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# Reducing standard errors by incorporating spatial autocorrelation into a measurement scheme for soil carbon credits

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**Abstract** Several studies have suggested that geostatistical techniques could be employed to reduce overall transactions costs associated with contracting for soil C credits by increasing the efficacy of sampling protocols used to measure C-credits. In this paper, we show how information about the range of spatial autocorrelation can be used in a measurement scheme to reduce the size of the confidence intervals that bound estimates of the mean number of C-credits generated per hectare. A tighter confidence interval around the mean number of C-credits sequestered could increase producer payments for each hectare enrolled in a contract to supply C-credits. An empirical application to dry land cropping systems in three regions of Montana shows that information about the spatial autocorrelation exhibited by soil C could be extremely valuable for reducing transactions costs associated with contracts for C-credits but the benefits are not uniform across all regions or cropping systems. Accounting for spatial autocorrelation greatly reduced the standard errors and narrowed the confidence intervals associated with sample estimates of the mean number of C-credits produced per hectare. For the payment mechanism considered in this paper, tighter confidence intervals around the mean number of C-credits created per hectare enrolled could increase producer payments by more than 100 percent under a C-contract.

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## 1 Introduction and background

The Kyoto Protocol, which took effect in February 2005, and the development and launch of a unified European market for trading in greenhouse gas (GHG) emissions have made the concept of trading credits for GHG reductions mainstream. Market based trading is one way to lower the costs of meeting GHG reduction targets and has been adopted by the European Union to create an incentive for European countries to meet their GHG reduction obligations. Although the United States (US) is not participating in the Kyoto protocol, there are many private and state initiatives to reduce emissions of GHGs or increase carbon (C) sequestration (Rosenzweig et al. 2002; Pew Center 2002, 2004).

Agricultural soils could be a part of US efforts to reduce atmospheric concentrations of GHGs (EPA 2005), potentially offsetting up to 9 percent of US GHG emissions (Lal et al. 1998). The potential to sequester additional soil C could present new economic opportunities to some agricultural producers if markets for C-credits continue to develop in the US.

Several studies have shown that agricultural producers can sequester C and create C-credits at costs competitive with other sectors of the US economy in the absence of transactions costs (Antle et al. 2001, 2002; Pautsch et al. 2001). Transactions costs are the additional costs associated with contracting that are over and above the actual purchase price of the C-credits; for example, legal fees related to drawing up the contract, time spent finding buyers or sellers, costs of measuring and monitoring the credits and provisions to offset risk among other factors. High transactions costs could reduce the economic competitiveness of soil C-credits. Several studies (Smith 2002; Mooney et al. 2004a, b and Kurkalova et al. 2004) have estimated the costs of measuring soil C-credits using a sampling scheme and find that transactions costs attributable to measurement are not large enough to negatively affect their economic competitiveness in a future US GHG market.

Existing studies have not considered how producer payments could be affected by the confidence intervals associated with estimating the mean number of C-credits per unit area e.g., hectare, under a sampling scheme. If confidence intervals are wide, credit purchasers are less certain about the number of credits purchased and could reduce the payments that producers receive for each hectare enrolled within a C-credit contract to account for this uncertainty. Several studies (Cerri et al. 2004; Conant and Paustian 2002; Mooney et al. 2004a, b) have suggested that geostatistical techniques could be employed with sampling data to reduce standard errors and confidence intervals associated with measuring the mean quantity of C-credits created per hectare. To our knowledge there have been no analyses that have tried this to date.

This paper examines how information about spatial autocorrelation can be used to decrease standard errors and tighten the confidence interval around sample estimates of the mean quantity of C sequestered per hectare within a region. A simple, low cost means of including spatial autocorrelation within a C-credit measurement scheme is proposed and applied to an empirical application covering three regions within the state of Montana. Incorporating spatial correlation without having to do "full-on" kriging can be an advantage to those who may not have access to kriging software. Results show that there are considerable benefits from accounting for spatial autocorrelation when measuring C-credits however; these were not uniform across cropping systems or the three regions examined. The standard errors associated with sample estimates of the mean number of C-credits per hectare decreased when information about the range of spatial autocorrelation of soil C was used. This reduced the uncertainty associated with the mean C-credit quantity sequestered on each hectare and could result in larger producer payments for each hectare enrolled in a contract to supply

C-credits, reducing transactions costs. Additional research is required to test the ideas outlined within the paper.

## 2 Transactions costs and contract design

### 2.1 Contract design and C-credit measurement

There are many ways to design and implement contracts to purchase C-credits (Feng et al. 2001). Two commonly suggested contract types are *credit based* contracts and *practice based* contracts. Under a credit based contract, producer payments are tied to the number of C-credits that they produce i.e., producers will receive a total payment equal to the market price per C-credit multiplied by the number of C-credits that they produce. Under a practice based contract, payments are not directly tied to the number of C-credits produced, instead producers receive a payment for each hectare that they convert to a new management practice that is thought to produce C-credits i.e., their total payment equals the number of hectares they convert to the new management practice multiplied by the payment offered for each hectare converted. Pautsch et al. (2001) and Antle et al. (2003) compare the relative economic efficiency of these contracts and show that, in the absence of transactions costs and perfect certainty about C-credit accumulation, credit based contracts are more efficient than practice based contracts; that is, credit based contracts produce C-credits at the lowest cost. However, in the real world there are transactions costs and there is not perfect certainty about C-credit accumulation. These factors could change the costs of exchanging C-credits under each contract and reverse the relative economic efficiency of each contract type (Antle et al. 2003; Mooney et al. 2004a, b; Kurkalova et al. 2004).

One of the biggest differences between transactions costs under credit based and practice based contracts is the cost associated with measuring the number of C-credits sequestered. Credit based contracts need to measure the quantity of C-credits created because producer payments are linked to C-credit quantity, while practice based contracts do not base payments on specific C-credit quantity. Previous work by Mooney et al. (2004a) and Kurkalova et al. (2004) shows that measurement costs are not large enough to reverse the relative economic efficiency of each contract type in the areas they studied.

Another factor influencing transactions costs is uncertainty related to the quantity of credits produced, which could affect the payments received by producers. Under a practice based contract, producers are assumed to create an "average" number of C-credits on each hectare for their region and management practices and receive a payment based on that number. In effect the number of C-credits created by each producer is unknown and can be higher or lower than the average, because of environmental and management heterogeneity. Under the credit based contract, the inability to measure C-credit accumulation over a region without error creates uncertainty. If there is high uncertainty over the number of C-credits created it is likely that producers will receive payments for a conservative number of C-credits. In the following section we discuss how uncertainty related to measured estimates of the number of C-credits created on each hectare enrolled within a credit based contract could lower payments received by producers.

