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Spatial variability of methane emissions from rice fields and implications for experimental design

M. A. K. Khalil¹ and Christopher L. Butenhoff¹

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[1] It is observed that side by side plots in rice fields, managed by the same practices, produce methane emissions that are often different by factors of 2 to 4. Similarly on a given day when many plots are sampled, the emissions from one plot may differ from another by factors of 3–4 on average. These large variations must be taken into account if these data are extrapolated to larger scales such as countries or the world. In this paper we analyze and delineate the nature of this variability. We distinguish temporal and spatial variability and examine the effects of both on the observed seasonal average emission rates. While temporal variability is managed well in most experiments because frequent measurements are taken, the spatial variability remains a potential major uncertainty in many experiments. Using the characteristics of the observed variability we use simulations to show that with a proper and realistic sampling strategy, it is possible to get to within 15%–20% of the true flux for most cases of interest. We calculate how many plots are needed and how often they should be sampled during the growing season to obtain a seasonal average flux within prescribed limits relative to the true flux.

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1. Introduction

[2] As global warming occurs, there is an increasing interest in understanding the sources and sinks of greenhouse gases such as methane and nitrous oxide. Emissions from various terrestrial ecosystems such as rice fields and wetlands are measured over small areas of a few square meters at a time, often using accumulation chambers. The results show significant spatial and temporal variability of emissions which must be taken into account if the data are to represent the region where samples were taken and are extrapolated to regional and global scales. Here we will quantify the variability of methane emissions from rice fields and develop methods for designing field experiments to control the uncertainties within prescribed limits. Our results can be applied to existing data from field or greenhouse studies. The issue of large observed space and time variability of trace gas emissions from soils, plants or water surfaces transcends the specific case of methane emissions from rice fields. The general principles we have described here apply equally well to other sources and gases, but for each gas and source there are nuances that need to be taken into account (see, for example, *Parkin et al.* [1987] and *Parkin* [1990] for analysis of nitrous oxide emissions from soils).

[3] The data for our study come from measurements of methane emissions taken from rice fields in China at several

disparate locations; namely Tuzu and Jinsha in Sichuan Province and Guangzhou and Qingyuan in Guangdong Province. The latter sites are in subtropical China where the climatic conditions support two or three crops of rice per year. In all of these experiments a number of side by side plots, up to 24 at a time, was sampled throughout the growing season. The number of fields and plots is shown in Table 1. The details of the measurements and the characteristics of the sites have been discussed in our other papers and the data are available to the readers for further research [*Khalil et al.*, 1998a, 1998b; 2008a, 2008b]. The measurements show complex changes of emissions during the growing season that contain valuable information about the processes that are responsible for methane emissions. However, for practical applications such as estimates of regional and global emissions, the seasonally averaged emission rate is the single most useful result of the field experiments. Even this averaged measure of the emissions can be highly variable and therefore affects the accuracy of any extrapolations made from field experiments. *Sass et al.* [2002a, 2002b] have reported empirical studies from Texas rice fields that have shown similar variability and potentially large uncertainties for extrapolating field measurements. We will focus our work here on the variability of the seasonally averaged emissions from a much larger and diverse data set.

[4] The nature of the variability is most simply demonstrated in Figure 1 which shows the seasonally averaged emission rate or flux ($\text{mg}/\text{m}^2/\text{h}$) from side by side plots for the sites mentioned above. There are a total of 18 cases or collections of data among these studies representing known similar conditions for the fields to be described in more detail later (7 from Tuzu, one for each year, 4 from Jinsha, 4 from

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Table 1. Database Characteristics: Spatial Sampling and Sampling Frequency

