Biases of Temporally Sparse Data and Measurement Scheduling on Flux Estimates

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INTRODUCTION

Estimates of baseline and event-driven greenhouse-gas (GHG) emissions from soils play an increasingly important role in numerous areas, including improving our understanding of ecosystem processes, climate change mitigation and agricultural yields. These emissions vary substantially in their temporal variability, spatial variability and response to periodic and episodic events, not only between different gas species but also across field sites and seasons for a single gas. Despite considerable research on the techniques and best practices for obtaining accurate gas emission estimates, comparatively few studies have examined the effects and possible biases that result from when and how often these measurements are collected.

The most common method of measuring these soil gas fluxes is through the use of accumulation chambers, which deploy a chamber on the soil surface and estimate the flux by measuring the rate of concentration change inside. This method is particularly useful for gas species with low soil-atmosphere gradients (such as CH\textsubscript{4} or N\textsubscript{2}O) as the elevated chamber concentrations improve measurement quality for lower precision instruments. Often these measurements are achieved through manual sampling, where several gas samples are extracted from the chamber during the measurement period and later analyzed using a gas chromatograph or similar equipment.

Depending on the concentration measuring technique, chamber sampling can be expensive and/or labour and travel intensive, often resulting in measurement schedules that are based on convenience, weather conditions, cost or habit. The important influences of sampling order, density and frequency on emission estimates are often overlooked. The common practice for most manual sampling involves collecting field measurements at the same time each visit, with the time of the measurements being implicitly determined by lab schedule and travel distance. Many of these studies also collect sparse or infrequent measurements, due to the complexity and expense of obtaining and analyzing gas samples. Depending on the measurement schedule, field site and gas species of interest, this low-data approach can suffice for seasonal totals, but may lead to critical episodic events being missed or misinterpreted.

Figure 1. Examples of an automated soil flux chamber (left) and a static soil flux chamber (right).
Researchers have adopted automated chamber techniques in order to collect more frequent emission measurements or to ensure that all significant emission events are observed. These systems deploy chambers and sample gases automatically, often using a linked gas analyzer to measure concentrations in situ. This automation produces a much higher temporal data density, both for the concentration time series used to estimate flux and the number of flux measurements over all. Despite the increased complexity of field deployment and power requirement, these systems offer improved accuracy for total emissions estimates and the means to examine diurnal ecological processes.

In this white paper we will look at three different types of flux data: periodic emissions, periodic emissions with events and event-driven emissions. These represent a spectrum of typical gas emission behaviour: from being primarily cyclical (controlled by temperature or photosynthesis) to primarily episodic (controlled by rainfall or treatment effects). Using examples of both automated and manual sampling, we will examine possible sources of bias in emission estimates stemming from measurement scheduling and sparse temporal data.

PERIODIC EMISSIONS

Many of the primary controlling factors of soil gas flux vary on diurnal or sub-diurnal scales, such as temperature, moisture, photosynthesis and wind. These environmental variables often exhibit periodic behaviour, such as the quasi-sinusoidal temperatures encountered at most field sites, leading to strong diurnal patterns in soil gas emissions. This poses several significant obstacles for measurement scheduling, particularly in studies where these variables are not observed or recorded.

Soil CO$_2$ flux is an example of a gas that is relatively straight-forward to measure as its (biological) flux is primarily driven by temperature (Lloyd and Taylor, 1994; Davidson 1998). Consider the example of two different researchers A and B, who are both using daily manual sampling to measure CO$_2$ fluxes and estimate total emissions. Researcher A collects their samples each day at 9:00 AM while researcher B collects samples at 12:00 PM. An example of this measurement scheme applied to field data is shown in Figure 2 for a three day period in late May 2011, with dashed lines showing interpolated trends.
Based on this data, we can see that each researcher will observe substantially different apparent trends in CO$_2$ flux. For the same field site, now add a third researcher C. Researcher C collects automated measurements at a one-hour interval for the entire three day period, with this data shown in Figure 3 along with air temperature measurements. This additional data reveals the underlying cause for the differences in A and B’s results: the emissions of CO$_2$ were being strongly driven by temperature, resulting in a pronounced diurnal cycle. Parkin and Kaspar (2003) offer a detailed study of this phenomenon, demonstrating that using a scheduled daily measurement for CO$_2$ flux estimates can result in a deviation of up to 30% from the daily mean. The net impact this bias has on estimated fluxes depends on the daily emission range, meaning that the estimation error will change with environmental and seasonal trends.
The dashed-lines of Figures 2 and 3 show what the apparent temporal trends look like using simple linear interpolation. Using these approximations to predict the total emission of CO$_2$ yields estimates of 30.9, 45.4 and 35.1 g CO$_2$ / m$^2$ over the three day period for researchers A, B and C respectively. Using researcher C’s estimate as an accurate measure of total emissions, we can see that researcher A underestimates total emissions by 12.1% while researcher B overestimates total emissions by 29.4%, showing that both temporal trends and cumulative emission estimates can be significantly influenced by time-of-day scheduling and the temporal resolution of measurements. Parkin and Kaspar (2004) applied a similar resampling technique to automated CO$_2$ flux measurements over a three month deployment, concluding that manually sampling as frequently as every two days biases the total emissions estimate by over 10%, while weekly sampling increases the deviation by up to 30%.

