Uncertainty Topic 2: Uncertainty in Emission Factors

Introduction

GTI Energy's Center for Methane Research (CMR) provides industry-wide technical and policy support resources focused on the presence, measurement, quantification, and potential impacts of methane in the atmosphere. The CMR is explaining the complex topic of uncertainty in estimating methane emissions through a series of easy-to-follow white papers. For additional background on uncertainty, we refer the reader to the first white paper in this series: An Introduction To Uncertainty

This paper is the second in the Uncertainty Series and introduces the topic of uncertainty associated with emission factors (EFs) that form the basis of inventory methane emission estimates in many government reports. These EF-based emission estimates often appear without acknowledging the uncertainty associated with the use of EFs. Therefore, when new studies of methane emissions emerge that do not agree with EF-based inventory estimates, the inventories are reported as being "wrong." That may not actually be the case when the actual, large uncertainty with the EFs is examined. Here we introduce the topic of uncertainty in EFs, explore why EFs are uncertain, and discuss the implications of not fully considering the uncertainty associated with EFs.

What is an emissions factor (EF)?

An emissions factor (EF) is a numerical value that represents the volume or mass of greenhouse gas emissions released per unit of activity (EPA 2022). EFs are frequently used to compute total greenhouse gas emissions by multiplying them with an activity factor (AF) for a particular emissions source. This factor-based framework is often described as a bottom-up approach. For example, methane emissions from residential natural gas meters can be computed by multiplying the EF (average methane emissions per meter) by the AF (the number of meters).

Emissions factors are created through various methods, including laboratory experiments, field measurements, and modeling. Emissions factors are usually an average of all available measurements or data of acceptable quality (EPA 2022). These averages are intended to represent the long-term average emissions for sources within the category. Continuing the residential meters example from above, an EF could be developed by measuring emissions from a sample of meters and computing the average of those emissions measurements. For instance, a 2021 study estimated an emission factor of 0.64 lbCH_4/meter per year for residential customer meters in California by measuring and quantifying 500 randomly selected meters sets across three utility companies (GTI 2020).

Why are EFs uncertain?

The values of EFs are uncertain because they are developed from a limited number of measurements, and these measurements have measurement errors. The limited number of measurements means that the EF estimates will be subject to *sampling variability*. *Measurement error* means that individual emissions measurements can differ from the actual emissions. Despite these known sources of variability, the EPA does not currently provide uncertainty quantification for EFs which can give the perception that EFs have little or no uncertainty. This lack of uncertainty quantification makes it difficult to compare bottom-up estimates with other estimates.

How does sampling variability affect EF estimates?

We return to the example of estimating an EF for residential meters to demonstrate how sampling variability and measurement error lead to uncertainty. For simplicity, assume that we have a population of 10 residential meters that each have a time-constant emission rate.

Meter Number	1	2	3	4	5	6	7	8	9	10	**Population EF (Popl'n Mean)**
Emission Rate (SCFH)	0	0.10	0	0.05	0.01	0	0	0.04	0.04	0.02	**0.0260**

Table 1: A hypothetical population of 10 residential natural gas meters. The population EF is 0.0260 SCFH.

The *population* is the entire collection of objects of interest, in this case all ten residential meters. The emission rate of each meter in the population is shown in Table 1. The *population EF* is 0.026 SCFH and is calculated by taking the mean of the emission rates from all 10 meters. In practice, we wouldn't know the emission rate of each meter or the population EF.

In practice, we estimate the unknown population EF for these meters using sampling. A *sample* is a randomly selected subset of the population. We can do this by taking a sample of meters, measuring their emission rates, and computing the mean of the sample to produce a *sample EF*. The sample EF is our best estimate of the unknown population EF.

Suppose that we are only able to measure four of these meters due to limited resources. Next, we consider how the limitation of our sampling and measurement errors create uncertainty in our estimation of the population EF.

Because we are only able to sample four of the ten meters, the sample EF used to estimate the population EF will be subject to *sampling variability*. Sampling variability refers to the idea that different random samples from the population will lead to different sample EF values. For example, if our random sample includes meters 2, 5, 6, and 7 (Sample A in Table 2 below), our sample EF is computed by taking the mean of the emission rates for those four meters and is 0.0275 SCFH.

If our sample includes meters 3, 6, 7, and 10 (Sample B in Table 2 below), our sample EF is 0.0050. Notice that Sample A provides a sample EF that is just slightly larger than the population EF, and Sample B provides a sample EF that underestimates the population EF by approximately 80%. In practice, we don't know the population EF, and we obtain a single realization of the sample EF generated by our random selection from the population. As a result, *we would not know how the sample EF compares to the population EF*.