Site	Year	Fields	Plots	Sampling Frequency		Valid Flux Samples
				Days Sampled	Days in Season	
Tuzu	1988	4	24	69	120	1131
	1989	4	24	67	126	1009
	1990	4	24	42	113	653
	1991	3	6	48	115	153
	1992	5	13	54	107	351
	1993	4	14	59	115	500
Jinsha	1994	4	20	51	104	696
	1996	5	15	56	96	814
	1997	6	18	49	96	825
	1998	5	15	66	111	978
	1999	3	9	60	120	524
Guangzhou	1996-1	44	12	27	83	321
	1996-2	4	12	30	80	354
Qingyuan	2003-1	3	9	31	98	125
	2003-2	3	9	24	75	197
	2004-1	1	3	36	81	102
	2004-2	1	3	42	97	120
Totals	17	63	230	47.7	102.2	8853

Qingyuan and 3 from Guangzhou). For these cases the average ratio of the maximum seasonally averaged flux from a plot to the minimum flux ($F_{\max}/F_{\min}$) is 3.1. For 15 of the 18 cases (83%) the ratio is ≥ 2 and for 5 of the 18 cases (28%) it is ≥ 4 . This sizable difference of factors of 2–4 in the annual average emissions among plots at the same location, in the same season and under seemingly similar environmental and agricultural conditions, can lead to large uncertainties in regional extrapolations and discrepancies among the measurements reported by different groups.

[5] Another view of this variability is shown in Figure 2. We have plotted the range of emissions measured on each day of sampling from the various plots as a function of the mean flux on that day. The number of plots is shown in Table 1 and the range is defined as $R(k) = [F_{\max}(k) - F_{\min}(k)]$ for a given day “k”, which we will express as days after rice is transplanted into the field ($k = 1, \dots, N$ = number of days sampled during the growing season, which when summed over all 18 collections, comes to 748 points in our data set). We see that the variability as measured by the range is proportional to the mean flux on the day of measurement. Additionally, the various sites with disparate environmental conditions and from different years have a consistent, and perhaps universal relationship between the variability and the flux. We will express this relationship in the form of power laws:

$$V = aF^b \quad (1)$$

where V is a measure of the variability such as the range or standard deviation and F is the mean flux, appropriately defined, and “a” and “b” are empirical constants. For the daily range shown in Figure 2, when the composite data from all sites are analyzed, $a = 2.8$ (range among sites 1.6–4.4) and $b = 0.9$ (range 0.7–0.9) with a correlation coefficient $r = 0.91$. It is noteworthy that the range of

observed fluxes on any day is more or less directly proportional to the average flux that day. We will analyze this phenomenon in more detail later in this study.

[6] One of the main goals of the field measurement is to obtain an accurate and precise estimate of the seasonally averaged flux representative of the location where the experiment was conducted. The results in the figures contain two forms of variability that impedes the reliability of this estimate, which may be called “Spatial” and “Temporal”. The temporal variability can be regarded as random fluctuations superimposed on a base function $\bar{F}(k)$ that describes the temporal shape of the methane flux as a function of time over the growing season for a single plot. This function is generally zero at the beginning and end of the growing season and has one or more maxima in between. The function $\bar{F}(k)$ and the random fluctuations around it affect the seasonally averaged flux through the sampling frequency and may be considered to represent the “precision” of the estimate for the plot. The “spatial” variability is more complex and comes about because side by side plots have systematically higher or lower emissions during parts or all of the growing season. It turns out that in our work most of the time the sampling frequency was high enough (see Table 1) that it has a small effect on the seasonally averaged emissions. Consequently most of the variability seen in Figure 1 is due to the spatial variability. The mechanisms that cause these forms of variability are fundamentally different. The spatial variability reflects the inhomogeneous nature of the major variables that affect emissions, such as uneven spreading of the fertilizers or even localized differences in water levels at some spots roughly the size of the chambers. When chamber methods are used, this type of variability can only be addressed by sampling many plots in the same region with similar

Figure 1. Seasonally averaged emissions of methane from rice fields at four locations. The points show results for each plot where samples were taken. These data are from actual rice fields managed by local farmers according to prevailing agricultural practices of the time and place. In most cases the fields sampled are managed in the same way. As is evident, the individual side by side plots have substantially different seasonally averaged emissions.

