Uncertainty Analysis of the NONROAD Emissions Model For the State of Georgia

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SUMMARY

Understanding uncertainty in emissions inventories is critical for evaluating both air quality modeling results as well as impacts of emissions reduction strategies. This study focused on quantification of uncertainty due to non-road emissions specifically for the state of Georgia using the EPA NONROAD emissions model.

Nonroad engines contribute significantly to anthropogenic emissions inventories, with national estimates for various criteria pollutants ranging from 14% to 22%. The NONROAD model is designed to estimate emissions for any area in the United States based on population, activity, and emissions data. Information used in the model comes from a variety of sources collected over many years.

A sensitivity analysis of the model determined the input variables that have significant effects on emissions. Results showed that model estimated emissions are significantly sensitive to increases in equipment population, activity, load factor, and emission factor. Increases in ambient temperature, fuel RVP, fuel sulfur (except on SO_2), and average useful life have smaller effects.

Emissions and activity data used in the NONROAD model were analyzed using statistical techniques to quantify uncertainty in the input parameters. Expert elicitation was also used to estimate uncertainties in emission factors, equipment population, activity, load factors, and geographic allocations of the emissions to the county level. A Monte Carlo approach using the derived parameter uncertainties and different input probability distributions was used to estimate the overall uncertainty of emissions from the NONROAD model for the state of Georgia. The uncertainties resulting from this analysis were significant, with 95% confidence intervals about the mean ranging from

–34% to +61% for THC, -46 to +68% for NOx, -43% to 75% for CO, and –48% to +75% for PM.

The sensitivity of ozone and CO for different regions in Georgia to NONROAD emissions in Georgia was also estimated. The analysis suggests that uncertainties in ozone and CO simulations due to NONROAD emissions uncertainties, averaged over the regions of interest, are not large, with resulting maximum coefficients of variation of 1% and 10% respectively.

CHAPTER 1

INTRODUCTION

Poor air quality in metropolitan areas causes many undesirable effects, including negative health impacts and deteriorating visibility. One of the major factors of air quality is anthropogenic emission of pollutants from various sources. Many current regulations focus air quality concerns on ozone (O_3) and particulate matter (PM) concentrations. Emissions of nitrogen oxides (NOx) and volatile organic compounds (VOC) play major roles in ozone formation. PM concentrations in the air are caused by both primary emissions and secondary formation of particulates from a variety of compounds.

Anthropogenic pollutant emissions are generally classified into stationary, area, on-road, and nonroad categories, with nonroad engines defined as equipment moved at least once every 12 months that do not fall under the category of motor vehicle.[1] Various mandated controls of emissions from stationary and on-road sources have been in effect for several decades as a result of the Clean Air Act of 1963 and its subsequent amendments. Reducing emissions from these sources have become more difficult and more expensive as controls and standards have become more stringent. On the other hand, nonroad engines, which escaped regulation for much of this time, are a large and untapped potential source of emissions reductions. For instance, heavy diesel engines are often used in construction equipment. Unregulated, these engines can emit large amounts of NOx and PM. Smaller gasoline-fueled engines dominate the lawn and garden equipment population and release significant amounts of VOC and CO.

In the past decade, nonroad engine emissions have increasingly become the focus of regulatory action and air quality improvement strategies. Nationally, nonroad emissions generally increased until the mid-1990s.[2] During this time, nonroad emissions also increased their share of the overall emissions total for most pollutants, especially since growth in stationary and on-road sources were being moderated by heavy regulation. Nonroad engines contributed 9% of national carbon monoxide (CO) emissions in 1940, but their share increased to 22% by the late 1990s. Similarly, the nonroad emissions share of the national inventory increased for volatile organic compounds (VOC) from 5% in 1940 to 14% in 1998. Particulate matter (PM) and sulfur dioxide (SO_2) nonroad emissions do not follow this same trend because of drastic reductions from locomotives between 1940 and 1970. However, recent years show much less progress in reducing emissions of these pollutants. Regulators and scientists, alike, still view nonroad emissions as a significant source of emissions and potential emissions reductions. Numerous upcoming and proposed regulations concerning nonroad engines and nonroad fuels reflect this view.

As emissions estimation methods for nonroad and other source categories become more sophisticated, interest in emissions uncertainty is also growing. One objective of quantifying uncertainty in emissions is to determine the improvement of inventory estimates as models and methods become increasingly more intensive and complex. Another objective of understanding uncertainty is to aid in making informed decisions about ways to reduce emissions and improve air quality.

Ayyub defines uncertainty as “knowledge incompleteness due to inherent deficiencies with acquired knowledge,” stemming from ambiguity or “the possibility of having multiple outcomes for processes or systems," approximations or "vagueness, coarseness, and simplification," and likelihood or "chance, odds, and gambling … [with respect to] randomness and sampling."[3] Uncertainty can be quantitatively described in many ways. Unless otherwise noted, uncertainty in this study refers to the double-sided 95% confidence interval about the mean. Emissions uncertainties are driven by a lack of data, and, in general, much less data for nonroad emissions currently exist than for either on-road mobile or stationary sources.

The techniques for quantifying uncertainty used in this study include expert elicitation and Monte Carlo numerical techniques of bootstrap analysis and simple random sampling (SRS). Use of numerical Monte Carlo techniques for analyzing and evaluating mathematical problems and models has become increasingly ubiquitous with the arrival and advancement of computer technology in the last half century.[4] Monte Carlo schemes involve the generation of randomized variables to simulate possible outcomes of a problem or model. Analysis can then be performed on the generated outcomes. Increasing the number of simulations in the Monte Carlo scheme decreases the error of calculations by a factor of $1/N^{1/2}$. This allows the actual algorithms of the problem or model to be treated as a black box. As the name implies, in SRS Monte Carlo, the randomized variables are simply generated based on distributions. More sophisticated methods of Monte Carlo exist, such as Latin hypercube sampling and the use of Markov chains to determine the accuracy of the distributions used. However, these are not necessary for and are beyond the scope of this work.

Bootstrap methods are used to determine the precision of a given set of data by generating simulated datasets of the same size as the original. The simulated datasets can be sampled with replacement from the actual data, the resampling or non-parametric method, or sampled from a distribution fit to the data, the parametric method. Bootstrap results help determine whether a dataset may have been biased by random errors and can provide quantification of the resulting uncertainties.[5]

Expert elicitation methods are commonly used to fill gaps where actual data is not readily available. Uncertainty studies are inherently a natural fit for the use of expert opinion. The advantage of using expert opinion in uncertainty estimates is that the experts can account for uncertainties not reflected in the actual data or algorithms, such as errors of representativeness or method. However, the major disadvantage of using expert judgment is the possible introduction of bias from many different sources.

When asked to provide opinions of uncertainty without the presence of hard data, experts will tend to rely on heuristics, or educated guesses based on common sense and past experience. Heuristics can be placed into many categories. Cooke defines "availability" as the ease with which an expert can grasp or recall a set of data. In this case, bias results from the tendency to inflate well-known data and overlook lesser-known, though equally important, data. Estimates based on availability also tend to be poorer when the conceptual problem is too large or values to be processed are too high. Another example of a heuristic is "representativeness." The expert uses a past experience and judges how similar the current experience is. Representativeness estimates may lead to errors when sample size or other differences between the past and current experiences are not taken into effect. Some other general sources of bias are overconfidence and poor judgment of relative values, as well as the "base rate fallacy," or the tendency to improperly use or ignore past probabilities or related information.[6] Finally, the principal problem in conducting an expert elicitation is defining what an expert is, which is, in of itself, a judgment call.

This study focuses on the state of Georgia, where nonroad engines in 2007 are estimated to contribute 19% of total NOx emissions.[7] The metropolitan Atlanta area is in nonattainment for both the 1-hour and 8-hour ozone standards and will likely be designated as nonattainment for PM2.5 in the fall of 2004. The Atlanta-Sandy Springs-Gainesville Combined Statistical Area (CSA) emits nearly half of the state total nonroad NOx emissions, even though it counts for only 20% of the total number of counties.[7]

In addition, the metropolitan areas of Columbus, Macon, and Augusta have also experienced ozone exceedances in recent years. The Columbus and Macon areas also are on EPA's recommended PM2.5 nonattainment list.[8] The Macon, Columbus, and Augusta Metropolitan Statistical Areas (MSA) account for 4, 3, and 2% of state total nonroad NOx respectively,[7] and their included number of counties are 4, 2.5, and 2.5% of the state. Meanwhile, again using number of counties as a rough area approximation, the rest of the state emits the remaining 43% of nonroad NOx emissions while comprising 70% of the number of counties.[7]

Nonroad engines certainly seem to be significant, though perhaps not dominant, sources of emissions in Georgia. The areas with the poorest air quality also tend to contribute more than their fair share to nonroad emissions. Thus, efforts to reduce pollution in Georgia will likely focus a considerable amount of attention on the nonroad category. With extensive ongoing and upcoming air quality modeling and regulatory activities in the metropolitan areas, emissions inventory uncertainties will also receive increased and well-deserved attention. The analysis of uncertainty of the nonroad inventory performed in this study can consequently aid in understanding the overall air quality problems in Georgia.

CHAPTER 2

EPA NONROAD MODEL BACKGROUND

In the mid-1990s, EPA developed software for estimating nonroad emissions for any area in the United States. Before this time, nonroad emissions inventory preparation involved tedious use of equipment and emission factor data from past studies. The NONROAD emissions model was first released publicly in 1998,[9] and included emissions estimating capabilities for all nonroad source categories except for aircraft, locomotives, and commercial marine vessels. Ultimately, the goal was to build a standard model for use in State Implementation Plan (SIP) preparation. The model was designed for easy user-modification to adjust for local conditions, and most data is not hard-coded in the program. Between 1998 and 2004, several versions of this model have been publicly released, although the model is still officially in draft form.[10]

EPA released the latest draft version of NONROAD (v. 2004) in May 2004,[11] but not in time for this work. EPA anticipates releasing of the final version of the model in late 2004.[12] This study used the publicly released draft version of NONROAD (v. 2002a) available at the start of this work in all analyses. Version 2004 includes some data improvements, but the model methods remain the same. The data improvements are important for modeling future years because of the inclusion of recently implemented regulations, such as the Clean Air Nonroad Diesel Final Rule just announced in May of 2004.[12] For modeling of past and recent years, however, the emissions outputs generally differ between the two versions by less or, in most cases, much less than 10% for all pollutants. The analyses performed and results obtained using Version 2002a should be applicable for the new model as well.

The NONROAD model estimates emissions for any area in the United States at the national, state, or county levels for hydrocarbons (HC), oxides of nitrogen (NOx), carbon monoxide (CO), carbon dioxide (CO_2), sulfur dioxide (SO_2), and particulate matter (PM). The model can also convert HC emissions to a variety of different forms, including volatile organic compounds (VOC). PM is characterized by particles with aerodynamic diameters of less than 2.5 microns (PM2.5) or less than 10 microns (PM10) aerodynamic diameter. The model can estimate emissions by year, season, month, and day of week (weekday or weekend).

The NONROAD model estimates emissions from over 260 specific equipment types within the broad categories of airport ground support, agricultural, commercial, construction and mining, industrial, lawn and garden, logging, railway maintenance, recreational, and recreational marine equipment.[10] Equipment population data, activity surveys, and emission testing results are used in the following basic equation.

Emissions = (population)x(rated power)x(load factor)x(activity)x(emission factor)

Equipment engines may be of the following types: diesel, 2-stroke gasoline, 4-stroke gasoline, compressed natural gas (CNG), and liquefied petroleum gas (LPG). The equipment type for each fuel type is further delineated by horsepower rating. The above equation is applied at the horsepower rating group level for each equipment and fuel type.

However, this rather simple equation is complicated by a number of other parameters that affect one or more of the above major components. For example, growth factors and geographic allocation influence equipment populations; season, month, and day of week affect activity parameters; corrections for temperature, fuel characteristics, deterioration, and age distribution modify emission factors; finally, scrappage and growth rates adjust the age distribution of the equipment.

Figure 1 shows a schematic of the NONROAD model algorithm. All of the variables shown in the figure can be modified by the user, except for the methods by which emission factor corrections for temperature, fuel sulfur, fuel Reid vapor pressure (RVP), and fuel oxygenate content are calculated.

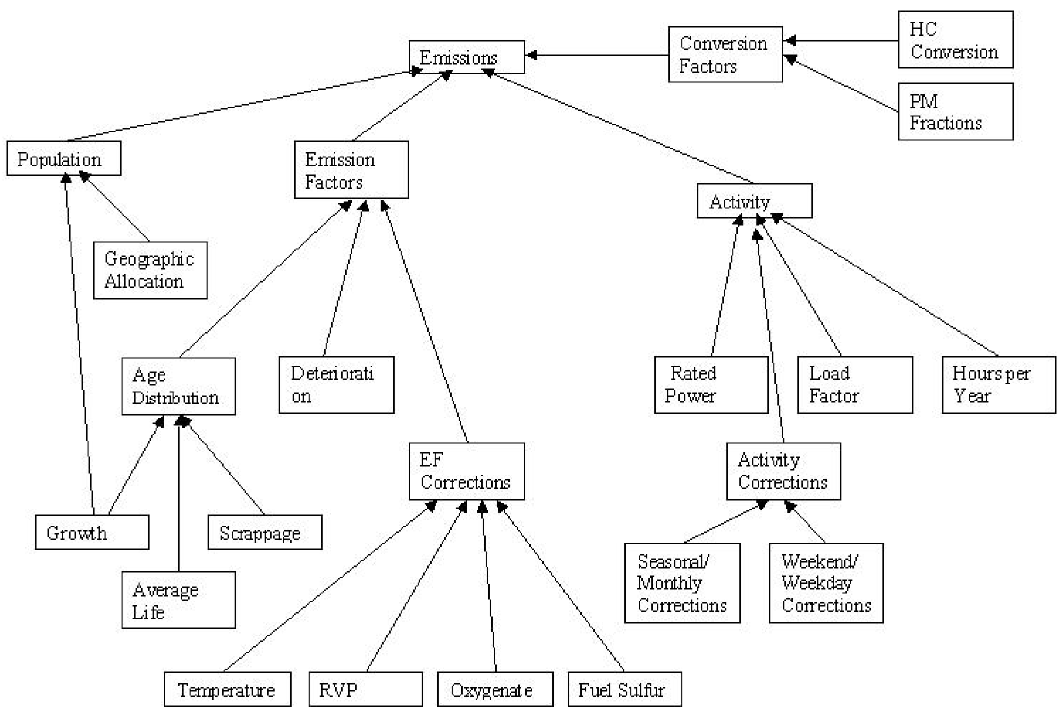

Figure 1. Schematic of EPA NONROAD emissions model components and their dependencies.

It should be noted that the current version of the model does not account for some pollutant sources and factors, such as tampering effects and some evaporative emissions. For example, running and resting losses are omitted in model calculations, but EPA asserts that these would be minor compared to diurnal evaporative emissions.[13] Uncertainties associated with various model assumptions of this type or problems in the model algorithms themselves are beyond the scope of this study.

As shown in Figure 2, many different source categories comprise NONROAD emissions. Certain prevalent equipment types and/or fuel types often characterize individual source categories and shape the emissions profile. NOx and PM are generally dominated by diesel construction equipment emissions, while gasoline-powered lawn and garden equipment contribute a large fraction of VOC and CO emissions. Different source categories also have varying amounts of influence across a given region, depending on urban/rural characteristics and dominant local industries. The NONROAD model attempts to take all these factors into account.

