CHAPTER 5

STRENGTHS AND WEAKNESSES OF CURRENT EMISSION INVENTORIES

This chapter provides a qualitative assessment of the strengths, weaknesses, and uncertainties of current emission inventories. It provides a bridge between the first four chapters of this Assessment and the remainder of the report. Chapters 1 and 2 describe the issues that are forcing change in the content and structure of North American emission inventories, and they provide a vision of what these future inventories should look like. Chapters 3 and 4 describe the current status and content of North American emission inventories, and they review the tools and methods that have been used to develop them. The final four chapters focus on the future. Motivated by the shortcomings summarized in this chapter, the remainder of the assessment reviews new technologies for improving emission inventory content, discusses methods for assuring their quality and for quantifying their uncertainty, and provides a set of recommendations for achieving the standard of data quality, documentation, and accessibility that will be needed in the future.

Emission inventories are subject to substantial (and typically unspecified) levels of uncertainty, and this uncertainty affects the confidence one can place in the air quality management strategies that are based on them. Better knowledge of these uncertainties, as well as better characterization of the basic strengths and weaknesses of emission inventories in general, provides the basis for developing targeted and cost-effective strategies for improving inventories and, for improving air quality management.

Over the past 40 years, emission inventories have improved dramatically in terms of accuracy and completeness in Canada, the United States, and Mexico. Air quality managers have a good understanding of the major sources of emissions that affect air quality, and they have turned this

Chapter 5 Objective: ***To provide a qualitative assessment of the strengths, weaknesses, and uncertainties of current inventories so that emission inventories can be used with the appropriate level of confidence and areas needing improvement can be identified.***

Strengths

- The major sources of emissions that affect air quality are well characterized.
- North American emission inventories and models can provide quantitative estimates of emissions at national, state, or provincial, and county levels.
- Confidence is high in data on emissions of SO_2, NO_x, and CO_2 from electric generating units as the result of the development and deployment of CEMS at these facilities.
- Emission trends over time can be used to evaluate the effectiveness of control strategies and projects.

Weaknesses

- Quality assurance and quality control procedures are not strictly applied in the development of most emission models and inventories.
- Emissions for mobile sources and many important stationary nonpoint source categories are uncertain and inadequately characterized.
- Emission estimates are frequently based on a small number of emission measurements that may not be representative of real world activity.
- Insufficient information is available on chemical composition – of both PM and gases – for many sources.

knowledge into effective programs for reducing these emissions. In Canada and the United States, for example, significant reductions in emissions have been achieved over the past 30 years in spite of increases in population, gross domestic product, and energy consumption (see Figures 3.4 and 3.5 and the supporting references in this Assessment). Two major source categories, stand out in terms of improvement. Characterization of emissions of SO_2, NO_x, and CO_2 from electric utilities has improved significantly as the result of the development and deployment of CEMS that are the backbone of the successful acid rain cap and trade program (Werner and Mobley, 2005). Likewise, the characterization of mobile source emissions has improved as a result of the research that underlies models such as the MOBILE series of emission models developed by the U.S. EPA. Most current inventories or models can provide quantitative estimates of emissions at national, state, and county levels;and these inventories and models can be used to compare the significance of different source categories. Emission estimates from current inventories and models can provide insights regarding air quality trends over time, they can be used to track pollution, control efficiency, and they can help decision-makers develop air quality management strategies.

5.1 STRENGTHS OF CURRENT EMISSION INVENTORIES

While much of this chapter focuses on shortcomings of emission inventories and the tools used to construct them, it is important to place the weaknesses in perspective by recognizing some of the key strengths of modern inventories and tools. For example, an analysis of the U.S. NEI provides a big-picture view of the importance of various sectors to air quality in the United States by showing that: (a) stationary sources contribute the largest portion of total NO_x and SO_2 emissions and a considerable portion of VOC emissions, but a relatively smaller portion of total CO emissions; (b) mobile sources are the largest contributor to the total CO emissions and a considerable contributor to total NO_x emissions; and (c) biogenic sources contribute the largest portion of total VOC emissions (U.S. EPA, 1996; Placet et al., 2000). For the most part there is a high degree of confidence in these major insights.