Figure 2. The daily range of flux measurements, taken at different plots, is shown as a function of the average flux for that day. The range of emissions increases proportional to the average flux at all the sites studied and has a generally consistent pattern from one experiment to the other. The relationship can be described as a power law with $\text{Range} = 2.8 \times (\text{Flux})^{0.9}$.

environmental conditions. It can therefore be considered to represent the “accuracy” of the measurement when applied to extrapolating the measured flux to the larger surrounding region.

[7] In the next section we will evaluate the two types of variability based on the field studies mentioned above. Power laws are used to obtain quantitative universal relationships that we believe would apply to all field experiments. In section 3 we will use these relationships and apply Monte Carlo simulation techniques to provide guidance on how frequently samples must be taken and how many plots should be sampled to obtain estimates of the fluxes from the region under study within prescribed limits of uncertainty.

2. Spatial and Temporal Components of Variability

2.1. Model

[8] The statistical model for the observed flux during the growing season can be written as:

$$F_{jk}(t) = \langle \bar{F}_k(t) \rangle + \beta_{jk}(t) + \Delta_{jk}(t) \quad (2)$$

Here $F_{jk}(t)$ is the measured flux for plot $j = (1, \dots, N)$ at time $t = \text{days after transplanting}$, and for the collection $k = 1, \dots, M$. We will define a collection as all plots sampled in the same year and at the same location where there are no known differences among the plots, in the treatments, or other factors that effect emissions. The plots in the

collection may span across several fields that have been managed in the same way. We also assume that the collection only includes the plots that were sampled at the same time, therefore experiments on multiple crops, even in the same year are treated as separate collections. This is appropriate because the two crops in the same year are known to have differences in the treatments that affect emissions. In our data sets there are altogether 18 such collections as enumerated earlier. The function $\beta_{jk}(t)$ describes the spatial variability of emissions from the plot j and collection k , and $\Delta_{jk}(t)$ is the temporal variation that occurs on short time scales of a few days. It may be thought of as high frequency noise and includes the effects of sampling variability as well as natural variability of emissions such as an occasional case of bubbling caught during the sampling period. $\langle \bar{F}_k(t) \rangle$ is the smooth flux averaged over all the plots sampled for each day of the growing season and represents the effect of the various processes that evolve during the growing season, such as plant growth, decomposition of organic matter and mid season drainage. It can be considered as the low frequency component of the time series of emissions during the growing season for a plot being sampled.

[9] Three types of averages are used in determining the components of equation (2). The first is the time average over the growing season of length T as in equation (3) (hat); the second is the spatial average as shown in equation (4) (brackets); and the third is $\bar{F}_j(t)$ (overbar) which represents the underlying function describing the flux without the short-term fluctuations (equation (5)).

$$\hat{F} \equiv \frac{1}{T} \int_0^T F(t) dt \quad (3)$$

$$\langle \bar{F}_k(t) \rangle \equiv \frac{1}{N} \sum_{j=1}^N \bar{F}_{jk}(t) \quad (4)$$

and

$$\bar{F}_{jk}(t) = \langle \bar{F}_k(t) \rangle + \beta_{jk}(t) \quad (5)$$

2.2. Temporal Variability

[10] In practice we obtain $\Delta_{jk}(t)$ by taking a short-term running average of the measured fluxes $F_{jk}(t)$ over times of a week or so. We then obtain:

$$\Delta_{jk}(t) = F_{jk}(t) - \bar{F}_{jk}(t)$$

$$\bar{F}_{jk}(t; \delta) = \frac{1}{\delta} \sum_{l=-\delta/2}^{1+\delta/2} F_{jk}(l)$$

$$\Delta(t) = \{ \Delta_{jk}(t) | j = 1, \dots, n_j; k = 1, \dots, M \} \quad (6)$$

[11] The $\Delta(t)$ are the pooled values across all collections and vary with the mean flux at time t . Each of these is the difference between the measured flux at a plot at time “ t ” from the average flux $\bar{F}$ at the same plot, where the average is taken over several days surrounding “ t ” as in equation (6).

