Agricultural and Forest Meteorology 228–229 (2016) 52–59

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

A two-stage sampling strategy improves chamber-based estimates of greenhouse gas fluxes

Yufeng He*, James Gibbons, Mark Rayment

School of Environment, Natural Resources and Geography, Bangor University, Bangor LL57 2UW, UK

ARTICLE INFO

Article history:
Received 16 November 2015
Received in revised form 20 June 2016
Accepted 21 June 2016
Available online 7 July 2016

Keywords:
GHG flux
Sampling
Chamber-based measurement
Spatial variability

ABSTRACT

Fluxes of greenhouse gases (GHG) are typically characterized by high spatial and temporal variability and large sample sizes (e.g. >30) are thus required to obtain a reliable estimate of the population mean and variance when using simple random sampling (SRS). Sample size, however, is often constrained by budget (time, labor) and therefore practical considerations induce significant (but unknown) measurement error and bias from sampling. In this paper we report a two-stage sampling strategy (2SS) by which the same level of sampling accuracy achievable by SRS can be achieved with significantly smaller sample sizes by optimizing sub-sample selection to retain the statistical characteristics of the sample population. Comparisons between 2SS and SRS were conducted using three datasets with low, medium and high coefficients of variance (*CV*). The size of the first (n′) and second (n) stage samples had significant effects on overall sample accuracy. Across all datasets, 2SS reduced *RMSE* of mean and variance by an average of 30%. The absolute reduction in *RMSE* of mean and variance was found to be nearly proportional to the value of *CV*, such that the dataset with the largest *CV* showed the largest benefit from 2SS. Logarithmic relationships were found between the difference in the *RMSE*s and the ratio, n′/n, serving as a guide to allocate sampling resources in practice. Employing 2SS will aid accurate quantification of soil GHG fluxes in all but the most homogeneous situations.

1. Introduction

Chamber-based measurements of the flux of greenhouse gases (GHG) emissions from soils at local scales (less than 1 km^2) are a pillar of Kyoto reporting, especially in agriculture and land use, land-use change and forestry (IPCC, 2000). Emission factors generated from chamber-based measurements of total or mean GHG emissions from land use categories are typically based on relatively few measurements in time and space. Errors or uncertainty in the quantified emissions are directly and linearly propagated into the total national accounts. What confidence do we have in the accuracy of our estimates? Very little, especially for CH_4 and N_2O where uncertainty spans orders of magnitude (Maljanen et al., 2010; Rayment and Jarvis 2000; Rochette and Eriksen-Hamel 2008; Venterea et al., 2009).

Comparisons of chamber measurements, scaled to the field scale, with eddy covariance (EC) measurements directly measuring at the field scale (i.e. two methods purporting to measure the same thing) often reveal large and unsystematic differences (Davidson et al., 2002; Goulden et al., 1996; Jones et al., 2011; Reth et al., 2005). However estimates of, for example, annual net fluxes are typically presented with uncertainty bounds so large as to suggest that the estimates are, in fact, in agreement. Without suggesting that either chamber-based measurements or EC-based estimates are inherently better than the other, it is arguable that the EC community have confronted measurement uncertainty squarely and openly (Baldocchi 2003; Hollinger and Richardson 2005; Oren et al., 2006), and have produced methodologies for assessing and reporting uncertainties, directed towards the ultimate aim of reducing them (Baldocchi et al., 2000; Gu et al., 2012; Foken et al., 2004). On the other hand, the chamber-based measurement community, though revealing error sources from decades of experience has been slower to explore measurement uncertainty caused by sampling (Davidson et al., 2002).

Amongst the literature there are many attempts to grapple with the surrounding chamber design and operation (Rochette and Eriksen-Hamel, 2008; Fang et al., 1998; Pumpanen et al., 2004; Rayment and Jarvis 1997), and methodological inter-comparison studies have attempted to harmonize the outputs from disparate methods for collecting and analyzing gas emissions from the soil surface (Butnor et al., 2005; Pumpanen et al., 2003). Similarly, effort has been made at the theoretical level to describe the relationship

* Corresponding author.
E-mail address: afp23e@bangor.ac.uk (Y. He).

http://dx.doi.org/10.1016/j.agrformet.2016.06.015
0168-1923/

between fluxes and environmental variables such as soil temperature, moisture and management, allow the interpolation and/or stratification of fluxes, and reducing the sample size needed for measurements accordingly (Rochette et al., 1991; Xu and Qi, 2001; Lin et al., 2011). Whilst these difficulties are not yet fully resolved, a complimentary approach is to develop a more efficient sampling strategy.

In soil science generally there is a significant amount of statistical guidance on the design of field experiments and surveys (Cochran 2007; John 1998) and this has served us well in our analysis of the effects of manipulative interventions and soil inventories. In trying to quantify soil GHG emissions, however, we face the simple practical constraint of sample size. The limited number of chambers (or collars) that can be deployed, the amount of time required for a single measurement (especially for CH_4 or N_2O fluxes), the limited number of gas samples that can be collected and analyzed (in off-line closed systems) or the limited number of chambers that can be multiplexed together (in open systems) all act to limit the number of locations that can realistically be sampled within any given project situation.

