probability of all values).

Probability densities are easily interpretable graphics of quantitative expressions of uncertainty. The likelihood that total carbon inventory will be within a given range, for example, is in proportion to the appropriate area under the PDF. Graphical presentations facilitate quick comparisons among a few such expressions of uncertainty, and numerical comparisons among whole distributions are similarly possible. However, interest in uncertainties in integrated assessments can often focus on specific values

such as thresholds or ranges. As such, summarizing PDFs using a few numbers is often desirable when integrating large amounts of information.

Uncertainty represented in tabular form is usually presented as either individual points or an interval along the PDF. Such summaries do not convey the exact shape of the distribution, but they do reduce discussion to a few key values. The use of individual points is shown in the carbon budget summary presented in table 7.1. A percentile indicates the portion of the PDF less than the given value; this can also be interpreted as the probability of results less than or equal to that value. For example, uncertainty in the model suggests that carbon inventory in 2000 will be less than 23.3 billion metric tons (Pg) with a probability of 0.90 (table 7.1 and fig. 7.3). Distribution percentiles such as the 10th, 50th, and 90th are commonly used to summarize low, median, and high simulation outputs, respectively. Intervals can be based on select percentiles (10th to 90th percentiles, for example) or formed around a central value such as the mean or median. Intervals around a central value can be expressed as relative or absolute values. For example, a symmetrical interval about the median carbon inventory in 2000 can be given as ±10 percent or ±2.2 Pg C–relative or absolute, respectively.

Tabular representations of uncertainty can be useful simplifications of results from uncertainty analyses. How uncertainty is summarized and presented should reflect the key features necessary for subsequent use of the information. There are two somewhat obvious, but important, caveats to note when using tabular summaries of uncertainties. The first is the link between the shape of the distribution and the interval. Selection of either interval or level of confidence determines the value of the other without reference to properties of a standard distributional form (also known as a parametric PDF, such a normal or lognormal, for example). An implication of this is that the interval of ±1 standard deviation about the mean does not necessarily enclose 68 percent of the distribution as would be the case under an assumption of normality for a PDF. However, a PDF obtained through Monte Carlo simulation can be represented by a close equivalent parametric PDF with the amount of information lost proportional to the closeness of the fit. The importance of such a compromise depends on the information represented by the PDF and its subsequent use. The second consideration is the distinction between representing uncertainty as a relative or an absolute interval. Both are reasonable representations of uncertainty, yet the dual definitions can be a source of confusion when making comparisons. The same absolute average range when applied to different median values can produce very different relative ranges. For example, the approximate ±4 percent of median inventory given in table 7.1 represents a considerably larger amount of carbon than the approximate ±15 percent of median

Table 7.1—Estimated total carbon inventory for private timberlands for 1990 and 2000, and average annual net carbon flux for the interval. Values are from the 10th, 50th, and 90th percentiles of the respective probability densities produced through Monte Carlo simulation. Positive flux indicates that carbon is being sequestered in the forest. Tg =1 million metric tons.

| Percentile | Total inventory (Pg C) | | Flux (Tg C y^{-1}) |
	1990	2000	1990–2000
10	20.7	21.4	63
50	21.7	22.4	74
90	22.6	23.3	86

flux. Simple and clear definition of how uncertainty is summarized can eliminate most confusion.

Choice of interval (or subset of PDF) to represent uncertainty presumably depends on the needs of the individual user. Here, an expression of confidence is simply the summed probability along this interval, obtained directly from the distribution. The relationship between an interval and confidence is determined by the shape of the probability distribution. These ideas are illustrated by figure 7.3. The interval analogous to the 95 percent confidence interval is between the 2.5 percentile and the 97.5 percentile (p([20.8,23.7])=0.95). This same interval can be expressed as averages of ±7 percent or ±1.5 Pg C around a median value of 22.4 Pg C. Here, the choice of a 95 percent level of confidence (probability=0.95) implicitly determined the size of the interval. Similarly, the choice of an interval, such as ±5 percent of the median, is simply the reverse of this process. Plus or minus five percent of the median value (1.1 Pg C) comprises about 86 percent of the distribution (p([21.3,23.5])=0.86). Note that the "plus or minus" values we present are averages of the two intervals for the nearly-symmetrical distributions, and methods of establishing confidence intervals vary among applications (Morgan and Henrion 1990; Cullen and Frey 1999).