Figure 3. The statistical distributions of the deviations of measured flux from the average for the each sampling day and plot are shown for different mean fluxes. The results, complementary to Figure 2, show that as the mean flux increases, the measured fluxes spread out. The results show the nature of the statistical distribution which is approximately of the Laplace form.

Therefore each $\Delta(t)$ has an associated average flux $\bar{F}$ from which it is calculated as a deviation. The $\Delta(t)$ are described approximately by the Laplace probability distribution function, with a mean of about 0 and a standard deviation $\sigma_{\Delta} = \sqrt{2} b$ which is related to the mean flux as described by equation (1).

$$b(F) = \frac{1}{N} \sum_{i=1}^N |\Delta(t; F) - \bar{\Delta}(t; F)| \quad (7)$$

The terms of equation (7) are generated as follows: We sorted the $\Delta(t)$ according to the associated fluxes $\bar{F}$. We then took $N = 1000$ point groups according to the sorted fluxes, each group representing elements with like fluxes, and calculated the $b(F)$ for the mean flux (F) in each of these groups. The $\bar{\Delta} \approx 0$ in equation (7), but actual values are included in the calculations. The frequency distributions for each of these groups of 1000 points are shown in Figure 3 (11,324 total points). It is apparent that the variability increases with flux and the $b(F)$, which is the quantitative measure of the variability, is seen to follow the power law of equation (1).

$$b(\bar{F}) = a_{\Delta} (\bar{F})^{b_{\Delta}} \quad (8)$$

[12] The values of the coefficients a_{Δ} and b_{Δ} are determined from the pooled measurements taken at the four sites and are: $a_{\Delta} = 0.53$ and $b_{\Delta} = 0.77$ with a correlation of 0.99. Figure 4 shows the values of $b(\bar{F})$ as a function of $\bar{F}$ from which the parameters a_{Δ} and b_{Δ} are calculated.

[13] Another source of temporal variability is the underlying function $\bar{F}(t)$ which represents the slow changes in the flux during the growing season and does not contribute to the variability as shown in Figure 2, or in the daily variability represented by the Δ values. We also note that this also does not affect the spatial variability as we have addressed it here. Nonetheless, the more complicated this function is the more samples are needed during the growing season to overcome its effect on the seasonal average. For our data, we conclude that three canonical forms are sufficient to describe most of the cases of this underlying function as shown in Figure 5. We will discuss the effect of this variability in section 3 along with the other forms of variability as expressed in equation (2).

2.3. Spatial Variability

[14] The spatial variability is contained in the $\beta_j(t)$ which is calculated from equation (5). To describe its structure we define the seasonal average $\hat{F}_j$ as in equation (3). This is the average value of the flux from plot j during the growing season, which in practice is calculated by the discreet form of the integral. It is apparent from equation (5) that:

$$\hat{\beta}_j = \hat{F}_j - \langle \hat{F} \rangle \quad (9)$$

The $\hat{\beta}_j$, ($j = 1, \dots, N$) are numbers, one for each plot j , ($\hat{F}_j$) that are the deviations of the seasonally averaged flux from plot j from the average flux for the season from all the plots sampled ($\langle \hat{F} \rangle$). These $\hat{\beta}_j$ are straightforward to calculate and are used to generate the $\beta_j(t)$ needed to describe the observed flux as in equation (2). The statistical structure of

Figure 4. The measure of the spread of values (b), for the Laplace distribution, which is proportional to the standard deviation, is shown as a function of the average flux. It is a quantitative measure of the temporal variability discussed in the text. The relationship is closely represented by a power law with $\text{Variability} = 0.53 \times (\text{Flux})^{0.77}$.