### 2.2 C-credit payment adjustment due to quantity uncertainty under a credit based contract

Sampling is a statistically based means of estimating the number of C-credits created within a region and enables the user to make confidence statements about the likelihood of sample estimates representing the true population. Confidence limits are generally used to describe the bounds within which the true population value is, with a chosen level of confidence, captured by the sample estimates. In the case of estimating the mean number of C-credits created per hectare enrolled within a credit based contract, 95 percent of sample means (over a very large number of hypothetical repeats of the study) are expected to fall within plus or minus 1.96 standard errors of the estimated sample mean per hectare, equation (1).

$$\bar{x} - 1.96S_{\bar{x}} < \mu < \bar{x} + 1.96S_{\bar{x}} \tag{1}$$

The sample mean number of C-credits sequestered per hectare is $\bar{x}$, $\mu$ is the true population mean and $S_{\bar{x}}$ is the standard error of the sample mean. Put another way, 95 percent of the time the limits set by equation (1) should capture the population mean. If $S_{\bar{x}}$ is small, the confidence interval will span a tight range of values and closely bracket the population mean. If $S_{\bar{x}}$ is large the confidence interval can span a wide range of values around the population mean and there is greater uncertainty as to whether the sample estimate is close to the true value of the mean.

Purchasers of C-credits may adjust the amount they pay to producers to reflect the degree of uncertainty associated with estimating the true number of C-credits produced. This paper assumes that the purchaser is very risk averse, and will provide payments for a quantity of C-credits that represent the lowest bound of the 95 percent confidence interval. That is, purchasers assume that the mean number of C-credits produced per hectare enrolled in the contract is equal to $\bar{x} - 1.96S_{\bar{x}}$ and are only willing to pay producers for this quantity of C-credits. Under this assumption, the payment received for producing C-credits on one hectare is $P(\bar{x} - 1.96S_{\bar{x}})$, where $P$ is the market price per C-credit. In effect this payment reflects a discount associated with measurement uncertainty and is an additional transaction cost. If $S_{\bar{x}}$ can be reduced, producers' revenue per hectare enrolled in the contract would increase at any given contract price because the confidence interval will be narrower. We have assumed this type of buyer behavior as *one example* to illustrate the possible costs of payment adjustments; there could be many variations on this behavior. As the C-credit market matures, and larger portfolios of C-credits from different sources or regions of the country become available C-credit purchasers may alter their buying strategies from the one we describe.

### 2.3 Reducing transaction costs using information about spatial autocorrelation

Let $S_{\bar{x}}^A$ be the initial standard error of the mean quantity of C-credits sequestered per hectare enrolled within a contract and, let $S_{\bar{x}}^B$ be the standard error associated with some change in the information used within the measurement procedure, where $S_{\bar{x}}^A > S_{\bar{x}}^B$. A smaller standard error associated with measuring the mean quantity of C-credits per hectare could increase producer payments for each hectare placed into a C-credit contract if purchasers discount their payments based on the size of the confidence interval. The percentage change in payment relative to the previously agreed upon credit price is shown by equation (2).

$$\text{Percentage change in payment} = \frac{1.96\left(S_{\bar{x}}^A - S_{\bar{x}}^B\right)}{\left(\bar{x} - 1.96S_{\bar{x}}^A\right)} \times 100 \tag{2}$$

We assume that credit suppliers and buyers conduct their transactions at the prevailing market price for C-credits. That is, the price per C-credit created is one of the contract terms set out at the beginning of the contract and does not vary over the contract duration. A lower standard error will increase producer revenues per hectare enrolled in a C contract. Further they would need to enroll fewer hectares to sell the same number of C-credits than was the case when the standard error is larger. It is possible that the market price for future contracts could be affected by the change in C-credit supply brought about by lowering the standard error and tightening the confidence intervals however, these secondary effects are beyond the scope of this paper. Williams, Peterson and Mooney (2005) discuss the effect of changes in a range of supply and demand conditions on the market price for C-credits.

A smaller standard error could also benefit C-credit purchasers because they would contract with fewer producers to reach some target number of C-credits, lowering their transactions costs. Additional information, such as the degree of spatial autocorrelation between soil C samples, could be used to reduce $S_{\bar{x}}^{A}$ to $S_{\bar{x}}^{B}$ within a soil C measurement scheme. Spatial autocorrelation is present when the value of a variable at one point on a surface is related to values at surrounding points i.e., the values are not completely random. The additional information contained by related points can be used to reduce the standard error and confidence intervals.

In the following section we outline a sampling procedure used in previous studies to measure C-credits. We then propose modifications to the scheme that could reduce the standard error of the mean C-credit estimate per hectare using information about the spatial autocorrelation between field soil C sample points.

## 3 Modified sampling design for estimating the number of C-credits

A protocol for measuring soil C-credits is outlined by Mooney et al. (2004a, b). In this paper it is altered to examine how standard errors and confidence intervals associated with the sample mean quantity of C per hectare can be reduced by accounting for spatial autocorrelation. The measurement protocol uses predictions from soil C models combined with field sampling to estimate the number of C-credits created within a region and is summarized below.

Individual contracts for C-credits are assumed to cover well defined geographic regions to simplify the issue of contracting for C-credits with very large numbers of producers. On each hectare enrolled in the C-credit contract there is a management change that increases the rate of C sequestration, creating C-credits. Soil C is sampled on some hectares enrolled within the contract to monitor C-credit accumulation. The population to be sampled is all hectares within a contract region that are placed into a contract for C-credits. A stratified random sample is suggested to measure changes in soil C because this method can increase the precision of information obtained for a given cost in comparison to a simple random sample. Each stratum is internally homogeneous with respect to a chosen characteristic. A further advantage is gained if the means of the attribute sampled differ among strata.

When measuring soil C under a credit based contract, all hectares within a region that are enrolled in a contract to produce C-credits at a given price could be subdivided into non-overlapping homogeneous groups (strata, $j$) on the basis of some criteria, for example the management system change. Once every hectare in the contract is assigned to a stratum, each stratum can be sampled independently using a random sampling design.

