Uncertainty in estimating carbon emissions from boreal forest fires

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[1] The uncertainty in carbon emissions from fire was estimated for the boreal region of Alaska over the 50 years of recorded wildfire. Building on previous work where carbon emissions were estimated using a geographic information systems-based model, the uncertainty attached to the different parameters of the basic equation was assessed and propagated through the equation using Monte Carlo simulation. The result is a distribution of possible values for total carbon and three carbon-based gases (CO_2, CO, and CH_4) that provides a measure of the uncertainty in the output estimates. Additionally, the relative impact of each input parameter on the output uncertainty has been quantified (sensitivity analysis). Assumptions were made in building the uncertainty model regarding the shape of the distribution of each model parameter since this information is unavailable. Because of the lack of information on the precision of input parameter estimates, a range of possible spread values for the probability distributions, as defined by the coefficient of variation (CV; standard deviation/mean), was considered. Using the "best guess" values for input CVs, the resulting estimate of total annual carbon emission can be as high as 10.6 TgC or as low as 1.1 TgC, a CV of 24%. Lowering the input CVs to 5% results in an output CV of 4.2% for total carbon emissions. For the three carbon-based gases the CV of simulated carbon distributions for the "best guess" scenario ranges from 23 to 27%. The sensitivity analysis reveals that ground-layer fraction consumed, β_g, is the most important parameter in terms of output uncertainty. The results of this work emphasize that current estimates of carbon emission from biomass burning are not well constrained because input data sets are incomplete and lack adequate error information. Furthermore, we conclude that although burn area estimates are improving, more effort is needed in quantifying fuel and consumption variables at fire sites if accurate estimates of carbon emissions from fire are to be made. *INDEX TERMS:* 0315 Atmospheric Composition and Structure: Biosphere/atmosphere interactions; 1615 Global Change: Biogeochemical processes (4805); 1694 Global Change: Instruments and techniques; *KEYWORDS:* biomass burning, carbon cycling, Monte Carlo simulations

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1. Introduction

[2] In recent years, attention has been paid to understanding the impact of wildland fire on atmospheric carbon [*Conard et al.*, 2002; *Dixon et al.*, 1994; *FIRESCAN Science Team*, 1996; *Harden et al.*, 2000; *Hinzman et al.*, 2003; *Kajii et al.*, 2002; *Kasischke and Bruhwiler*, 2002; *Kasischke et al.*, 1995a; *Kasischke and Stocks*, 2000; *Stocks et al.*, 2002]. Both the immediate and long-term effects of fire are seen as important factors in carbon cycling, by directly influencing levels of carbon-based gas in the atmosphere. Although the problem of quantifying direct emissions from wildland fire has received attention, very little has been done to assess the uncertainty in the resulting estimates. In studying the impact of fire on atmospheric carbon, variations in vegetation structure, vegetation type, soil carbon, weather, fuel moisture, and fire behavior need to be considered. Models used in estimating carbon and carbon-based gases released during biomass burning need to account for these variables, either by directly including the variable in the model or by acknowledging the inherent variation within each model parameter.

[3] Much of the recent effort to improve estimates of fire's impact on the atmosphere has focused on improving the estimates of how much land is subjected to fire (area

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burned) [*Eva and Lambin*, 1998; *Fraser et al.*, 2000; A.I. Sukhinin et al., unpublished manuscript, 2004]. In some biomes, such as tropical savannahs, the amount of area that is subjected to fire during a given time period is the greatest unknown; vegetation and fire conditions in these regions are such that variations are small in fuel and fire type. Boreal forest ecosystems, however, support a broad range of fuel types, with various densities and that burn in a variety of severities depending on time of season, climate, etc. [*Amiro et al.*, 2001; *Shvidenko and Nilsson*, 2000; *Stocks and Kauffman*, 1997]. Boreal fires are generally large and relatively easy to map, and the larger fires represent 98% of the total area burned within a year [*Kasischke et al.*, 2002; *Murphy et al.*, 2000; *Stocks et al.*, 2002]. In the boreal regions, therefore, the largest uncertainties are likely the fuel and fire conditions, which are more difficult to measure and quantitatively characterize than area burned.

[4] In the study presented in this paper, we have endeavored to quantify the uncertainty in estimates of emissions from wildfire in Alaska based on the uncertainty present in the model inputs. Such a propagation of uncertainty extends the work presented in the work of *French et al.* [2002] where GIS-based estimates of carbon and carbon-based gases released from fire in Alaska were described. The basic model used for this study is the same as presented in the work of *French et al.* [2002] (see below) and is based on the standard equation presented by *Seiler and Crutzen* [1980]. The objectives of the research were twofold:

[5] 1. Assess the uncertainty attached to the different parameters of the basic equation, and propagate this uncertainty using Monte Carlo simulation, yielding a distribution of possible values for total carbon and three carbon-based gases released during burning in Alaska.

[6] 2. Quantify the relative impact of each input parameter on the output uncertainty (sensitivity analysis) to identify priorities in terms of data collection and information accuracy.

[7] The purpose of this paper is to present the approach and results of our propagation of uncertainty model that illustrates how the various factors contribute to uncertainty. We review the sources of uncertainty in estimating carbon emissions, including the uncertainty of each model input. We also discuss how the community can begin to improve our understanding of emissions from wildfire by working toward a common terminology and quantifying error in measured or modeled data.

2. Estimating Carbon Emissions From Boreal Fires

[8] As reviewed in the work of *French et al.* [2002], calculating total carbon released during biomass burning (C_t) is generally done by estimating the area affected by fire along with the amount of fuel (carbon) consumed during the fire [*Amiro et al.*, 2001; *Cahoon et al.*, 1994; *Conard and Ivanova*, 1997; *Conard et al.*, 2002; *French et al.*, 2000, 2002; *Kasischke et al.*, 1995b; *Seiler and Crutzen*, 1980; *Shvidenko et al.*, 1995; *Stocks*, 1991]. The emission of a particular gas species (E_g) is calculated from C_t using experimentally derived emission factors (E_{fg}), the ratio of gas released to total carbon released. For the boreal region, the analysis is often separated into two fuel components, the aboveground or aerial component, which includes trees and shrub components above the ground surface, and the ground-layer organic material component, which includes ground surface vegetation and fully to partially decomposed organic material in the upper portion of the ground surface (also known as duff). This separation is made because of the large differences in these two pools in carbon content, fuel composition (quality, moisture and other factors), and consumption during burning. In estimating the contributions of each gas species, the proportion of flaming and smoldering burning is defined for each component to account for differences in emission factors for the two combustion types. Typically the amount of carbon dioxide (CO_2), carbon monoxide (CO) and methane (CH_4) released from fires is estimated. By separating carbon pools and combustion type, these fundamental variables are accounted for within the model parameter set. The following equations have been used in modeling fire emissions in previous analyses [*French et al.*, 2000] and were used as a basis for calculations in the current study:

