Uncertainty of NONROAD Emissions in Georgia

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ABSTRACT

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

EPA's current NONROAD model is used for this purpose. We first conducted a sensitivity analysis to determine the variables that have significant effects on emissions. Results showed that increase in equipment population, activity, load factor, and emission factor have normalized sensitivity coefficients of 70 percent or higher. Increases in ambient temperature, fuel RVP, fuel sulfur (except on SO_2), and average useful life have normalized sensitivity coefficients of 30 percent or lower, and these parameters are viewed as typically less uncertain as well. Thus analysis of uncertainties of these parameters was not as much of a priority in this study.

Emissions and activity data that are 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 probability distributions were used to estimate the overall uncertainty of emissions from the NONROAD model for the state of Georgia. The uncertainties resulting from this analysis, represented here as standard deviation as % of the mean, ranged from 23 to 26% for THC, 27 to 33% for NOx, 27 to 32% for CO, and 28 to 33% for PM.

INTRODUCTION

In the past ten years, nonroad engine emissions have increasingly become the focus of regulatory action and emission reduction strategies. Nationally, nonroad emissions have generally increased until the mid-1990s.[1] During this time, nonroad emissions have also increased their share of the overall emissions pie for most pollutants. Nonroad engines comprised 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.

In the mid-1990s, EPA developed software for the use of estimating nonroad emissions for any area in the United States. The NONROAD emissions model was first released publicly in 1998.[2] Before this time, nonroad emissions inventory preparation involved tedious use of equipment and emission factor data from past studies. 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 program. Between 1998 and now, several versions of this model have been publicly released, although the model is still officially in draft form.[3]

It is widely recognized that uncertainty in nonroad emissions estimation may be significant. Some past studies of photochemical grid modeling have included determination of the uncertainty of the nonroad emissions inventory. 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.[4] 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.[5] However these studies were conducted in more of 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 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 very limited. Past studies of nonroad engine emission factor uncertainty by Frey and Bammi have estimated uncertainties based on 95 percent confidence intervals using parametric bootstrap analysis of data assembled from several engine-testing studies. Two-stroke total hydrocarbons (THC) and NO_X emissions uncertainties in Lawn & 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.[6] 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. In our study we analyze uncertainty more specifically for the NONROAD model and also we include uncertainties of population and activity parameters as well as emission factors.

METHODOLOGY & RESULTS

In this study, we used EPA's current publicly available draft NONROAD model[7] 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 methodology used.

Sensitivity Analysis

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. In this case, the base case modeled a typical summer weekday for the state of Georgia in 1999. 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 ease of modification and suspected significant emissions impact. Each parameter was varied individually at 110% and 90% of the base parameter value while keeping all other parameters constant. The model output resulting from these modifications was used to calculate normalized sensitivity coefficients for each of the input parameters of interest. Figure 1 presents the results for these analyses. These analyses showed that increase 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 increase 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, $PM_{2.5}$, but was assumed to have obvious important effect on emissions for all pollutants.

Increases in ambient temperature, fuel RVP, fuel sulfur (except on SO_2), and average useful life found to have normalized sensitivity coefficient of 30 percent or lower. 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. Therefore, in this analysis we focused on uncertainties in the equipment population, activity, load factor, and emission factor parameters.

This work focuses on the exhaust THC, NOx, CO, and PM pollutants. CO_2 and SOx are 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 is 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.

Statistical Analysis

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 test data are provided in the model documentation.[8] Thus, the emission test results can be used directly in uncertainty analysis. 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,[6] this analysis retained the horsepower groupings to most accurately reflect what is actually used by NONROAD.

The uncertainty in the mean emission factors was estimated using two bootstrap sampling methods. The first method involved using a bootstrap resampling technique in MATLAB. Sets of emission factors and their associated sales fractions were randomly sampled and averaged several thousand times. The resulting 95% confidence intervals about the mean were determined based on these data sets. Table 1 presents the results of this analysis. Uncertainties of the mean were approximately ± 30% for THC, ± 6% for NO_X, ± 25% for CO, and ± 15% 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 -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.

The uncertainty in the mean emission factors for diesel certification test data were also estimated by parametric bootstrap analysis using the Analysis of Uncertainty and Variability Tool (AuvTool) software.[9] An empirical distribution was fit to samples using this software. The software calculates the 95% confidence interval of a given sample using a parametric bootstrap method.[10] Table 2 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.

Expert Elicitation

Uncertainty analysis of most other NONROAD inputs parameters is difficult due to lack of available data. Therefore, expert elicitation was used to determine 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 equipment population.

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. 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 (PSR).[11] 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 allocations, because the explicit methods are not public. However, NONROAD does also use a surrogate allocation method in which population, engine survey data, economic parameters, etc.

are used to distribute the national total emissions.[12] Simple fractions, based on the relative surrogate values, apportion the emissions to each county.