Figure 5. The three main underlying functions describing methane emissions during the growing season in our experiments. These calculations represent spatially averaged running averages of measured emissions where the where the smoothing window is about 7 days.

the $\hat{\beta}_j$ is $N(0, \sigma_{\hat{\beta}})$, that is, a normal distribution with mean 0 and standard deviation $\sigma_{\hat{\beta}}$. The observational data from the four sites provides an empirical relationship between this standard deviation and the mean flux similar to equation (1) and written as:

$$\sigma_{\hat{\beta}} = a_{\hat{\beta}} \langle \hat{F} \rangle^{b_{\hat{\beta}}} \quad (10)$$

The data cast in the form of $\hat{\beta}_j$ and $\langle \hat{F} \rangle$ are shown in Figure 6 and is used to estimate the values of $a_{\hat{\beta}}$ and $b_{\hat{\beta}}$ which are 1 and 0.55 respectively with a correlation coefficient of 0.82.

[15] To complete the description of the variability as expressed in equation (2) we need $\beta_j(t)$. There are several ways to generate the $\beta_j(t)$ from the knowledge of the $\hat{\beta}_j$. We choose the following method. We note, based on the observed fluxes, that the relationship between the flux at

plot j and the spatial distribution shown in equation (2) can also be written as:

$$\bar{F}_j(t) = \alpha_j \langle \bar{F}(t) \rangle \approx \langle \bar{F}(t) \rangle + \beta_j(t) \quad (11)$$

unlike the β_j , the α_j are simple numbers and not functions of time. By taking the seasonal average of both sides of equation (11) we get:

$$\alpha_j = \frac{\hat{\beta}_j}{\langle \bar{F} \rangle} + 1 \quad (12)$$

We see that we can generate the fluxes from the more easily calculated rather than the time dependent $\beta_j(t)$. The α_j have a distribution with a mean of 1 and a standard deviation σ_{α} and can also be used directly to describe the observed fluxes with the modification to the model in equation (2) by replacing the spatial variability described by β_j with the form shown in the first part of equation (11).

[16] We have now delineated the nature of the observed variability of methane emissions from rice fields. It consists of two forms: temporal and spatial. Both can be related to the mean measured flux, where the averaging is defined differently for the two cases. For temporal variability the mean flux is the value of the measured time series filtered over a period of about a week at the center of the filter window. For the spatial variability, the mean flux is the average of the filtered flux taken over all the plots and

Figure 6. Spatial variability as a function of the average flux. Spatial variability represents the differences of emissions from side by side plots after the temporal variability has been removed. As with the other cases of variability discussed in this study, spatial variability can also be represented by a power law as Standard Deviation = (Flux)^{0.55}.

Figure 7. Using our methods to generate seasonally averaged fluxes from the power law characteristics of the observed variability, we calculated the expected fluxes for the various cases in our data set. The figure shows the relationship between measured and simulated fluxes.

further averaged over the growing season. The variability is calculated as standard deviations in time or space related to these measured average fluxes. We can now generate the variability for any situation where we know the sampling frequency and the mean flux over the growing season or we can determine how many plots are needed and what sampling frequency is needed to attain a measure of the seasonally averaged flux from the rice field of our choice within specified limits of accuracy.

3. Applications to Design of Field Experiments

[17] We start with the three canonical functions for the underlying function that describes the shape of the methane flux function during the rice-growing season. We add the random variations in flux from day-to-day (temporal variability) and across fields from plot-to-plot (spatial variability). These forms of variability add “noise” to our measurements and reduce the accuracy of our estimate of the seasonally-averaged field flux $\langle \bar{F} \rangle$ which for simplicity of notation we will call the flux, F , from here on. To quantify the impact of the variability on the flux we designed a series of computational experiments that simulate the measurement of methane fluxes during the growing season. The experiments simulate fields where the flux follows the canonical functions with seasonal averages ranging from 10 to 70 mg CH₄ m⁻² h⁻¹. We can sample these simulated fields using any number of plots we choose at any sampling rate we desire. For this work we set the maximum number of plots per field at forty and allow the sampling rate to be as high as daily.