A single example can usefully reiterate the ideas presented in the two preceding paragraphs. Simply stating that a level of uncertainty is ±10 percent: 1) ignores much of the information from a PDF such as change in expectation across that range; 2) implies that uncertainty is strictly a function of the size of the expected value; and 3) says nothing about confidence in the range provided. Level of ambiguity in specifying uncertainty does not imply any level of "correctness" for an analysis, but it can influence confidence. Simply put, tabular summaries, even "±10 percent," can be entirely appropriate; however, the key issue is information provided or lost. Understanding both the information needed and the information available can lead to informed choices about tradeoffs.

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USDA Forest Service Gen. Tech. Rep. RMRS–GTR–59. 2000.

The benefit of summarizing PDFs should exceed the relative cost of lost information.

Summing 216 Forest Management Units for an Aggregate Total Uncertainty

Results from the carbon budget model presented here are aggregate uncertainties that represent the sum of PDFs from 216 forest management units. While our examples are taken from a simulation model, decisionmakers are likely to face similar considerations with multiple PDFs. Information is commonly acquired from a number of separate sources, and this can present the need for comparing or summing a number of results. Therefore, considering relatedness among PDFs is an appropriate addition to a discussion of PDF summaries. The simplest procedure for summarizing and summing many PDFs is probably through application of the central limit theorem (Morgan and Henrion 1990; Cullen and Frey 1999). This assumes relatively balanced contributions among each of the PDFs summed and independence among PDFs. Under these conditions, the sum is expected to be normally distributed, and the variance of the sum is equal to the sum of the variances.

Disparity among size of the 216 forest management unit carbon inventory pools can influence control over total carbon and total uncertainty. If most of the total carbon inventory is attributable to a few large forest units, then research to improve the parameter estimates of these units will usually contribute more to improve estimates of total carbon inventory than improving the parameters of smaller forest management units. The larger 12 percent of the private timberland units simulated for this study account for more than two-thirds of the total carbon (fig. 7.4). That is, only 12 percent of the management units exceed 0.2 Pg C (the second size class in fig. 7.4), yet they account for over two-thirds of the total C inventory. The uncertainty of parameters of the smaller units would have to be extremely large to produce greater absolute uncertainty than the large units. The disparity in size among the 216 forest management units suggests that the PDF of an aggregate total could not be determined through simple application of the central limit theorem.

Determination of independence, or conversely dependence, among PDFs depends on both prior knowledge of the values and the modeling process. The meaning assigned to uncertainty of input PDFs, or FORCARB parameters, becomes critical as the separate pools are summed. We use uncertainty as an expression of our expected level of ignorance. For example, uncertainty includes our inability to translate an independent variable such as an exact volume of timber on an exactly specified area of land to a precise quantity of carbon in the system. If our ability to make that estimate is sim-
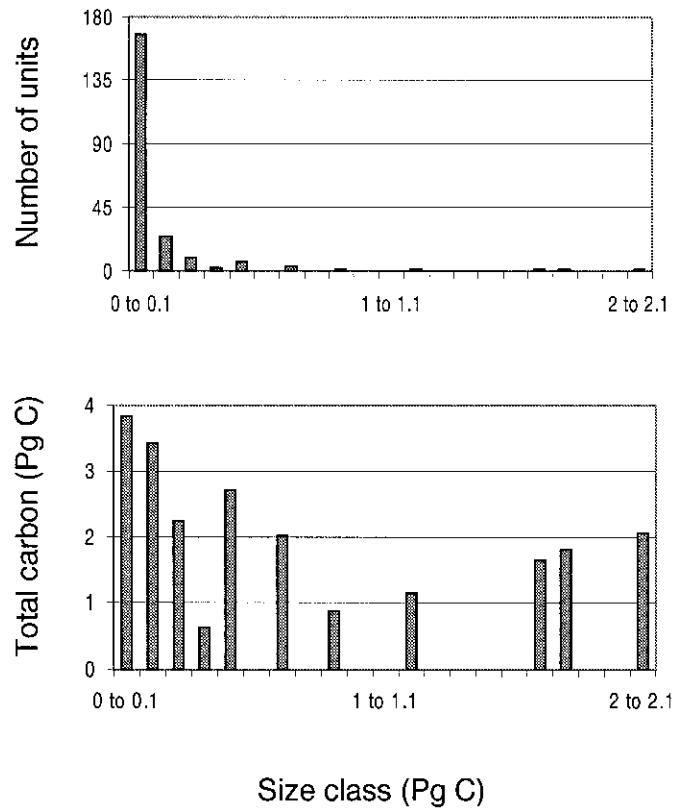
Figure 7.4—Histograms illustrating the disparity in size of carbon inventories among the 216 forest management units contributing to the national estimate for the year 2000, in terms of (a) number of forest management units per size category and (b) total carbon (sum of units) per size category (billion metric tons).

ilar across forest types and regions then the estimates of uncertainty would be jointly related or highly correlated. However, as the estimates become more dependent on elements of biology, management, ecology, or biogeochemistry of the respective forests, the degree of independence among the separate estimates will tend to increase. Similarly, if we view uncertainty as simply random variability, then the separate estimates made for different forest types would also be considered independent.