PSR provided some rough estimates of uncertainty of different parameters.[13] 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 and does not account for the modifications or substitutions EPA makes for the NONROAD model. 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, since this work focused on a bottom-up uncertainty analysis approach. Seven companies/agencies with vast past experience in nonroad emissions were contacted. Five responded, one refused to respond, and one was not reachable with repeated contact attempts. The survey asked for uncertainty estimates (95% confidence intervals) for specific NONROAD input parameters.

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 was used to weight the responses when computing averages, so that the opinion of the most experienced experts had greater influence on the average than those with less experience. Table 3 presents the 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 +150% and –50%. Uncertainties of the activity estimates fell in the range of +65% and –40%. Unlike most other input parameters in the survey, the experts determined a negatively skewed 95% confidence interval for load factor, since this variable is a fraction bounded at a value of 1. These uncertainties fell in the range of +36% and –40%. Finally, the experts determined that PM emission factors were the most uncertain of the four pollutants in this study for SI engines at +52% and –29%, while CO emission factors for compression ignition (CI) engines were most uncertain overall at +96% and –29%.

In this work, emission factor uncertainties for CI 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 much more conservative than 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 more intangible issues. Thus, the overall much higher uncertainty estimates from the experts is 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 much lower uncertainties for NO_X than the other three pollutants. This can be used as evidence for validation of the expert opinions.

Monte Carlo Simulation

Method

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 basic scenario was run for a typical summer weekday for the state of Georgia in 1999. The NONROAD model was run in batch mode, with each run consisting of a randomly generated set of inputs. The randomly generated inputs were generated based on the 95% confidence interval survey results. Three

Monte Carlo simulations were conducted: generating random inputs using normal distributions with unequal halves (to account for positively or negatively skewed confidence intervals), using triangular distributions, and using uniform distributions. These three set-ups were conducted to compare the importance of the distribution used in the analysis. Using the uniform distribution would capture the most extreme, most conservative case, while the normal distributed data was thought to represent the least conservative case in terms of uncertainty of the output. The MC simulations were run until the running average and standard deviation. Figure 2 and Figure 3 show an example of the calculated running average and standard deviation for NONROAD PM emissions output. Figure 2 shows both the MC running average and the base case scenario emissions. In all cases, the MC simulations result in higher state total emissions than the base case. The graphs show that the calculated parameters generally stabilize by 1500 model runs.

Allocation of the emissions down to the county level was done in a separate MC step outside of the NONROAD model runs, with these uncertainties compounded with the uncertainties of the state total emissions derived directly from the model. However, 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. This was done for the normal distribution MC simulation only. In order to determine the county emissions with uncertainties of the allocations, the emissions output had to be separated into the allocation source groups, as shown in **Figure 4**. NOx and PM are generally dominated by construction equipment emissions, while lawn and garden equipment contribute a large fraction of THC and CO emissions. Since the geographic allocations and emission factors uncertainties vary by source category and pollutant respectively, uncertainty results by county would be affected in varied amounts, depending on which source categories and pollutants are prevalent in certain areas. Georgia has 159 counties. 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.

Results

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. However, 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 % of the mean) did not differ by more than 5% for any pollutant, e.g. the uncertainties of PM emissions ranged from 28% to 33% for the three simulations, as shown in Table 4.

Because several input parameters had confidence intervals that were positively skewed, it is not surprising that the distributions of emissions for all simulations were also positively skewed. The normal distribution simulation had higher positive skewness than either the triangle or uniform distribution simulations, as expected. Figure 5 shows an example of the resulting probability distribution of the normal distribution simulation results for CO emissions from NONROAD.

In the county allocation simulation, the uncertainties averaged over all counties were very similar to the uncertainties resulting from the whole state simulation. However, individual counties varied significantly in the amount of uncertainty calculated, likely due to different uncertainties assigned to the various allocation source categories. The emissions from different counties are dominated by different source categories. Table 1 summarizes the uncertainty results for the county allocation. The final uncertainties of emissions at the county level all range between 18 and 38% when represented by the standard deviation as % of the mean. Figure 6 to Figure 9 show the spatial allocation of emissions for the four pollutants resulting from the Monte Carlo simulation. Generally, the highest emissions are found in northern Georgia in and around Atlanta. Figure 10 to Figure 13 show the uncertainties by county. Interestingly, uncertainties for PM emissions are highest right in Atlanta, where emissions are also highest. Finally Figure 14 to Figure 17 show the overall change in emissions by county from the base case scenario to the MC simulation results. Recall that the overall state emissions always increase in the MC simulations when compared to the base case. These maps show how the overall state emissions increase is distributed by county. Generally, the highest percent increases occur in areas of low emissions, where small changes in allocation may have a large effect.