The total number of samples, $n$, required to estimate the mean number of C-credits supplied by each hectare enrolled within the contract in a given region can be calculated using equation [3], the standard formula for estimating sample size under a stratified random sampling scheme (McCall 1982).

$$n = \frac{Z^2\left(\sum_{j=1}^{J} N_j \hat{\sigma}_{est,j}\right)^2}{N^2\psi^2 + Z^2 \sum_{j=1}^{J} N_j \hat{\sigma}_{est,j}^2} \qquad (3)$$

$Z$ is the value from a standard normal table corresponding to the desired level of confidence in the parameter estimate (e.g., $Z = 1.96$ for 95% confidence level). The confidence level is a measure of how sure you wish to be about your estimate. $N$ represents the total number of hectares enrolled in a carbon contract; $N_j$ represents the number of hectares in the $j$th stratum. The estimated standard deviation of C-credit quantity within each stratum over the duration of the contract is $\hat{\sigma}_{est,j}$. In equation (3) $\psi$, the absolute error, is calculated as the weighted average of the allowable error in the mean number of C-credits created per hectare in all strata, $\varepsilon_j$, which is calculated by multiplying the estimated mean number of C-credits per hectare in each strata by the desired relative margin of error $\varepsilon$ i.e., $\psi = (\frac{\sum_{j=1}^{J} N_j \varepsilon_j}{N})$ and $\varepsilon_j = \varepsilon \bar{X}_j$. The error bound is a measure of how close you want to be to the mean number of C-credits per hectare. When asked to specify $\varepsilon$, it is often easier to begin with a relative margin of error for example, "I would like to get to within 10% of the truth" (or some other choice of percentage).

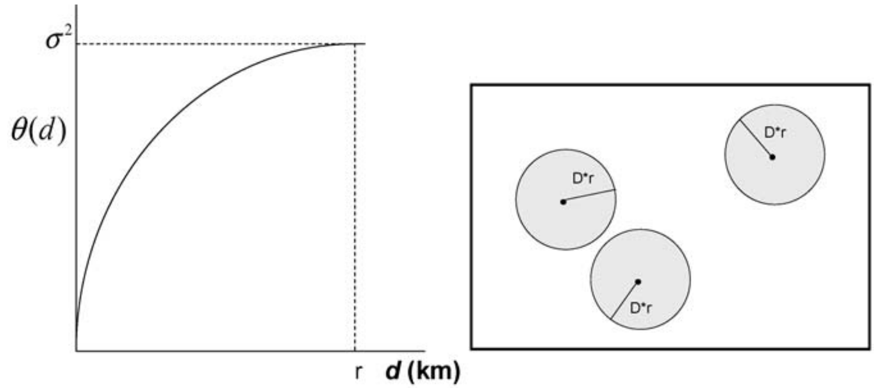
Sampling effort is allocated efficiently between strata using the following standard allocation formula, $n_j = \frac{n N_j \hat{\sigma}_{est,j}}{\sum_{j=1}^{J} N_j \hat{\sigma}_{est,j}}$, where $n_j$ is the sample size in stratum $j$ (McCall 1982). Each sample represents one hectare so $n_j$ also represents the total number of hectares sampled within the stratum. Once the sample size has been determined, the next step in measurement is to take field soil C samples. The actual field data can then be used to calculate the standard error of the mean C-credit quantity per hectare using equation (4) and then used to estimate confidence intervals for the mean number of C-credits sequestered per hectare by stratum, consistent with equation (1).

$$S_{\bar{x}_j} = \frac{\hat{\sigma}_{field,j}}{\sqrt{n_j}} \sqrt{1 - \frac{n_j}{N_j}} \tag{4}$$

$N_j$, and $n_j$ are as defined previously and $\hat{\sigma}_{field,j}$ is the standard deviation of the soil C samples taken in the field. The term $\sqrt{1 - \frac{n_j}{N_j}}$ is the finite population correction factor, and is used to adjust the standard error when sampling without replacement from a finite population. If we do not account for any spatial autocorrelation in C accumulation the standard errors are calculated implicitly assuming that the value obtained at each sample point is independent of information gathered at other locations. However, it is possible that sample data exhibit spatial autocorrelation and there is some relationship between characteristics or information contained at points closer together on the landscape. If this is the case, when points that are close to each other are sampled, redundant information is collected because most of the information could be obtained by sampling only one of the points. Conceptually, the information contained at a single point can be thought of as representing a larger area. If spatial autocorrelation is present, the sample of field C measurements can be used to estimate the degree of spatial correlation of soil C across the landscape enrolled in the C-contract.

If the degree of spatial autocorrelation is known *a priori* a smaller sample size can be used to achieve a given standard error (reducing sample costs). This paper assumes it is not known *a priori* but is calculated by analyzing field soil samples and then used to reduce the standard errors associated with the sample.

In a spatially-adjusted analysis we would normally estimate the number of C-credits created over the landscape using kriging (essentially regression-type predictions, but modified to account for the spatial correlation present). The result is more precise estimates (smaller standard errors) than an analysis that ignores that correlation. Access (literally and conceptually) to kriging software and tools is not as widespread now as it will be in the future, which motivated the following idea. Suppose we take each observed data point to be the




$\theta(d) = \sigma^2 - \mathrm{cov}(s_1, s_2)$

r = range, or distance at which the degree of covariance between individual points $s_1$ and $s_2$ is negligible. The interplot distance at which the correlation is 0.05 is often used as a cutoff for range.

D = percentage in decimals

**Fig. 1** Variogram (left) and representation of range information being applied to a single sample (right)

center of a circle (whose radius will be some proportion of the range of spatial correlation) such that we are reasonably comfortable that the observed value is representative of the circle as a whole, Fig. 1. The collection of such circles (henceforth called sampling circles) will represent a measurable amount $M_j$ of the landscape being surveyed in each stratum such that $M_j = n_j \times A_j$, where $A_j$ is the number of hectares represented by each circle in stratum $j$. The total number of hectares represented by the sample, $M_j$ can be substituted for $n_j$ in equation (4), reducing the standard error and narrowing the confidence interval. We conjecture (and propose to study in the future via simulations) that use of the standard errors calculated using a sample of circles, whose radius is the correct proportion of the range of spatial autocorrelation, will approximate the shrinkage in standard errors one would get through kriging. If our future simulations show that a single proportion works in a wide range of situations, then one could sidestep the process of kriging, and get to the (essentially) same end point via an easier method.

Figure 2 summarizes the main steps proposed to develop a sampling technique to measure soil C-credits and estimate their range of spatial autocorrelation. The analysis presented in the following sections implements the idea of using some proportion of the range of spatial autocorrelation to adjust individual sample points to represent a larger area and examines the impact of this adjustment on standard error, confidence intervals and transactions costs.