[18] Our experiment then simulates twenty-one different field conditions corresponding to the three flux functions at seven different field averages $F_{\text{true}} = 10, 20, 30, 40, 50, 60$, and 70 mg CH₄ m⁻² h⁻¹. To each of these field conditions we add the spatial and temporal variability as specified by the power law relations derived from the field measurements. We “measure” flux from these simulated fields using different sampling strategies. We define a sampling strategy by the number of plots we sample per field (P , range is 1 to 40) and the sampling rate (D , 1 to 100% of the total number of days in the growing season, evenly distributed in time). The number of samples that are measured per season ($P \cdot D$) then ranges from one (one plot sampled once per season) to 4000 (40 plots sampled every day) for a 100-day growing season. We thus perform a total of 84,000 different experiments using all permutations of field conditions (21) and sampling strategies (4000).

[19] Owing to the random nature of the prescribed spatial and temporal variability, each experiment was performed 500 times to gather the required statistics to assess the mean and standard deviation of the underlying distribution which is nearly normal. The number of simulations is a compromise between computational efficiency and the robustness of the statistical parameters. In Figure 7 we show the relationship between the simulated and measured fluxes as plotted in Figure 1. The relationship is $\text{Simulated} = -0.7 (\pm 5.8) + 1.025 (\pm 0.3) \times \text{Measured}$, with a correlation coefficient of 0.92.

[20] In Figure 8 we show the simulated spatial variability (scale factors of the average field flux) in 50 m $\times$ 50 m fields on spatial scales of 1 m $\times$ 1 m. The latter dimensions are typical of the field area sampled by standard flux chambers. Though these graphs are for visualization only, we chose field and chamber dimensions to be representative of typical conditions. Simulated fields with average seasonal fluxes of 10, 30, 50, and 70 mg CH₄ m⁻² h⁻¹ are shown.

[21] These plots reflect the relationship observed in the real field measurements described above, namely fields with lower emissions have higher relative spatial variability. Owing to their higher spatial variability, low emission fields require more intensive sampling to reduce uncertainties in the seasonally averaged flux, though it is important to remember that the absolute uncertainties are still lower than in the high emission fields. It is the spatial not the temporal variability that primarily determines the relationship between sampling strategy and the true field flux.

[22] Results from our experiments are shown in Figures 9–12. Each figure is a response to a question posed while evaluating or designing an effective sampling strategy to measure methane flux in the field. The figures quantify the relationship between the number of measured flux samples and the accuracy of the estimated field flux. They are meant to help the researcher achieve the accuracy required in their research plan with the minimal number of samples, or alternatively to evaluate measurements already completed.

[23] We address the following questions: (1) Using a sampling strategy that has P plots and D sampling days, how close will the measured flux be to the true field flux (Figure 9)? (2) Given a standard sampling schedule (e.g., weekly, biweekly, and once every two weeks) what is the minimum number of plots required for the flux to be within a specified percentage of the true field flux (Figure 10)?

Figure 8. Simulated variability of the seasonally averaged field flux over a spatial scale of 1 m². This resolution corresponds roughly to the size of a standard flux chamber. The panels represent four fields with average source strengths of (a) 10, (b) 30, (c) 50, and (d) 70 mg CH₄ m⁻² h⁻¹. The data are the ratios between the flux of the grid cell and the average flux of the entire field. A cell with a value of 1.2 in Figure 8a, for example, has a flux of 12 mg CH₄ m⁻² h⁻¹. The simulated data reproduce the pattern of declining relative variability with flux strength observed in actual field measurements.

Figure 9. The percent offset between the simulated seasonally averaged field flux and the true flux for a range of experimental designs (P, D) and average field fluxes (F_{true}). Areas of white indicate offsets greater than 100%. This figure is used to determine how close we expect measured field fluxes to be to the true field fluxes for different sampling strategies. $F_{\text{true}} =$ (a) 10, (b) 30, (c) 50, and (d) 70 $\text{mg CH}_4 \text{ m}^{-2} \text{ h}^{-1}$. For example, if we measure fluxes from 15 plots at a sampling rate of 15% for a field of low source strength (Figure 9a) we expect the measured flux to be within 30% of the true flux. We expect the relative accuracy of the measured field flux to improve with source strength. The data shown here are for the type II flux function but are similar to the other functions.