CONCLUSIONS

The uncertainty of the NONROAD model emissions for the state of Georgia appear to range between -23 and +33%, represented as the standard deviation as % of the mean. The distributions of the emissions uncertainty are always positively skewed, likely fit best by lognormal or other positively skewed distributions.

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 assumed either 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.

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Nonroad emissions, Monte Carlo, uncertainty.

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TABLES

Table 1 Resampling Bootstrap Uncertainties of Diesel Engine Certification Emission Test Results

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	-5.63%	6.56%	-12.86%	12.17%	-2.84%	2.94%	-18.84%	24.71%	-11.21%	13.21%
1996	300-600	-10.56%	18.18%	-37.82%	53.65%	-9.70%	13.44%	-15.50%	8.87%	-20.25%	29.20%
1996	600-750	-5.55%	5.17%	-55.38%	65.90%	-6.72%	5.81%	-23.28%	24.44%	-19.64%	17.86%
1997	100-175	-12.31%	10.01%	-20.30%	20.41%	-5.25%	7.14%	-10.36%	15.87%	-21.94%	9.10%
1997	175-300	-5.32%	6.61%	-30.24%	28.52%	-4.61%	4.48%	-14.20%	18.59%	-8.73%	9.53%
1997	300-600	-11.32%	21.27%	-31.04%	31.04%	-4.75%	8.03%	-48.74%	27.33%	-27.05%	21.04%
1997	600-750	-6.90%	4.28%	-54.49%	66.51%	-5.42%	6.37%	-28.15%	21.70%	-13.29%	7.30%
1998	50-100	-7.82%	7.02%	-42.08%	28.41%	-7.33%	7.61%	-49.21%	31.03%	-21.43%	13.40%
1998	100-175	-12.92%	12.34%	-13.29%	9.16%	-5.34%	5.48%	-34.39%	41.84%	-13.96%	6.95%
1998	175-300	-8.34%	12.53%	-8.67%	13.24%	-2.19%	3.50%	-11.71%	19.70%	-7.96%	5.68%
1998	300-600	-10.52%	13.36%	-28.68%	56.12%	-6.68%	5.95%	-28.62%	23.10%	-12.36%	14.74%
1998	600-750	-6.73%	8.99%	-43.90%	28.99%	-3.62%	1.76%	-30.85%	22.18%	-24.73%	19.83%
Average		-8.66%	10.53%	-31.56%	34.51%	-5.37%	6.04%	-26.15%	23.28%	-16.88%	13.99%

Table 2 Parametric Bootstrap Uncertainties of Diesel Engine Certification Emission Test Results (using AuvTool)

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	-3.05%	3.45%	-8.75%	9.68%	-2.14%	2.09%	-17.59%	15.79%	-6.48%	8.10%
1996	300-600	-7.01%	6.90%	-24.01%	24.39%	-5.34%	5.13%	-7.96%	7.60%	-11.27%	11.72%
1996	600-750	-4.39%	4.13%	-48.96%	44.80%	-5.59%	5.11%	-19.18%	19.79%	-14.03%	14.60%
1997	100-175	-4.59%	4.78%	-13.12%	14.02%	-3.08%	2.61%	-14.07%	14.47%	-8.86%	8.91%
1997	175-300	-3.16%	3.00%	-14.75%	13.12%	-3.01%	2.71%	-10.22%	10.23%	-6.16%	6.38%
1997	300-600	-7.13%	6.78%	-14.94%	16.43%	-3.89%	3.60%	-15.65%	16.30%	-11.78%	11.34%
1997	600-750	-4.40%	4.95%	-44.50%	45.66%	-5.13%	4.83%	-20.14%	19.41%	-10.33%	8.92%
1998	50-100	-2.11%	2.14%	-15.88%	15.15%	-3.71%	3.86%	-19.40%	19.29%	-9.85%	11.66%
1998	100-175	-5.02%	5.80%	-3.53%	3.50%	-2.30%	2.36%	-20.13%	23.33%	-6.77%	6.74%
1998	175-300	-4.42%	5.04%	-7.78%	7.41%	-1.89%	1.76%	-14.07%	13.29%	-4.04%	3.78%
1998	300-600	-5.84%	6.29%	-24.42%	27.86%	-3.11%	2.69%	-13.82%	14.22%	-8.92%	8.29%
1998	600-750	-6.52%	6.33%	-26.64%	27.50%	-3.33%	3.57%	-19.27%	17.30%	-18.42%	17.40%
Average		-4.80%	4.97%	-20.61%	20.80%	-3.54%	3.36%	-15.96%	15.92%	-9.74%	9.82%