## 4 Models, data and application

Parties to any contract for soil C-credits have many options open to them in crafting the specific terms of their agreement (Mooney et al. 2004a). Similar to Antle et al. (2003), and Mooney et al. (2004a, b), this study maintains that producers will enter into 20 year contracts to create C credits. Annual payments received by producers are equal to one twentieth of

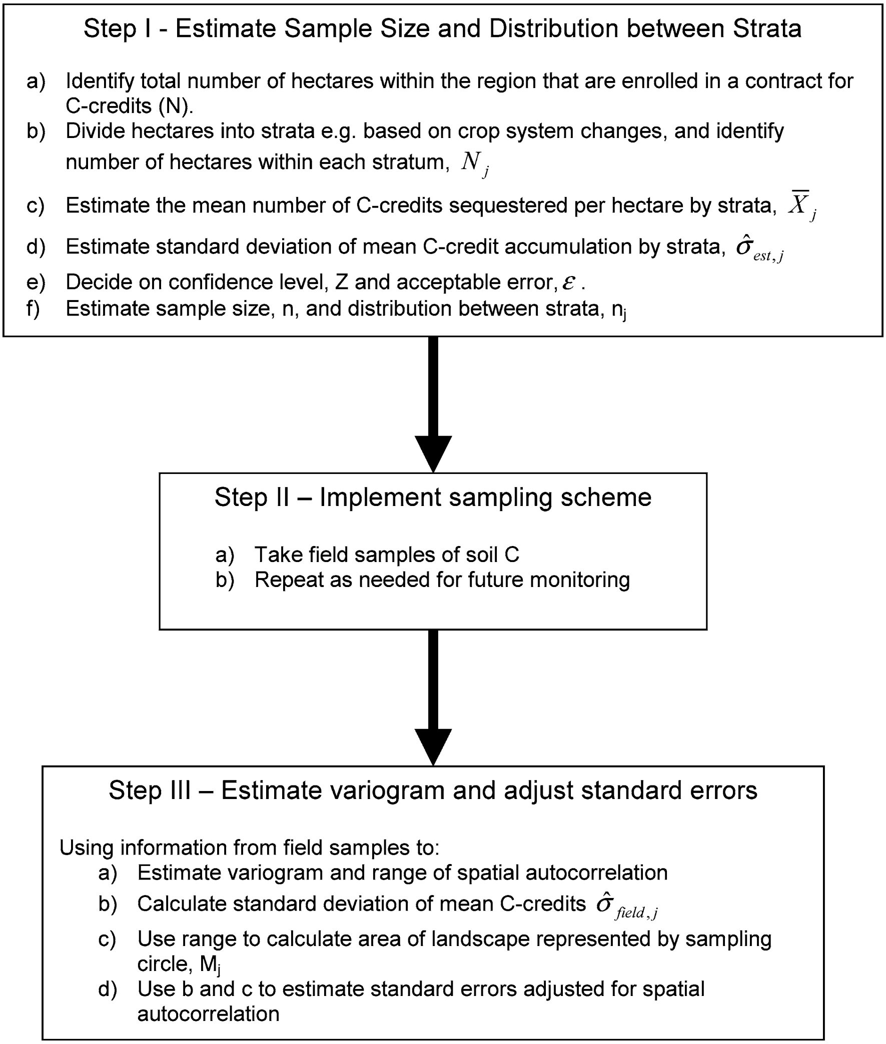



**Fig. 2** Flow chart summarizing steps undertaken to implement a measurement protocol for soil C-credits and estimate range of spatial autocorrelation

the total number of C-credits they are expected to produce over the contract lifetime. The potential future market price of C credits within the US is unknown at the present time (Williams et al. 2005) so changes in producer management choices are examined over a range of possible prices; \$10, \$30 and \$50 per C-credit, defined as 1 tonne of C. Producers are assumed to receive payments for a quantity of credits represented by the lowest bound of the 95 percent confidence interval around the mean quantity of C-credits created per hectare enrolled in a contract region. This payment rule raises the possibility that producers may require an additional risk premium to enter into the C-contract. This issue is important but lies outside the scope of this paper.

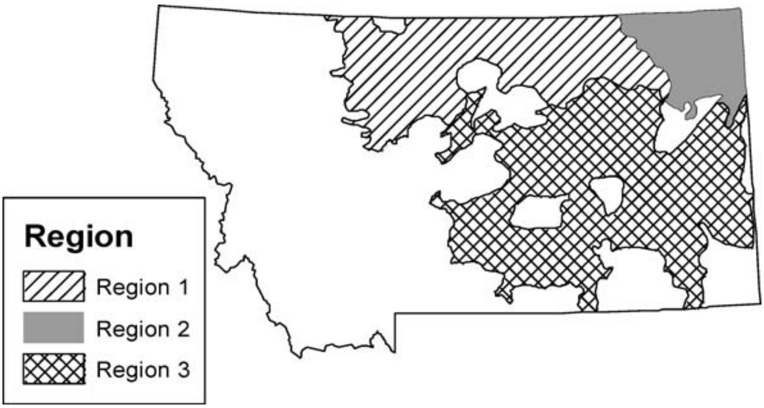



**Fig. 3** Map of Montana showing the three regions studied

## 4.1 Calculating the total sample size $N$ for a contract region

Three different regions within the dry land crop producing area of Montana are chosen for our empirical application, Fig. 3. The land area contained within each region has similar climatic, soil and growing conditions. More than one region is used in the analysis because the efficacy of including information about spatial autocorrelation in measurement schemes for C-credits may differ across geographic areas.

In a real world implementation, the number of producers in each region that enter into a contract to supply C-credits ($N$ and $N_j$) at the offered price per C-credit would be known at the time the contract was signed. This paper uses a combination of economic and biophysical modeling techniques to simulate how many producers within each region would change cropping practices in response to a payment for producing C-credits. The models are parameterized using field level production data collected using a personal interview survey of the crop production practices of 425 farms within Montana as well as secondary data sources.

Seven cropping systems are represented by the models: spring wheat fallow (SWF); barley fallow (BLF); winter wheat fallow (WWF); grass (GRA); continuous spring wheat (CSW); continuous barley (CBL) and continuous winter wheat (CWW). Payments for C-credits are provided for any crop system change that results in additional C being sequestered. In total, there are 38 possible management changes that could be implemented to create C-credits, Table 1. The rate of change in soil C accumulation in response to management practices is estimated using a field scale version of Century, a crop-ecosystem model that includes soil dynamics (Parton et al. 1994; Paustian et al. 1996). The availability of spatially explicit, individual hectare, Century estimates of C-credit accumulation in response to 38 possible crop system changes at individual farm sites within Montana, provides a unique opportunity to explore the potential for incorporating spatial autocorrelation into a soil C measurement scheme. This was not possible in previous studies by Antle et al. (2003) and Mooney et al. (2004a, b) because they did not have access to spatially explicit (individual hectare) estimates of changes in C at that time and relied on values aggregated over a larger area. Estimates of soil C accumulation from Century are then used as inputs to an economic simulation model that compares the expected net returns from each cropping system on each hectare. A cropping system that maximizes net returns per hectare is chosen for each hectare represented by the model. Management changes in response to payments offered under a contract for C-credits

**Table 1** Possible Crop system changes (stratum, $j$)

| Initial cropping system | Subsequent cropping system | | | | | | |
|---|---|---|---|---|---|---|---|
| | SWF | BLF | WWF | GRA | CSW | CBL | CWW |
| SWF | | | X | X | X | X | X |
| BLF | | | X | X | X | X | X |
| WWF | X | X | | X | X | X | X |
| GRA | X | X | X | | X | X | X |
| CSW | X | X | X | X | | | X |
| CBL | X | X | X | X | | | X |
| CWW | X | X | X | X | X | X | |

SWF = spring wheat fallow, BLF = barley fallow, WWF = winter wheat fallow, GRA = grass CSW = continuous spring wheat, CBL = continuous barley, CWW = continuous winter wheat. The quantities of carbon sequestered by spring wheat and barley systems are approximately equal. Thus a change from SWF to BLF and vice versa does not sequester additional carbon and crop system changes between CSW and CBL do not sequester additional carbon.