$$C_t = A\left(C_a\beta_a + C_g\beta_g\right) \tag{1}$$

$$E_g = A\left[C_a\beta_a\left(0.8\,E_{fg-f} + 0.2\,E_{fg-s}\right) + C_g\beta_g\left(0.2\,E_{fg-f} + 0.8\,E_{fg-s}\right)\right], \tag{2}$$

where A is the area burned (hectares, *ha*); C_a is the carbon density of the aboveground component, which is assumed to be 0.5 of the biomass ($t\ ha^{-1}$); C_g is the carbon density of the organic material found in the ground-layer, which is composed of the litter and duff layers ($t\ ha^{-1}$); β_a and β_g are the proportions of the aboveground vegetation and ground-layer organic carbon, respectively, consumed in the burn; and E_{fg} is the emission factor for each of three gas species, CO_2, CO, and CH_4 (in units of gas released per unit of carbon consumed).

[9] The analysis using (2) is carried out for each gas independently. The f and s subscripts on the emission factor terms in (2) refer to flaming and smoldering combustion, respectively. For simplicity in understanding fire emission uncertainty we have assumed that 80% of the consumption in the aboveground happens in a flaming combustion and 20% happens in smoldering combustion, while 20% of ground-layer burning is flaming combustion and 80% is smoldering combustion based on the rationale presented in previous studies [*Kasischke and Bruhwiler*, 2002]. The analysis is performed with geographically defined input data; for example, using spatially explicit data on where the fire occurred and the carbon present at the site, as well as consumption information specific to the region of the burn.

3. An Approach for Assessing Uncertainty in Carbon Emissions

3.1. Uncertainty in Model Inputs

[10] In developing a model of uncertainty, the error present in each model term needs to be understood and

statistically described. This error is then propagated through the base model to come up with the distribution of possible values for carbon and carbon gas emissions. Error can be modeled statistically if enough measurements are made. In the case of Alaska, the data used in estimating fire emissions is, in some cases, limited, and in other cases poorly documented and described, so several assumptions were made in modeling the output uncertainty (see model implementation section).

[11] Four types of parameters are used to quantify fire emissions: area burned, carbon density, fraction of carbon consumed, and emission factors. Estimates for the nine parameters in (1) and (2) are described in detail in the work of *French et al.* [2002]; the uncertainty in these input data is described here.

[12] The map of area burned in Alaska originates from fire records held by the Alaska Fire Service. These records contain fire boundaries for 1950 to the present, with varying levels of accuracy over the years [*Kasischke et al.*, 2002; *Murphy et al.*, 2000]. From the records, a database of fires, called the Alaska large fire database (LFDB), has been created. It contains the digitized boundary of Alaskan fires greater than 200 ha recorded since 1950. Errors are present in the LFDB; in particular, unburned regions within a fire are often unmapped, leading to an overestimate of total area burned. Burn maps in some older records are difficult to interpret and properly geographically locate, and the outer boundary of the burn can also be poorly mapped, introducing either overestimations or under-estimations from a disregard of the complexity of the burn edge. Despite these defects, the LFDB contains the most complete record of fire location and timing for Alaska. *Kasischke et al.* [2002] have determined that the database contains a reasonable sample of fire activity for the last 50 years despite some missing records for the early decades.

[13] According to *Kasischke et al.* [2002], missing maps amount to approximately 15% of the total area burned. For a similar LFDB for Canadian fires, *Amiro et al.* [2001] assume an upper bound of 9% to 13% more than the input estimate based on the fact that the fire maps used do not include smaller fires (fires <200 ha), some fire records are missing, and there is a small discrepancy due to complex fire edges that may not be accurately represented in the fire boundary maps. Unburned islands and nonfuel areas within mapped burn areas, which are not accounted for in burn boundary records, and inaccuracies in burn boundary mapping define the lower error bound at 15% [*Amiro et al.*, 2001]. Fire records for Alaska are in similar form as those for Canada, and so can be assumed to have similar error sources.

[14] In our analysis, fuel consumption is derived by combining estimates of carbon present in the aboveground and ground-layer pools (C_a and C_g) and estimates of the fraction of each carbon pool that was converted to atmospheric carbon (β_a and β_g). While information related to these parameters are available from soil and forest inventories, and field-based observations collected during experimental burns, development of estimates of fuel consumption in areas that burn in wildfires is much more difficult to quantify than area burned for fire in boreal regions. Examination of the error in each of these terms has been minimal.

Table 1. Estimated Fractions Consumed for Three Fire Year Classes in the Three Alaskan Boreal Ecozones[a]

	Alaska Boreal Interior		Boreal Cordillera		Taiga Plains	
Fire Year Class	β_a	β_g	β_a	β_g	β_a	β_g
High	0.26	0.19	0.17	0.41	0.28	0.10
Average	0.22	0.15	0.13	0.35	0.26	0.08
Low	0.15	0.10	0.09	0.25	0.22	0.06
Uncertainty, %	±23	±46				

[a]Uncertainty is assumed to be the same for all ecozones.

[15] For this analysis, estimates of C_a and C_g are drawn from published maps on carbon density of Alaska for two components, aboveground [*Kasischke et al.*, 1995b] and soil carbon (carbon in the top 30 cm of soil; *Lacelle et al.* [1997]). These maps are derived from field data, with no information on uncertainty.

[16] The β_a and β_g terms are defined by ecozone and year of burn using a weighting method for fraction consumed based on the assumed severity of fires in a given year. Higher than average consumption is assumed during high fire years, when at least twice the average area has burned, while lower consumption is assumed in low fire years, when less than half of the average area has burned. The boreal region of Alaska is covered by three ecozones, each with different consumption patterns, so the consumption estimates are determined separately for each ecozone. The weighting is similar to what was done by *French et al.* [2000, 2002], but refined based on improvements in our understanding of annual and seasonal fire patterns [*Kasischke et al.*, 2002]. Analysis of fire records have shown that burning in later months of the fire season (August and September), when conditions are driest, occur almost exclusively in high fire years. Years with low area burned typically burn within a 6-week period in June and July, when sites are not as dry as later in the summer. The weighting method for defining consumption takes into account the higher levels of burning due to these seasonal variations in burn conditions. The result is a set of nine estimates of fraction consumed for each carbon pool based on ecozone and year of the burn (Table 1).