Current emission inventories estimate emission trends over time and give some indication of the effectiveness of particular control strategies and projects. Emission inventories are also key inputs for air quality modeling, and they can be used to evaluate the effect of different pollution strategies on the ambient air quality. There is a high degree of confidence regarding some major changes in total emission inventories at the national level, such as reductions in SO_2 and NO_x from electric utilities in the United States associated with acid rain provisions of the *Clean Air Act Amendments of 1990*.

Inventories help decision-makers allocate resources and develop air quality management strategies. Knowledge of emissions contributed from different source categories helps decision makers set priorities for air quality improvement in allocating limited resources to those sources with the greatest potential to reduce emissions (Frey et al., 1999; Frey and Zheng, 2002). For example, in urban areas facing ozone problems, the relative importance of NO_x versus VOC control can be assessed taking into account both urban scale and regional geographic scales, and the key source categories that should be the focus of control efforts can be broadly prioritized.

Mobile-source emission inventories can be used as inputs to air quality models to simulate regional and urban dispersion of pollutants. They are also used in developing national, regional and urban emission inventories for criteria pollutants and toxic air pollutants. The MOBILE models are useful in evaluating regulatory strategies and state implementation plans, because they utilize an aggregate approach for wide areas under average conditions (NRC, 2000). The NONROAD model predicts exhaust emissions for HC, CO, NO_x, SO_x, PM, CO_2, as well as diurnal and refueling evaporative HC emissions, and the volume of fuel consumed by nonroad equipment except locomotives, aircraft, and commercial marine vessels. The level of detail from NONROAD includes fuel type (diesel, gasoline, LPG, and compressed natural gas), individual source category classification, power range, geographic area (nationwide, state, or county), and temporal (annual, seasonal, monthly, weekday/weekend) for calendar years 1970 to 2050 (Harvey et al., 2003).

The success of past and ongoing emission control programs means that maintaining and improving future air quality will require emission reduction programs that are more focused on specific sources and pollutants. Developing these programs will require accurate and detailed knowledge of emissions from sources that are smaller, more widely dispersed, and more difficult to characterize. These needs will require improved inventories that fill information gaps and reduce emission uncertainties that have been less important in the past.

Table 5.1, which is based on a previous review of emission inventories (NARSTO, 2004), provides a qualitative overview of the level of confidence of these experts in emission inventories in Canada, the United States, and Mexico for four important pollutant classes: SO_2, NO_x, VOCs, and HAPs. This type of assessment is a useful starting point for summarizing the current state of knowledge regarding key components of emission inventories and for identifying the principal weaknesses that must be attacked if confidence in current emission inventories is going to be increased.

5.2 WEAKNESSES OF CURRENT EMISSION INVENTORIES

Qualitative assessments of emission inventory uncertainties, such as the one summarized in Table 5.1, have revealed a number of specific shortcomings and information gaps in the inventories of Canada, the United States, and Mexico. These problems are summarized below.

5.2.1 Quality Assurance and Uncertainties

Quality assurance and quality control procedures often are not strictly applied in the development of emission models and inventories, and the documentation of uncertainties and data sources in emission inventories is not adequate.

Strict quality evaluation during the development of emission inventories can reduce errors such as misclassification of sources or their mislocation. Many different agencies and stakeholders may contribute data to an inventory, and QA/QC procedures for evaluating emission data and key assumptions are not uniform or uniformly followed. In addition, uncertainties that can arise from measurement or sampling error are rarely characterized and reported. These problems are typical for all source categories whether the emission data are based on direct measurements or are estimated from emission models using activity and emission factors that are not always well documented in terms of uncertainty or pedigree.