(and the number of hectares within each region making a specific change) are induced by changing the expected net returns producers would receive if they alter their initial cropping systems and switching to a system that creates C-credits. A full description of the models and underlying data can be found in Antle et al. (2003) and Antle and Capalbo (2001).

The economic simulation model is used to estimate the total number of hectares within each region that switch crop production practices ($N$) in response to C-credit payments and the type of crop system change that occurs on each hectare which can be used to calculate $N_j$. All hectares entering a contract for C-credits within a region that have the same initial cropping system and then make the same management change are considered to be a single stratum, $j$; for example all hectares initially in a SWF crop system that switched to a CSW system that created C-credits would form a single stratum while those hectares that were initially in SWF and changed to WWF as a consequence of entering into the contract would form another stratum and so on. In a real world implementation of the contract this information would be obtained from actual observations.

The estimated mean C-credit accumulation per hectare, $\bar{X}_j$, for each stratum is calculated as a simple average of the C changes predicted by Century for all hectares within the contract region. The error bound, $\psi$, is calculated from the weighted mean change in C over all strata multiplied by the percent desired relative margin of error, $\varepsilon$ (we chose $\varepsilon = 10$ percent to ground the study empirically, error bounds around this figure are common in empirical studies). The estimated standard deviation of each stratum, $\hat{\sigma}_{est,j}$, is also calculated using Century output. Information from predictive models such as Century will likely be necessary to create initial estimates of the mean and standard deviation of C-credit quantities within strata in a real world application prior to field sampling. Information about $N$, $N_j$, $\psi$ and $\hat{\sigma}_{est,j}$ generated from this modeling exercise is used to estimate total sample size $n$ and number of field soil C samples for each stratum $n_j$ that would be needed to measure C-credit quantities under a contract for C-credits following equation (3).

## 4.2 Estimating empirical sample standard errors

The empirical standard errors, $\hat{\sigma}_{field,j}$, associated with sampling field soil C within each strata would normally be calculated from field soil C data collected by the sampling effort. In this paper we approximate these field data by "sampling" a modeled landscape of possible sample fields (each field is one hectare). The mean and variance of each stratum $\bar{X}_j$ and $\hat{\sigma}_{est,j}$ (estimated from Century results), are used as inputs into a random number generator that draws/creates fields with soil C changes (C-credit accumulation) that are statistically representative of the population within each region. Estimates of C-credit accumulation from the hectares that are drawn (sampled) are used to represent the actual field data soil C results that would be available from a real world application of the sampling procedure. C-credit accumulations from these modeled hectares are then used as if they were the actual field soil C results to create the standard deviation of mean C-credit accumulation by stratum for the hectares sampled, $\hat{\sigma}_{field,j}$, and the standard errors of mean C-credit accumulation per hectare consistent with equation (4). In a real world application this would not be necessary as field data would be used to estimate the standard errors.

## 4.3 Spatially adjusted sample standard errors

The degree and type of spatial autocorrelation present in the point estimates of C-credit accumulation by hectare can be estimated by fitting a primary regression model followed by spatial autocorrelation modeling on the residuals of that regression. In this paper we only consider the possibility that the data exhibit an isotropic autocorrelation relationship; that is the covariance between C values at any two points within a given region depends only on the distance between possible hectare pairs and not the direction in which they are separated and that the mean, variance and covariance structure exhibited by the data do not drift as we move between locations within the region (Bailey and Gatrell 1995). Three primary models of C-credit spatial autocorrelation are considered for each stratum within each of the three regions: no trend, a linear trend across the landscape and a quadratic trend. To each model, we add isotropic correlation, using a simple exponential decay model (Appendix A). The model with the best fit can be used to create a variogram that explores the relationship between the degree of covariance between two individual points (or hectares) and the relative strength of their covariance as the distance between them increases, Fig. 1 (Bailey and Gatrell 1995).

Fitting a primary regression model and using its residuals to estimate the range of spatial correlation can be accomplished without much difficulty using standard statistical packages. Geostatistical software is not necessary for these steps and this technique is potentially accessible to a relatively broad audience at low cost. Often the next step after creating a variogram is to use that information in kriging to predict values of the variable of interest (in this case number of C-credits) at unobserved points over the landscape to minimize error variance. Ultimately, kriging is the "correct" approach to reducing standard errors of the mean C-credit estimate per hectare however; kriging requires specialized software not commonly available in most offices. Because of this, we propose a somewhat easier method to incorporate information about spatial autocorrelation using the range of autocorrelation within a C measurement scheme that we believe can yield answers very similar to kriging.

We show the effect of using information about the range of spatial autocorrelation on sample standard errors and size of the confidence interval using sampling circles of three sizes, with radii set to 10 percent, 15 percent and 20 percent, of the range of autocorrelation. These values were chosen because at this distance there is a high correlation between sample points within the circles (Fig. 1 shows that as the range increases i.e., distance between two individual hectares increases, correlation between the hectare pairs decrease). Other range values could be used to implement the method we describe and to some extent this would be a decision faced by each person implementing the procedure. We chose our values to ensure a high degree of correlation between points within the range bound. The area represented