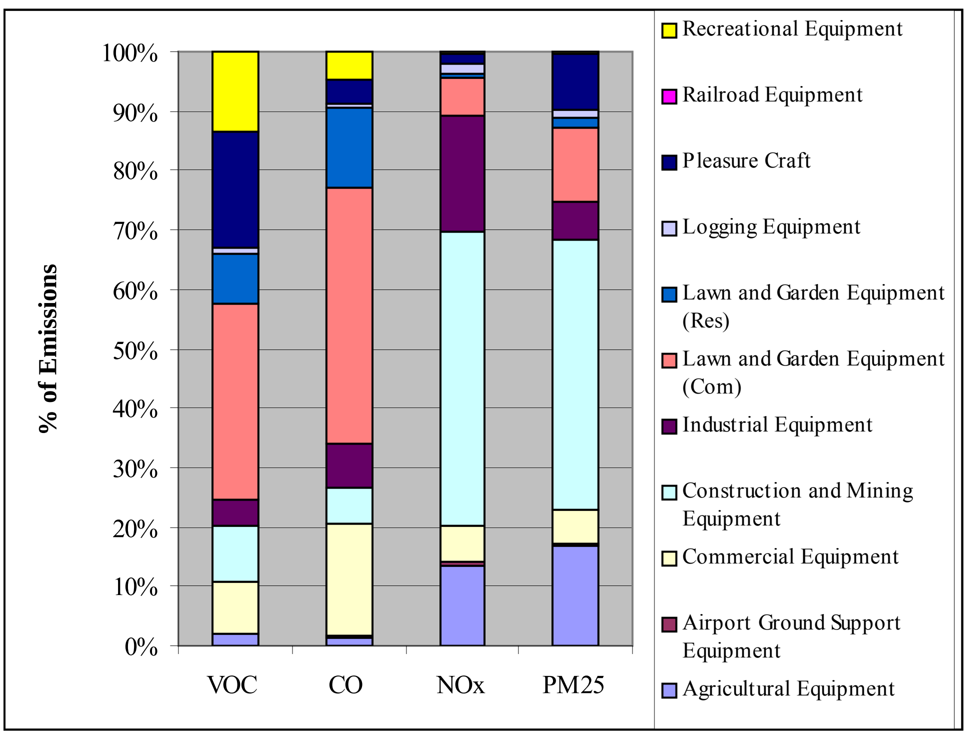

Figure 2. NONROAD model-estimated emissions contributions of source categories for 1999 Georgia typical summer weekday.

The NONROAD model attempts to account for the many factors that impact engine emissions at a very detailed level. Because of the large number of equipment types and subcategories and the various input variables affecting the emissions estimate, an analytical uncertainty analysis would be difficult and tedious. However, because most of the input parameters are accessible and can be modified, the NONROAD model is an ideal candidate for numerical uncertainty estimation.

CHAPTER 3

LITERATURE REVIEW OF EMISSIONS UNCERTAINTIES

The study of uncertainties of emissions inventory estimates is still a developing field. It is widely recognized that uncertainty in nonroad emissions estimation is significant, but currently data and past study in this specific field are limited. In broader terms, Lee et. al. estimated global nitrogen oxides (NOx) emissions from fossil fuel combustion to have uncertainties of ±41%.[14] This was based on Dignon's 1992 estimate of 1980 base inventory total emissions of 11 TgN/yr and aggregated uncertainty estimates by Intergovernmental Panel on Climate Change (IPCC) and others that ranged between ±20% and ±50%. For North America and Europe, the NOx emissions uncertainty was estimated to be ±25%.[14]

The National Acid Precipitation Assessment Program (NAPAP) funded a study to estimate uncertainties in its 1980 NAPAP emissions inventory for the United States. This study estimated uncertainties of emission factors and activity data using both expert judgment and analysis of data variability.[15] The 1980 emission factor uncertainty values for NOx were ±31% for transportation emissions and ±25% for other sources. Corresponding values for VOC were ±50% and ±100%. Activity uncertainties were estimated at ±15% for point sources and ±25% for other sources.[16] These values were applied to individual source categories and propagated through the emissions calculations for grid-level, state-level, regional, and national emissions inventories, resulting in ±31%, ±8%, ±4%, and ±1% uncertainties respectively.[15] However, the NAPAP study did not account for possible bias or procedural errors, and most view the uncertainty estimates as unrealistically low.[15]

Gschwandtner elaborated on the NAPAP results to determine trends in emissions inventory uncertainties over time.[16] He assumed various adjustment factors for the NAPAP emission factor and activity uncertainty values based on the historical procedures used for estimation. For example, past data estimates based on using surrogate information were given uncertainty values twice as large as the 1980 NAPAP "standard" values, while data originating from "best guesses" were assigned uncertainties ten times greater. Gschwandtner also used a more conservative approach, assuming the uncertainty values applied to the national emission factor and activity data, rather than at the local source level. As a result, the study found that uncertainties in the national NOx emission inventory decreased from ±38% to ±18% from 1900 to 1980. The VOC inventory uncertainty decreased by a factor of 28 in the same period, from over ±500% to less than ±20%. Gschwandtner asserts that under such extreme uncertainties for VOC in 1900, conclusions about changes in emissions from 1900 to 1980 cannot be made.[16]

Battye also estimated uncertainties and biases related to the national VOC inventory based on data from the 1985 NAPAP and the Regional O_3 Modeling for Northeast Transport (ROMNET) emissions estimating activities.[15] He noted that on-road vehicles miles traveled (VMT) activity data used in NAPAP were estimated by the Argonne National Laboratory to have uncertainties of ±5%, while the effects of temperature on emission factors could lead to ±25% uncertainty when using average temperatures for a given day. Battye also found that the solvent VOC inventory had potential biases of –15% due to omitted compounds and +3 to +18% due to double counting. The effects of variable control efficiencies across the nation were estimated to possibly contribute to a ±10 to ±33% error in the solvent VOC inventory. Finally, Battye noted that neglecting rule effectiveness in the NAPAP and ROMNET point source inventories led to underestimation of VOC emissions by 60%.[15]

More specifically, some past studies of photochemical grid modeling have included determination of the uncertainty of broad emissions inventory categories that include nonroad engines. A study by Hanna et.al. that elicited opinion from 10 experts found the uncertainty of anthropogenic area source emissions to be ± 40% for nitrogen oxides (NO_X), and ± 80% for VOC.[17] These values represented 95% confidence intervals about the median. A follow-up study that surveyed 20 experts then found the uncertainty of area mobile source emissions to be a factor of 2 (under a log-normal distribution) for both NO_X and VOC.[18]

The studies by Hanna were conducted in a top-down approach in terms of emissions uncertainty, with determinations of only the overall uncertainty of the inventory for the purpose of air quality modeling. The work described here in this report focuses on a more bottom-up approach, obtaining uncertainty of different components of the NONROAD emissions model, and working up to the overall inventory uncertainty. An important first step in using the bottom-up approach would be determination of uncertainty of emissions coming from individual nonroad engines. Thus far, study in this area has been limited. Past analyses of nonroad engine emission factor uncertainty by Frey have estimated uncertainties based on 95 percent confidence intervals using parametric bootstrap analysis of data assembled from several engine-testing studies.[19, 20] Two-stroke total hydrocarbons (THC) and NO_X emissions uncertainties in lawn and garden equipment were found to be -32% to +38% and -46% to +65% respectively. Analysis of 4-stroke engines yielded uncertainties of -38% to +45% for THC and -25% to +38% for NO_x.[19] In a different study, Frey also used parametric bootstrap analysis for engines in the construction, farm, and industrial category.[20] Analysis of the gasoline engines led to NOx emission factor uncertainties of –32% to +38%, and THC emission factor uncertainties of –22% to +17%. For diesel-fueled equipment, 2-stroke engines displayed uncertainties of –21 to +20% for NOx and –48 to +49% for THC; the uncertainties for 4-stroke engines were –10 to +11% for NOx and ±26% for THC.[20] These studies did not directly use the emission factor data in the NONROAD model due to lack of available sources, but used available emission factor studies that should be similar to what is used by EPA in the model.

The nonroad emission factor studies by Frey and his colleagues relied on test data from only similar test cycles.[19, 20] A test cycle generally takes an engine through several different set speeds with the goal of simulating the different possible operating conditions in the real world. In reality, no individual test cycle can capture the potential operating conditions used by actual equipment. Because of a general lack of data, comparisons across different test cycles for nonroad emission factors could not be made. However, on-road vehicle test data is much more abundant and readily available for many different driving cycles. Frey conducted uncertainty analysis for light-duty vehicle CO emission factors and found that the standard Federal Test Procedure (FTP) driving cycle results yielded random errors of only ±10%. However, emission factors from 10 other driving cycle tests all had uncertainties of at least twice as much, ranging up to –70% to +66%. Furthermore, the different driving cycle results showed significant bias when compared to the EPA MOBILE5b on-road emission factor model results.[21] The bias for eight driving cycles ranged from -64% to +36% when compared to MOBILE5b predictions, with the FTP cycle having a relatively small bias at +8%. Researchers at West Virginia University quantified uncertainty in on-road heavy-duty diesel vehicles over different driving cycles using the Mobile Emissions Measurement System (MEMS) and found NOx potential errors to be about 8% or less.[22]

On-road emission factor data is not directly comparable to nonroad, most notably because of differences in emission standards, fuel characteristics, control technologies, and operating modes. However, basic engine construction and behavior is often similar for the two source categories. Also, looking at on-road analyses can be helpful to determine possible uncertainty patterns and important variables in nonroad engines because of the lack of available nonroad data. Furthermore, the aforementioned on-road studies represent bottom-up approaches to emissions uncertainty estimates that take into about emission factors and activity data (driving cycles). Such studies are not currently available for nonroad engines.

Overall, much work needs to be done in the area of emissions uncertainties before such estimates can gain wide acceptance for all of the major source categories. Currently, one of the major roadblocks to comprehensive emissions inventory uncertainty analysis is the lack of data availability or consistency across various datasets and studies. However, in particular, the nonroad source category requires more study in both basic nominal estimates and the uncertainties of populations, activity, and emissions. As new regulatory focus shifts from on-road and stationary sources to nonroad sources, study of emissions estimation and the associated potential errors must also increasingly emphasize the nonroad category. This work aims to take a step towards remedying the shortage in study of this source category.

CHAPTER 4

METHODS

In this study, we used the EPA publicly available draft NONROAD model[11] for quantification of uncertainty for nonroad emissions in the state of Georgia. For this purpose, we first conducted a sensitivity analysis in order to identify variables that have significant impact on emissions. Statistical methods as well as expert elicitation results were used to quantify uncertainty in nonroad emissions. For overall uncertainty, a Monte Carlo technique was applied. This section provides detailed information on the methods used.

Modeled Scenario

Modeling of Georgia nonroad emissions in this study was based on scenarios set up for the Fall-line Air Quality Study (FAQS) conducted by Georgia Tech for the Georgia Department of Natural Resources (GA DNR). The FAQS project was conducted by Georgia Tech with funds provided by the State of Georgia Department of Natural Resources and Department of Transportation. This study focused on the metropolitan areas of Macon, Columbus, and Augusta in an attempt to proactively improve the air quality in these areas. In the recent past, all of these areas have experienced occasional ozone and PM exceedances. The study began in the year 2000 and is currently ongoing with the goal of taking steps to reduce air pollution. While much past study has focused on the Atlanta area, since it has been exceeding air quality standards for 25 years, much less data exists for the other metropolitan areas of Georgia. FAQS efforts include air quality monitoring, detailed emission inventory development, air quality scenario modeling, and evaluation of all of the above.

FAQS and this study target August episodes for years 1999 and 2000.[23] This thesis focuses more on the 2000 episode, although 1999 nonroad emissions were examined as well. These calendar years were chosen to represent past periods of high ozone levels in the metropolitan areas of Georgia. During these episodes, ozone exceedances were measured not only at monitors in Atlanta, but also in other areas across the state. During the 2000 episode, which covers August 11^{th} to 20^{th}, ozone exceedances occurred on each day from the 13^{th} to the 19^{th}. On the worst air quality day of the episode, August 17^{th}, 2000, monitors recorded 8-hour and 1-hour ozone violations in all three FAQS metropolitan areas, as well as Atlanta.

Although the NONROAD model contains default data for population, activity, emission factor, and other input parameters that do not always need to be changed, some scenario variables must be defined each time the model is used. These include the period of interest, temperatures, and fuel characteristics for the particular episode and region. The Georgia Environmental Protection Division (GA EPD) provided the NONROAD model inputs for these variables, shown in Table 1, for the August episodes.

Technically, the gasoline fuel sulfur content for the Atlanta nonattainment and surrounding counties should be at most 150ppm or 0.015%. However, test runs with the NONROAD model show that the sulfur reduction results in a less than 2% decrease in the SO_2 emissions estimate and an imperceptible change in PM emissions for the applicable counties. Statewide, the total SO_2 emissions decrease less than 1%. Thus, all subsequent modeling ignores the low sulfur gasoline requirement in the Atlanta area and models sulfur levels for all counties the same. This allows the NONROAD model to be run at the state level instead of the county level.

Table 1. NONROAD model scenario inputs for Georgia.

Calendar Year	1999	2000
Fuel RVP for gas	7	7
Oxygen Weight %	0	0
Gas sulfur %	0.034	0.034
Diesel sulfur %	0.33	0.33
CNG/LPG sulfur %	0.003	0.003
Minimum temper. (F)	69.7	67.7
Maximum temper. (F)	93.9	90.4
Average temper. (F)	81.8	79.1
Altitude of region	LOW	LOW

Table 1 characterizes the episodes used in this study for the emissions modeling. For all other input parameters not listed in the table above, the default NONROAD values were used to represent the base case.

Sensitivity Analysis of NONROAD

A sensitivity analysis of the NONROAD model was conducted to determine the relative importance of different input parameters to the model outcomes. The sensitivity was conducted using a "brute force" method where the model was run at a base scenario, then varied in subsequent runs to observe output changes. The sensitivity analysis was performed for the summer 1999 scenario. However, the inputs are similar and statewide emission estimates for 1999 and 2000 differ by less than 2%, and thus the sensitivity results apply to either year.

The parameters to be studied in this case were: equipment population, emission factors, activity, load factor, useful life, temperature, RVP, and fuel sulfur content. Although NONROAD incorporates several other input parameters, these were picked based on their likelihood to significantly impact emissions. For example, the useful life parameter was chosen as the most readily modified representative input dealing with deterioration, scrappage, and age distribution effects. On the other hand, this study did not examine growth factor effects, because the base year equipment populations in the model are virtually all developed from 1998 and 1999 data. Thus, the forecasting of growth required to estimate 1999 and 2000 emissions adds very little; it is assumed that growth contributions to uncertainty are negligible compared to the other parameters.

Each chosen parameter was varied individually at 110% and 90% of the base parameter value while keeping all other input variables constant. The model output resulting from these modifications was used to calculate sensitivity of emissions to each of the input parameters of interest according to the following equation:

$$S = (E_{110\%} - E_{90\%}) \ / \ (P_{110\%} - P_{90\%}),$$

where S is the sensitivity, E is emissions output, and P is the parameter value. The normalized sensitivity coefficient was calculated as follows:

$$S_{norm} = S \times (P_{base}/E_{base}).$$

The normalized sensitivity coefficients were then used to compare the relative impacts of different input variables.

Bootstrap Analysis of Emission Factors

In general, bootstrap techniques involve random sampling from available datasets or fitted distributions to create a large number of pseudo-datasets on which statistical analysis is performed. The pseudo-datasets contain the same number of elements as the original, but the elements have been picked at random with replacement. This type of analysis can quantify uncertainty about the mean of the data on hand, accounting for random errors.[5]

For the more recent diesel engine model years (1996 and on), NONROAD uses Tier 1 and Tier 2 engine test certification data to calculate the emission factors used by the model. These grams per horsepower-hour (g/hp-hr) test results are provided in the model documentation.[24] Thus, the emission test results can be used directly in an uncertainty analysis of emission factor values. The test data were grouped by engine horsepower and each data point was associated with a specific engine sales fraction. The sales fraction and data were used together to estimate a mean emission factor for each horsepower grouping. Although past work has suggested that the horsepower groupings used by the model are not actually statistically significant for calculation of mean emission factors,[19] this analysis retained the horsepower groupings to most accurately reflect what is applied by NONROAD.

Bootstrap analyses were performed for data from model years 1996 to 1998 using both a resampling technique, applied using MATLAB©, and a parametric method, using the Analysis of Uncertainty and Variability Tool (AuvTool) software.[25] The resampling method involved random sampling with replacement from the actual emission factor data to create 10,000 bootstrap datasets. The AuvTool calculates the 95% confidence interval of a given sample using a parametric bootstrap method.[26] An empirical distribution was fit to samples using this software and 200 random datasets were generated for each case. Although far few trials were used in the AuvTool method, increasing the number of datasets did not significantly alter the results. For both bootstrap techniques, 95% confidence intervals about the mean were calculated for each model year and horsepower group dataset.