Table 3 Expert Elicitation Aggregated Results

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

Table 4 Monte Carlo Simulation of NONROAD Model Results Using Different Probability Distributions for Inputs

Input Distribution	Average (Tons Per Day)			
	THC	NOx	CO	PM

Normal	204.42	204.60	2580.59	23.81
Triangle	219.56	213.90	2804.44	26.34
Uniform	226.96	221.91	2930.71	28.05
Input Distribution	**Standard Deviation (Tons Per Day)**			
	THC	NOx	CO	PM
Normal	48.13	58.82	758.42	7.17
Triangle	50.74	58.30	775.18	7.43
Uniform	59.13	73.22	939.75	9.31
Input Distribution	**Standard Deviation as % of Average (%)**			
	THC	NOx	CO	PM
Normal	23.55	28.75	29.39	30.13
Triangle	23.11	27.26	27.64	28.21
Uniform	26.05	33.00	32.07	33.20
Input Distribution	**Skew**			
	THC	NOx	CO	PM
Normal	0.98	0.93	1.05	1.00
Triangle	0.70	0.55	0.80	0.68
Uniform	0.72	0.57	0.77	0.70

Table 5 Monte Carlo Simulation Results for County Allocations of NONROAD Emissions Output

	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	34.75	18.88	23.37	23.55
NOx	33.49	20.48	29.34	28.75
CO	37.52	19.47	27.78	29.39
PM	36.78	22.48	30.91	30.13

FIGURES

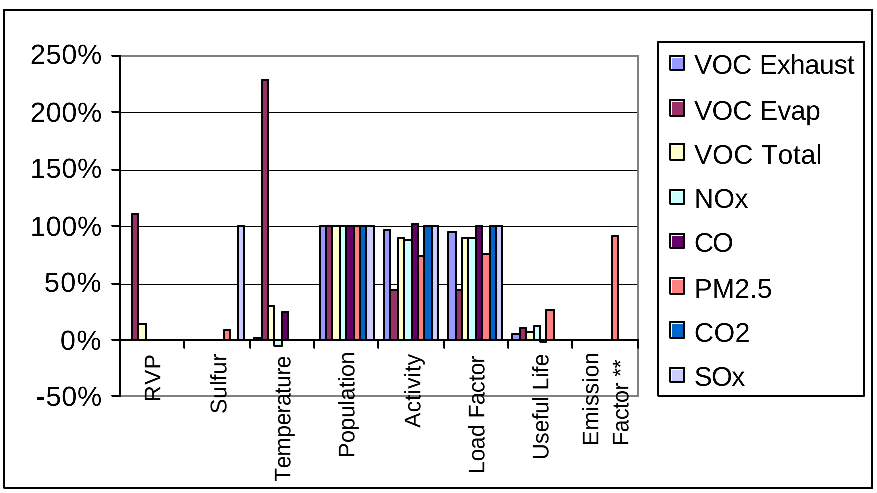

Figure 1 Normalized Sensitivity Coefficients for Various NONROAD Input Parameters. **Emission factor sensitivity analysis performed for PM2.5 only. All other parameters include sensitivities for ALL pollutants listed.