Sample	Meters Selected	Sample EF	Comparison of *sample EF* to *population EF*
A	2, 5, 6, 7	0.0275	0.0015 SCFH larger (6% greater) than population EF
B	3, 6, 7, 10	0.0050	0.0210 SCFH smaller (80% less) than population EF

Table 2: Two random samples of meters with and without random measurement error included. Samples A and B represent two different random samples of four meters that are measured for their emission rate. With perfect measurement, the sample EF is the mean of the emission rate from the selected meters, but when measurement error is present, it induces additional variability in the sample EFs.

How does measurement error affect EF estimates?

Measurement errors will also cause our sample EF to differ from the population EF. A *measurement error* is the difference between the estimated flow rate of an emission source and the actual flow rate. These can occur due to a variety of reasons such as variation in concentration readings from an instrument or human error. Measurement error may also be used to describe errors resulting from models or calculations that convert concentration readings to a flow rate.

For example, we can look more closely at Sample A in Table 2 above and assume that the measurements of emission rate from each sampled meter are subject to random measurement error. Table 3 below, then shows an example of the sample EF calculated from the emission rates that include measurement errors for Sample A. Measurement error induces additional variability in the sample EF values. The magnitude of this variability will be related to the magnitude of the measurement errors.

Meter Number	2	5	6	7	Sample EF
Actual Emission Rate (SCFH)	0.10	0.01	0	0	0.0275
Measured Emission Rate (SCFH)	0.11	0.05	0	0	0.0400

Table 3: An example of emissions measurements collected with measurement errors for Sample A from Table 2 above. Measurement errors will introduce additional variability, and therefore uncertainty, in estimates of EFs.

Implications of the Lack of Uncertainty in EFs

Because EFs are typically not reported with uncertainty, it is difficult to compare EFs with estimates of emissions from new studies. For example, suppose the inventory EF for our population of residential meters is 0.020 SCFH. A new study of residential meters reports an estimated EF of 0.040 SCFH with an uncertainty interval of (0.025, 0.055). The left panel of Figure 1 below demonstrates the comparison. We can be quick to dismiss the inventory EF as “wrong” because it is not in the reported uncertainty interval of the new study. However, if the inventory EF also had an associated uncertainty interval, say (0.08, 0.032), we can begin to assess the degree of agreement or disagreement of the two estimates. The right panel of Figure 1 illustrates this comparison.

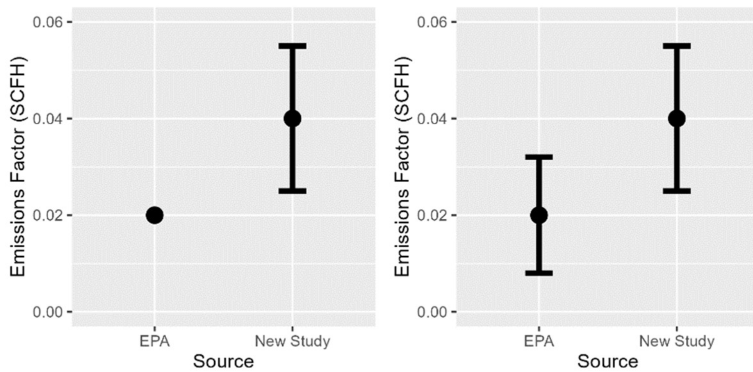

Figure 1: Emissions factors without uncertainty (left) and with uncertainty (right). Uncertainty quantification is necessary to compare the degree to which two EF estimates agree or disagree.

Upon closer examination of the right panel in Figure 1, it becomes clearer that the estimates may not be as far apart as originally thought, before the uncertainty for the EF estimate were shown. These are the types of comparisons that cannot be completed due to the lack of uncertainty bounds with reported EFs. This can therefore result in mislabeling of estimates as categorically "disagreeing" or "agreeing."

Summary

Of course, this simple example doesn't consider every feature that gives rise to variability in EF estimates. Among the factors not considered here are non-constant emissions over time and differences in emissions caused by meter manufacturing, design, age and degradation of meters. This induces additional variation in EF estimates.

To summarize, EF values are uncertain because they are subject to sampling variability and measurement error, but the uncertainty in reported EFs used in bottom-up inventories is not always stated. In practice, we do not know how our estimated EF compares to the real, underlying population EF. Uncertainty quantification is necessary to compare the degree to which two EF estimates agree or disagree.