[17] The basis for the estimates of fraction consumed for the Alaska Boreal Interior are field measurements of aboveground and ground-layer consumption at burn sites in interior Alaska [*Kasischke et al.*, 2000]. According to these field measurements, β_a can range from 0.05 to 0.30 while β_g can be as high as 0.90. However, areas where consumption of ground-layer carbon is 0.90 are very small, so mean fraction consumed values used for ecozone-wide estimates are never so high. Analysis of the raw field data for the Alaska Boreal Interior reveals the uncertainty in β_a to be ±23%. The β_g uncertainty is much higher, ±46%, based on the field data.

[18] Emission factors have been determined from airborne sampling of smoke plumes. The uncertainty in these sample measurements was determined from the reported measurement uncertainty for three sampling missions [*Cofer et al.*, 1990, 1989, 1996]. Comparison of emission factor measurements from these experiments shows that

Table 2. Coefficient of Variation (CV) Values Used in Three Uncertainty Model Runs

	"Best Guess" Uncertainty	Low Uncertainty	High Uncertainty
Area burned[a]	0.15	same	same
Aboveground C	0.10	0.05	0.25
Ground-layer C	0.10	0.05	0.25
Aboveground β	0.23	0.05	0.25
Ground-layer β	0.30	0.05	0.25
Emission factor	CO_2		
flaming[a,b]	CO	same	same
	CH_4		
	0.02		
	0.09		
	0.15		
Smoldering	0.03		
	0.06		
	0.08		

[a]The CVs for area burned and emission factors were the same for all analyses.

[b]Calculated from *Cofer et al.* [1989, 1990, 1996] assuming 0.5 kgC/kg biomass.

the uncertainty in these factors is collectively relatively low.

3.2. Uncertainty Model Theory

[19] For each component of equations (1) and (2), the model of input uncertainty takes the form of a probability distribution that gives the set of possible values with the corresponding probability of occurrence. Depending on the type of information available, the distribution can take simple forms (e.g., uniform, triangular, Gaussian) characterized by a few parameters (e.g., minimum and maximum values, mean, variance) that can either be inferred from experimental data or correspond to "prior guess"(a priori information).

[20] The total amount of carbon released by wildfire (C_t) in Alaska was assessed from a given number (K) of sites that are known to have burned in the past 50 years. Let $\mathbf{u}_k$ denote the vector of spatial coordinates of the polygon centroid corresponding to the k-th burn site, and $A(\mathbf{u}_k)$ be the area of that burn. The total carbon emission for Alaska would then be:

$$C_t = \sum_{k=1}^{K} A(\mathbf{u}_k)\left[C_a(\mathbf{u}_k)\beta_a(\mathbf{u}_k) + C_g(\mathbf{u}_k)\beta_g(\mathbf{u}_k)\right], \quad (3)$$

where each parameter in the model is now regionalized; that is it has a value that is site-specific and depends on factors related to its geographic location, including ecozone, soil type, carbon density, etc.

[21] The uncertainty attached to model predictions of C_t is assessed using a combination of stratified random sampling of input parameters probability distributions and Monte Carlo simulation [*Goovaerts et al.*, 2001; *Heuvelink et al.*, 1989]. The basic idea is to sample randomly the different distributions of input variables and to feed each combination of sampled values ($A^{(l)}(\mathbf{u}_k)$, $\beta_a^{(l)}(\mathbf{u}_k)$, $\beta_g^{(l)}(\mathbf{u}_k)$, $C_a^{(l)}(\mathbf{u}_k)$, $C_g^{(l)}(\mathbf{u}_k)$) into function (4) to retrieve the corresponding simulated carbon value $C_t^{(l)}$:

$$C_t^{(l)} = \sum_{k=1}^{K} A^{(l)}(\mathbf{u}_k)\left[C_a^{(l)}(\mathbf{u}_k)\beta_a^{(l)}(\mathbf{u}_k) + C_g^{(l)}(\mathbf{u}_k)\beta_g^{(l)}(\mathbf{u}_k)\right]. \quad (4)$$

[22] Uncertainty in model predictions for emissions of each gas (E_g) is assessed with the same simulation methodology.

$$E_g^{(l)} = \sum_{k=1}^{K} A^{(l)}(\mathbf{u}_k)\left[C_a^{(l)}(\mathbf{u}_k)\beta_a^{(l)}(\mathbf{u}_k)\left(0.8\ E_{fg-f}^{(l)} + 0.2\ E_{fg-s}^{(l)}\right) + C_g^{(l)}(\mathbf{u}_k)\beta_g^{(l)}(\mathbf{u}_k)\left(0.2\ E_{fg-f}^{(l)} + 0.8\ E_{fg-s}^{(l)}\right)\right]. \quad (5)$$

The concept is easy to understand but its implementation can become computationally challenging as the number of sites and input parameters involved increases, in particular in presence of correlation among input parameters and/or sites.

3.3. Model Implementation

[23] A Fortran-based program was written to implement the uncertainty model. The program uses inputs for each model parameter which originated as an ArcGIS® attribute table; they are the same data used by *French et al.* [2002] with the exception of the consumption fractions shown in Table 1. All of the data, except E_{fg} for each gas and combustion type, are held as spatially variable parameters within ArcGIS®-based tables; emission factors do not vary across the region and are assumed constant for each location. Information on each parameter, therefore, is geographically defined, allowing a spatially explicit analysis of carbon released. The input data table contains a list of "sites" representing a burn location with unique information on the size of the site, the year of burn (which allows an annual analysis), aboveground carbon density, ground-layer carbon density, and ecozone, which defines the fraction-consumed values. The input database is shown graphically in Figure 1, which displays the results of the analysis using equation (1) at each site, the same analysis performed in our previous study [*French et al.*, 2002].

[24] Practical implementation of the Monte Carlo simulation required making assumptions regarding the characteristics (shape, spread) of the probability distributions of input parameters since precise information is not available. The uncertainty about the area burned was modeled using a uniform distribution with minimum and maximum values set to 85% and 115% of the GIS-based estimates, which amounts to considering a maximum error of ±15%. The uncertainty about each of the four other input parameters was modeled using a Gaussian distribution centered on the parameter estimates, as given in the ArcGIS®-based table. Because the precision of input parameter estimates is poorly known, a range of possible spread values for the probability distributions, as defined by the coefficient of variation (CV = standard deviation/mean) was considered (Table 2).