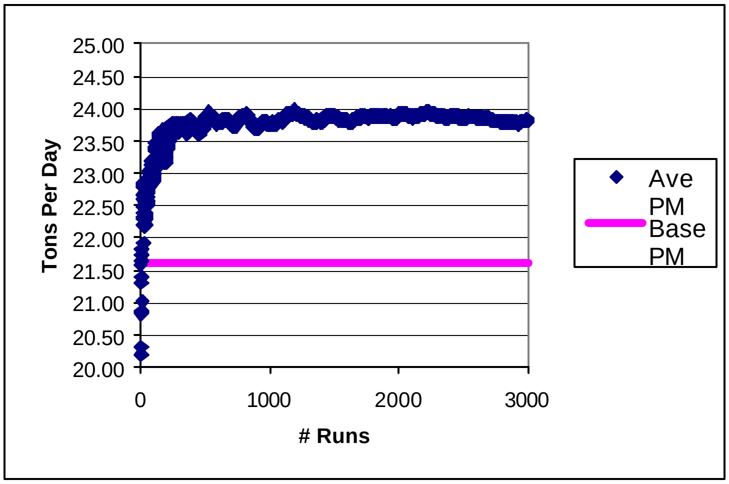

Figure 2 Monte Carlo Simulation Running Average of NONROAD Emissions Output

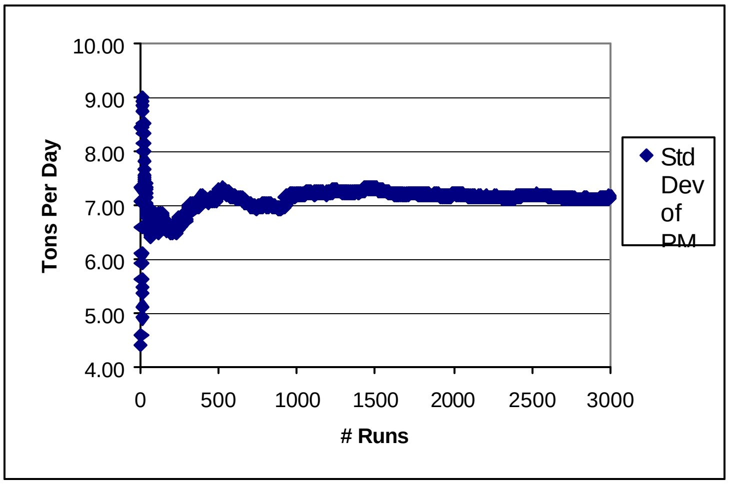

Figure 3 Monte Carlo Simulation Standard Deviation of NONROAD Emissions Output

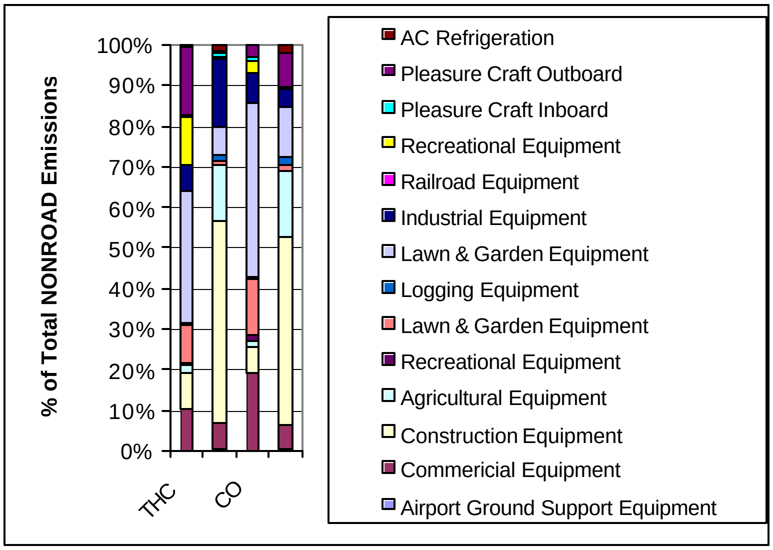

Figure 4 NONROAD Emissions Contribution of Source Categories for Georgia, Summer 1999

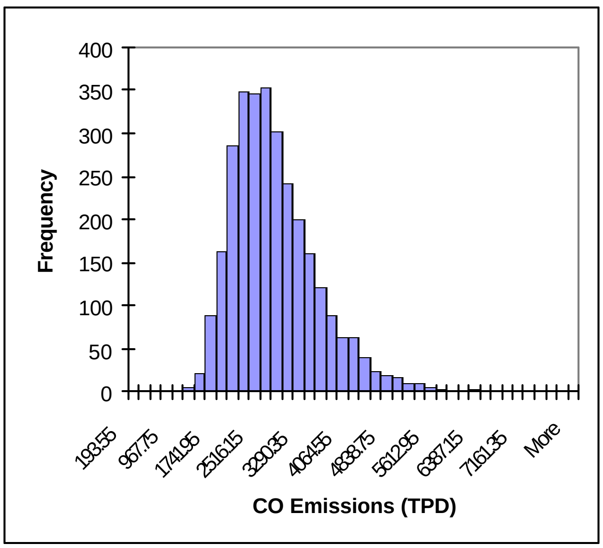

Figure 5 Monte Carlo Simulation NONROAD Emissions Output Probability Distribution