Assumptions about covariability among 216 separately determined forest carbon pools can have a tremendous effect on the apparent uncertainty of the total. FORCARB simulations in Heath and Smith (2000) reflected a relatively high degree of joint correlation–generally with coefficients of correlation between 0.60 and 0.98. Figure 7.5 shows the possible effects of covariability among the forest management units. The 216 distributions were specified as having joint correlations with coefficients of correlation of approximately 0.05, 0.50, and 0.95 (low to high covariability) based on modifying their rank orders from the Monte Carlo simulation (Iman and Conover 1982). This was simply a numerical manipulation to dem-
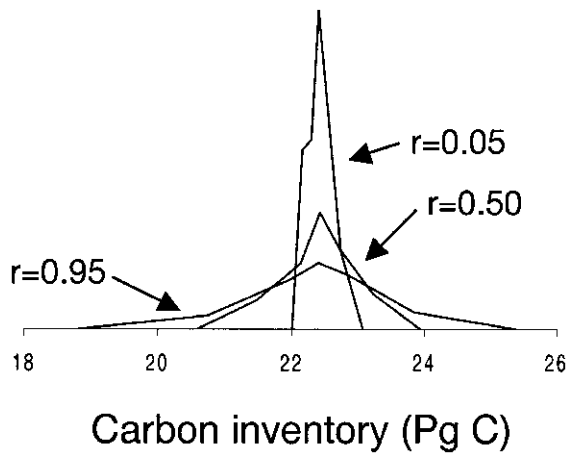
Figure 7.5—Hypothetical estimate of carbon inventory (billion metric tons) of private timberlands for the year 2000 as affected by covariability among PDFs for each of the 216 forest management units. Before summing the separate PDFs, correlation coefficients were set at approximately 0.05, 0.50, and 0.95 to produce narrowest to widest distributions for the total, respectively.

onstrate the effect of covariability on apparent uncertainty. The probabilities of high-valued samples are largely canceled out by low-valued samples when the summed distributions are considered largely independent (with coefficient of correlation, r=0.05). This central tendency produces a relatively narrow distribution in contrast to high correlation where factors leading to higher-valued samples of carbon in one system would also lead to higher-valued samples in another. The interval between the 10th and 90th percentiles was 4.5 times greater with r=0.95 than with r=0.05. We emphasize that manipulations done here were simply a means of demonstrating the consequences of covariance terms and the importance of any assumption about independence.