Figure 10. The minimum number of plots required to ensure the measured field flux is within 10 (diamonds), 20 (squares), 30 (solid triangles), 40 (pluses), and 50% (open triangles) of the true flux for three typical sampling rates: (a) 5%; (b) 15 %; (c) 30%. The rates were chosen to represent biweekly, weekly, and semiweekly sampling for a 120-day field season. A dotted line indicates that the minimum number of plots required exceeds our simulated maximum of 40. Data are for the type 2 flux function (Figure 5) but are similar to others. In Figure 10a, neither the 10% nor the 20% threshold is achievable with 40 plots or less.

(3) What is the minimum number of samples ($P \cdot D$) required for the measured flux to be within a specified percentage of the true flux (Figure 11)? (4) Are there diminishing returns if we increase the intensity of the sampling strategy (Figure 12)? (5) What is the probability that the measured flux will be within 10% of the true field flux if the most practically intensive sampling strategy is adopted?

[24] For concision, we only show results for a single canonical function or averages over all three functions. There are only small differences in the results using different underlying functions, so the data displayed here are representative of all three functions. This also gives us confidence that our conclusions are valid for other functions not considered in this work.

[25] We also remind the reader that our results are probability-based. For each experiment involving field condition and sampling strategy, we determine the normal distribution of the simulated flux. The flux for any one run, that is, a single growing season of field measurements, will vary over a range of values defined by the distribution. We do not know how close the flux from any one run will be to the true flux, but can only state the probability that it will be within some percentage of the true flux. For the remainder of the paper we adopt the criterion of 90% probability. Thus question 1 is more accurately stated as: given P plots and D sampling days, there is a 90% chance that the measured flux will be within a specified percentage of the true flux. To aid readability we omit this reference to the 90% criterion in the remainder of the paper.

[26] For question 1, Figure 9 shows results from all 4000 simulation experiments for four field conditions. The flux function for all four plots is type II and the season averages are 10, 30, 50, and 70 mg CH₄ m⁻² h⁻¹. For each experiment, we sample fluxes from the simulated field over the entire growing season using the specified sampling strategy. After the run, we calculate the average flux over the season and compare it to the true flux. We repeat the experiment 500 times to build the distribution of fluxes. From the distribution we can then calculate how close the flux is to the true flux. We call this the offset percentage. The figure illustrates how the accuracy of the measured flux is expected to change with sampling strategy. For the low emission conditions (10 mg CH₄ m⁻² h⁻¹), if we want our measurements to lie within 30% of the true flux, we need to sample 15 plots at a rate of 15% of the growing season. As we would expect, the accuracy improves as we increase the number of plots and sampling rate. We see also that relative accuracy improves as field emissions increase. This is due to the nature of the spatial variability as discussed previously.

[27] Question 2 is addressed in Figure 10 where we give the minimum number of plots required to ensure that the measured flux is within 10, 20, 30, 40, and 50% of the true flux for three typical sampling rates (5, 15, 30%). These

Figure 11. Minimum number of samples required to attain the specified accuracy limits. The sample size is the number of plots times the sampling rate assuming a 100-day field season. For other season lengths, multiply by the ratio (new season length: 100). These results are averages across all flux functions.

Figure 12. The figures quantify the impact of increasing the experimental design by one unit (i.e., by one plot or by one sampling rate percentage point) on the accuracy of the measured field flux. In effect, the figures help us determine the point of diminishing returns when increases in the accuracy of our field flux estimate become negligible. dC/dN is the rate at which the percent offset from the true flux changes with an increase of one rate percentage point (i.e., one sampling day for a 100-day field season). dC/dP is similar but with an increase of one plot. In Figure 12a we show how dC/dN changes with the sampling rate, and in Figure 12b we show how dC/dP changes with the number of plots. For example, if we increase the number of plots from three to four, we expect the accuracy (expressed as percent offset from the true flux) to increase by 4%.

rates roughly correspond to sampling intervals of biweekly, weekly, and semiweekly, respectively, for a 120-day growing season. The dotted line indicates levels that are not achievable within our 90% probability criterion.