[25] Another difficulty in implementation of the Monte Carlo simulation was that probability distributions at different sites could not be sampled independently since for some parameters, such as β values, one might expect a systematic overestimation or under-estimation of the values for the different ecozones. To account for this expected systematic under/overestimation of β values over the three ecozones, the same random ordering was used for the three zones. For example, if the upper tail of the

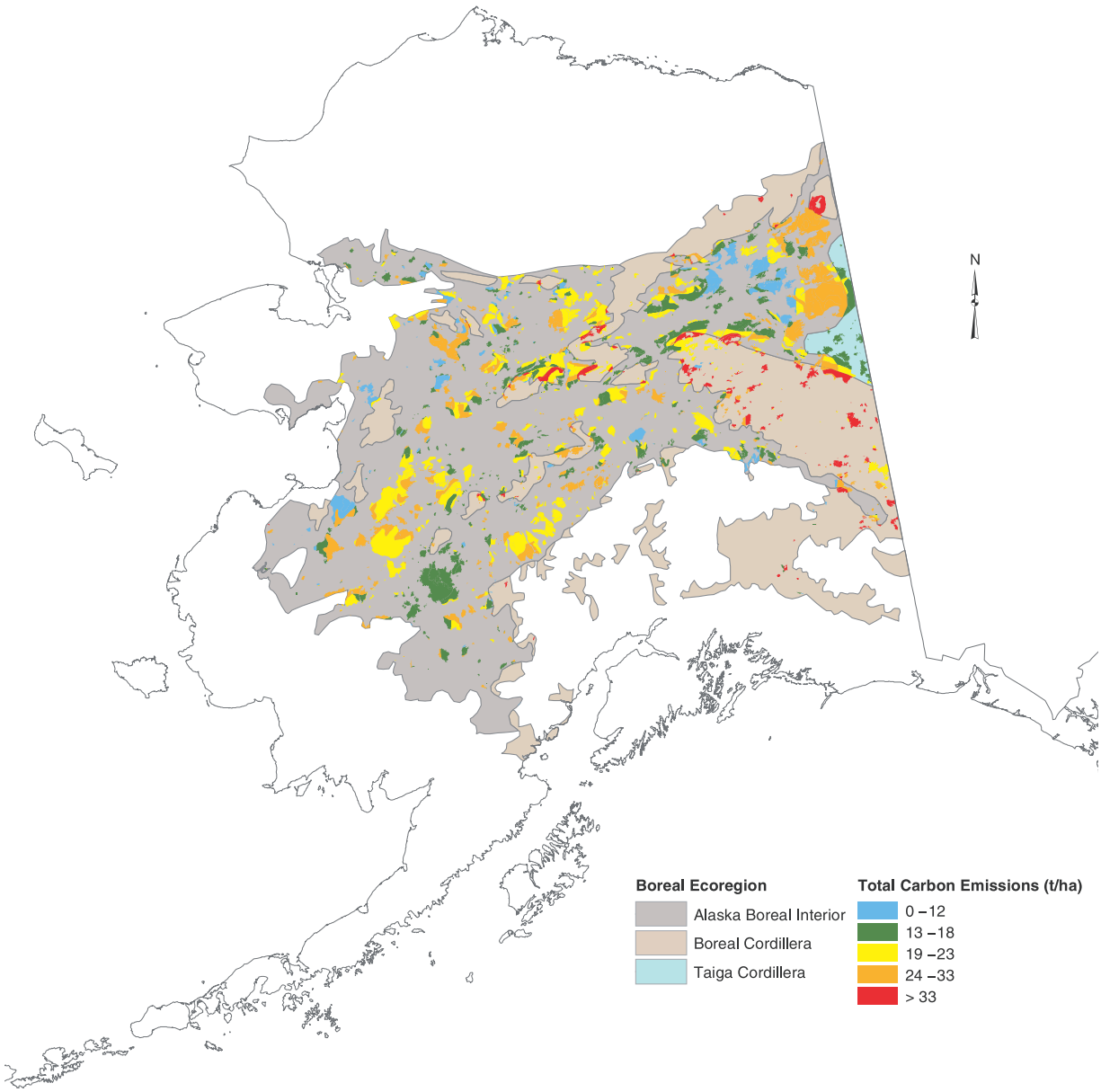

Figure 1. Map of carbon emissions (t-ha^{-1}) for 50 years of fire across the boreal regions of Alaska. Estimates are the result of combining maps of fire occurrences with aboveground and ground-layer carbon and expected fraction of carbon consumed in the fires as described in the work of *French et al.* [2002] (see equation (1)).

probability distribution of β_a for Boreal Cordillera is sampled, the same part of the probability distribution of β_a for Alaska Boreal Interior and Taiga Cordillera is sampled. As a consequence, some realizations of the spatial distribution of β values over Alaska will be characterized by high average values (where the upper tail of the probability distributions at all K sites has been sampled), while other realizations will display low average values (where the lower tail of the probability distributions at all K sites has been sampled). In contrast, the large number of categories for the other input parameters (e.g., 42 for C_a and 76 for C_g) coupled with their independent sampling (no systematic over/under-estimation of C_a and C_g values is envisioned for forest or soil types) means that the average value of these parameters over Alaska should be fairly constant across realizations. In other words, the sampling of the upper tail of probability distributions for some categories would be balanced by sampling of lower tail of probability distributions for other categories.

[26] The sampling of probability distributions was performed as follows:

[27] 1. For each input parameter, the set of different values (referred to later as "categories") found in the database was retrieved. For example, nine values for β_a corresponding to three fire classes and three ecozones (see Table 1).

[28] 2. For each category, a probability distribution centered on the estimate found in the database is built at each site. This distribution is then stratified into L equally probable classes (number L is specified by the user; set at 2000 for calculations of C_t and 1000 for E_g) and a value is randomly drawn within each class, yielding a set of L-simulated values or realizations at each site. Finally, these L values are randomly ordered. The same set of L simulated values was used for all sites belonging to that category.

[29] In creating the output distribution, the sampling procedure is repeated many times (e.g., L = 2000 realizations) for different combinations of CV values for the probability distributions of input parameters. The spread of the resulting distribution of L-simulated C_t or E_g values provides an assessment of the uncertainty attached to the prediction of carbon emission from each site. Total carbon and carbon gas emitted from Alaskan fires is then determined by summing results obtained at the individual site level. To avoid generating negative simulated parameter values, CV values larger than 30% were not used. The range of a normal distribution is approximately six times the standard deviation, hence there is a small (0.0013) probability that negative values are generated if the standard deviation exceeds one third of the mean or, equivalently, as the coefficient of variation exceeds 33%. To avoid negative values, the program was written to flag any instances of negative draws during a run, which happened very rarely.

[30] Several scenarios were performed, related to high, low, and "best guess" uncertainties (Table 2). The low input CVs and high input CVs scenarios were run to help visualize the impact of input CV on the results. The CVs chosen for this exercise were arbitrarily determined for illustration purposes only. The low CVs for the carbon and consumption factors were set at 5%; the high CVs were set at 25%. For these cases, the CVs for area burned and emission factors were not changed since these uncertainties are fairly well known and, in the case of EF, are small.