Average annual carbon flux is based on the difference between PDFs representing carbon inventory estimates (fig. 7.6). Here too, the value of the covariance term is important. With independence between the two inventories, uncertainty of the flux estimate is directly proportional to uncertainty in the two distributions. However, non-zero covariance affects the size of the flux PDF, as illustrated in figure 7.6 by manipulations of the coefficient of correlation between the two inventory PDFs. In general, range of uncertainty in estimated average annual flux
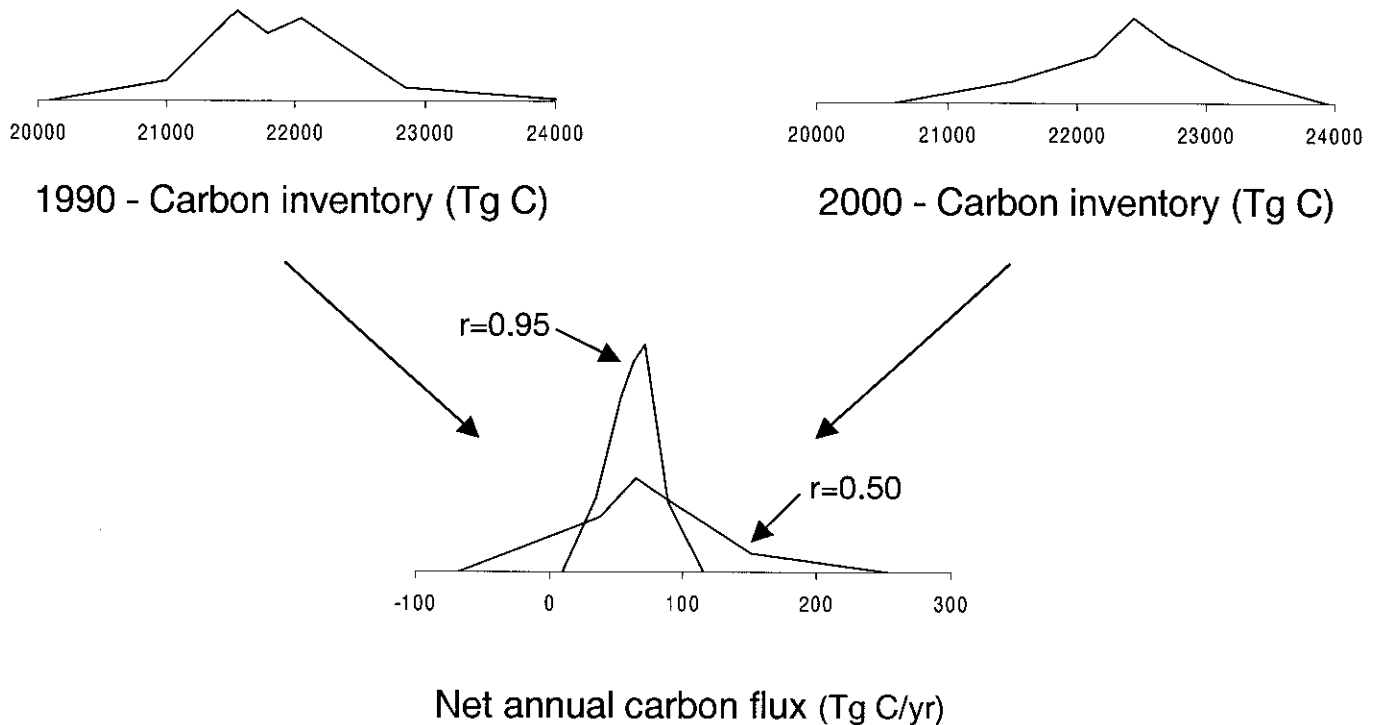
Figure 7.6—Examples of the effects of covariability between estimates of carbon inventory (million metric tons) on average annual net flux (million metric tons per year) uncertainty. Estimates for carbon inventory of private timberlands for years 1990 and 2000 were based on joint correlations among forest units set at r=0.5. Hypothetical average annual flux PDFs were calculated using correlation coefficients between years set at 0.50 and 0.95, producing wide and narrow distributions, respectively. Flux calculations were based on annualized difference between 1990 and 2000 distributions. Positive flux indicates that carbon is being sequestered in the forest.

is inversely proportional to covariance between inventories. If similar information was used to estimate carbon in each of the two years then the two distributions would be highly correlated. This was the case here (table 7.1) where age and volume were specified without uncertainty and FORCARB model parameters (similarly applied in each year's estimate) were the only sources of uncertainty.

Sums and differences of related PDFs depend on addition and subtraction of covariance terms, respectively. These are straightforward calculations if complete variance-covariance tables are readily available. Such information may be provided with original data sets, or it can be explicitly simulated within models. However, full knowledge of covariances is not a very realistic expectation when facing separately acquired estimates of uncertainty from independent sources. Nevertheless, even simple qualitative information can be usefully applied to sorting through post-analysis PDFs. For example, simply knowing that some positive, but unspecified, level of correlation exists between a pair of variables would lead an analyst to place more confidence in summaries where values were jointly drawn from similar regions of the respective PDFs. Another example of information provided by even limited knowledge of covariability is the effect of uncertainty in two inventory PDFs on uncertainty in estimated flux. The assumption of independence between inventories is a conservative assumption leading to large uncertainty in flux. Any knowledge of relatedness between the two inventories will reduce flux uncertainty, even without reducing uncertainty of the respective inventory PDFs.

Implication for a Larger External System

Decisionmakers are seldom provided probabilistic estimates of uncertainty without any accompanying information applicable to its use or context. Similarly, they are unlikely to be faced with summing 216 separate PDFs. The modeling examples were provided here to illustrate considerations for summarizing PDFs as descriptions of uncertainty. The effects of tabular summaries and relatedness are also useful when addressing issues of many uncertainties in a complex system.