Expert Elicitation of Uncertainties

Uncertainty analysis of non-emission factor NONROAD input parameters is difficult due to lack of available data. Therefore, expert elicitation was used to determine the uncertainties of the important input parameters as selected during the sensitivity analysis. In addition, expert elicitation was used to determine uncertainties in the geographic allocation of the emissions.

The engine population and activity data are, in many cases, taken from or based on the Power Systems Research (PSR) engine databases. The PSR database is based on an on-going survey of at least 10,000 engine owners per year and includes engine population, activity, and load factor information. PSR also conducts some analyses to determine appropriate geographic allocations of the equipment populations down to the county level. PSR uses 22 types of surrogate data to estimate county populations, including economic, geographic, demographic, and meteorological surrogates.[27]

However, the database is proprietary, and thus the data and explicit methods are not publicly available.

The NONROAD model uses much of the national engine population and activity data from PSR, but does make substitutions in many instances based on EPA studies, often from rulemakings. EPA also does not use the PSR geographic allocation, because the explicit methods are not public. However, NONROAD does use a surrogate allocation method in which population, engine survey data, economic parameters, etc. are used to distribute the national total emissions.[28] Simple fractions, based on the relative surrogate values, apportion the emissions to each county.

PSR provided some rough estimates of uncertainty for different parameters in their database.[29] They estimated the uncertainty of engine life to be ± 10%, annual hours of activity to be ± 5%, and load factor to be ± 4%. The geographic distributions by state of the equipment were estimated to have ± 6% uncertainty by engine type, ± 4% by horsepower grouping, and ± 7% by application. The geographic distributions by county of the equipment were estimated to have ± 12% uncertainty by engine type, ± 9% by horsepower grouping, and ± 15% by application.

PSR expert opinion was not directly used in the ensuing analysis because it was based on their database only and does not account for the modifications or substitutions EPA makes for the NONROAD model. The uncertainty values are also rather small and possibly overconfident. Thus, these values were deemed not fully applicable to this study. However, they likely represent a lower bound on the uncertainty and can be used to assess those found via other methods.

Instead, an email-based survey was conducted of known experts in the NONROAD emission field. Experts were identified based on emphasis of emissions modeling experience, not air quality modeling experience, to maintain focus on a bottom-up uncertainty analysis approach. Five of seven companies/agencies with vast past experience in nonroad emissions responded to the survey. The survey asked for uncertainty estimates (95% confidence intervals) for 42 specific NONROAD input parameters in the categories of equipment population, activity, load factor, geographic allocation, and emission factor. A sample survey is provided in Appendix A and shows that information on the data source and estimation methods were supplied for each NONROAD input parameter.

Experts were "scored" based on self-ratings of their knowledge and experience in nonroad emissions inventory preparation, nonroad model development, nonroad engines emissions testing, and nonroad emissions uncertainty. This scoring, a 1 to 10 rating in each category, was used to weight the responses when computing averages. The opinion of the most experienced experts had greater influence on the average than those with less experience. All four knowledge and experience categories were considered equally important, and the quality of each expert's responses was assumed to be directly proportional to his or her self-ratings. Thus, if Expert A rated himself a 10 out of 10 in all categories and Expert B rated himself a 5 out of 10 in all categories, Expert A's responses would have twice the weighting of Expert B.

This work focuses on the exhaust THC, NOx, CO, and PM pollutant emissions. CO_2 and SO_2 were not dealt with here because their estimations in NONROAD are not emission factor based, but depend on fuel consumption rates only. This study did not include uncertainty of fuel consumption rates. Also, evaporative THC emissions were ignored in this analysis because it makes up only a small fraction of total THC. Furthermore, for the state of Georgia, THC emissions from man-made sources are less important overall. These elements were omitted from the survey as part of efforts to limit the already large number of questions the experts were asked to answer.

SRS Monte Carlo Simulations of NONROAD

Monte Carlo (MC) simulations were performed on the NONROAD model to determine the overall emissions uncertainty based on the various uncertainties of the specific inputs. The NONROAD model was run in batch mode, with each run consisting of a randomly generated set of inputs based on the 95% confidence interval survey results. Each of the 42 input parameters included in the survey apply to several hundred different subvalues used in the NONROAD model, varying by equipment type, county, etc. Thus random numbers are generated for the 42 input data groups, and the same random numbers are applied to all subvalues for any given simulation.

Three Monte Carlo simulation approaches were conducted for the summer 1999 scenario for Georgia statewide NONROAD emissions: generating random inputs using normal distributions with unequal halves (to account for positively or negatively skewed confidence intervals), using uniform distributions, and using triangular distributions. In the ensuing analyses, these scenarios will be referred to as 99a, 99b, and 99c respectively. In each case, the default parameter value was set to be the mode of the distribution. These three set-ups were conducted to compare the importance of the distribution used in the analysis in an uncomplicated way. The uniform distribution captures the most extreme, most conservative case, while the normal distributed data represents the least conservative case in terms of uncertainty of the output. While these setups do not necessarily reflect likely real-world data patterns, they do reflect the most straightforward way to apply the uncertainty values to distributions en masse since the actual uncertainty distributions are unknown.

Two MC scenarios were used for the summer 2000 episode. One set of simulations, henceforth referred to as 00a, employed the discontinuous normal distributions, using the same techniques as described for 1999. The second set of simulations, 00e, attempted to use more realistic distributions where possible and to retain the default values as mean quantities. Thus, for the 00e simulations, all default values were treated as the **mean** of the distribution rather than the mode. All uncertainty values were fit to lognormal distributions where possible. When lognormal distributions did not provide a good fit to the 95% confidence intervals, either triangle, beta, pareto, or clipped lognormal distributions were used. Normal distributions were avoided to eliminate the possibility of negative input values. Distribution fits were determined with the assistance of the BW D-Calc© software program, with the criteria that the upper and lower confidence interval bounds must not differ from the target values by more than 5%. For each of the five scenarios, between 2000 and 3000 MC simulations were run to ensure that the running average, standard deviation, and skew of the output stabilized.

Allocation of the emissions down to the county level was done outside of the NONROAD model runs for the 00e scenario. Although NONROAD includes geographic allocation capabilities, the county-level estimates increase the run time and output file size with the number of counties. For Georgia, that entails a factor of nearly 160 cost in computing space and about a factor of 6 in computing time. Instead, the same data was used and the same procedure was performed on the state-level output in a separate MC step. Since the allocations are simple fractions of the emissions, conducting the apportionment with uncertainties outside the model is equivalent to running the model with the allocations.

In this analysis, the allocation fraction for each county was randomly adjusted based on the uncertainties of each allocation group specified in the expert elicitation results. The fractions for all 159 counties were then normalized to the state total so that this analysis would only involve the uncertainty of spatial allocation and not overall emissions.

Air Quality Modeling: CMAQ Sensitivity to NONROAD Emissions

This study attempted to evaluate possible impacts of NONROAD emissions uncertainty by examining the sensitivity of ozone and CO concentration predictions when using the Models-3/Community Multiscale Air Quality (CMAQ), version 4.3,[30] modeling system. CMAQ uses an Eulerian, mass balance approach to estimating transport and formation of species at the grid level, according to the following equation where C_i represents concentrations.[31]

$$\frac{\Delta C_i}{\Delta t} = [\,advection\,] + [\,diffusion\,] + [\,deposition\,] + [\,chemistry\,] + [\,emissions\,] + [\,clouds\,]$$

Researchers at Georgia Tech have developed a modified version of CMAQ that estimates air quality (gas-phase pollutant concentrations) sensitivity to various parameters via the decoupled direct method (DDM).[32] This method implements sensitivity calculations simultaneously with the model air quality algorithms by calculating the derivatives of concentrations to various input parameters according to the following equation.[7]

$$S_{i,j}^{(1)}(x,t) = \frac{\partial C_i(x,t)}{\partial \varepsilon_j}$$

In this equation, $S^{(1)}$ is the first-order sensitivity of C to the particular input parameter of interest, while ε_j is the fractional change to a base case model input. One advantage of the DDM implementation is that the need for multiple air quality model runs to observe the effects of changes in parameters are eliminated. Furthermore, using DDM enables characterization of both the nominal values and changes in sensitivity of air quality to the whole possible range of a particular input parameter in a single run.

The modified version of CMAQ can calculate first and second order sensitivities, capturing possible non-linearities in air quality changes with respect to input parameter changes. For small perturbations of input parameters, using only first order, linear sensitivities is usually sufficient to accurately capture changes in the model output.[7] However, most expect large uncertainties in emissions inventories. Changes in air quality modeling due to large changes in emissions inputs may be significantly influenced by a non-linear relationship, and thus the use of second order sensitivities would be required.[33] The following equation illustrates the approach used to calculate concentration changes based on both first and second order sensitivities, where $C_{i,0}$ is the concentration for the base case, $C_{i,j}$ is the concentration when changing the model input of interest by ε_j, and $S_{i,j}^{(1)}$ and $S_{i,j,j}^{(2)}$ are the first and second order sensitivity coefficients.[7]

$$C_{i,j}(x,t) = C_{i,0}(x,t) + \varepsilon_j S_{i,j}^{(1)}(x,t) + \tfrac{1}{2}\varepsilon_j^2 S_{i,j,j}^{(2)}(x,t)$$

This study used the Models-3 setup for the August 2000 episode designed for the FAQS work, including the SAPRC99 gas phase chemical mechanism and the MM5 meteorological modeling.[7] The only exception was that Georgia NONROAD emissions were modified at the county level. The original FAQS nonroad emission inventory was based on the EPA National Emission Inventory (NEI) and an older version of the NONROAD model. All other emissions and model parameters were retained in the FAQS form.

The modeling domain consisted of a 12-km grid covering the entire state of Georgia, as well as part of Florida, Alabama, Tennessee, South Carolina, and North Carolina. Details of the domain and model inputs are detailed in Hu et. al.[7] NONROAD sensitivity was evaluated with a six day modeling episode from August 13 to 18. Normally, at least a one-day ramp-up period is considered necessary for the air quality model to establish initial conditions for the rest of the episode. Thus, the August 13th results were ignored. The August 14-18th period covers Monday through Friday and does not conflict with the weekday uncertainty analysis performed for NONROAD.

Sensitivity of CMAQ model results to NONROAD emissions were evaluated for six regions: the entire state of Georgia, the Atlanta 13-county ozone nonattainment area, the Columbus Metropolitan Statistical Area (MSA), the Macon MSA, the Augusta MSA, and the Atlantic coastline. These areas were chosen based on their relatively high emissions in one or more of the pollutant categories examined in the NONROAD uncertainty analysis (see SRS Monte Carlo Simulations of NONROAD Results). Figure 3 shows the five subregions of interest in Georgia.

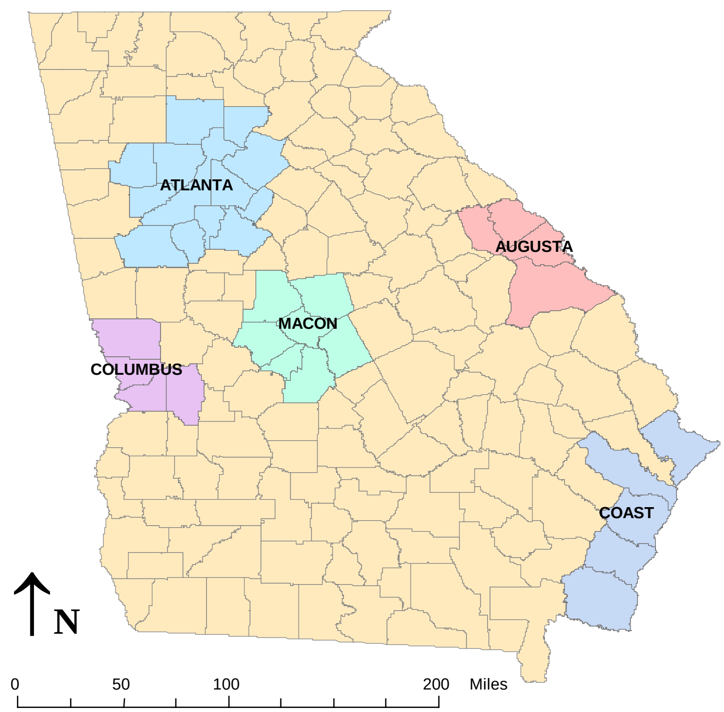

Figure 3. Georgia air quality modeling sensitivity target regions for NONROAD emissions uncertainty analysis.

The DDM-enabled version of CMAQ can calculate sensitivities specifically to nonroad emissions. However, the nonroad category includes aircraft, locomotive, and commercial marine emissions not accounted for in the NONROAD model. The CMAQ sensitivities to emissions are in units of parts per million (ppm) per ton per day (TPD); the seminormalized sensitivity coefficients use units of ppm. Thus, applying adjustments to account for the fraction of non-NONROAD emissions was necessary to obtain the true sensitivities related to the uncertainties quantified in this study. Another similar adjustment was necessary to take evaporative emissions out of the VOC estimates. Table 2 shows the details of this data for the pollutant categories of interest for the CMAQ sensitivity analysis.

Table 2. Data related to adjustment of CMAQ sensitivities to NONROAD emissions uncertainty analysis.

Georgia Typical Summer Weekday Year 2000	VOC	NOx	CO
Total Nonroad Emissions (TPD)	216.3	314.7	2421.1
Aircraft, Locomotive, Commercial Marine Emissions	11.2	122.1	52.6
NONROAD Emissions Fraction	0.95	0.61	0.98
Total NONROAD Exhaust Emissions (TPD)	216.3		
Total NONROAD Evaporative Emissions (TPD)	22.9		
NONROAD Emissions Fraction	0.89		
Final NONROAD Uncertainty Emissions Fraction	0.85	0.61	0.98

Finally, the sensitivities of the air quality model results and the uncertainty of NONROAD emissions were combined to estimate uncertainties in ozone and CO concentration predictions due to the NONROAD inventory. The following equation provides an approximation of the concentration uncertainties, where σ_c is the standard deviation of the concentration, σ_i is the standard deviation of applicable NONROAD emissions species, and $S_{c,i}$ is the sensitivity coefficient of the concentration to each emissions species.

$$\sigma_C^2 = \Sigma(\sigma_i^2 (S_{C,i})^2)$$

For these approximations, the uncertainty in ozone due to uncertainty in the NONROAD inventory was assumed to depend on both VOC and NOx emissions. CO concentration uncertainties, however, were assumed to depend only on NONROAD CO emissions uncertainties.

These methods of quantifying and applying emissions uncertainties to air quality model predictions help illustrate the relative importance or insignificance of the results of this analysis. This approach can also highlight which parameters, species, or emissions future work should focus on.

CHAPTER 5

RESULTS

Sensitivity Analysis of NONROAD

The sensitivity analysis of the NONROAD model differentiated between parameters of high and low importance for estimating uncertainties. Figure 4 presents the results for the sensitivity analyses. These analyses showed that increases in equipment population, activity, load factor, and emission factor have a normalized sensitivity coefficient of 70 percent or higher, meaning that a unit increase in these parameters increases emissions by 70 percent. As expected, engine population had a 100% direct impact on emissions. Activity and load factor inputs had varied effects by pollutant, and emissions were less sensitive to these parameters than population. This was likely due to the influences these factors have on deterioration rates in the model. The base emission factor sensitivity was tested for only one pollutant, $PM_{2.5}$, because this parameter is much more tedious to change than the other inputs. However, the results for $PM_{2.5}$ were assumed to be similar for the other emission factor-based pollutants (VOC, NOx, and CO).

Increases in ambient temperature, fuel RVP, fuel sulfur (except on SO_2), and average useful life were found to have normalized sensitivity coefficient of 30 percent or lower. Further, the uncertainties in these parameters are not large. Thus, uncertainties in RVP, temperature, sulfur, and average useful life were neglected in the ensuing work. RVP, temperature, and fuel sulfur are also viewed as typically less uncertain, further justifying their omission in the model uncertainty analysis. In this analysis we focused on uncertainties in the equipment population, activity, load factor, and emission factor parameters.