[31] The "best guess" CVs were defined based on our best assessment of the magnitude of measurement errors as discussed above; most are between the high and low scenarios, but not all, since the high and low cases are chosen for demonstration only. Data for the fuel and consumption model parameters are sparse, so defining the "best guess" CVs is somewhat arbitrary. "Best guess" estimates of uncertainty for β_a was set at 0.23 to match the limited field data available from Alaska. The "best guess" CV for β_g was set at 0.30, although field data tell us that the uncertainty is higher. This is due to limitations of the Monte Carlo sampling procedure, which limits input CV to less than 33% to avoid negative values in the output distribution. "Best guess" estimates of uncertainty in the aboveground carbon density values were set at 10%, based on a report regarding uncertainty in aboveground biomass estimates from forest inventory data in Russia [*Alexeyev et al.*, 2000] since no information on the precision of the actual input data is available. The ground-layer uncertainty was arbitrarily set at 10% (the same as the aboveground CV) since no uncertainty data are available.

[32] The output of the uncertainty model is a set of results for C_t and E_g for all of Alaska over the 50 years of fire records and for a selection of individual sites. The detailed results of calculations at individual sites are shown as examples of the types of results possible at the site level; they were randomly chosen. The distribution of the L realizations is given for the total carbon and each carbon-based gas released, which was then annualized to come up with a distribution of results for the average annual emissions. An analysis of four individual years was also conducted to compare difference in results from high to low fire years and with other studies.

[33] Using the uncertainty model, a sensitivity analysis was performed for calculating C_t. The relative impact of a particular input parameter on output uncertainty was estimated by the increase in the spread of C_t values as larger coefficients of variation were considered for the probability distribution of that parameter. This increase was computed on average for all possible combinations of CV values for other input parameters. This analysis was completed by the computation of correlation coefficient and partial R^2 between CV of C_t values and CV of input parameters, allowing one to assess how much of the variability in total carbon values is due to the different input parameters. Such sensitivity analysis can become computationally expensive if a large number of different CV values is used for all input parameters, so for this analysis five levels of CV were considered. They ranged between 5 and 25% for four parameters, C_a, β_a, C_g, β_g. In light of the computation load that multiple parameters entails, the sensitivity analysis was not performed for E_g. This is acceptable because uncertainty in the E_{fg} values is known to be much smaller than for the other variables, so their impacts would not be the most critical to the results.

4. Uncertainty Model Results

[34] The uncertainty model output is a set of predictions from the L-realizations generated. The simulated mean should approximate the actual emission estimate obtained from calculating emissions with the original input values (held in the GIS-derived input table). For all runs the model-predicted mean emission estimate came within 0.1% of the original emission estimate, indicating that the uncertainty predictions are being properly calculated (Table 3).

[35] Using the "best guess" values for input CVs, the simulated average annual total carbon emissions (C_t) from Alaska over 50 years range from 1.1 to 10.6 TgC-yr^{-1} (1 Tg equals 10^6 tons (t) or 10^9 kg), with an output CV of 24% (Figure 2a and Table 3). Improving the input CVs to an optimistic 5% for the fuel and consumption parameters results in an estimate that ranges between 4.9 and 6.7 TgC-yr^{-1} with a CV of 4%; the mean is similar to the "best guess" case, while the resulting distribution of predicted values is much more narrow. The "high uncer-

Table 3. Total Carbon Emissions (C_t) for Alaska (Average Annual Emissions, in Tons of Carbon (*tC*)) and Three Example Sites Using Three Sets of Input CVs[a]

	Alaska, tC/year	Example Sites, tC		
Original Emissions Estimate				
	5,860,302	2331	449,097	895,371
"Best Guess" CVs				
Predicted average	5,860,711	2332	448,756	894,874
Standard deviation	1,382,497	559	142,393	193,031
CV	0.236	0.240	0.317	0.216
Low CVs				
Predicted average	5,860,308	2331	449,039	895,305
Standard deviation	244,285	236	49,059	88,694
CV	0.042	0.101	0.109	0.099
High CVs				
Predicted average	5,861,122	2331	448,710	894,728
Standard deviation	1,216,967	649	159,972	235,976
CV	0.208	0.278	0.357	0.264

[a]See Table 2.

tainty" case (CVs of 0.25 for the fuel and consumption parameters) shows that if confidence in the carbon density values is worse than expected, but the estimation of ground-layer consumption improves, the result is mixed. Output CV for individual sites is larger than in the "best guess" case, but the region-wide case improves because of the strong influence of the ground-layer consumption values on region-wide uncertainty (see discussion below).

[36] For three example sites (Figures 2b–2d), the CVs of simulated carbon distributions for the "best guess" scenario are 24%, 32%, and 22%; the median CV of all of the site-specific predicted emissions is 27%. The CV for C_t, 24%, is expected to be on the lower end of the ones observed at individual sites because of site averaging. When summing site-specific predicted values to compute the total amount of carbon released (C_t) over Alaska, some variability is averaged out: Overestimation at some sites is compensated for by under-estimation at other sites. This result is better demonstrated in the low input CV cases, where the Alaska-wide CV for emissions uncertainty is 4% while the site-level CVs are near 10% (Table 3). Another consequence of the averaging process is that the histogram of predicted total carbon release is symmetric (application of the central limit theorem), while at some individual sites the histogram is slightly skewed, usually positively (smaller proportion of high values and mean higher than median). Looking at results from individual years reveals that uncertainty in C_t tends to increase slightly as annual area burned decreases (Table 4). This can be attributed to compensation through averaging in years when more area has burned.