The system defined by the FORCARB model is clearly a subset of a larger integrated system. Concern over the prospect of rapidly growing uncertainties as more elements are brought into an analysis cannot be quantitatively addressed without comprehensive uncertainty analyses. However, the results provided here do illustrate: 1) the effects of covariability among parts; and 2) how the definition of an interval affects the perception of uncertainty. For example, the interval between the 10th and the 90th percentiles of the 1990 carbon inventory PDF for the Northeastern Forest Industry Maple-Beech-Birch

forest management unit (result not shown) is about 10 percent of the median. The corresponding interval for the national total, after adding the additional 215 forest management units, is only about 9 percent of the median (table 7.1). The same interval could range from 3 and 12 percent of the median by simply adopting different assumptions about covariability among forest management units as illustrated in figure 7.5. Relative uncertainty (one definition of an interval) decreased while absolute uncertainty (another definition of an interval) increased as forest units were summed under an assumption of independence. This was because both median and variance terms increased linearly making the 10th to 90th percentile interval (which increased in proportion to the square root of the variance) an increasingly smaller proportion of the median.

Models structured to serve as accounting systems (for example, total forest carbon inventory) can be naturally organized into two sequential steps. First, determine a per-unit value of the quantity (for example, carbon per pool per hectare), and second, sum these units across an appropriate index (for example, forest area). This pattern appears in models (Nilsson and Schopfhauser 1995; Heath et al. 1996) and national summaries (Birdsey and Heath 1995; Kurz et al. 1995) as well as IPCC recommendations for greenhouse gas inventories (IPCC/OECD/ IEA 1997b). Choices and assumptions made in the course of modeling affect the form and relatedness of intermediate PDFs, and these can affect final results.

Recommendations for pooling uncertainties often contain implicit but not clearly stated assumptions of independence (for example, Volume 1, p. A1.5, IPCC/OECD/IEA 1997b). Such relationships among uncertainties may be reasonable and accurate but could easily and inadvertently be hidden in assumptions as models are iteratively analyzed and revised. Clearly, issues of uncertainty continue to change and are unlikely to be entirely resolved–the state of science and the questions society asks of science change continuously. Therefore, a model structure that clearly and as simply as possible states basic assumptions is essential for subsequent use of uncertainty.

Decisions are seldom made on the basis of a single uncertainty analysis; generally, multiple influences need to be considered and merged by decisionmakers (Joint Climate Project 1992; Reckhow 1994; Klabbers et al. 1996; Paoli and Bass 1997). Probabilistic expressions resulting from analyses are useful to decisionmakers for considering multiple influences (Hoffman and Hammonds 1994; Morgan and Dowlatabadi 1996). A systems perspective is even more important when the array of external influences, and accompanying uncertainties, are considered. Global change will affect forest composition and growth as well as management practices and timber markets. Climate sensitivity and forest sector projections contain additional uncertainties that we plan to incorporate in

our analyses. Where and how these added uncertainties appropriately link with the existing model can strongly influence rate of propagation.

eling or using the results from modeling. These are not complicated sets of rules but examples of the need for clear statements of definitions and assumptions.

Summary

Probabilities are commonly employed to quantify uncertainty. Discussion in this chapter focused on how summaries of probability distributions, or their subsequent use, can affect the interpretation of uncertainty. Model results presented here represent preliminary estimates of a portion of the uncertainty in carbon budgets for private U.S. timberlands.

Tractable use of results from uncertainty analyses often require tabular summaries of probability density functions (PDFs). The utility of a simpler format for expressing uncertainty should exceed the likely loss of information from a continuous distribution. Obviously, such summaries should still reflect the essential information desired by users. In other words, summarizing is fine, and understanding the form of the summary can help assure a net benefit. The relatively brief set of results we present here illustrate some basic considerations for ensuring this link and are summarized as follows:

- Tabular summaries (for example, "±10 percent") do not fully define distributions resulting from probabilistic simulations. Thus, summaries should focus on specific aspects of PDFs.
- Absolute and relative levels of uncertainty are useful summaries, yet they are distinctly different measures. Comparisons among estimates of uncertainty can be confusing unless definitions are clearly stated.
- A specified range for uncertainty includes an implicit assumption of likelihood based on the PDF. This should be explicitly stated as a range and associated confidence, for example.
- The use of a number of PDFs sometimes requires including additional characteristics in the summary, especially when summing a total uncertainty from separately obtained estimates. Size disparity and covariability among parts then become important considerations.

Probabilistic models, such as the implementation of FORCARB referenced here, explicitly account for such characteristics of PDFs. These guidelines are applicable whenever uncertainty is described in terms of probabilities, including policy and management decision making. That is, the use of probabilistic definitions of uncertainty requires many of the same considerations whether mod-

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