**Table 2** Total number of hectares within each stratum and sample size (each year) at C-credit prices of $10, $30 and $50/C-credit

| | Credit price $10/C-credit | | Credit price $30/C-credit | | Credit price $50/C-credit | |
|---|---|---|---|---|---|---|
| | *Nj* (hectares) | $n_j$ Samples | *Nj* (hectares) | $n_j$ Samples | *Nj* (hectares) | $n_j$ Samples |
| Crop system change | | | Region 1 | | | |
| SWF_CSW | 23,033 | 415 | 71,347 | 409 | 112,919 | 411 |
| SWF_CWW | 2,247 | 58 | 6,180 | 51 | 11,798 | 62 |
| WWF_GRA | 0 | 0 | 562 | 3 | 562 | 2 |
| WWF_CSW | 2,809 | 60 | 12,359 | 84 | 17,415 | 76 |
| WWF_CWW | 562 | 16 | 2,809 | 25 | 4,494 | 26 |
| CSW_WWF | 0 | 0 | 0 | 0 | 562 | 3 |
| CSW_GRA | 562 | 18 | 562 | 6 | 1,124 | 8 |
| **Total** | 29,213 | 567 | 93,819 | 578 | 148,874 | 588 |
| | | | Region 2 | | | |
| SWF_GRA | 797 | 7 | 2,921 | 13 | 5,045 | 16 |
| SWF_CSW | 12,481 | 45 | 24,696 | 48 | 35,849 | 48 |
| SWF_CWW | 266 | 3 | 531 | 4 | 1,328 | 6 |
| CSW_GRA | 1,062 | 15 | 3,718 | 27 | 6,373 | 33 |
| **Total** | 14,605 | 70 | 31,866 | 92 | 48,595 | 103 |
| | | | Region 3 | | | |
| SWF_GRA | 4,726 | 215 | 7,877 | 120 | 11,553 | 98 |
| SWF_CSW | 7,877 | 337 | 22,056 | 314 | 32,559 | 257 |
| SWF_CWW | 525 | 21 | 3,676 | 48 | 11,553 | 84 |
| WWF_GRA | 1,050 | 39 | 1,575 | 20 | 2,626 | 18 |
| WWF_CSW | 1,050 | 56 | 5,777 | 102 | 10,503 | 103 |
| WWF_CWW | 1,050 | 45 | 3,151 | 45 | 5,777 | 46 |
| CSW_GRA | 525 | 31 | 1,050 | 21 | 1,575 | 18 |
| **Total** | 16,804 | 744 | 45,162 | 670 | 76,145 | 624 |

SWF = spring wheat fallow, WWF = winter wheat fallow, GRA = grass, CSW = continuous spring wheat, CWW = continuous winter wheat

by each sampling circle is represented by $A_j$, and is calculated by converting the area of the circle into hectares. Each individual sample point is assumed to represent the number of hectares contained by the sampling circle, increasing the effective number of hectares sampled within a stratum from $n_j$ to $M_j$. We note that in some settings, care is required to ensure that the intersection of any overlapping circles is accounted for by subtracting the area of intersection from $M_j$. The range of spatial autocorrelation is estimated from the initial Century model estimates and assumed to hold for the actual sample. In field implementation, the range of spatial autocorrelation would be estimated using actual data from the soil C samples gathered in the field.

## 5 Results

The total number of hectares, $N$, entering a credit based contract for C-credits, the number of hectares per stratum, $N_{j,}$ and the calculated sample size, $n$, are shown in Table 2 for the three C-credit prices examined in each of the three regions. Although there were 38 possible crop system changes that could sequester additional soil C, only seven distinct cropping changes (strata) were selected by the economic simulation model as economically feasible for regions 1 and 3, and four system changes (strata) in region 2 (Table 2). These systems represent the most economically efficient means of creating C-credits within each region given the underlying physical and economic conditions. The remaining crop system changes do not appear in the solution because they were not an economically efficient way to create C-credits in these areas, based on the underlying data. Each region exhibits a different relationship between total sample size and the total area to be sampled (i.e., the number of hectares within a contract for C-credits) reflecting the unique biophysical and economic conditions within each region. These conditions influence the cropping system changes chosen by producers and the number of hectares they enroll in contracts at each C-credit price (Mooney et al. 2004b). As C-credit price increases we expect that a larger number of producers find it profitable to enter a contract to supply C-credits and as a consequence the number of hectares, area to be sampled, increases as shown in Table 2.

Over the three prices studied, each region exhibits a different relationship between the size of the population to be sampled (number of hectares enrolled within the C contract) and the number of samples needed to estimate the mean number of C-credits sequestered per hectare (Table 2). In regions 1 and 2 there is a positive relationship between the number of hectares within a contract and the sample size over the C-credit prices considered; while in region 3 there is a negative relationship between population size and number of samples. Total measurement costs will follow the same pattern as sample size i.e., they are positively correlated. The response of sample size to an increase in the number of hectares enrolled in a C-credit contract within a region due to a change in C-credit price is not intuitive. The response is a function of the number of hectares within each stratum at each price within the region, C variability within each stratum at each price, and the estimated mean number of C-credits per hectare within each stratum among other factors. It is not possible to predict whether these factors increase or decrease in size in response to a change in the price offered for C-credits *a priori*. This issue is explored in detail by Mooney et al. (2004b).

The number of C-credits accumulated on each hectare within our modeled landscape over twenty years was tested for spatial autocorrelation by stratum within each region using three different trend patterns. Corrected Aikaike Information Criteria was used to determine whether a regression model with no trend, linear trend or quadratic trend of autocorrelation best fit the C-credit increases "measured" within each stratum. These results were used to construct variograms representing the range of spatial autocorrelation for each stratum by region. Models fitting no trend and a linear trend in C-credit accumulation were selected for all strata in regions 1 and 2 while the C-credit accumulation within region 3 best fit models with a linear trend only, Table 3.

The range of autocorrelation varies between negligible and 1.36 km across all strata and regions. The effective sample size for all strata in region 3 can be increased by accounting for spatial autocorrelation, while only four of seven strata in region 1 benefit and one stratum in region 2. Interestingly, the range of autocorrelation attributed to the same stratum in different regions varies considerably, Table 3, reflecting differences in the underlying bio-physical conditions within each region. For example, the range of spatial autocorrelation exhibited within strata that represent hectares whose crop systems are changed from continuous spring wheat to grass (CSW_GRA) extend from 0.53 kilometers in region 2 to 1 kilometer in region 3 and 1.36 kilometers in region 1, Table 3.