[37] Similar results are obtained when predicting emissions of three carbon-based gases, E_g (Table 4 and Figure 3);

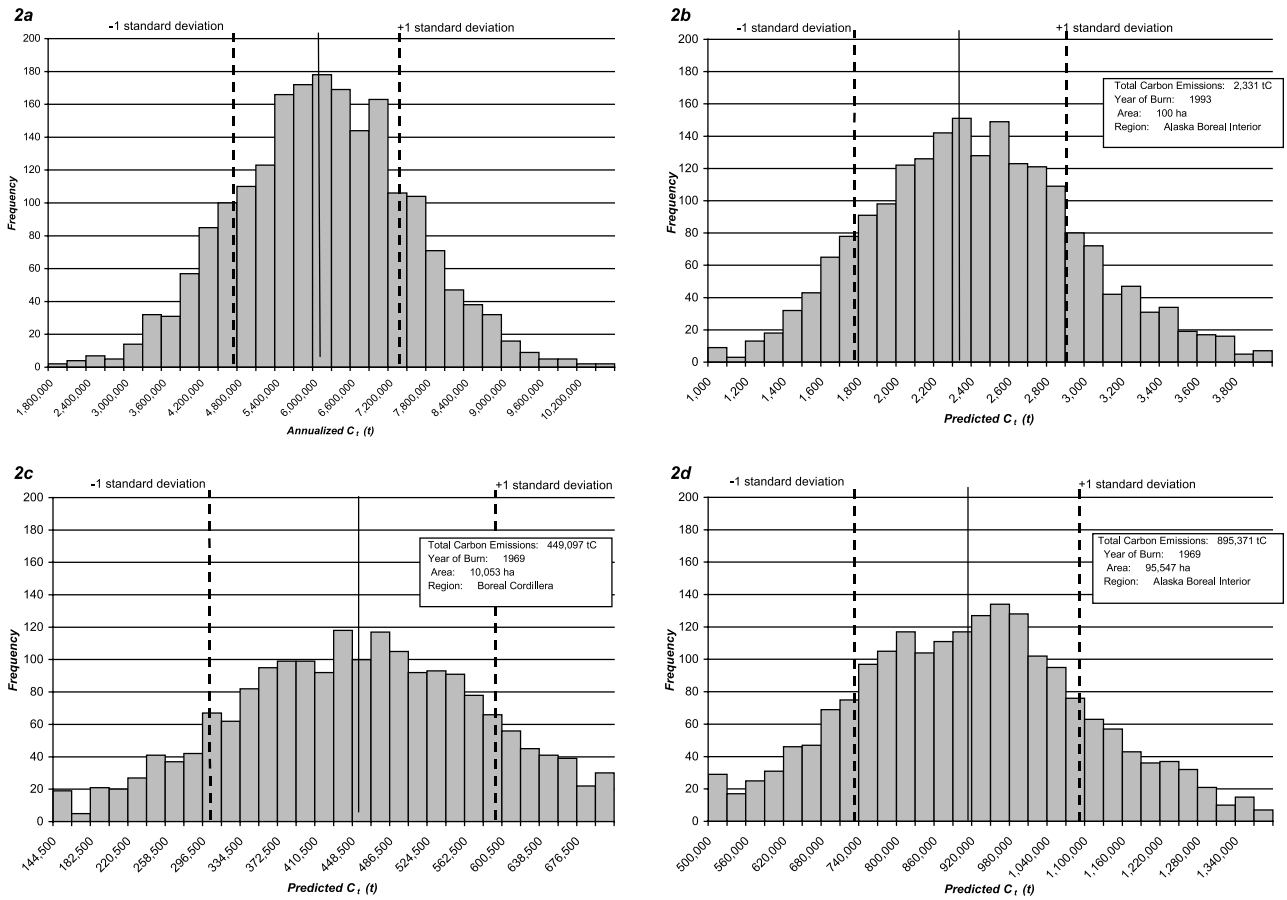

Figure 2. Distributions of total carbon emissions predictions from the uncertainty model for (a) mean annual emissions from Alaska, and (b–d) three example sites. Example sites were arbitrarily chosen to demonstrate the results at individual sites. Number of realizations (L) = 2000.

Table 4. Predicted Total Emissions and Uncertainty in Estimated Emissions of Carbon and Three Carbon-Based Gases for Average Annual Fire in Alaska and Four Individual Years

	Average Annual	1990	1997	1994	1989
Area burned, ha	261,558	1,228,554	703,302	103,334	20,464
		Total C Emissions (tC)			
Average	5,860,711	30,948,599	16,270,248	1,706,643	348,054
Standard deviation	1,382,497	7,299,560	3,976,713	410,391	86,878
CV	0.236	0.236	0.244	0.240	0.250
		Total CO_2 Emissions (tCO_2)			
Average	16,229,446	85,773,334	44,942,342	4,715,489	961,679
Standard deviation	3,703,048	19,683,969	10,907,079	1,098,207	243,000
CV	0.228	0.229	0.243	0.233	0.253
		Total C Emissions As CO_2 (tC)			
Average	4,429,283	23,408,957	12,265,506	1,286,935	262,458
		Total CO Emissions (tCO)			
Average	1,745,088	9,176,084	4,881,808	511,375	105,001
Standard deviation	436,230	2,316,359	1,290,857	131,738	28,988
CV	0.250	0.252	0.264	0.258	0.276
		Total C Emissions As CO (tC)			
Average	748,302	3,934,751	2,093,344	219,280	45,025
		Total CH_4 Emissions (tCH_4)			
Average	64,632	339,035	181,400	18,981	3903
Standard deviation	17,268	90,879	50,571	5185	1115
CV	0.267	0.268	0.279	0.273	0.286
		Total C Emissions As CH_4 (tC)			
Average	48,389	253,831	135,811.86	14,211	2922

uncertainty ranges from 23% to 27%. There is less uncertainty in CO_2 estimates than the two other gases because of less variation in the emission factors for CO_2 than CO or CH_4 (see Table 2).

[38] Our emissions estimates compare well with recent studies. Because mean data inputs for fractions consumed and emission factors varied between this study and our previous study [*French et al.*, 2002], the outputs are not the same. Using our estimates of uncertainty from this study, however, the results do agree. The results also agree with *Goode et al.* [2000] who estimate that 46 ± 11 Tg of CO_2 emitted from 1997 Alaskan fires.

[39] In assessing the impact of the four input parameters on uncertainty in C_t, we find, as expected, the less certain the input parameters, the more variability in carbon predictions (all values in the sensitivity analysis table are positive), although for some of the parameters the increase is of small magnitude (Table 5). The most influential variables are C_g and β_g which represent the carbon emissions originating from ground layers. Because C_g and β_g are multiplied in the carbon model, their respective influence cannot be discriminated in the sensitivity analysis. The same comment applies to C_a and β_a. Clearly, the ground-layer fraction consumed, β_g, is the most important parameter in terms of output uncertainty. The reasons are threefold: (1) this parameter multiplies the amount of ground-layer carbon, which is on average twice the amount of aboveground carbon, hence has a larger impact on the total amount of carbon released; (2) only nine different estimates are used over all of Alaska; and (3) the β_g values have not been simulated independently over the three ecozones because of the assumption that the values for the ecozones would be jointly under-estimated or overestimated. Consequently, some realizations will be characterized by high simulated β_g values at all sites, leading to high simulated values. Conversely, other realizations will have low simulated β_g values at all sites, resulting in low simulated C_t values. Thus, the distribution of all simulated carbon values will tend to have a large range (hence large coefficient of variation) in presence of high uncertainty regarding β_g values. This result is confirmed by the partial R^2 that indicates that 95% of the variance of C_t values is explained by CV of local probability distributions of β_g values (Table 5).