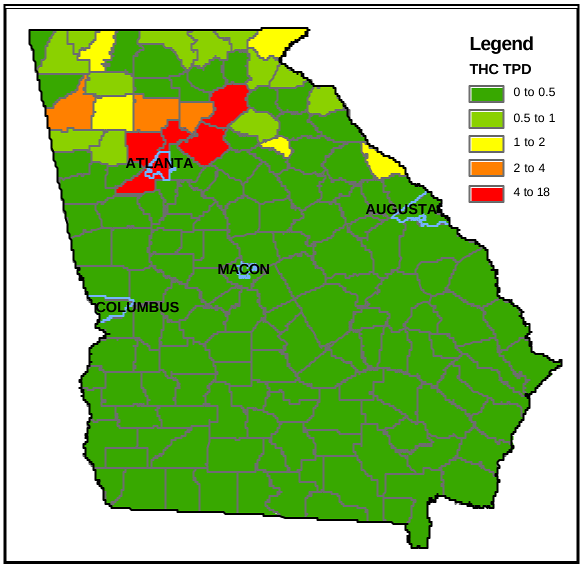

Figure 6 Monte Carlo Simulation Average NONROAD THC Emissions at County Level

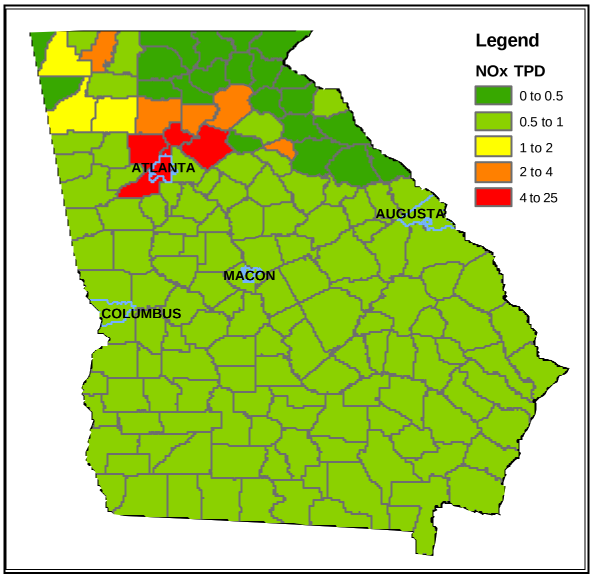

Figure 7 Monte Carlo Simulation Average NONROAD NOx Emissions at County Level

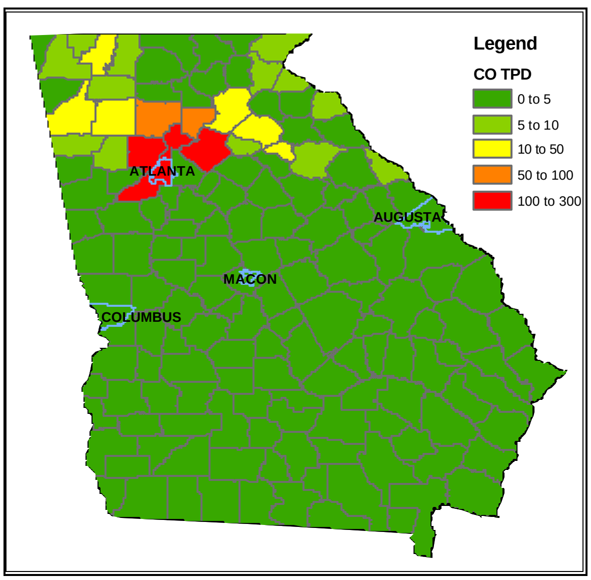

Figure 8 Monte Carlo Simulation Average NONROAD CO Emissions at County Level

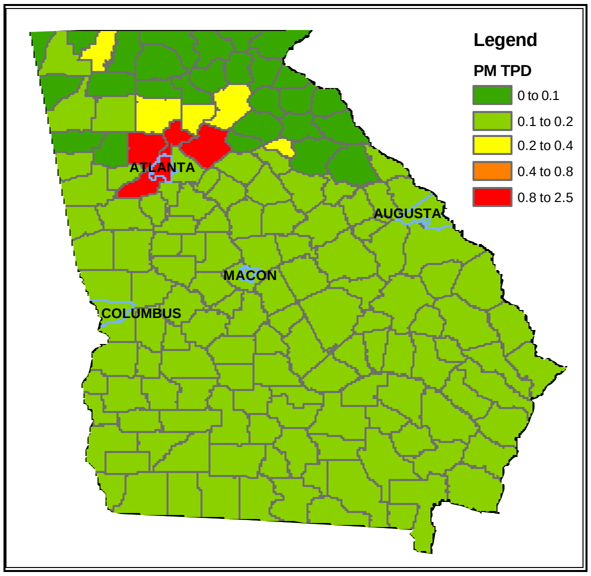

Figure 9 Monte Carlo Simulation Average NONROAD PM Emissions at County Level

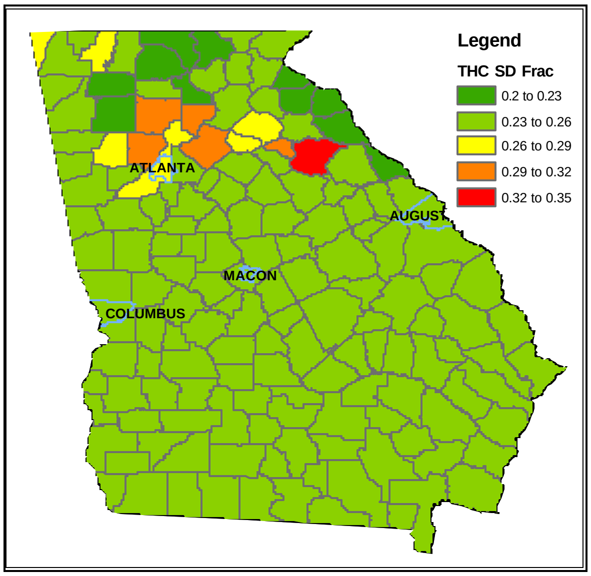

Figure 10 Monte Carlo Simulation NONROAD THC Emissions at County Level Uncertainty As Standard Deviation Fraction of Mean