The number of hectares included within a sampling circle with a radius of ten percent, fifteen percent and twenty percent of the range are also presented in Table 3. Using ten percent of range (the strongest spatial autocorrelation) the area represented by each hectare sampled within a stratum increases between zero and 5.78 hectares in region 1; there is no

**Table 3** Primary Model type for variogram, range of spatial correlation and aerial extent represented by a single sample. In all cases isotropic spatial autocorrelation was used

| Strata | Variogram best trend Model | Range (kilometers) | 10 percent range (hectares) | 15 percent range (hectares) | 20 percent range (hectares) |
|---|---|---|---|---|---|
| | | | Region 1 | | |
| SWF_CSW | Linear | * | * | * | * |
| SWF_CWW | Linear | * | * | * | * |
| WWF_GRA | None[1] | 0.67 | 1.40 | 3.15 | 5.60 |
| WWF_CSW | Linear | 0.37 | * | * | 1.72 |
| WWF_CWW | Linear | 0.57 | 1.01 | 2.27 | 4.03 |
| CSW_WWF | Linear | * | * | * | * |
| CSW_GRA | Linear | 1.36 | 5.78 | 13.00 | 23.11 |
| | | | Region 2 | | |
| SWF_GRA | Linear | * | * | * | * |
| SWF_CSW | None | * | * | * | * |
| SWF_CWW | None | * | * | * | * |
| CSW_GRA | None | 0.53 | * | 1.96 | 3.49 |
| | | | Region 3 | | |
| SWF_GRA | Linear | 0.69 | 1.48 | 3.34 | 5.93 |
| SWF_CSW | Linear | 1.31 | 5.41 | 12.18 | 21.66 |
| SWF_CWW | Linear | 1.23 | 4.72 | 10.62 | 18.88 |
| WWF_GRA | Linear | 0.70 | 1.54 | 3.45 | 6.14 |
| WWF_CSW | Linear | 1.21 | 4.57 | 10.28 | 18.27 |
| WWF_CWW | Linear | 1.27 | 5.07 | 11.40 | 20.27 |
| CSW_GRA | Linear | 1.00 | 3.13 | 7.03 | 12.51 |

SWF = spring wheat fallow, WWF = winter wheat fallow, GRA = grass, CSW = continuous spring wheat, CWW = continuous winter wheat

[1] fitted with only a mean (see appendix A)

*Area represented not greater than 1 hectare

increase in region 2 and sample points within region 3 exhibit increases in the area they represent of between 1.48 and 5.41 hectares. As the percentage of range used to establish the size of the sampling circle represented by a single sample point is increased, the area represented by each sampling circle also increases. An increase in the area represented by each sample point effectively increases the size of the sample. For example, at a price of \$30 per C-credit, samples on 314 hectares are required to measure mean C accumulation in the stratum SWF_CSW in region 3. If we account for spatial autocorrelation exhibited by that stratum, at 10 percent of range each hectare sampled represents 5.41 hectares, and so those 314 hectares are equivalent to sampling 1,699 hectares (i.e., 314*5.41). Increasing the effective sample size decreases the standard error associated with C-credit measurement and tightens the confidence interval bracketing the mean number of C-credits per hectare.

Differences between the 95 percent confidence interval lower bound C-credit estimate for all strata, in all regions, ignoring autocorrelation and then using a proportion of the range of spatial autocorrelation are shown in Table 4. The increases represent the additional number of C-credits per hectare that producers would receive payments for under a C-credit measurement scheme that accounts for spatial autocorrelation under the method proposed in this paper. For example, in region 1, at a price of \$10 per C-credit, accounting for spatial autocorrelation increases the 95% confidence level lower bound estimate of the mean number of C-credits per hectare by 4.35 C-credits over a 20 year period in the case of switching

**Table 4** Difference in 95% confidence interval lower bound C estimate over 20 years, between standard error calculated without accounting for spatial autocorrelation and standard error estimates calculated using 10 percent, 15 percent and 20 percent of autocorrelation range

| | \$10 | | | \$30 | | | \$50 | | |
|---|---|---|---|---|---|---|---|---|---|
| Payment | 10 % Range | 15% Range | 20% Range | 10% Range | 15% Range | 20% Range | 10 % Range | 15% Range | 20% Range |
| Crop system change | Region 1<br>Increase in 95% estimate of lower bound (tonnes C) | | | | | | | | |
| SWF_CSW | * | * | * | * | * | * | * | * | * |
| SWF_CWW | * | * | * | * | * | * | * | * | * |
| WWF_GRA | * | * | * | 0.54 | 1.53 | 2.02 | 0.65 | 1.84 | 2.44 |
| WWF_CSW | * | * | 1.06 | * | * | 0.84 | * | * | 0.90 |
| WWF_CWW | 0.05 | 4.82 | 7.26 | 0.04 | 3.89 | 5.83 | 0.04 | 3.88 | 5.81 |
| CSW_WWF | * | * | * | * | * | * | * | * | * |
| CSW_GRA | 4.35 | 5.52 | 6.28 | 4.94 | 6.15 | 6.79 | 6.19 | 7.70 | 8.47 |
| | Region 2<br>Increase in 95% estimate of lower bound (tonnes C) | | | | | | | | |
| SWF_GRA | * | * | * | * | * | * | * | * | * |
| SWF_CSW | * | * | * | * | * | * | * | * | * |
| SWF_CWW | * | * | * | * | * | * | * | * | * |
| CSW_GRA | * | 2.00 | 3.25 | * | 1.47 | 2.39 | * | 1.42 | 2.30 |
| | Region 3<br>Increase in 95% estimate of lower bound (tonnes C) | | | | | | | | |
| SWF_GRA | 0.13 | 0.32 | 0.43 | 0.17 | 0.43 | 0.57 | 0.19 | 0.49 | 0.64 |
| SWF_CSW | 0.30 | 0.38 | 0.45 | 0.29 | 0.37 | 0.41 | 0.32 | 0.40 | 0.44 |
| SWF_CWW | 1.02 | 1.34 | 1.56 | 0.78 | 1.01 | 1.13 | 0.58 | 0.75 | 0.84 |
| WWF_GRA | 0.23 | 0.56 | 0.73 | 0.35 | 0.84 | 1.09 | 0.33 | 0.80 | 1.04 |
| WWF_CSW | 0.88 | 1.19 | 1.46 | 0.62 | 0.82 | 0.92 | 0.61 | 0.80 | 0.89 |
| WWF_CWW | 4.06 | 5.32 | 6.23 | 3.92 | 5.01 | 5.59 | 3.82 | 4.86 | 5.40 |
| CSW_GRA | 2.72 | 4.03 | 4.88 | 3.65 | 5.28 | 6.15 | 3.93 | 5.67 | 6.56 |

SWF = spring wheat fallow, WWF = winter wheat fallow, GRA = grass, CSW = continuous spring wheat, CWW = continuous winter wheat

*Change in 95% lower bound is zero (where area represented by autocorrelation is less than 1 hectare) or negligible.

from a continuous spring wheat system to a grass system (CSW_GRA). As the proportion of range representing the degree of autocorrelation increases from ten percent to twenty percent, the confidence intervals associated with sampling become tighter and the 95 percent confidence lower bound estimate of the number of C-credits sequestered increases further. Tight confidence intervals could result in larger payments for each hectare enrolled within a contract for C-credits, benefiting producers. Using ten percent of range as an example, producers switching from continuous spring wheat to grass (CSW_GRA) in region 1 could receive payment for an additional 4.35 to 6.19 C-credits per hectare over 20 years (depending on the credit price). Producers within each stratum receive different benefits from accounting for spatial autocorrelation. Producers in region 1 strata SWF_CSW and SWF_CWW and in region 2 strata SWF_GRA, SWF_CSW and SWF_CWW do not gain any advantage from accounting for spatial autocorrelation while producers within the remaining strata do have the potential to benefit.