In some soil systems, particularly agricultural ones, intensive management has the effect of reducing spatial heterogeneity to manageable levels, thereby reducing the number of measurements required to capture population variance accurately. This is not generally true and spatial heterogeneity combined with limited sample size presents considerable opportunity for bias to enter into our measurements such that even when attempts are made to stratify sampling according to known sources of variance, uncertainty estimates remain large (Raupach et al., 2005).

A large number of samples are required to maintain the accuracy of measurements because of the high spatial variability of the GHG fluxes (Ambus and Christensen 1994; Dai et al., 2012; Rayment and Jarvis 2000; Rodeghiero and Cescatti 2008). For a finite population, the number of samples needed for a given error in the population mean can be derived by:

$$n = \frac{n_0 N}{n_0 + N - 1}, n_0 = \frac{z^2 CV^2}{E^2} \quad (1)$$

where N is the population size, z = 1.96 (for 95% confidence), E (%) is half-length of the confidence interval as a fraction of the population mean and *CV* is the coefficient of variation of the population. In practice, a pilot study or an investigation of historical data is necessary to estimate the *CV* (or at least establish an upper limit).

Constrained by several limitations such as labor effort, time and budget, the sample size required by simple randomized design is usually too large to apply in practice. Stratified sampling by vegetation or soil types (Fiener et al., 2012; Panosso et al., 2009; Schelde et al., 2012; Kreba et al., 2013), or topography (Imer et al., 2013; Fang et al., 1998) is widely used to reduce overall variance by applying simple random sampling to each strata. These stratifying methods may become invalid when the spatial variability of the GHG fluxes is controlled (even partially) by an unknown driver, or dominated by factors such as soil temperature and moisture that vary at the finest scale, even within strata (Rochette et al., 1991; Stoyan et al., 2000; Allaire et al., 2012). For these reasons, chambers have limited ability to measure accurately fluxes at such small scales and applying simple random sampling to each stratum may introduce large errors and biases in the estimate of population mean and variance.

With the aim of reducing measurement errors and biases associated with limited resources, here we present a staged approach to sampling that retains the essential characteristics of the population distribution within a small sample size. Related, but less effective approaches have been investigated previously (Folorunso and Rolston 1984; Rodeghiero and Cescatti 2008). Our method (see details below) expands the approach used in (Rodeghiero and Cescatti 2008), where a heterogeneous field was divided into subregions by a pre-sampling stage, which reduced the total variance of the whole region. There is an extent to which our method can be viewed as a mathematical stratification, leading to a completely general sampling method. Drawing on published datasets of soil GHG emissions across a range of spatial variability, we show that this sampling strategy reduces uncertainty in all cases compared with the simple random sampling, and particularly where sources of variance are large.

2. Methods and data

Two sampling strategies were modeled using simulation: (1) simple random sampling (SRS); (2) a resampling or two-stage sampling (2SS). Staged sampling consisted of an initial survey where a relatively large number of samples were made. Two descriptive statistics (mean & variance) were calculated for this set of samples; the mean is of primary concern when quantifying total GHG flux and variance is the critical factor revealing spatial variability. A Monte Carlo method and a cost function were then used to select a sub-sample from the 1st-stage sample such that the descriptive statistics of the sub-sample were closest to those of the 1st-stage sample. Three datasets with low, medium and high variability or coefficient of variance (*CV*) were explored. Three analyses were made to compare 2SS with SRS and investigate the effects of sample size on the improvements: (1) the error distributions of the final-stage sample mean and variance; (2) the effects of the final sample size on the root-mean-square errors (*RMSE*s) of the sample mean and variance; (3) the relation between the *RMSE*s and the initial and final sample size.

2.1. Assumptions and sampling strategies

For calculation purposes, we assume that the GHG emissions for a given area are discretized to a finite population size of *N*. For simple random sampling (SRS), *n* final samples are directly drawn randomly from *N*. The two-stage sampling (2SS) developed here invokes an extra initial sample set of size *n′* between the population and the final samples (Fig. 1). The systematic/artificial errors between two independent measurements are assumed small enough to be negligble compared to the errors caused by the sampling methods as shown by (Mathieu et al., 2006).

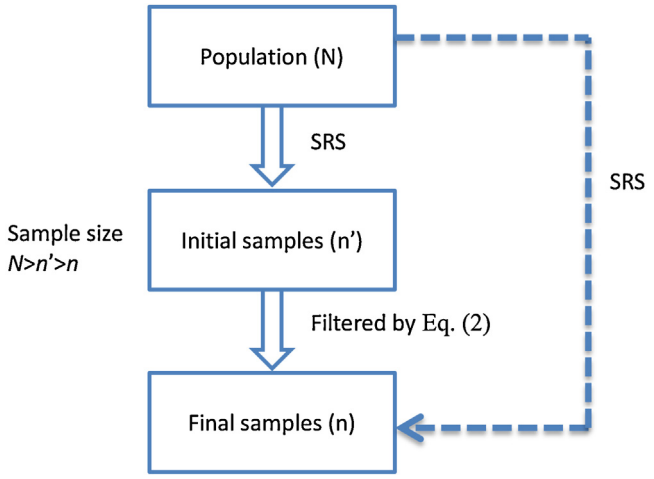

Fig. 1. Workflow of the two-stage sampling (2SS), compared with the simple random sampling (SRS).

Note that $n' > n$; the filtering process from the initial sample to the final sample is performed by minimizing the cost or objective