5. Reducing Uncertainties in Model Inputs: The Steps Beyond Estimating Area Burned

[40] The uncertainty in estimates of emissions from fire can originate from both the construction of the emissions model and the input data. Early studies of boreal fire emissions considered only the aboveground carbon pool [*Seiler and Crutzen*, 1980], neglecting large carbon pools in the ground-layer. They often used average estimates for the input values over large regions [*Cahoon et al.*, 1994] rather than regionalizing the input data (as in the work of *Amiro et al.* [2001], *French et al.* [2000, 2002], and *Kasischke et al.* [1995b]). These generalizations were warranted in early analyses when it was apparent that information on the amount of fire in the boreal region was unclear. Their main

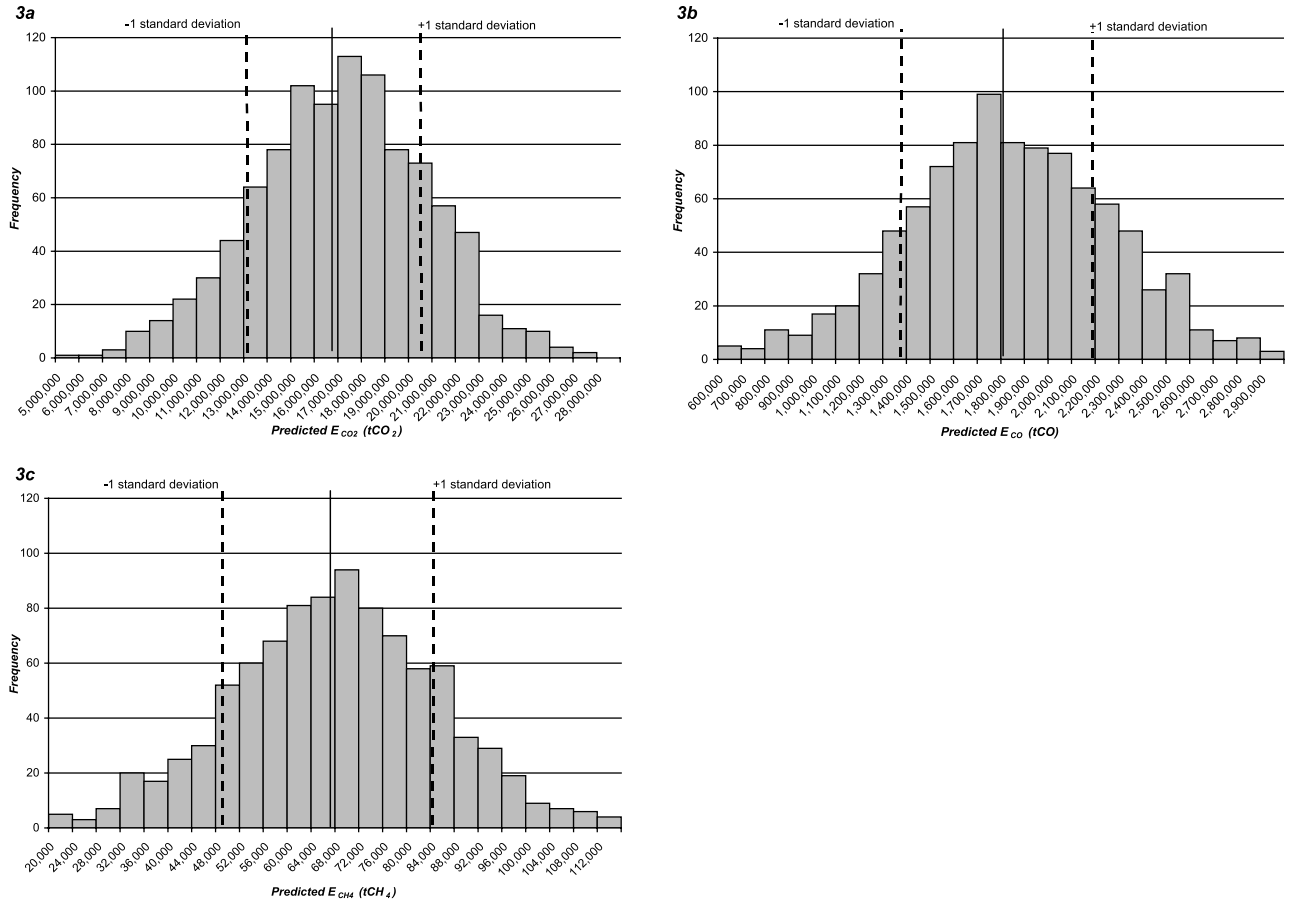

Figure 3. Distributions of predicted mean annual emissions of (a) CO_2, (b) CO, and (c) CH_4 for Alaska. Number of realizations (L) = 1000.

intent was to produce first-order estimates of emissions using the best available information on burn area. Now, however, data on burned area has improved through more careful analysis of fire records and the introduction of remote sensing-based fire area estimations [*Fraser et al.*, 2000; *Stocks et al.*, 2002; A.I. Sukhinin et al., unpublished manuscript, 2004], calling for more detailed attention to the fuel and fuel consumption parts of the problem. In most recent analyses, the consumption portion of the models has become more complex than the original approach of *Seiler and Crutzen* [1980] by separating variation in consumption based on fuel type, geographic location, and other factors.

[41] Other analyses of fire emissions have used model parameters or approaches different than those shown in (1) and (2). *Amiro et al.* [2001] used an approach to estimate total carbon emissions from Canada which was similar to (1), including separate consideration of aboveground and surface fuel components, but they employed a fire behavior model to estimate fuel consumption at each fire site rather than separately estimating fuel amounts and fraction of the material consumed as done in our study. In their case, fuel and the proportion of fuel consumed are linked within the prediction model. Assumptions are made about carbon density (fuel load) based on ''type,'' and the variability in density is captured within the classifications of fuel type, rather than explicitly within the model as in the model we have used. There has been a consensus, however, in boreal forest fire emissions estimation, that carbon and burning in the aboveground component are different from carbon and burning in the ground layer, leading to models which explicitly define input variables for each component. This distinction is not as important in systems where one component is the predominant source of carbon emission; in those systems, variation in burning can be accounted for as an uncertainty in the input parameter data rather than in the structure of the model. As improvements are made in our understanding of boreal fire emissions, the construction of the model should be reviewed to separate out variables that could help refine the emission estimates or combine parameters which need not be separate.