[28] These experiments show the difficulty in reaching the highest accuracy levels at these modest sampling rates. In fact, the highest accuracy expected using a small number of plots ($P \leq 3$) is typically 30–40%. Only for those fields with large methane emissions do we expect the measured flux to be within 20% of the true flux if three or fewer plots are used.

[29] To answer question 3, we considered the total number of measurements required over the course of the growing season to meet our accuracy standards (Figure 11). The numbers given in the figure are based on a 100-day field season but are easily modified to accommodate any season length.

[30] The number of samples required range from 1400 per season to ensure the measured flux is within 10% of the true flux for the lowest emission fields to only five samples to meet the 50% mark in the highest emission fields. In general we never need more than about 20 samples per season to reach the 50% mark for any field flux. However if we wish to reach the 10% standard, we have to sample more than 200 times.

[31] Question 4: From our results in Figure 10 we see that improvements in the accuracy of the measured flux decreases rapidly with increasing plot number and sampling rate and in fact become negligible past a certain sampling intensity. Clearly there is no need to increase the level of sampling past this point. We quantify the diminishing returns of increasing the sampling intensity by defining an offset gradient relative to both the number of plots and sampling rate. The offset gradient (dC/dD) is simply the change in the offset percentage (βC) divided by the change in sampling rate (βD) or number of plots (βP , in which case the offset gradient is dC/dP). It tells us how fast the offset is changing as we increase our sampling. We choose βD and βP to be three and calculate the gradients over all grid points for the data in Figure 9. We divide the gradients by two so that the resultant is the change in the offset percentage per unit increase (either plot number or sampling rate). These are plotted in Figure 12.

[32] We see that rapid improvements in accuracy diminish past about ten units in each plot. Further gains in accuracy past this point can only be achieved by significantly intensifying the sampling strategy. Unfortunately this may be required. If we locate the (10, 10) sampling strategy in the offset percentage graphs in Figure 9, we see that this strategy only takes us to within 30–40% of the true flux. In many cases we would like to achieve a higher standard than this, which will require more flux measurements.

[33] Finally for question 5, there is a practical limit to the intensity of sampling. A reasonable limit may be set at twenty plots sampled every other day. This would require 1200 flux measurements over a 120-day growing season. Doing so we find we can get to within 7 to 14% of the true flux depending on the average field flux.

4. Discussion and Conclusions

[34] We have examined the observed variability of methane emissions from rice fields and delineated its components. The nature of this variability affects the accuracy of regional and global extrapolations and the reliability of field experiments. The prevailing sampling practices tend to have fairly frequent measurements of about once a week and more. Because of that, the temporal variability is not likely to be a major source of uncertainty in the calculated seasonally averaged flux. The spatial variability however is large, and is not as well handled in the usual sampling strategy by triplicate plots. It is a convenient minimum number that allows statistical comparisons, but according to our results, it leads to large uncertainty in the calculated flux of 40%–60%.

[35] When the flux is low, our calculations show that it takes an unrealistically large number of replicates to overcome the effects of spatial variability. This is partly because we have defined accuracy as a relative measure. Therefore if

the true flux is 1 mg/m²/h, to be within 20% we have to be able to have a sensitivity of measurement that can distinguish 1 mg/m²/h from 1.2 mg/m²/h, which is nearly impossible. But for a large flux, say 20 mg/m²/h, to be within 20% requires us to distinguish between 20 and 24 mg/m²/h which is possible. On the other hand, a great deal of accuracy for low emitting fields is not needed since such fields do not make a large contribution to the regional or global emissions. While these statements are true for rice fields, for other sources such as wetlands, the problem is not so easily dismissed. There are cases where the flux is low over most of an extensive area. Then the low fluxes are the major contributors to the regional and global emissions. In such cases chamber methods looking at small areas are less reliable than for rice fields.

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