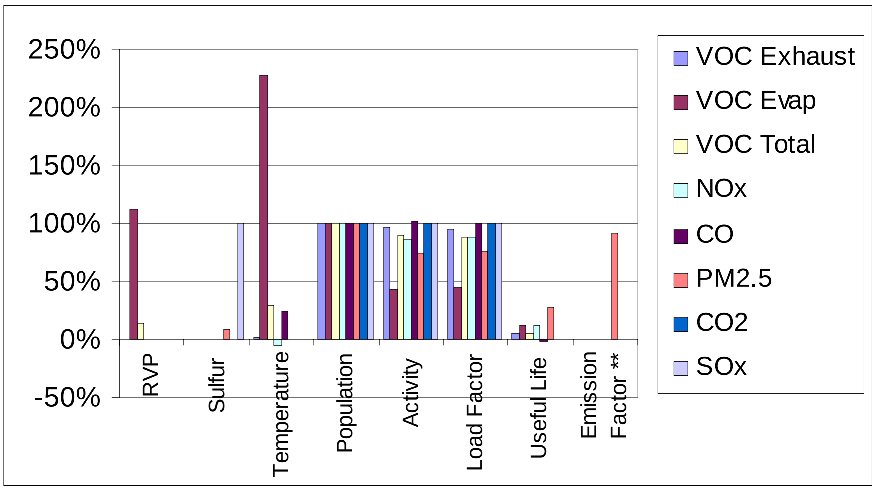

Figure 4. Normalized sensitivity coefficients for various NONROAD input parameters for 1999 Georgia typical summer weekday. **Emission factor sensitivity analysis performed for PM2.5 only. All other parameters include sensitivities for ALL pollutants listed.

Bootstrap Analysis of Emission Factors

Table 3 presents the results of the resampling bootstrap analysis of nonroad diesel engines. Uncertainties of the mean were approximately ± 30% for THC, ± 6% for NO_X, ± 25% for CO, and ± 15% for PM when averaged over model years and horsepower grouping. However, individual categories of model years and horsepower show considerable variation in the results, ranging from -55% to + 66% for THC, -10% to +13% for NO_X, -49% to +42% for CO, and -27% to +29% for PM. Note that these uncertainties of the mean emission factors are due to variability of engine test results only. They do not include uncertainties due to representativeness of the data or the certification test or other unknowns.

Table 3. Resampling bootstrap uncertainties of diesel engine certification emission test results used as the basis of default emission factor values the NONROAD model.

Model Year	HP Range	HP 95% Confidence		HC 95% Confidence		NOx 95% Confidence		CO 95% Confidence		PM 95% Confidence	
1996	175-300	-6%	7%	-13%	12%	-3%	3%	-19%	25%	-11%	13%
1996	300-600	-11%	18%	-38%	54%	-10%	13%	-16%	9%	-20%	29%
1996	600-750	-6%	5%	-55%	66%	-7%	6%	-23%	24%	-20%	18%
1997	100-175	-12%	10%	-20%	20%	-5%	7%	-10%	16%	-22%	9%
1997	175-300	-5%	7%	-30%	29%	-5%	4%	-14%	19%	-9%	10%
1997	300-600	-11%	21%	-31%	31%	-5%	8%	-49%	27%	-27%	21%
1997	600-750	-7%	4%	-54%	67%	-5%	6%	-28%	22%	-13%	7%
1998	50-100	-8%	7%	-42%	28%	-7%	8%	-49%	31%	-21%	13%
1998	100-175	-13%	12%	-13%	9%	-5%	5%	-34%	42%	-14%	7%
1998	175-300	-8%	13%	-9%	13%	-2%	4%	-12%	20%	-8%	6%
1998	300-600	-11%	13%	-29%	56%	-7%	6%	-29%	23%	-12%	15%
1998	600-750	-7%	9%	-44%	29%	-4%	2%	-31%	22%	-25%	20%
Average		-9%	11%	-32%	35%	-5%	6%	-26%	23%	-17%	14%

Table 4 shows the parametric bootstrap emission factor uncertainty results. Uncertainties of the mean were approximately ± 20% for THC, ± 3.5% for NO_X, ± 16% for CO, and ± 10% for PM when model years and horsepower grouping results are averaged. However, individual categories of model years and horsepower show considerable variation in the results, ranging from -49% to + 56% for THC, -6% to +5% for NO_X, -20% to +23% for CO, and -18% to +17% for PM. In general, the parametric analysis yielded lower uncertainties than the resampling method.

Both bootstrap methods used showed that the mean emission factors were relatively less uncertain for NOx than for any of the other three pollutants. VOC uncertainties were 5 to 6 times greater than NOx uncertainties. This shows that the NOx emission factor data has much less random error than the VOC data, and likely suggests the quality and reliability of NOx test results are higher than for VOC. Both methods also showed considerable variation in the uncertainty estimates for horsepower groupings within each pollutant. However, there was no clear pattern to these differences.

Table 4. Parametric bootstrap uncertainties estimated by AuvTool of diesel engine certification emission test results used as the basis of default emission factor values the NONROAD model.

Model Year	HP Range	HP 95% Confidence Interval		HC 95% Confidence Interval		NOx 95% Confidence Interval		CO 95% Confidence Interval		PM 95% Confidence Interval	
1996	175-300	-3%	3%	-9%	10%	-2%	2%	-18%	16%	-6%	8%
1996	300-600	-7%	7%	-24%	24%	-5%	5%	-8%	8%	-11%	12%
1996	600-750	-4%	4%	-49%	45%	-6%	5%	-19%	20%	-14%	15%
1997	100-175	-5%	5%	-13%	14%	-3%	3%	-14%	14%	-9%	9%
1997	175-300	-3%	3%	-15%	13%	-3%	3%	-10%	10%	-6%	6%
1997	300-600	-7%	7%	-15%	16%	-4%	4%	-16%	16%	-12%	11%
1997	600-750	-4%	5%	-45%	46%	-5%	5%	-20%	19%	-10%	9%
1998	50-100	-2%	2%	-16%	15%	-4%	4%	-19%	19%	-10%	12%
1998	100-175	-5%	6%	-4%	4%	-2%	2%	-20%	23%	-7%	7%
1998	175-300	-4%	5%	-8%	7%	-2%	2%	-14%	13%	-4%	4%
1998	300-600	-6%	6%	-24%	28%	-3%	3%	-14%	14%	-9%	8%
1998	600-750	-7%	6%	-27%	28%	-3%	4%	-19%	17%	-18%	17%
Average		-5%	5%	-21%	21%	-4%	3%	-16%	16%	-10%	10%

While the bootstrap methods do not take all uncertainties into account, the results give an idea about the approximate magnitude and relative magnitude of uncertainties for the different species. If all possible factors could be taken into account, the overall uncertainty of the emission factors would then be expected to be at least as great as the results of this analysis.

Expert Elicitation of Uncertainties

The expert elicitation aimed to capture uncertainties in model parameters not accounted for in bootstrap and other analyses. Experts from five of seven companies/agencies responded to the survey. In some cases, the experts did not provide uncertainty estimates for all parameters included in the survey. However, for each of the 46 specific variables, at least three experts gave adequate responses.

Based on the self-scoring results, the five experts ranged in experience from an average rating of 9 out of 10 (with 10 being the highest) for the four surveyed knowledge and experience categories to an average of 2 out of 10. Some experts rated themselves as highly knowledgeable in all categories, while others only had experience in select aspects of NONROAD emissions.

Table 5. NONROAD model uncertainties expert elicitation self-scoring results, ratings from 1 to 10 with 10 being the most knowledgeable.

Experience	Expert B	Expert A	Expert C	Expert D	Expert E
NONROAD emissions inventory preparation	10	8	10	10	1
NONROAD model development	10	8	4	1	1
Emissions testing of nonroad engines	8	8	1	1	1
Uncertainty of nonroad emissions	8	8	2	1	5
Overall average	9	8	4.25	3.25	2

Table 6 presents the aggregated findings of the expert elicitation. For equipment population, the uncertainties generally ranged from 20 to 30%, with a much higher 70% positively-skewed uncertainty for small (<25hp) spark ignition (SI) engines. For geographic allocation surrogates, the uncertainties varied widely by emissions source category, with agricultural equipment determined to be the least uncertain at ±10%, and commercial equipment and pleasure craft estimated to be the most uncertain at 95% confidence interval of –50% and +150%. Uncertainties of the activity estimates fell in the range of –40% and +65%. Unlike most other input parameters in the survey, the experts determined generally negatively skewed 95% confidence intervals for load factor, since this variable is a fraction bounded at a value of 1. These uncertainties fell in the range of –40% and +36%.

Table 6. NONROAD uncertainty expert elicitation averaged results, weighted by experts' self-ratings.

Category	Parameters	95% Confidence Interval (%)	
Population	Large SI equipment population	23.95	-29.38
	Small SI equipment population	68.15	-25.04
	CI equipment population	29.38	-22.72
Geographic Allocation	Agricultural Equipment allocation	10.00	-10.00
	Airport GSE Equipment allocation	13.21	-13.21
	Commercial Equipment allocation	105.56	-46.44
	Construction Equipment allocation	38.89	-38.89
	Industrial Equipment allocation	194.44	-50.00
	Lawn and Garden (Com) Equipment allocation	61.11	-38.89
	Lawn and Garden (Res) Equipment allocation	61.11	-38.89
	Logging Equipment allocation	51.23	-29.01
	Pleasure Craft Equipment allocation	101.43	-46.04
	Railroad Equipment allocation	29.38	-29.38
	Recreational Equipment allocation	73.83	-51.60
	Oil Field Equipment allocation	15.68	-15.68
	Underground Mining Equipment allocation	97.65	-38.54
	A/C Refrigeration Equipment allocation	21.60	-21.60
Annual Activity Hours	PSR-database based equipment activity	59.86	-39.48
	Small SI Lawn & Garden equipment activity	64.81	-38.40
	Recreational Marine equipment activity	32.08	-25.02
	ATV activity	28.40	-25.00
	Off-road Motorcycle activity	34.81	-31.42
Load Factors	PSR-database based SI equipment load factors	23.21	-36.54
	Small SI Lawn & Garden equipment load factor	18.77	-40.99
	CI equipment transient cycle load factors	36.54	-40.99
	Recreational Marine load factor	23.21	-21.88
SI Equipment zero-mile steady-state emission factors	HC	20.39	-17.40
	NOx	31.13	-21.67
	CO	16.05	-13.83
	PM	51.60	-29.38
CI Equipment zero-mile steady-state emission factors	HC	49.51	-29.27
	NOx	15.67	-15.60
	CO	96.05	-29.38
	PM	54.81	-19.26
SI Equipment transient emission factors adjustments	HC	46.79	-22.10
	NOx	46.79	-26.05
	CO	61.11	-30.99
	PM	40.49	-31.60
CI Equipment transient emission factors adjustments	HC	38.89	-22.10
	NOx	29.01	-13.21
	CO	61.11	-30.99
	PM	62.72	-40.49
Overall Emissions	HC	26.94	-21.77
	NOx	37.58	-16.94
	CO	27.26	-16.94
	PM	44.52	-23.87

Concerning emission factors, the experts suggested that PM data were generally the most uncertain of the four pollutants in this study, with uncertainties for SI engines at –29% and +52%. The largest specific emission factor uncertainty was –29% and +96% for CO emissions from compression ignition (CI) engines. The experts judged NOx diesel emission factors to be the most certain at ±15%.

In this work, emission factor uncertainties for diesel engines of model years 1996-1998 were estimated in three ways: resampling bootstrap, parametric bootstrap, and expert elicitation techniques. Generally, the parametric bootstrap estimates were less conservative, yielding lower uncertainties, than the resampling bootstrap method. However, the estimates from both these methods followed similar patterns. Expert opinion of emission factor uncertainties were more conservative than the average values from either bootstrap method. The advantage of using expert opinion in this case is that the experts can account for not only variability of data used to calculate mean emission factors, but also take into consideration representativeness of the data and other intangible issues. Thus, the overall, much higher, uncertainty estimates from the experts were expected. Interestingly, however, there was some agreement between the experts and the bootstrap results in the relative uncertainties when comparing different pollutants. All techniques agreed in lower uncertainties for NO_X than the other three pollutants. Thus there is some agreement between the methods for the relative uncertainties of emissions.

The results of the expert elicitation show that uncertainties between and within major input parameters vary greatly. Thus, the experts judged that, based on the sources of data and techniques used to estimate parameter values, the quality of information varied significantly from category to category.

SRS Monte Carlo Simulations of NONROAD Results

The SRS Monte Carlo analyses of the NONROAD model yielded uncertainty estimates for a total of five different scenarios. These scenarios included runs for the years 1999 and 2000, as well as different methods of random sampling of the input parameter values. In each case, the NONROAD model was run between 2000 and 3000 times to achieve stabilization of the output emissions running average, standard deviation, and skewness.

1999 Summer Scenarios Results

Figured 5-7 show examples of the calculated running average, standard deviation, and skew for NONROAD PM emissions output resulting from Monte Carlo simulations under the 99a scenario. The graphs show that the calculated parameters generally stabilize by about 1500 model runs. Figure 5 shows both the MC running average and the base case scenario emissions. In all cases for the year 1999, the MC simulations result in higher state total emissions than the base case. Because the default data were always treated as the expected rather than the average value, the mean of the data tended to shift higher, depending on the skew of the input uncertainties.

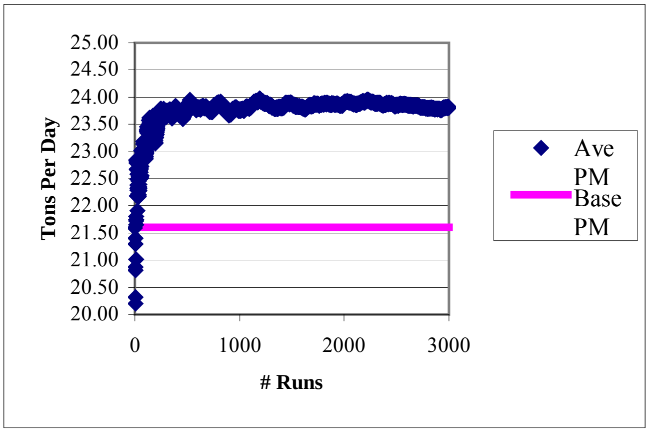

Figure 5. Monte Carlo simulation running average of NONROAD PM emissions output for 1999 Georgia typical summer weekday statewide emissions, Case 99a.

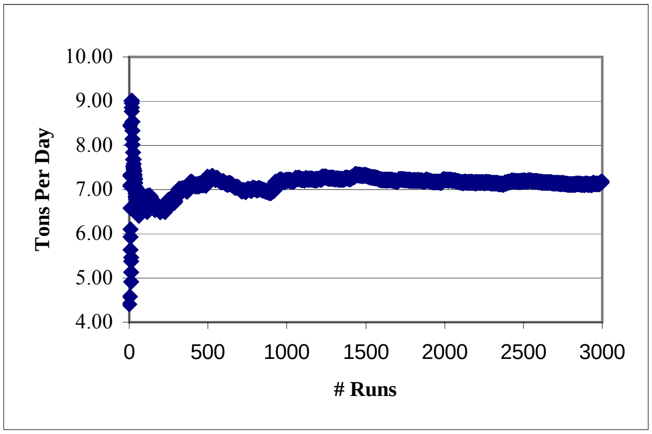

Figure 6. Monte Carlo simulation running standard deviation of NONROAD PM emissions output for 1999 Georgia typical summer weekday statewide emissions, Case 99a.