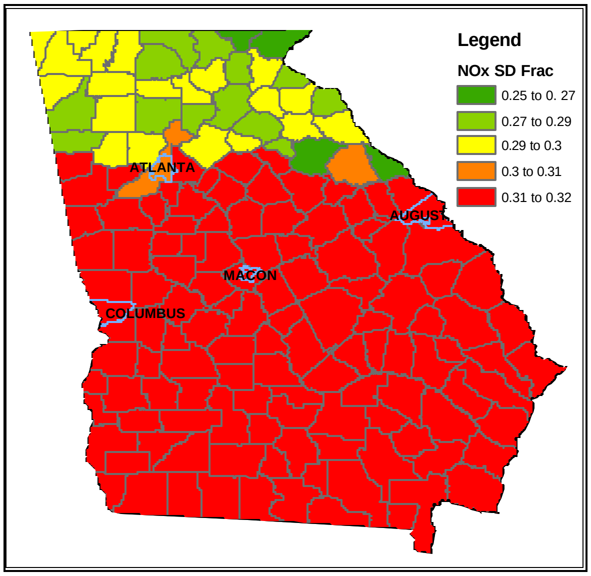

Figure 11 Monte Carlo Simulation NONROAD NOx Emissions at County Level Uncertainty As Standard Deviation Fraction of Mean

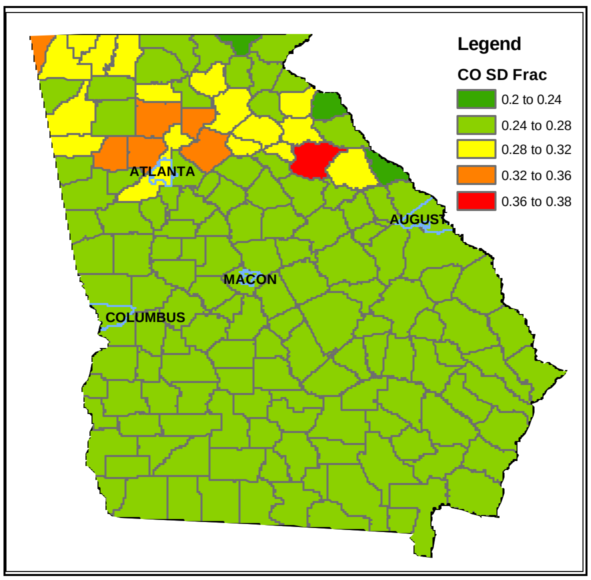

Figure 12 Monte Carlo Simulation NONROAD CO Emissions at County Level Uncertainty As Standard Deviation Fraction of Mean

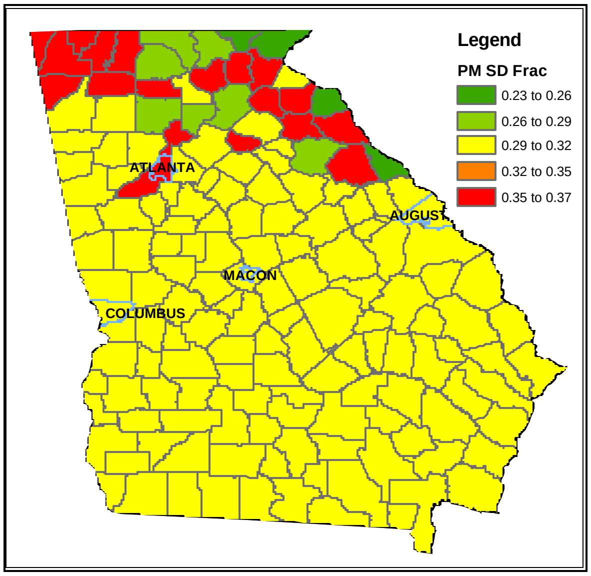

Figure 13 Monte Carlo Simulation NONROAD PM Emissions at County Level Uncertainty As Standard Deviation Fraction of Mean