Table 5. Results of Sensitivity Analysis Showing Increases in Carbon Emission Uncertainty as Input CV Increases at 5% Intervals

CV for Input Parameters	CV Increase for Carbon Emission			
	C_a	β_a	C_g	β_g
0.0000	0.0000	0.0000	0.0000	0.0000
5.0000	0.0000	0.0007	0.0003	0.0137
10.0000	0.0002	0.0032	0.0018	0.0426
15.0000	0.0005	0.0073	0.0045	0.0764
20.0000	0.0010	0.0124	0.0080	0.1120
25.0000	0.0017	0.0186	0.0122	0.1485
Correlation coefficient	0.12	0.01	0.10	0.98
Partial R^2	0.000	0.015	0.010	0.957

[42] The scale of the emissions analysis, or the requirement of the study, can also dictate what model parameters are needed and how they are defined. The area burned term (A) and the fraction consumed terms (β) can both account for the spatial impact of fire. At coarse scales, the area burned may be defined as the amount of area where some percent of the material is consumed. This may be dictated by the measurement precision, in the case of a remote sensing-based estimate of burn area, or by the objectives of the study. At a finer scale, a location designated as unburned in a coarse-scale analysis may actually have burned in a very light burn, dictating a designation of burned but with a low consumption fraction. Depending on the scale and situation, therefore, the burn area and consumption terms could be combined into a ''level of burning'' designation, rather than a definitive burn/unburn designation, for each location.

[43] For the study presented here, the inputs are drawn from existing data. Assumptions regarding the mean input values, the uncertainty in the mean values, and the characteristics of the probability distributions of the input variables were necessary because of the paucity of data available for most of the model parameters. A large source of uncertainty in emissions estimates using the methods presented here derives from the estimation of carbon held in the various pools subjected to fire. Data for these inputs are sparse. In our study we used data collected at a few sites across Alaska that had no information on uncertainty. The CV values used for our ''best guess'' scenario are based on the limited evidence available, where possible. In the case of C_g, no uncertainty information on the data used or any similar data set is available, so we chose 10%, the same value used for the aboveground carbon uncertainty. It is likely that this value is lower than the true uncertainty, and it is very possible that the input mean values are not accurate. This type of data gap limits the usefulness of the results we have found, but shows that our knowledge of carbon (fuel) pools is poor.

[44] Much of the output uncertainty found in this analysis results from having nonsite specific information for the consumption values, due to our general lack of spatial information for consumption. We know from site specific field data and analysis that within a single burn there can be highly variable fuel consumption [*Isaev et al.*, 2002; *Michalek et al.*, 2000]; however, we have very little information on how consumption varies across the entire region. Better, spatially defined consumption values would help minimize the impact of this term on the overall uncertainty in emissions. For example, the model could define consumption based on ecosystem type rather than ecozone. These values could then be modeled as independent factors, rather than assuming, as we did, a systematic overestimation or under-estimation of the values for the different ecozones, which created higher uncertainty when propagated through the model.

[45] Data are lacking for some ecosystems types, limiting implementation of an ecosystem type-based approach. *Amiro et al.* [2001] estimated consumption for each burn, but their work assumed that the landscape comprised ''typical'' fuel types, which may have led to an underestimation of total emissions from not including situations such as burning in peatlands or re-burn areas. It is estimated that 15 to 20% of the boreal forest region is covered by peatlands [*Kasischke*, 2000], which can hold very large carbon reserves. *Turetsky et al.* [2002] and *Turetsky and Wieder* [2001] have shown that significant levels of organic soil can be consumed during fires in boreal peatlands, but the current data for carbon density and consumption have not properly accounted for burning in this cover type. High levels of carbon can be consumed in very dry years, when many observations of fire's impacts have been made. This may mean our understanding of peatland burning is biased toward dry/severe fires. However, it is unclear if emission from fire in peatland are over or under estimated since little work has been done to systematically measure this situation. More data are needed for peatland and other ''nontypical'' ecosystems types if we are to properly define consumption across the boreal region.

[46] In addition to improving the emissions model and input data, there are also some improvements that can be made to the uncertainty model itself. First, since we know that fire records and the maps of burn area are more complete and accurate in recent years [*Kasischke et al.*, 2002], the model could allow varying uncertainty in the burn area term (A) by year. Similarly, we may be able to have spatially varying input CVs if, for example, we have better estimates of C_a in one region than another. In addition, once more is known about the input data, the assumptions regarding the distribution of the input data can be refined to create probability distributions for the simulation which may be more complex than the Gaussian and uniform distributions used here.

[47] For the analysis presented here, we have tried to account of the range of uncertainty in the set of model parameters shown in (1) and (2). It is important to recognize, however, that researchers have disparate definitions of some of the commonly used input variables used in modeling emissions, because researchers come from a variety of backgrounds (traditional site-level ecology, fire science, atmospheric science, remote sensing, global climate modeling). The result can be a disparity between the required input data, as the model is constructed, and the data that are actually available and used as inputs. An example is the biomass or carbon density parameters (C_a and C_g in this study). Some researchers measure and work with biomass or fuel that is potentially subject to burning in a fire; the term ''available fuel'' is often used. Some measure and work with total fuel or with carbon stocks. Sometimes these data originate from forest inventories, and sometimes from field measurements designed for fire emissions research. All of these terms connote different portions of the carbon held in a terrestrial ecosystem, and each can be quantified in various manners. The distinction between the needs of the model and the data available for modeling are often not made or stated in fire emission studies. It will be very important, as more work is conducted in this field, to better define the terms used in models and to be sure that the measurements made are appropriate for populating the data inputs for the model parameters of interest.

6. Conclusions

[48] This paper presents a general approach for propagation of error and assessment of the uncertainty given model

inputs and their statistical characteristics. The results of our analysis add to our understanding of the uncertainty in estimates of fire emissions from Alaskan wildfire; more importantly, the exercise was quite valuable for learning the problems associated with emissions estimation. The results of this work show that current estimates of carbon emission from biomass burning are not well constrained because our base data sets are incomplete and lack adequate error information. The analysis shows that improvement in measurements and measurement uncertainty will improve our estimates of fire-related emissions, especially at the regional level (see Table 3). From this work, it has become apparent that data are not available to assess uncertainty properly in a simple model. In the future, attention should be given to creating data sets that include uncertainty estimates so that calculations made using these data sets can be properly interpreted. Additionally, improvements must be made in characterizing fuels and fuel consumption in less-typical forest types, such as peatlands and areas that re-burn within a few years. The exercise presented in this paper points out the extensive work needed to improve estimates of carbon emissions from biomass burning beyond simply quantifying area burned.

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