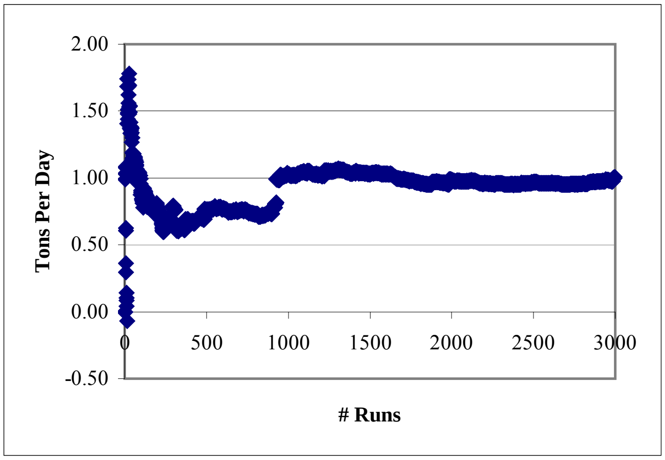

Figure 7. Monte Carlo simulation running skewness of NONROAD PM emissions output for 1999 Georgia typical summer weekday statewide emissions, Case 99a.

As expected, the uniform distribution MC simulation produced the most conservative results, with highest emissions and the highest standard deviations (as % of total emissions) and thus highest uncertainties as shown in Table 7. The normal distribution did not produce the least conservative results and lowest uncertainties as expected. The triangle distribution simulation may have resulted in less uncertainty because the triangle distribution does not allow for the extreme highs and lows captured in the tails of the normal distribution. However, between the three simulations, the resulting uncertainties, represented as standard deviation as percent of the mean or coefficient of variance (COV), did not differ by more than 5% for any pollutant, e.g. the standard deviations of PM emissions ranged from 28% to 33% for the three simulation scenarios.

Table 7. Monte Carlo simulation of 1999 Georgia summer weekday statewide NONROAD model results using various probability distributions for random inputs generation.

Random Input Distribution	Average (Tons Per Day)			
	THC	**NOx**	**CO**	**PM**
Normal (99a)	204	205	2581	24
Uniform (99b)	227	222	2931	28
Triangle (99c)	220	214	2804	26
Random Input Distribution	**Standard Deviation (Tons Per Day)**			
	THC	**NOx**	**CO**	**PM**
99a	48	59	758	7
99b	59	73	940	9
99c	51	58	775	7
Random Input Distribution	**Coefficient of Variance (%)**			
	THC	**NOx**	**CO**	**PM**
99a	24%	29%	29%	30%
99b	26%	33%	32%	33%
99c	23%	27%	28%	28%
Random Input Distribution	**Skew**			
	THC	**NOx**	**CO**	**PM**
99a	0.98	0.93	1.05	1.00
99b	0.72	0.57	0.77	0.70
99c	0.70	0.55	0.80	0.68

Because several input parameters had confidence intervals that were positively skewed, it is not surprising that the distributions of emissions for all 1999 simulations were also positively skewed. The normal distribution simulation had higher positive skewness than either the triangle or uniform distribution simulations, as expected. Figure 8 shows an example of the resulting histogram of the normal distribution simulation results for CO emissions from NONROAD.

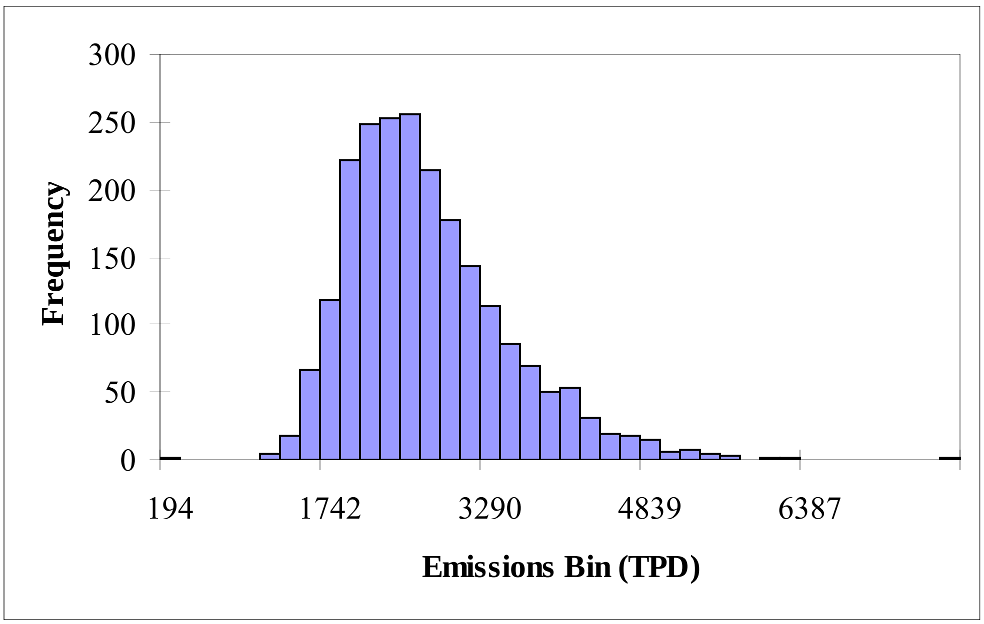

Figure 8. NONROAD CO emissions histogram for Monte Carlo simulation results for 1999 Georgia typical summer weekday statewide emissions, Case 99a.

2000 Summer Scenarios Results

Results for years 1999 and 2000 were similar for both emissions and uncertainty results, under identical normal random input generation schemes (scenarios 99a and 00a). In contrast, the 00e scenario, treated default input data as the means rather than modes of the randomized input parameters, with lognormal, triangle, pareto, beta, and clipped lognormal distributions fit to the input uncertainties as shown in Table 8.

Table 8. Chosen random input distributions and characteristic parameters for NONROAD Monte Carlo simulation scenario 00e.

Category	Input Parameters	Selected Distribution	Distribution Parameter A	B	C
Population	Large SI equipment	triangle	0.60	1.12	1.29
	Small SI equipment	pareto	0.80	4.88	
	CI equipment	lognormal	-0.01	0.13	
Geographic Allocation	Agricultural Equipment	lognormal	0.00	0.05	
	Airport GSE Equipment	lognormal	0.00	0.07	
	Commercial Equipment	clipped lognormal	-0.18	0.45	0.51
	Construction Equipment	beta	11.96	11.96	
	Industrial Equipment	pareto	0.54	2.17	
	Lawn and Garden (Com) Equipment	lognormal	-0.03	0.26	
	Lawn and Garden (Res) Equipment	lognormal	-0.03	0.26	
	Logging Equipment	triangle	0.66	0.69	1.66
	Pleasure Craft Equipment	clipped lognormal	-0.21	0.45	0.54
	Railroad Equipment	lognormal	-0.01	0.15	
	Recreational Equipment	lognormal	-0.05	0.31	
	Oil Field Equipment	Zero equipment populations for Georgia			
	Underground Mining Equipment	Zero equipment populations for Georgia			
	A/C Refrigeration Equipment	lognormal	-0.01	0.11	
Annual Activity Hours	PSR-database based equipment	lognormal	-0.03	0.25	
	Small SI Lawn & Garden equipment	lognormal	-0.04	0.27	
	Recreational Marine equipment	lognormal	-0.01	0.15	
	ATV	lognormal	-0.01	0.13	
	Off-road Motorcycle	lognormal	-0.01	0.17	
Load Factors	PSR-database based SI equipment	triangle	0.52	1.24	1.24
	Small SI Lawn & Garden equipment	triangle	0.52	1.24	1.24
	CI equipment transient cycle	triangle	0.44	1.13	1.44
	Recreational Marine	lognormal	-0.01	0.11	
SI Equipment zero-mile steady-state emission factors	HC	lognormal	0.00	0.10	
	NOx	lognormal	-0.01	0.13	
	CO	lognormal	0.00	0.08	
	PM	triangle	0.66	0.69	1.66
CI Equipment zero-mile steady-state emission factors	HC	lognormal	-0.02	0.20	
	NOx	lognormal	0.00	0.08	
	CO	pareto	0.73	3.73	
	PM	pareto	0.83	5.88	
SI Equipment emission factors including transient emission factors adjustments	HC	triangle	0.68	0.68	1.65
	NOx	lognormal	-0.03	0.23	
	CO	triangle	0.60	0.60	1.79
	PM	lognormal	-0.04	0.28	
CI Equipment emission factors including transient emission factors adjustments	HC	lognormal	-0.03	0.26	
	NOx	lognormal	-0.01	0.14	
	CO	clipped lognormal	-0.47	0.55	0.59
	PM	triangle	0.47	0.50	2.03
	Distribution Parameter Key	lognormal	mu	sigma	
		triangle	min	mode	max
		pareto	mode	shape	
		beta	A	B	
		clipped lognormal	mu	sigma	cutoff

The 00e Monte Carlo simulation scenario yielded emissions estimates identical to the base case. Because the means of each input were not shifted, the average of the MC results also converged to the base estimate. Figure 9 shows an example of this outcome for 2000 summer PM emissions.

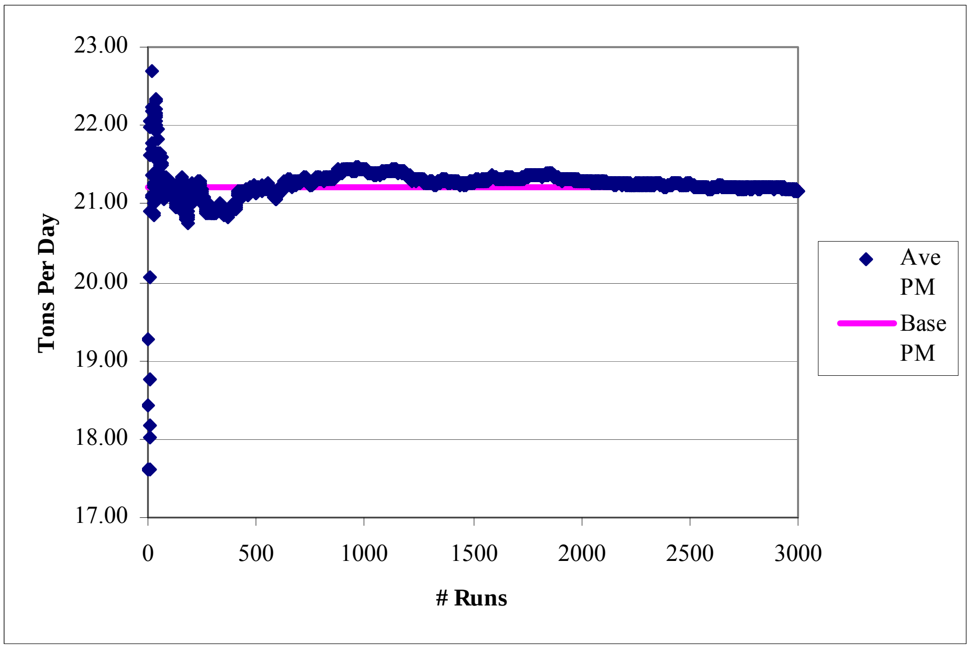

Figure 9. Monte Carlo simulation running average of NONROAD PM emissions output for 2000 Georgia typical summer weekday statewide emissions, Case 00e.

While the 00e scenario produced 6 to 10% lower average emissions estimates than the 00a case, the absolute value of the standard deviations showed a smaller decrease of only 2 to 4%. Thus, the resulting coefficients of variance, and estimated uncertainties, were higher for the 00e scenario. Table 9 shows that the differences between the COVs for the 00e and 00a scenarios range between 3 to 5%. This represents a 13 to 22% increase in uncertainty values when comparing 00e to 00a.

Table 9. Monte Carlo simulation of 1999 and 2000 Georgia statewide NONROAD model results using various probability distributions for random inputs generation.

Input Distribution	**Average (Tons Per Day)**			
	THC	NOx	CO	PM
Normal (99a)	204	205	2581	24
Normal (00a)	205	205	2593	23
Mixed (00e)	189	193	2364	21
Input Distribution	**Standard Deviation (Tons Per Day)**			
	THC	NOx	CO	PM
99a	48	59	758	7
00a	49	58	765	7
00e	48	56	736	7
Input Distribution	**Standard Deviation as % of Average**			
	THC	NOx	CO	PM
99a	24	29	29	30
00a	23	27	28	28
00e	26	33	32	33
Input Distribution	**Skew**			
	THC	NOx	CO	PM
99a	0.98	0.93	1.05	1.00
00a	1.00	0.92	1.06	0.98
00e	2.02	0.86	1.93	0.92

Table 10 translates the uncertainties of the 00e statewide NONROAD emissions results to 95% confidence intervals about the mean. While the magnitude of the standard deviations do accurately reflect the overall degree of uncertainty, it does not reveal information about the skewness of the data. It may be useful to determine whether emissions are much more uncertain in the positive or negative directions. The 95% confidence interval provides this type of information. According to these results, PM emissions exhibited the highest uncertainty range at -48% to +75%, while THC estimates were more certain at -34% to +61%.

Table 10. 2000 Georgia summer weekday statewide NONROAD emissions and uncertainties for Monte Carlo simulation scenario 00e.

	Emissions (TPD)					
Pollutant	**Average**	**2.50%**	**97.50%**	**95% Confidence Interval (%)**		**SD % of Ave**
THC	190	125	305	-34%	61%	25%
NOx	193	105	323	-46%	68%	29%
CO	2368	1341	4147	-43%	75%	31%
PM	21	11	37	-48%	75%	33%

In the county allocation simulations for scenario 00e, the uncertainties averaged over all counties were generally higher than the uncertainties resulting from the whole state simulation. This result was expected as higher spatial resolution generally brings about increased uncertainty. It is always harder to predict behavior in a specific locale than to estimate general attributes of a large area. This is significant because air quality modeling usually requires data at fine spatial resolution. Although this work only deals with county level data, we should expect that grid level emissions used in air quality models exhibit even greater uncertainties than those estimated here. However, analyzing uncertainties at the grid level is beyond the scope of this work.

Additionally, individual counties varied significantly in the degree of uncertainty calculated, as shown in Table 11. These differences arose from the local population and industrial characteristics and the uncertainties associated with the various source categories. Different source categories dominated and thus characterized uncertainty county to county. For example, emissions from a rural county typified by farming activities would likely exhibit less uncertainty than an urban county with high construction activity, since the experts estimated uncertainty in the geographic allocation of the agricultural and construction categories to be ±10% and ±39% respectively. However, because emissions in each county are comprised of many source categories, populations, fuel types, etc., it is difficult to predict the uncertainty level for a given area. Using this Monte Carlo analysis method allowed us to determine emissions uncertainties at the county-level without conducting detailed study for each individual region.

Table 11. Uncertainty results for county allocations of 2000 Georgia summer weekday NONROAD emissions output for Monte Carlo simulation scenario 00e.

	Standard Deviation for Emissions as % of Average with 159 County Allocations			**Standard Deviation for Emissions as % of Average for Whole State**
	Maximum	**Minimum**	**Average**	
THC	57%	24%	33%	25%
NOx	106%	26%	39%	29%
CO	55%	25%	36%	31%
PM	49%	31%	38%	33%
	Confidence Interval Lower Bound (2.5%) for Emissions as % of Average with 159 County Allocations			**Confidence Interval Upper Bound (2.5%) for Emissions as % of Average for Whole State**
	Maximum	**Minimum**	**Average**	
THC	-56%	-37%	-43%	-34%
NOx	-58%	-41%	-51%	-46%
CO	-59%	-38%	-46%	-43%
PM	-62%	-45%	-53%	-48%
	Confidence Interval Upper Bound (97.5%) for Emissions as % of Average with 159 County Allocations			**Confidence Interval Upper Bound (97.5%) for Emissions as % of Average for Whole State**
	Maximum	**Minimum**	**Average**	
THC	116%	56%	79%	61%
NOx	146%	63%	87%	68%
CO	116%	59%	84%	75%
PM	117%	71%	89%	75%

Figures 10-13 show the spatial allocation of emissions for THC, NOx, CO, and PM respectively resulting from the Monte Carlo simulation. Generally, the highest emissions are found in and around Atlanta, with high emission pockets also found around the metropolitan areas of Macon, Columbus, and Augusta, as well as along the Atlantic coastline. Figures 14-17 show the COVs for the emissions by county. The uncertainties do not display an apparent spatial pattern and are thus characterized by a variety of local characteristics.