Uncertainties are rarely or not rigorously quantified in emission inventories and models (NRC, 2004; NARSTO, 2004; Frey et al., 1999; Frey and Bammi, 2002). For example, almost no emission estimation models, including the widely used MOBILE and NONROAD models for mobile source emissions, and BEIS3 for biogenic emissions, contain a component that can assess uncertainty in model inputs and structure. Emission inventories developed based upon these models rarely quantify uncertainty in emission estimates. Although there are some examples in which uncertainties had been quantified for an emission inventory (e.g., Frey and Zheng, 2002; Zhao and Frey 2004; Hanna and Wilkinson, 2004), most of these examples are demonstrative case studies. In routine practice, uncertainties are typically ignored. The most readily available, and best known, information regarding uncertainty is the quality ratings of stationary-source emission factors listed by U.S. EPA in AP-42 (U.S. EPA, 2005).

5.2.2 Mobile Source Inventories

Significant uncertainties exist in mobile source inventories with regard to the magnitude of CO emissions, the temporal trend of NO_x emissions, the representativeness of the emission projections from MOBILE6, and the accuracy of emission estimates for nonroad sources. There are significant uncertainties in mobile source inventories particularly regarding the speciation of VOCs, the magnitude of CO emissions, and the temporal trend of NO_x emissions.

Table 5.1. Estimated Relative Confidence Levels of Emission Inventories.				
Pollutants	**Source**	**Estimated Confidence Levels in Overall Inventory**		
		Canada	**U.S.A**	**Mexico**
SO_2	Utilities	high	high	high
	Other point sources	medium	medium	low-medium
	On-road mobile	medium	medium	low
	Nonroad mobile	low-medium	medium	low
	Stationary nonpoint sources	low	low	low
	Biogenic source	low	low	low
	Other man-made sources (non-combustion)	low	low	low
NO_x [a]	Utilities	medium-high	high	medium
	Other point sources	medium	medium	medium
	On-road mobile	medium-high	medium-high	medium
	Nonroad mobile	medium	medium	low
	Stationary nonpoint sources	low	low	low
	Biogenic source	low	low	low
	Other man-made sources (non-combustion)	medium	medium	low
VOC[a]	Utilities	medium-high	medium-high	medium
	Other point sources	low-medium	low-medium	medium
	On-road mobile	low-medium	low-medium	low
	Nonroad mobile	low-medium	low-medium	low
	Stationary nonpoint sources	low	low	low
	Biogenic source	low	low	low
	Other man-made sources (non-combustion)	medium	medium	low
HAP	Utilities	medium	medium	medium
	Other point sources	low-medium	low-medium	low
	On-road mobile	low-medium	low-medium	low
	Nonroad mobile	low-medium	low-medium	low
	Stationary nonpoint sources	low	low	low
	Biogenic source	low	low	low
	Other man-made sources (non-combustion)	low	low	low
[a]NARSTO PM Assessment (NARSTO, 2004)				

MOBILE6 may under- or over-predict onroad emissions for certain pollutants from certain vehicle types. MOBILE6 is not user-friendly and requires users to research and write detailed input files. Even though this enables users to create highly detailed and specific input files, the process is time consuming, tedious, and error prone. The problems with CO emissions and NO_x trends are discussed in some detail in Chapter 7.

Existing onroad emission factor models, such as MOBILE, are not well suited to deal with mesoscale or microscale emission estimates that take into account local effects of specific transportation control measures or highly resolved (both temporally and spatially) characterization of emission hotspots, such as at intersections. As such, these models are poorly suited for analysis of the impact of specific transportation improvement projects or for conducting corridor-level analysis. This shortcoming introduces substantial uncertainty in the assessment of future transportation improvements or controls with respect to air quality management (NRC, 2000). Mobile-source tailpipe emissions are also typically estimated based upon test procedures that are of limited duration (e.g., 10 to 40 minutes in many cases). These short-term tests may not be representative of emissions over a longer time period.