**Table 5** Percentage increase in payments for each hectare enrolled within a C credit contract as a result of tightening the confidence interval

| | $10 | | | $30 | | | $50 | | |
|---|---|---|---|---|---|---|---|---|---|
| Payment | 10% Range | 15% Range | 20% Range | 10% Range | 15% Range | 20% Range | 10% Range | 15% Range | 20% Range |
| Crop system change | | | | | Region 1 | | | | |
| SWF_CSW | * | * | * | * | * | * | * | * | * |
| SWF_CWW | * | * | * | * | * | * | * | * | * |
| WWF_GRA | * | * | * | 32.80 | 92.69 | 122.81 | 29.51 | 83.33 | 110.35 |
| WWF_CSW | * | * | 5.61 | * | * | 4.50 | * | * | 4.85 |
| WWF_CWW | 0.32 | 31.85 | 47.99 | 0.20 | 20.12 | 30.15 | 0.20 | 20.09 | 30.08 |
| CSW_WWF | * | * | * | * | * | * | * | * | * |
| CSW_GRA | 27.76 | 35.23 | 40.07 | 33.05 | 41.18 | 45.48 | 41.02 | 50.99 | 56.15 |
| | | | | | Region 2 | | | | |
| SWF_GRA | * | * | * | * | * | * | * | * | * |
| SWF_CSW | * | * | * | * | * | * | * | * | * |
| SWF_CWW | * | * | * | * | * | * | * | * | * |
| CSW_GRA | 0.00 | 23.08 | 37.62 | 0.00 | 12.73 | 20.71 | 0.00 | 13.06 | 21.25 |
| | | | | | Region 3 | | | | |
| SWF_GRA | 1.93 | 4.96 | 6.57 | 2.69 | 6.83 | 8.93 | 3.01 | 7.63 | 9.97 |
| SWF_CSW | 4.19 | 5.44 | 6.41 | 4.14 | 5.22 | 5.81 | 4.54 | 5.71 | 6.31 |
| SWF_CWW | 15.21 | 20.10 | 23.30 | 10.78 | 13.95 | 15.62 | 7.78 | 10.03 | 11.19 |
| WWF_GRA | 4.89 | 11.84 | 15.50 | 7.93 | 19.06 | 24.71 | 7.63 | 18.30 | 23.67 |
| WWF_CSW | 12.50 | 16.86 | 20.66 | 8.21 | 10.72 | 12.08 | 8.05 | 10.47 | 11.73 |
| WWF_CWW | 19.01 | 24.89 | 29.15 | 18.43 | 23.54 | 26.27 | 18.13 | 23.06 | 25.62 |
| CSW_GRA | 21.62 | 32.08 | 38.84 | 39.59 | 57.31 | 66.67 | 65.47 | 94.38 | 109.27 |

SWF = spring wheat fallow, WWF = winter wheat fallow, GRA = grass, CSW = continuous spring wheat, CWW = continuous winter wheat

*Represents no change in C-payment because there was no change in the 95% confidence interval lower bound in Table 4.

The percentage increase in C-credit payments per hectare, as a result of tightening the confidence intervals around the mean number of C-credits by accounting for spatial autocorrelation when measuring soil C, are shown in Table 5. Adjusting the number of hectares represented by the sample by ten percent of the range of autocorrelation could increase payments on each hectare enrolled in a C contract between zero to approximately sixty five percent depending on the C-credit price. As the percentage of autocorrelation range used to adjust the standard error is increased to fifteen percent, payments per hectare enrolled increase further by up to almost 95 percent. When 20 percent of the range of autocorrelation is used, payments for each hectare within stratum CSW_GRA in region 3 increase by more than 100 percent.

## 6 Conclusions and caveats

In this paper we develop a simple, accessible, method to reduce the standard errors and narrow the confidence intervals associated with measuring soil C-credits that could reduce the transactions costs of credit-based contracts. We demonstrate how information about the range of spatial autocorrelation could be incorporated in practice and the possible benefits that its inclusion might have to producers. Further testing and experimentation needs to be undertaken to explore the ramifications of accounting for spatial autocorrelation into a measurement scheme in practice.

Our empirical results show that accounting for spatial autocorrelation in the manner suggested here (using single sample points to represent areas) does not affect either the sample size or the costs of measuring C-credits sequestered by agricultural soils i.e., this part of transactions costs is constant each region at a particular price for C-credits (if we knew the degree of spatial autocorrelation *a priori* it would be possible to reduce sample size and transactions costs associated with sampling).

The standard error of the estimated mean C-credit accumulation per hectare by stratum were calculated for the initial sample ignoring the presence of spatial autocorrelation and then recalculated, assuming that each sample point represented an area equal to some proportion of the range of spatial autocorrelation. This adjustment greatly reduced the standard errors associated with the sample, tightened the confidence intervals, and significantly reduced transactions costs by increasing the payments received by producers for each hectare enrolled within the C-contract between zero to a maximum of 30 percent, at ten percent of range, and between zero percent to over 100 percent, at twenty percent of range. The benefits of accounting for spatial autocorrelation are not uniform across strata or regions and it is difficult to predict *a priori* which regions or strata would benefit most. Information about the range of spatial autocorrelation could be extremely valuable for reducing transactions costs associated with contracts for C-credits and maintaining the competitiveness of soil C sequestration in any future market for C-credits.

The framework presented in this paper is purely an example of a potentially low cost way of accounting for spatial autocorrelation within measurement schemes for C-credits, and is suggested in part because it uses tools that are commonly available. Further testing using more advanced techniques, such as kriging, are necessary to develop useful heuristics that can be used to implement this procedure in practice and are planned for future study. Other gaps in information that could benefit from future research are how information about spatial autocorrelation, and its effect on producer payments per hectare enrolled within a contract might alter producer behavior, particularly the decision to adopt a given practice to create C-credits.

## 7 Appendix A

We used a simple model for the spatial correlation between locations: $corr_{ij} = e^{-3d_{ij/r}}$, where $r$ represents the range of correlation, $d_{ij}$ is the distance between observations $i$ and $j$, and the $-3$ is an arbitrary (but conventional) constant that sets the correlation to be 0.05 when the interplot distance equals the range. This model is isotropic: it depends only on the distance between to points, not on their relative orientation.

The three primary models we used were: mean only (no change across the landscape), mean modeled with latitude and longitude (effectively a regression model with two predictors), and the mean modeled as a quadratic (latitude, longitude, each of them squared, and their product).

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