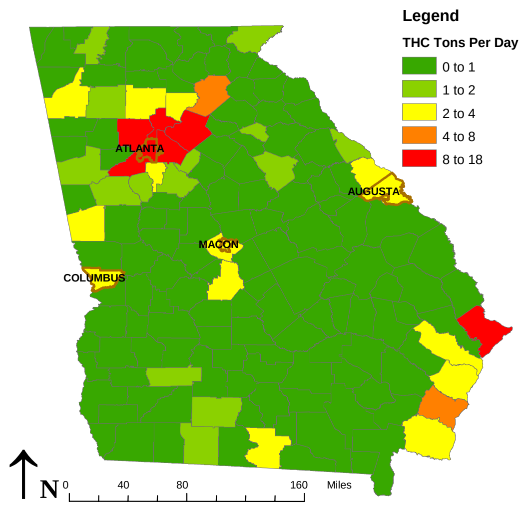

Figure 10. Baseline 2000 Georgia summer weekday average NONROAD exhaust THC emissions at the county level.

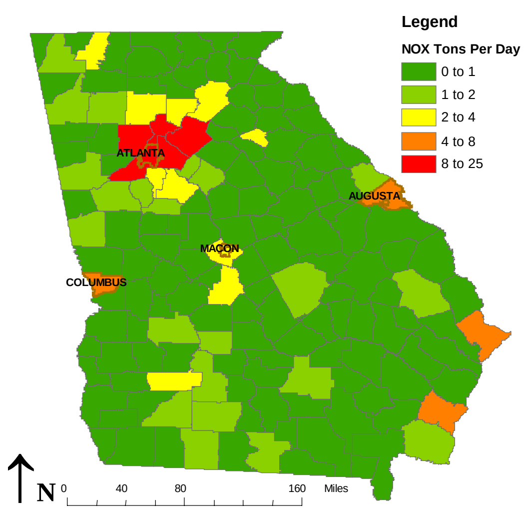

Figure 11. Baseline 2000 Georgia summer weekday average NONROAD NOx emissions at the county level.

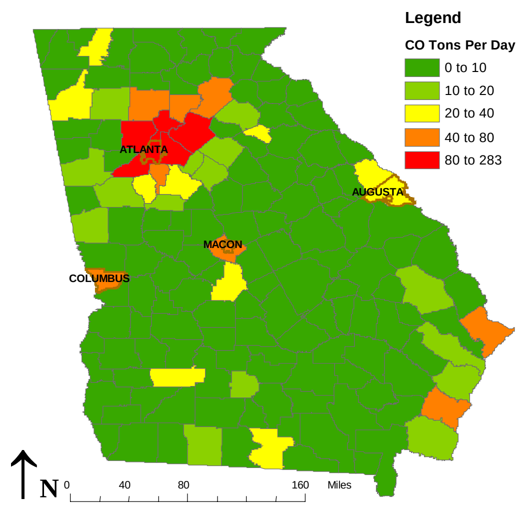

Figure 12. Baseline 2000 Georgia summer weekday average NONROAD CO emissions at the county level.

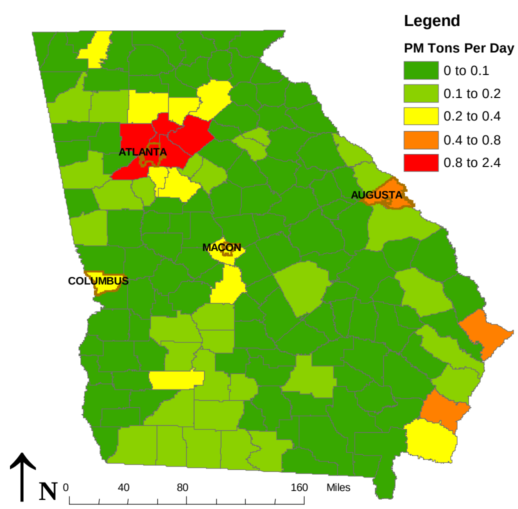

Figure 13. Baseline 2000 Georgia summer weekday average NONROAD PM emissions at the county level.

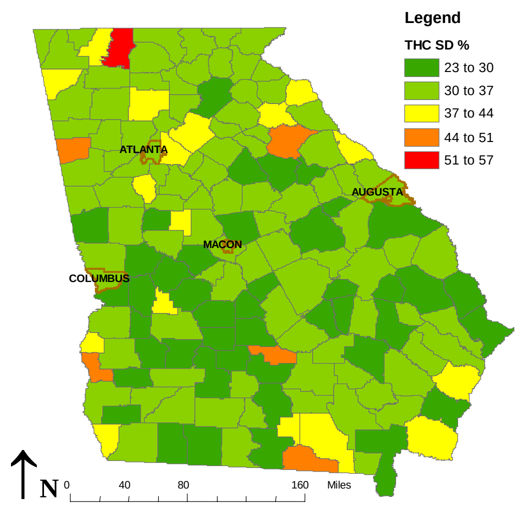

Figure 14. 2000 Georgia summer weekday average NONROAD exhaust THC emissions coefficients of variation for Monte Carlo simulation scenario 00e.

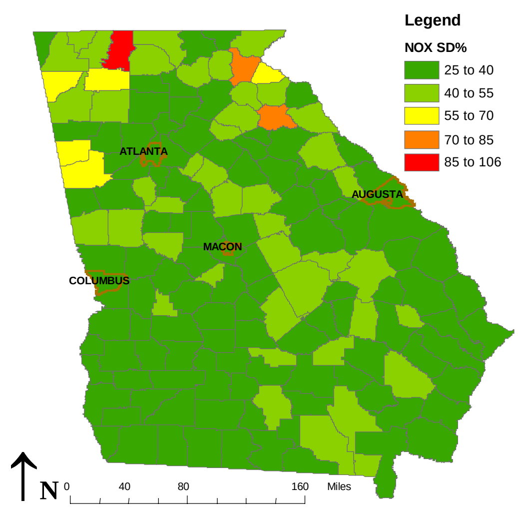

Figure 15. 2000 Georgia summer weekday average NONROAD NOx emissions coefficients of variation for Monte Carlo simulation scenario 00e.

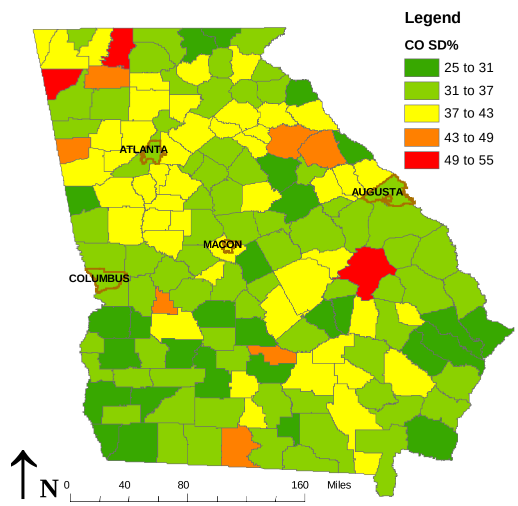

Figure 16. 2000 Georgia summer weekday average NONROAD CO emissions coefficients of variation for Monte Carlo simulation scenario 00e.

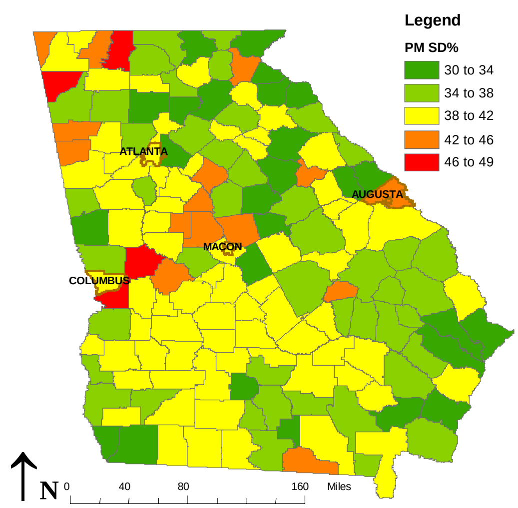

Figure 17. 2000 Georgia summer weekday average NONROAD PM emissions coefficients of variation for Monte Carlo simulation scenario 00e.

The calculated bottom-up uncertainty estimates were much larger than the judgments given for the overall NONROAD emissions inventory in the expert elicitation. Three of five experts surveyed provided overall inventory uncertainties that ranged from -10% to +20% to ±50%. In this analysis, average county-level uncertainties were about

–40 to -50% and +80 to 90%. In the latest study by Hanna,[18] the top-down factor of two uncertainty estimates for the mobile and area source emissions are close to the results in this study. However, Hanna's uncertainties may be applied at the grid, rather than county, level; in that case, we would expect his estimates to be significantly higher than the county estimates in this work.

In summary, while predicting which areas of Georgia should have high emissions is straightforward, estimating the uncertainties in NONROAD emissions for various pollutants and different counties depends on too many factors for individual analysis. We cannot necessarily predict the magnitude of the uncertainty based on geography and a few general local characteristics. Therefore, the Monte Carlo analysis was useful in accounting for the many different factors in the emissions uncertainty estimate.

Air Quality Modeling: CMAQ Sensitivity to NONROAD Emissions

CMAQ sensitivity modeling resulted in estimates of concentrations and sensitivity coefficients for each hour of the episode for each 12-km grid cell. However, keep in mind that the NONROAD analysis quantified uncertainty only for an average summer weekday at the county level. Thus, the estimated sensitivities of CMAQ results related to NONROAD emissions uncertainties at the daily weekday, county level. This work did not account for uncertainties of hourly or grid-level emissions.

CMAQ Results

In general, Georgia does not have a problem or nonattainment of the to the National Ambient Air Quality Standards (NAAQS) for CO. This is reflected in the air quality modeling results as CO concentrations do not reach anywhere near the 9ppm 8-hour standard.[34] Figure 18 shows the grid-level 8-hour CO concentrations of the modeling domain for the time and date during the episode of highest Georgia statewide average levels. Even at this time, CO concentrations in all of Georgia remain below 3ppm, with the highest concentrations clustered in the Atlanta area.

On the other hand, ozone exceedances are a major problem in several areas of the state. The current NAAQS for ozone are 0.12ppm for the 1-hr average[35] and 0.08ppm for the 8-hr average.[36] On August 17th, 2000, monitors at Atlanta, Macon, Columbus, and Augusta, as well as areas in North and South-Central Georgia, all showed one- or eight-hour ozone exceedances. In the period of August 14 to18, the 17th had the highest measured maximum ozone concentrations throughout the state.[7] Figure 19 shows the CMAQ results of 1-hour ozone concentrations in the modeling domain at 4:00PM, the time of highest modeled statewide average ozone. As expected, many areas show ozone levels near or above the ozone NAAQS.

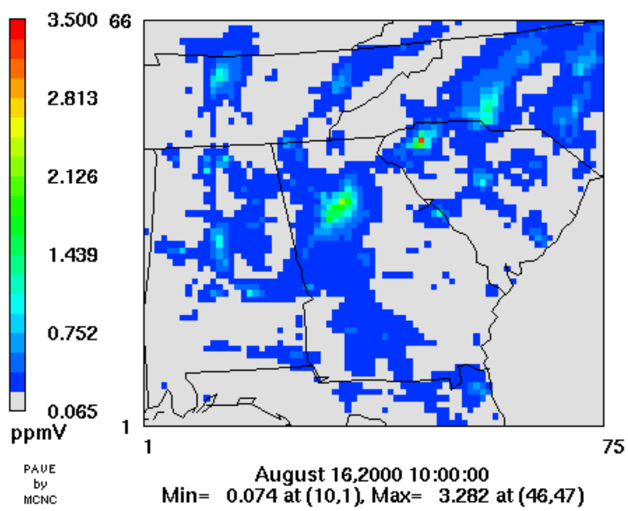

Figure 18. CMAQ predicted 8-hr average CO concentrations at time of maximum modeled Georgia statewide average CO for August 2000 episode.

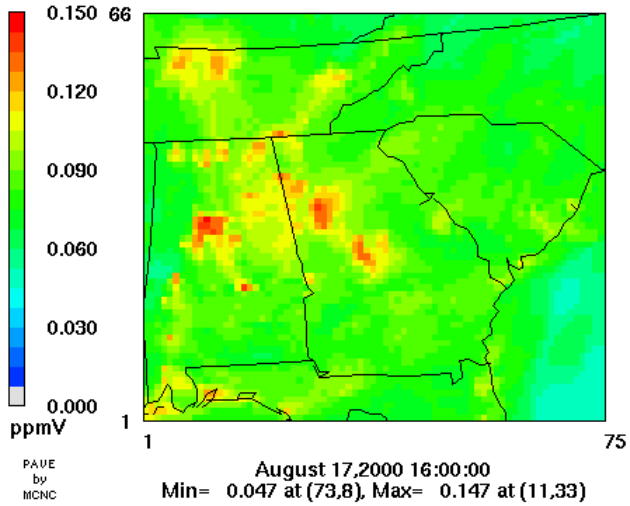

Figure 19. CMAQ predicted 1-hr average ozone concentrations at time of maximum modeled Georgia statewide average ozone for August 2000 episode.

CMAQ Sensitivity Results

The episode dates and times shown in Figure 18 and Figure 19 were used to further evaluate ozone and CO concentration sensitivities to NONROAD emissions. Since NONROAD emissions are only a fraction of the overall emissions inventory, CMAQ sensitivities to NONROAD are not expected to be large. The uncertainty analysis estimated 95% confidence intervals about the mean for all applicable pollutants to be approximately within a factor of 2 (-50% to +100%) for most of the county-level NONROAD inventory, although some individual counties exhibited slightly greater uncertainties.

Figure 20 and Figure 21 show the potential changes in average ozone and CO concentrations statewide due to –50% to +100% perturbations in Georgia VOC, NOx, and CO NONROAD emissions. The concentrations of ozone and CO only change by only a few percent across the entire range of possible NONROAD emissions uncertainties. Although second order sensitivities have been accounted for, the relationships are still virtually linear. Again, note that NONROAD emissions are only a fraction the total emissions inventory. The first order and first and second order sensitivity relationships of concentrations to the total emissions inventory have been shown to be significantly different for large reductions in domain-wide emissions in past work.[7]

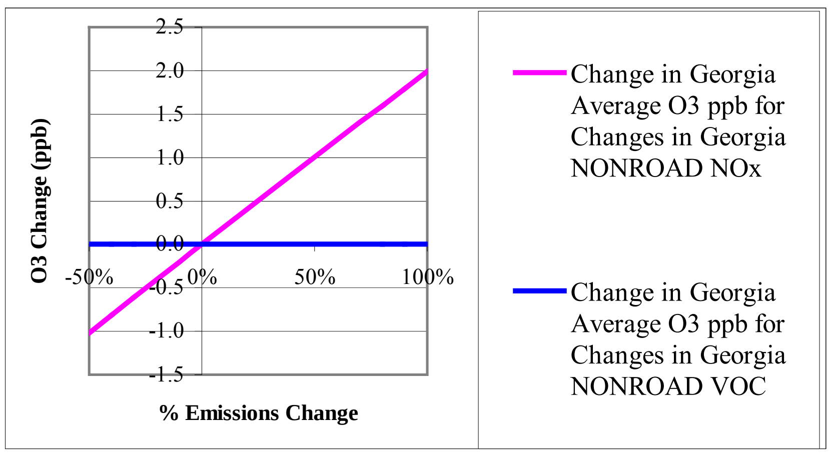

Figure 20. CMAQ prediction statewide average ozone sensitivity to Georgia NONROAD emissions with baseline ozone concentration of 92ppb for August 17th, 2000, 4:00PM.