Other concerns with emission estimates for onroad mobile sources are:

- Standard test procedure measurements made using dynamometers, whether chassis or engine, may not adequately capture the effects of real-world conditions that could substantially affect emissions.
- Treatment of the effects of emission spikes that come from variability in engine loads and the importance that such spikes have in overall emission inventories are not adequately addressed (Barth et al., 1997; NRC, 2000; Hallmark et al., 2001).
- A disproportionate amount of emissions are typically attributed to a relatively small percentage of high-emitting motor vehicles (NRC, 2001); however, high emitters are probably not adequately treated by current mobile source emission models. High emitters are typically conceived to be older vehicles as well as newer vehicles that are malfunctioning in some manner.

Although nonroad sources are becoming an increasingly important part of total emissions, nonroad models are suspected of not accurately estimating emission inventories. There is also little information about the accuracy or uncertainty of such models (Frey and Bammi, 2002; NRC, 2004b).

5.2.3 Nonpoint Stationary Sources

Emissions for many important categories such as PM and their precursors, biogenic emissions, toxic air pollutants, NH_3, fugitive emissions, open biomass burning, and many other area sources are uncertain and inadequately characterized

Emissions from nonpoint stationary sources are much more uncertain than for criteria pollutants from stationary sources. The individual sources may be smaller and widely dispersed (Placet et al., 2000, Hanna and Wilkinson, 2004; Zhao and Frey, 2004; TNRCC, 2003; NARSTO, 2004). Or, as in the case of fugitive emissions, they may result from unknown sources or from offnormal operating conditions. In some cases, such as biogenic emissions, agricultural-related ammonia, or biomass burning, emissions may be from processes or activities that contain considerable inherent variability and are difficult to measure, characterize, and express in emission models.

The CMU Ammonia Model's activity data and emission factors for agricultural sources are uncertain. As described in Section 4.4.11 of Chapter 4, the CMU Ammonia Model is a database containing activity data and emission factors for NH_3 emissions. Agricultural operations are particularly large emitters of NH_3, and the identified weaknesses make emission estimates uncertain. However, as noted in Section 7.5, recent work has made progress in reducing this uncertainty.

Compared to other source categories, nonpoint stationary-source emission inventories have the highest uncertainty in emission rates (NARSTO, 2004). Because direct measurement of nonpoint stationary emission sources is resource-intensive (Placet, et al., 2000), nonpoint stationary-source inventories are constructed generally through calculations. In some situations, surrogates for emission and activity factors are used for emission estimates. The quality of the estimates depends on how well the surrogate activity factor correlates with the emission rate for the source.

5.2.4 Measurements

Emission estimates are frequently based on a small number of emission measurements that may not be representative of real world activity. Accordingly, the precision and accuracy of estimates developed from these measurements will be limited.

Because the number of measurements used either to represent a class of sources or to develop emission and activity factors is always limited, the sample data set may not be large enough to provide a statistically robust estimate (NRC, 1991; 2000; 2001; 2004b; GAO, 2001; Placet et al., 2000; Mangus, 1997; Barth et al., 1997; NRC, 2000; Hallmark et al., 2001). Even for CEMS-based emission estimates, CEMS are not available for all pollutants (e.g., less than 1 percent of the CEMS at large point sources measure hydrocarbon emissions or toxic air pollutants). In addition, some CEMS do not record measurements during startup, shutdown, or upset conditions. Moreover, bias errors can be introduced when CEMS are temporarily out of service or if there are missing data (typically a default maximum emission estimate is used to fill in for missing data).

Uncertainties arising from measurement error are often ignored. Because of imperfections in instruments and procedures, measurement errors inevitably appear in emission data. However, current emission inventories rarely report how measurement errors affect emission estimates. Even when some types of errors are acknowledged, such as detection limits, the methods used in practice are often simplistic and subject to bias. This is especially important for pollutants such as HAPs that are emitted at very low concentrations. Uncertainty arising from measurement error is typically not characterized or systematically reported, and yet is a key component of uncertainty especially for these pollutants.