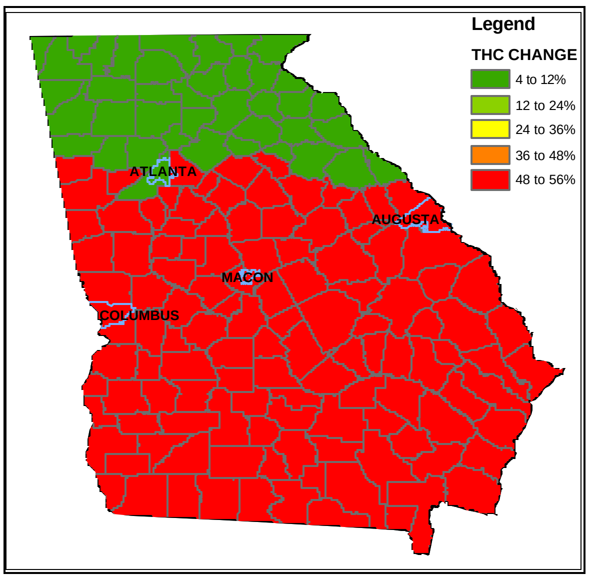

Figure 14 Monte Carlo Simulation NONROAD THC Emissions at County Level % Change from Base Case

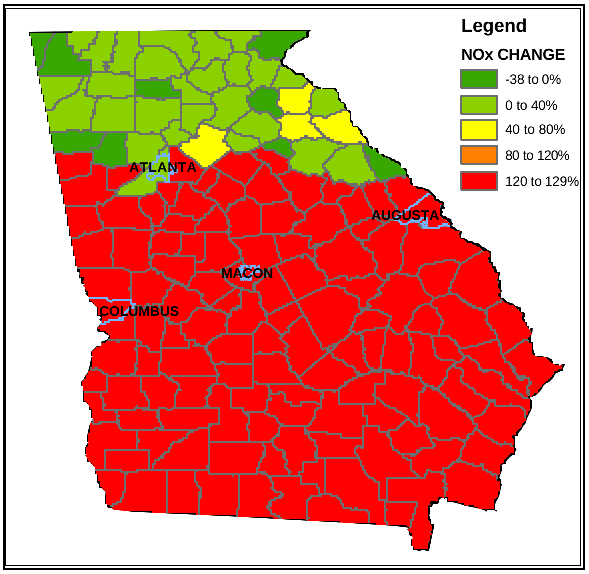

Figure 15 Monte Carlo Simulation NONROAD NOx Emissions at County Level % Change from Base Case

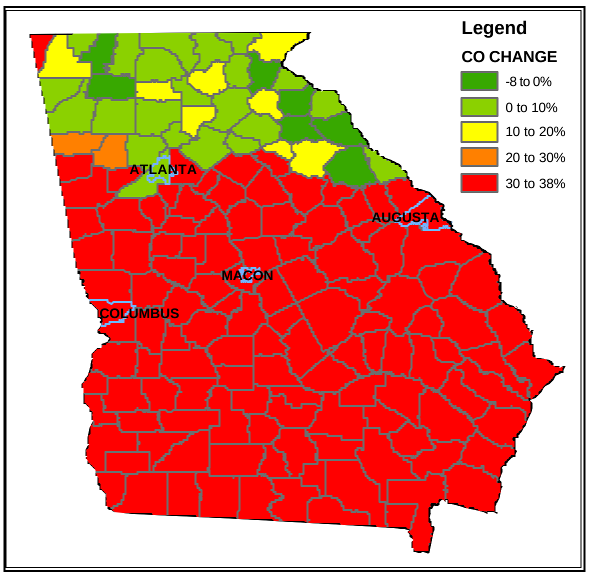

Figure 16 Monte Carlo Simulation NONROAD CO Emissions at County Level % Change from Base Case

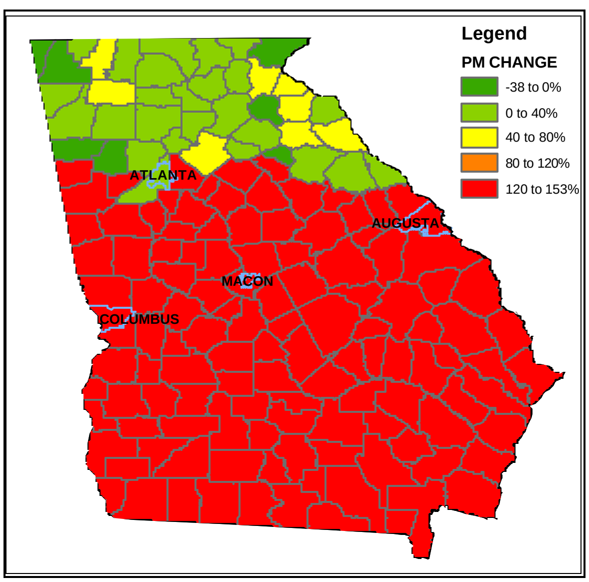

Figure 17 Monte Carlo Simulation NONROAD PM Emissions at County Level % Change from Base Case