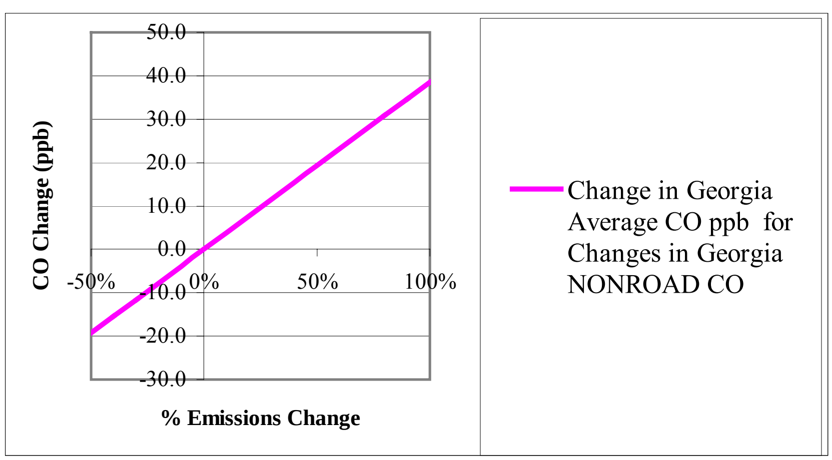

Figure 21. CMAQ prediction statewide average CO sensitivity to Georgia NONROAD emissions with baseline CO concentration of 310ppb for August 16th, 2000, 10:00AM.

For almost all cases, ozone shows virtually zero sensitivity to VOC emissions, whether statewide or in one of the subregions. The exception is the Atlanta area. Although Atlanta ozone shows some sensitivity to VOC emissions, the potential changes in modeling results are still extremely small, as shown in Figure 22.

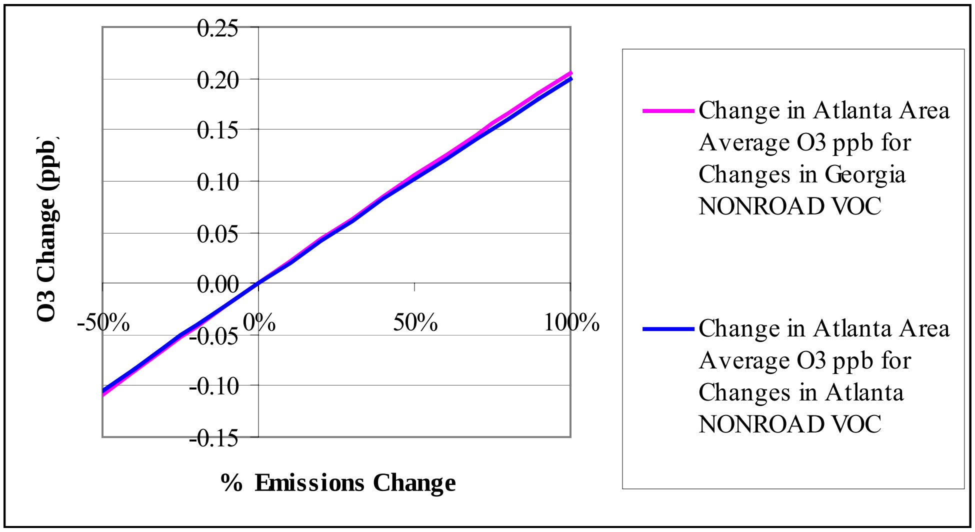

Figure 22. CMAQ prediction Atlanta area average ozone sensitivity to Georgia and Atlanta NONROAD emissions with baseline ozone concentration of 112ppb for August 17th, 2000, 4:00PM.

The sensitivity of ozone in the subregions to NOx emissions was most significant in the Atlanta and Macon Areas. The sensitivities to all regions in Augusta, Columbus, and the Atlantic Coast Areas were significantly less, likely due to meteorological conditions (i.e. wind direction) and lower NONROAD NOx emissions in those areas. Wind direction and magnitude of emissions were also the reasons the Macon Area was much more sensitive to Atlanta than vice versa, as shown in Figure 23 and Figure 24. However, again, overall changes in CMAQ predictions were less than 3% over a factor of 2 range of possible emissions estimates.

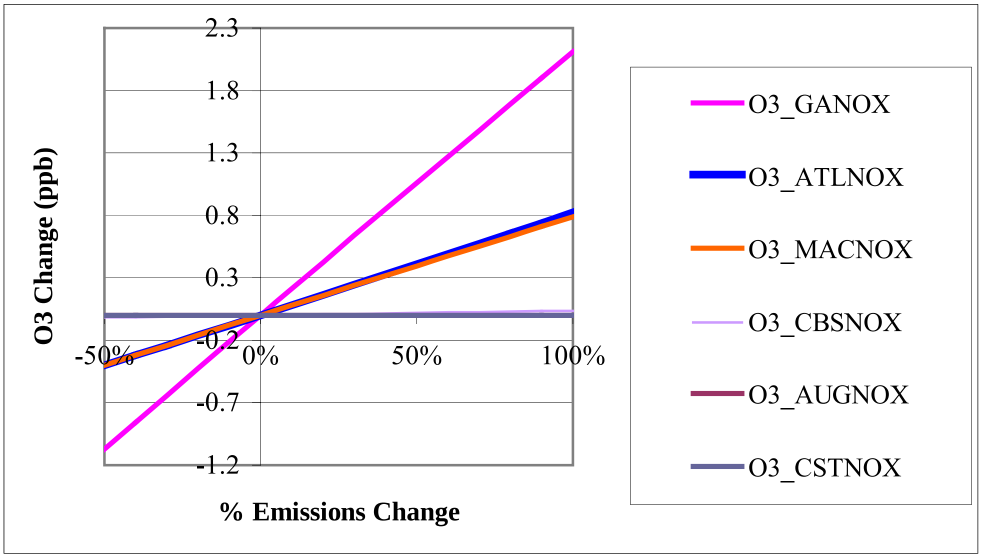

Figure 23. CMAQ prediction Macon area average ozone sensitivity to regional NONROAD emissions with baseline ozone concentration of 110ppb for August 17th, 2000, 4:00PM.

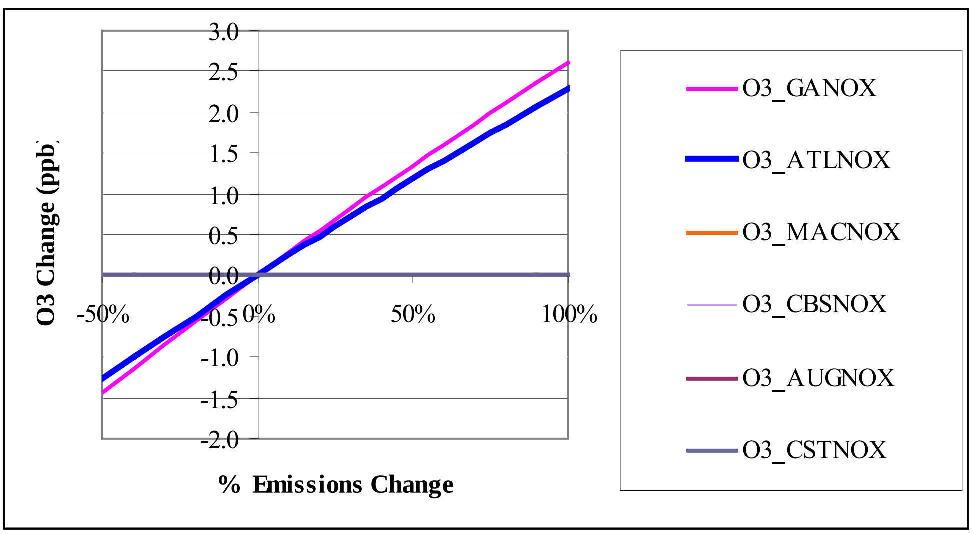

Figure 24. CMAQ prediction Atlanta area average ozone sensitivity to regional NONROAD emissions with baseline ozone concentration of 112ppb for August 17th, 2000, 4:00PM.

Finally, Figure 25 shows the potential changes in ozone at the grid-level with a 100% increase in statewide NONROAD NOx emissions during the high ozone date and time of the episode. The concentration changes are more exaggerated at the grid-level than in the aggregated region averages shown in the figures above. However, the changes are still at most between –12ppb and +6ppb at a time when concentrations over the state range between 60ppb and 150ppb.

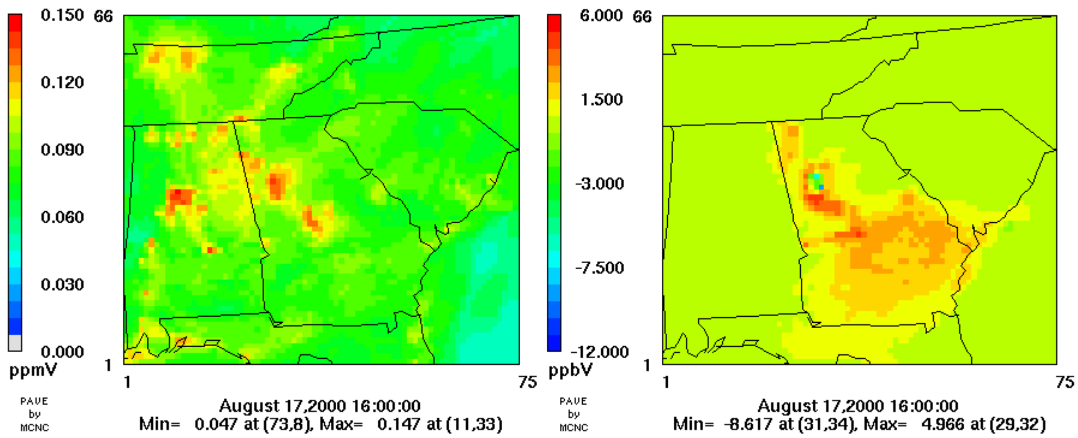

Figure 25. CMAQ base predicted ozone concentration (left) and change in ozone concentration for 100% increase in Georgia NONROAD NOx emissions (Right) for August 17th, 2000, 4:00PM.

Quantification of CMAQ Results Uncertainty

The NONROAD emissions uncertainties were propagated with the CMAQ sensitivities to determine the uncertainty in model CO and ozone predictions due to the NONROAD inventory. Since all the six regions modeled in the CMAQ sensitivity run were affected the most by changes in the Georgia state inventory, the error propagation was completed only for sensitivities to statewide emissions. Also, because second order sensitivity coefficients were found to be insignificant overall in this analysis, they are ignored in the uncertainty propagation.

Table 12 shows the resulting uncertainties in CMAQ-predicted 8-hour CO concentrations for the August 16, 10:00AM hour of the episode. The standard deviations as percent of the base value ranged from just 1.8% for the Atlantic Coast region to nearly

10% for the Atlanta area. Thus, the average CO prediction for the Atlanta 13-county area has about a 10% uncertainty (COV) due to the uncertainty of the statewide NONROAD emissions inventory. Note that CO prediction uncertainties may be significantly larger when examined at the grid or county level, as opposed to the effects here averaged over multiple-county regions.

Table 12. Uncertainty in CMAQ 8-hour CO predictions due to statewide NONROAD emissions uncertainty for August 16, 2000 10:00AM.

Region	CO Concentration (ppb)	CO Sensitivity Coefficient to Georgia CO (ppb)	$(\sigma_{CO} * S_{CO,CO})^2$ (ppb^2)	Standard Deviation CO, σ_{CO} (ppb)	COV CO (%)
Georgia	309	39.42	149	12.22	4.0%
Atlanta	779	243.20	5684	75.39	9.7%
Macon	353	48.59	227	15.06	4.3%
Columbus	348	57.26	315	17.75	5.1%
Augusta	300	28.47	78	8.83	2.9%
Coast	224	12.87	16	3.99	1.8%

Table 13 shows the resulting uncertainties in CMAQ-predicted 1-hour ozone concentrations for the August 17, 4:00PM hour of the episode. The COV values are much smaller than for CO, ranging from just 0.3% for the Atlantic Coast and Augusta regions to just over 1% for the Atlanta area. The average ozone prediction for the Atlanta area has only about a 1% uncertainty (COV) due to the uncertainty of the statewide NONROAD emissions inventory. Again, ozone prediction uncertainties may be significantly larger when examined at a higher spatial resolution, as opposed to the regionally-averaged effects in this analysis.

Table 13. Uncertainty in CMAQ 1-hour ozone predictions due to statewide NONROAD emissions uncertainty for August 17 2000 4:00PM.

Region	Ozone Concentration (ppb)	Ozone Sensitivity Coefficient to Georgia NOx Emissions (ppb)	Ozone Sensitivity Coefficient to Georgia VOC Emissions (ppb)	$(\sigma_{NOx} * S_{O3,NOx})^2$ (ppb^2)	$(\sigma_{VOC} * S_{O3,VOC})^2$ (ppb^2)	Standard Deviation Ozone, σ_{O3} (ppb)	COV Ozone (%)
Georgia	92	2.38	0.0291	0.48	5.31E-05	0.69	0.8%
Atlanta	119	4.53	0.2515	1.73	3.95E-03	1.32	1.1%
Macon	110	3.48	0.0417	1.02	1.09E-04	1.01	0.9%
Columbus	88	2.06	-0.0014	0.36	1.23E-07	0.60	0.7%
Augusta	95	1.09	0.0025	0.10	3.77E-07	0.32	0.3%
Coast	95	1.09	0.0025	0.10	3.77E-07	0.32	0.3%

These results show that CO emissions have a much more direct effect on CO concentration than ozone precursors have on ozone concentrations. This outcome agrees with widely accepted models of the atmosphere. Generally, CO concentrations directly result from primary emission sources, with virtually no secondary formation. On the other hand, ozone concentrations do not result from any primary emissions. Secondary formation of ozone also does not just depend on emissions of precursors, but has strong dependencies on meteorological conditions. Thus, we expect ozone precursor emissions to have a much less direct effect on ozone concentration. Consequently, NONROAD emissions uncertainties have only small effects on the uncertainty of ozone predictions.

Overall, the effects of NONROAD uncertainties, as estimated in this analysis, on CMAQ predictions appear to be small. The results of this work suggest that uncertainties in the nonroad emissions inventory at the state and county levels may be less important than other factors in the grand scheme of air quality modeling for the state of Georgia. However, a more comprehensive analysis of CMAQ result sensitivity and uncertainty to NONROAD would require quantification of emissions uncertainty at the grid, rather than county, level, as well as examination of grid level air quality predictions. Grid level uncertainties should be significantly higher than county level uncertainties, and may show a much larger effect on air quality modeling. Work performed by Houyoux et. al. suggest that ozone concentration predictions at the grid level may change as much as 20ppb due to grid level uncertainties in utility NO_x emissions in a Charlotte, North Carolina area test case.[37] However, accounting for input and prediction uncertainties at the grid level requires a huge computational effort that may be impractical for most modeling endeavors at this time. For example, modeling for Houyoux's Charlotte test case was carried out on a network of 9 moderate to high-powered computers for a period of five days.[37]

Pertaining to the present analysis, uncertainty in most other emissions sources and factors in air quality modeling have yet to be definitively quantified. Models like CMAQ account for a vast number of parameters at a high level of detail. With past study and data lacking, we cannot, at this time, adequately judge the importance of NONROAD uncertainty relative to other emissions sources or other model variables for Georgia.

CHAPTER 6

CONCLUSIONS

This study completed several steps towards a comprehensive uncertainty analysis of NONROAD model emissions for the state of Georgia for the August 2000 episode. The sensitivity analysis and bootstrap simulations for emission factor data shed light on which aspects of the NONROAD model were most important for uncertainty work. The expert elicitation survey and SRS Monte Carlo methods quantified uncertainty of both individual factors and the NONROAD emissions inventory as a whole. Finally, air quality modeling was used to determine the effect of emissions uncertainty on air quality predictions, as well as the uncertainty in estimated concentrations due to possible errors in the NONROAD inventory.

The uncertainties of the NONROAD model emissions for the state of Georgia were found to range between 25 and 33% when represented as the coefficient of variance for exhaust emissions of THC, NOx, CO, and PM. The distributions of the emissions uncertainty were always positively skewed, likely fit best by lognormal or other positively skewed distributions. The uncertainties found were quite large, with the 95% confidence intervals about the mean ranging as wide as –48% to +75%.

The calculated bottom-up uncertainty estimates did not agree with the judgments given for the overall NONROAD emissions inventory in the expert elicitation but showed some agreement with past expert elicitation study by Hanna.[18] Eventually, the goal would be for the different estimates of both the nominal values and uncertainties of emissions to converge, using top-down and bottom-up techniques and different methods and data sources.