Emission factors typically should not be used to estimate emissions for individual sources because they are based upon averages from multiple sources. The use of emission factors for estimating emissions of a single source could occur when estimating emissions for a permit or when dealing with a geographic area that has only one emission source of a particular type. Because of inter-individual variability among sources, which implies that the emissions of any individual source could be much smaller or larger than the average, the use of an average emission factor applied to a particular source could be subject to a large error.

Most emission inventories generally do not include emissions from startup, shutdown, malfunctions, or accidental releases. For some facilities in some areas (e.g., Houston), these emissions can dominate the emissions from typical or normal operations.

5.2.5 Spatial and Temporal Allocations

The process for developing information on emissions with the degree of spatial and temporal resolution needed for location-specific air quality modeling is problematic, and it is a source of unquantified uncertainty in model results

Emission inventories do not provide emission data at the spatial and temporal scale needed for air quality modeling (NRC, 2000; Sawyer et al., 2000; NARSTO, 2000; 2004). Emission estimates with the required spatial detail and temporal resolution are provided by emission processors that are based on a variety of assumptions. Emissions from smaller point sources, stationary nonpoint sources, and mobile sources are a particular problem. As mentioned previously, emission factors, for example, are typically based upon averages of many representative sources. They are not intended to be used to estimate emissions from individual sources, and doing so can result in significant errors. In addition, the averaging times used to generate emission factors are typically different from the time resolution required by air quality models. This mismatch is a source of additional error and uncertainty. Finally, current mobile source models are not designed to provide the kind of mesoscale and microscale source distribution needed to account for emission hotspots, such as intersections or high-traffic corridors. Similar problems exist for emissions of toxic air pollutants.

Emission factors should not be used to estimate emissions for averaging times that are substantially different from the temporal or activity basis of the measurements upon which the factors are based. For example, using emission factors based upon the average of a few days of operation can be problematic when applied to estimating annual average emissions. Allocation of mobile source emissions both temporally and spatially, such as required for gridded air quality models, involves assumptions for which data may be lacking and thus introduces additional uncertainty (Sawyer et al., 2000; NARSTO, 2000).

5.2.6 Speciation

Insufficient information is available on chemical composition – for both PM and gases – for many sources. Methods used to estimate emissions of individual chemical species in many emission models are out of date and produce estimates that are not reliable.

It is well known that many speciation profiles in the U.S. EPA's SPECIATE program date back to the 1980s. U.S. EPA has identified VOC and PM on- and offroad chemical speciation profiles as being the most out-of-date and the most likely to have changed. This is an especially serious problem in all three countries.

Many emission factors contained in the U.S. EPA's FIRE program are out of date. In addition, no guidance is provided to developers of emission inventories regarding the applicability of an emission factor to specific sources.

5.3 CONCLUSIONS

From the preceding overview of the reliability and shortcomings of current emission inventories and tools, Several important conclusions can be drawn from the preceding overview of the reliability and shortcomings of current emission inventories and tools

First, in using emission inventories to develop air quality management policies and control strategies it is critical to evaluate the robustness and reliability of the conclusions drawn from the emission inventory data. In general, criteria pollutant emission data from large stationary sources are more accurate than emission data from smaller sources or emission data on individual toxic chemical species.

Second, most of the low-hanging fruit has been picked. Whereas there are large quality assured databases of criteria pollutant emissions from stationary and mobile sources, few reliable data are available for fine PM, toxic air pollutants, and NH_3. The data that do exist for these pollutants are generally derived not from direct measurements, but from models that frequently rely on limited out-of-date data, and which are rarely subject to analyses of uncertainty.

Third, although mobile source emission models are useful in evaluating regulatory strategies and state implementation plans, they are not accurate enough to provide the kind of information needed to characterize emissions on the local scale or to provide accurate information on VOCs, fine PM, and toxic air pollutants.

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