While beyond the scope of this discussion, it is worth noting that this problem also affects sequentially measured spatial data (including automated sampling), as the sequence and length of chamber measurements can lead to a similar time-of-day influence. This temporal-spatial convolution can be extremely difficult to detect and correct for, due to the high degree of spatial variability most gas species exhibit. As a result, attempting to correct for this bias would become even more difficult when comparing emissions estimates between different treatment sites or field experiments, as the line between true experimental differences and schedule-induced biases would blur.
PERIODIC EMISSIONS WITH EVENTS

The discussion so far has focused on how measurement scheduling can influence the observation of a periodic and (relatively) predictable flux time-series, driven almost entirely by diurnal temperature variation. We will now look at how these measurement effects can change with the addition of short-term, high output events. Soil emissions of CO$_2$ exhibit a strong response to sudden moisture change, whether through proportional microbial response or through more dramatic processes such as the “Birch effect” (Birch, 1964). This response can create a short-lived peak in emissions, often several times larger than the daily mean. Consider now the same three researchers at the same field site mentioned previously, one day in the future when a significant rain event occurs, as shown in Figure 4. This episodic event results in a dramatic but short-term release of CO$_2$ from the soil that quickly decays back to the previous periodic baseline. The three apparent trends disagree substantially as to what this response looks like, as do the new total emission estimates of 63.4, 67.1 and 52.0 g CO$_2$ / m$^2$ for researchers A, B and C respectively. If we assume once again that researcher C’s estimates accurately reflect the cumulative total, measurement schedule A resulted in an overestimation of 22% while B’s resulted in an overestimation of 29.1%.

The majority of the CO$_2$ response to this rain event took place over a six hour period. We can see that if the daily measurements had been taken only a few hours earlier or later in the day, this event would have been missed entirely. As the frequency of flux measurements decreases from daily to weekly or even coarser, a periodic sampling approach is likely to produce increasingly biased estimates.

Figure 4. Observed flux estimates from researchers A, B and C during a significant rain event on the fourth day of measurements.
EVENT-DRIVEN EMISSIONS

Some gas species such as N$_2$O typically follow low emission seasonal baselines with occasional dramatic pulses due to strong rain or treatment effects (Millar and Robertson, 2014; Butterbach-Bahl et al., 2004). Often the non-event sections of the time-series can be closely approximated by a baseline trend, meaning that the vast majority of emissions variability occurs within short-lived response periods. For sparse sampling, excluding or only partially resolving these events can significantly bias the estimates of cumulative emissions. Figure 5 shows how these discrete pulses can be several orders of magnitude larger than the typical background rate for N$_2$O. In their discussion, Cavigelli et al. (2014) lay out three common approaches for temporal sampling of N$_2$O emissions: Periodic, Episodic and Combination. Each approach strikes a different balance between convenience, cost and ability to capture short-term events, while also striving to minimize the error in total emission estimates.

As shown by several researchers (Cavigelli et al., 2014; Smith and Dobbie, 2001), simply using a regularly scheduled sparse sampling routine will at best provide a reasonable estimate that relies on offsetting errors (“getting the right answer for the wrong reason”). This method may suffice for approximating total emissions but is unlikely to provide sufficient temporal data for treatment or process analysis studies and may be difficult to design for sites where N$_2$O is strongly correlated with varying temperature and moisture (Butterbach-Bahl et al., 2004).

Where automated sampling is not possible, the Combination approach (Flessa et al., 2002) is a particularly useful method of extending the utility of manual sampling. Using this principle, periodic measurements are augmented by dense data collection during and after episodic events such as rainfall or land management treatments. By capturing regular estimates of the baseline trend as well as episodic events, this technique improves the ability of manual sampling to estimate total emissions and can also provide process level insight for event-driven studies.

Figure 5. N$_2$O emissions showing high magnitude pulses during several rain events, as modified from Cavigelli et al., 2014.
CONCLUSION

Many of the potential biases discussed herein are a product of sparse data and low temporal resolution. Depending on the specific area of study and field site, researchers have attempted to address this lack of data through event-focused sampling routines or through the use of automated chamber systems. Automated systems offer several advantages, including more standardized sampling, lower labour requirements and complete and highly-resolved temporal data not readily obtainable through manual sampling methods. However, these instruments have non-trivial power requirements and often lack the flexibility and spatial coverage of sampling methods, and so the specific needs and resources of the study will determine the ideal approach. Given the importance of characterizing a field site to establishing an effective sampling routine, a combination of automated deployment and targeted manual sampling may be an effective alternative, as suggested by Cavigelli et al. (2014).

REFERENCES