This analysis attempted a comprehensive uncertainty analysis of the NONROAD model for the state of Georgia. However, many considerations were still unaccounted for, including fuel consumption, growth factors, equipment age distributions, PM and HC speciation profiles, temporal activity adjustments (seasonal and weekday/weekend), fuel sulfur effects, and evaporative emissions. These factors were judged to be less important for this analysis or beyond the scope of this work. For example, uncertainty in forecasting of future emissions deals with a great deal more than just basic emissions modeling. In that case, one must consider future rules and regulations, economic patterns, technological advances, etc. PM size apportionment and HC species (NONROAD calculates VOC, NMOG, NMHC, etc.) are currently calculated using simple multiplicative factors on emissions by source category. Dealing with these uncertainties will likely require further study before good estimates can be made. While this study did not have to forecast emissions significantly, upcoming work may focus attention on uncertainties of emissions in future years, such as when dealing with air quality modeling for target attainment years.

Dealing with only one of out the four major anthropogenic emission source uncertainties did not result in significant changes in air quality modeling output for ozone and CO. NONROAD uncertainties contributed only at most 10% and 1% error (COV) for CO and ozone predictions, respectively. Although NONROAD emissions uncertainties calculated here were large, the effect was dampened when added to the overall inventory. Estimating uncertainties of each of the other major emission source categories is necessary to make better judgments about the effects of emissions uncertainty on air quality predictions. However, based on the relative results of the air quality modeling, less focus should be placed on VOC uncertainties in future work for the state of Georgia. Because of the much greater biogenic emissions, uncertainties in anthropogenic VOC estimates will likely have a small impact on ozone simulations. The exception would be for specific local cases, such as Atlanta, where extremely high NOx emissions creates times and areas of VOC-limited ozone formation. However, even in those cases, NOx uncertainties appear to be more important overall.

Future work should involve improvement of uncertainty estimates of the NONROAD emissions model as well as for on-road, area, and point source inventories. Both top-down and bottom-up emissions and uncertainty estimating methods should be used as verification of one another. Expert elicitation methods should also be compared with data analysis wherever possible. Surveys of emission source populations and activity should also be conducted when possible. Local survey data can be used not only to improve or verify the baseline emission inventory estimate, but also can provide more raw data for statistical analysis and comparison.

Future expert elicitation methods of quantifying emissions uncertainties should include more efforts to validate the judgments of survey participants. For instance, methods can be implemented to determine how well an expert is calibrated. One check of how well an expert is calibrated is to test his or her understanding of and feel for the magnitude and relative magnitude of known values. Experts can also be asked to rate each of their responses, or the responses of fellow experts. Follow-up surveys or workshops can also be used to try to gain agreement between different experts.

Future analyses of air quality sensitivities to emissions uncertainties should be conducted at a more detailed level. PM air quality sensitivities to emissions uncertainties can also be analyzed in upcoming work, as a DDM-enabled version of CMAQ for aerosols is currently under development at Georgia Tech. As technological advances make large-scale uncertainty analysis of air quality modeling more computationally feasible, more people may embark on efforts similar to and building upon those described in Houyoux et. al. [37], in which grid level input uncertainties are propagated through air quality models. Grid level analysis will likely better capture emission estimates and uncertainty for hot spots, where air quality standard exceedances are most likely to occur.

Although the current study was not able to definitively deduce the ultimate effects of NONROAD uncertainties on air quality model results, the potential error of the emissions estimates was large and will likely be important as the different pieces of air quality uncertainty come into focus. Emissions uncertainties will continue to be a major issue in Georgia and other areas, affecting emission control strategies as well as air quality predictions, as EPA designates new nonattainment areas and implements new regulations.

APPENDIX: Sample Expert Elicitation Materials

NONROAD Uncertainty Analysis Expert Elicitation

Conducted by Georgia Institute of Technology
January 2004

Please provide the following background information:

Name: _____

Company: _____
Address: _____
_____
Phone Number: _____
E-mail Address: _____

How would you characterize your expertise in the field of nonroad emissions? Please provide the number of years of experience you have for each nonroad-related topic below. Please check the rating you would give yourself on a scale of 1 to 10 with 10 being ***most knowledgeable*** and 1 being ***least knowledgeable***.

a. Using the NONROAD model for emissions inventory preparation: _____ yrs
☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10

b. NONROAD model development: _____ yrs
☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10

c. Emissions testing of nonroad engines: _____ yrs
☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10

d. Uncertainty of nonroad emissions: _____ yrs
☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10

e. Other (please specify) _____: _____ yrs
☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10

Please identify names of other individuals, companies, or agencies that you feel qualify as experts in nonroad emissions (optional): _____

Please answer questions 1-6 to the best of your knowledge. We will assume uncertainty estimates you provide will be according to 95% confidence about the mean unless you indicate otherwise. You can also choose to provide different positive and negative uncertainties. If you want to provide other forms of uncertainty estimates (e.g. standard deviation, lognormal parameters, etc.), please indicate this in the "Notes" space for each value.

1. **National NONROAD Equipment Populations**

NONROAD uses the Power Systems Research (PSR) 1998 engine databases and other information from industry for its base year **national** population estimates. The major categories and their data sources are shown in the table below.

Equipment Category	**National Population Estimate Source**
Large SI	PSR 1998 engine population database
Small SI (<25hp)	Phase 1 Rulemaking sales data submitted by manufacturers
CI	PSR 1999 sales database with the NONROAD2002a input values for load factor, activity, median life and the default scrappage curve

For this and each subsequent question, please provide uncertainty estimates for the more detailed breakdown of data in the category if possible. However, if you do not feel comfortable providing the more detailed estimates, please give your judgment of uncertainty for the overall category.

In your expert judgment, please provide % uncertainty estimates for the following:

- Large SI equipment population + ______ ; - _____ ; Notes: ______
- Small SI equipment population + ______ ; - _____ ; Notes: ______
- CI equipment population + ______ ; - _____ ; Notes: ______

AND/OR

- Overall NONROAD equipment population + ______ ; - _____ ; Notes: ______

2. Geographic Allocation of Equipment Populations to County-Level

NONROAD allocates national equipment populations to the county level using a variety of surrogates. These are shown in the table below.

Classification	**Geographic Allocation Surrogates**
Agricultural Equipment	US Census Bureau USA Counties database harvested cropland
Airport Equipment	County Business Patterns (CBP) number of people employed in air transportation
Commercial Equipment	CBP number of wholesale establishments
Construction Equipment	FW Dodge construction dollar value data weighted by 1998 Environ survey of Houston, TX construction activity
Industrial Equipment	CBP number of employees in manufacturing
Lawn and Garden Equipment (Com)	CBP number of employees in landscaping and horticultural services
Lawn and Garden Equipment (Res)	1990 Census single and double family housing units, adjusted by 1997 Census populations
Logging Equipment	CBP number of employees in logging
Pleasure Craft	Allocation to states using ORNL fuel consumption data. Allocation to counties using water surface area.
Railroad Equipment	1990 and 1996 US Census populations

Recreational Equipment	Allocation to states using Motorcycle Industry Council data. Allocation to counties using CBP number of camps and recreational vehicle parks.
Oil Field Equipment	CBP number of employees in oil and gas extraction
Underground Mining Equipment	CBP number of employees in coal mining
A/C Refrigeration Equipment	1990 and 1996 US Census populations

In your expert judgment, please provide % uncertainty estimates for the following:

- Agricultural Equipment allocation + ______ ; - _____ ; Notes: ______
- Airport GSE Equipment allocation + ______ ; - _____ ; Notes: ______
- Commercial Equipment allocation + ______ ; - _____ ; Notes: ______
- Construction Equipment allocation + ______ ; - _____ ; Notes: ______
- Industrial Equipment allocation + ______ ; - _____ ; Notes: ______
- Lawn and Garden (Com) Equipment allocation + ______ ; - _____ ; Notes: _____
- Lawn and Garden (Res) Equipment allocation + ______ ; - _____ ; Notes: _____
- Logging Equipment allocation + ______ ; - _____ ; Notes: ______
- Pleasure Craft Equipment allocation + ______ ; - _____ ; Notes: ______
- Railroad Equipment allocation + ______ ; - _____ ; Notes: ______
- Recreational Equipment allocation + ______ ; - _____ ; Notes: ______
- Oil Field Equipment allocation + ______ ; - _____ ; Notes: ______
- Underground Mining Equipment allocation + ______ ; - _____ ; Notes: ______
- A/C Refrigeration Equipment allocation + ______ ; - _____ ; Notes: ______

AND/OR

- Overall NONROAD county equipment allocations + ______ ; - _____ ; Notes: _____

3. Hours Per Year Activity

NONROAD mainly uses PSR annual activity hours for equipment use data with some exceptions. Details are listed below.

Classification	**Activity Data Source**
Most SI and CI Equipment	PSR 1998 Databases
Small SI Lawn and Garden	Phase 1 Rulemaking sales data submitted by manufacturers
Recreational Marine	Data collected during the recreational marine rulemaking process, provided by the National Marine Manufacturers Association and individual marine vessel manufacturers

ATV	Phone survey sponsored by Honda of owners of TRX model utility ATVs, reporting odometer and hour-meter readings; database of warranty claim information provided by another manufacturer, including odometer and hour-meter readings; national survey of ATV population and usage sponsored by the Consumer Product Safety Commission; "market panel" survey of ATV usage sponsored by major manufacturers
Off-road Motorcycle	EPA assumption that published fuel economy value (~50mpg) is too high for actual off-road operation, revising estimate to 40 mpg, resulting in ~2400 miles/yr activity

In your expert judgment, please provide % uncertainty estimates for the following:

- PSR-database based equipment activity + ______ ; - _____ ; Notes: ______
- Small SI Lawn & Garden equipment activity + ______ ; - _____ ; Notes: _____
- Recreational Marine equipment activity + ______ ; - _____ ; Notes: ______
- ATV activity + ______ ; - _____ ; Notes: ______
- Off-road Motorcycle activity + ______ ; - _____ ; Notes: ______

AND/OR

- Overall NONROAD annual activity + ______ ; - _____ ; Notes: ______

4. Load Factor

NONROAD load factor values come from a variety of sources.

Classification	Load Factor Data Source
Most SI Equipment	PSR 1998 Databases
Small SI Lawn and Garden	Phase 1 Rulemaking sales data submitted by manufacturers
CI Equipment	Transient cycle development and engine tests conducted by Southwest Research Institute under contract to EPA. Seven transient cycles developed: agricultural tractor, backhoe loader, crawler dozer, rubber-tire loader, skid-steer loader, arc welder, and excavator. These lumped into "high" (agricultural tractor (LF=0.78), crawler dozer (LF=0.58), rubber-tire loader (LF=0.48), and excavator (LF=0.53)), "low" (backhoe/loader LF=0.21), skid-steer loader (LF=0.23), and arc welder (LF=0.19)), and "steady-state" (average of 7 cycles) categories. Each CI equipment type assigned to a load factor category.
Recreational Marine	Load factor reflects the average load for the marine engine certification test cycle (20.7%).

In your expert judgment, please provide % uncertainty estimates for the following:

- PSR-database based SI equipment load factors + ______ ; - _____ ; Notes: _____

- Small SI Lawn & Garden equipment load factor + ______ ; - _____ ; Notes: _____
- CI equipment transient cycle load factors + ______ ; - _____ ; Notes: ______
- Recreational Marine load factor + ______ ; - _____ ; Notes: ______

OR

- Overall NONROAD load factor values + ______ ; - _____ ; Notes: ______

5. Emission Factors

NONROAD emission factors are based on several values: zero-mile steady-state emission factors, transient operation adjustments, deterioration factors, fuel adjustments, and temperature adjustments. Here we will **only** focus on zero-mile steady-state emission factors and their transient operation adjustments. We will also ignore pre-1988 emission factors, as these are minimally significant for our analysis.

The table below shows zero-mile steady-state CI exhaust emission factor sources.

Classification	**Emission Factor Data Source**
Tier 0 (1988-Tier 1) <50hp	ARB OFFROAD model
Tier 0 (1988-Tier 1) >50hp	Recent studies with ISO-C1 test results, 18 engines from 6 studies
Tier 1	EPA certification data
Tier 2 300-600hp	EPA certification data
Tier 2 Engines <300hp and >600hp and Tier 3 Engines	Use of EPA certification data from previous Tier or other hp category, use of emission standard, use of default and highway engine compliance margins.

The table below shows zero-mile steady-state SI exhaust emission factor sources.

Classification	**Emission Factor Data Source**
SI <25hp	Base emission factors based on those in the Small Engine Model. PM emission factors for the entire category (both baseline and controlled) are based on NEVES. Phase 1 and 2 emission standards based on engine class are phased in 1997 and on and use Small SI Engine Federal Steady-State Test Procedure.
SI >25hp	2-stroke and PM emission factors from NEVES; 4-stroke from draft regulatory support document for the proposed rule, based on a summary of available test data.
ATVs and motorcycles	HC, CO, and NO_x emission data for ATVs and motorcycles provided by a manufacturer, representing various makes, models, model years, and engine sizes.
Recreational Marine	Emission factors (HC, CO, and NO_x) from 1996 rulemaking for new emission standards for these engines. BSFCs and PM emission factors were derived from NEVES.

The table below shows transient operation adjustment sources.

Classification	Emission Factor Data Source
SI Equipment <25hp	Conflicting results from various studies, so no adjustments made.
SI Equipment >25hp	Based on emission measurements from highway engines comparable to uncontrolled large SI engines, transient emission levels are 30 percent higher for HC and 45 percent higher for CO relative to steady-state measurements. No adjustments for other pollutants.
CI Equipment	Transient cycle development and engine tests conducted by Southwest Research Institute under contract to EPA. Seven transient cycles were developed: agricultural tractor, backhoe loader, crawler dozer, rubber-tire loader, skid-steer loader, arc welder, and excavator.

In your expert judgment, please provide % uncertainty estimates for the following:

- SI Equipment zero-mile steady-state emission factors:
  - HC + ______ ; - _____ ; Notes: ______
  - NOx + ______ ; - _____ ; Notes: ______
  - CO + ______ ; - _____ ; Notes: ______
  - PM + ______ ; - _____ ; Notes: ______
- CI Equipment zero-mile steady-state emission factors:
  - HC + ______ ; - _____ ; Notes: ______
  - NOx + ______ ; - _____ ; Notes: ______
  - CO + ______ ; - _____ ; Notes: ______
  - PM +/+ ______ ; - _____ ; Notes: ______
- SI Equipment transient emission factors adjustments:
  - HC + ______ ; - _____ ; Notes: ______
  - NOx + ______ ; - _____ ; Notes: ______
  - CO + ______ ; - _____ ; Notes: ______
  - PM + ______ ; - _____ ; Notes: ______
- CI Equipment transient emission factors adjustments:
  - HC + ______ ; - _____ ; Notes: ______
  - NOx + ______ ; - _____ ; Notes: ______
  - CO + ______ ; - _____ ; Notes: ______
  - PM + ______ ; - _____ ; Notes: ______

AND/OR

- Overall SI Equipment NONROAD emission factor values:
  - HC + ______ ; - _____ ; Notes: ______
  - NOx + ______ ; - _____ ; Notes: ______
  - CO + ______ ; - _____ ; Notes: ______
  - PM + ______ ; - _____ ; Notes: ______
- Overall CI Equipment NONROAD emission factor values:
  - HC + ______ ; - _____ ; Notes: ______
  - NOx + ______ ; - _____ ; Notes: ______

- CO + ______ ; - _____ ; Notes: ______
- PM + ______ ; - _____ ; Notes: ______

6. Overall NONROAD emissions inventory

In your expert judgment, please provide % uncertainty estimates for the following:

- Overall NONROAD emissions inventory:
    - HC + ______ ; - _____ ; Notes: ______
    - NOx + ______ ; - _____ ; Notes: ______
    - CO + ______ ; - _____ ; Notes: ______
    - PM + ______ ; - _____ ; Notes: ______

Additional Comments _____

Other possible parameters of interest not included in this survey (please comment above if desired):

- Growth
- Age Distribution
- PM and HC speciation profiles
- Temporal activity adjustments (seasonal, weekday/weekend)
- Fuel sulfur effects
- Evaporative emissions

Please direct any questions to:

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