Available online at www.sciencedirect.com
SCIENCE DIRECT®

ACADEMIC PRESS

Journal of Environmental Economics and Management 46 (2003) 231–250

JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT

http://www.elsevier.com/locate/jeem

Spatial heterogeneity, contract design, and the efficiency of carbon sequestration policies for agriculture ☆

John Antle,[a,b,*] Susan Capalbo,[a] Siân Mooney,[c] Edward Elliott,[d] and Keith Paustian[e]

[a] Department of Agricultural Economics and Economics, Montana State University, P.O. Box 172920, Bozeman, MT 59717-2920, USA
[b] Resources for the Future, Washington, DC 20036, USA
[c] Department of Agricultural and Applied Economics, University of Wyoming, Laramie, WY 82071, USA
[d] Department of Soil and Crop Sciences, School of Natural Resource Sciences, University of Nebraska, Lincoln, NE 68583, USA
[e] Department of Soil and Crop Sciences, Natural Resource Ecology Laboratory, Colorado State University, Fort Collins, CO 80523, USA

Received 31 January 2001; revised 28 May 2002

Abstract

In this paper we develop methods to investigate the efficiency of alternative contracts for Carbon (C) sequestration in cropland soils, taking into account the spatial heterogeneity of agricultural production systems and the costs of implementing more efficient contracts. We describe contracts being proposed for implementation in the United States and other countries that would pay farmers for adoption of specified practices (per-hectare contracts). We also describe more efficient contracts that would pay farmers per tonne of soil C sequestered, and we show how to estimate the costs of implementing these more efficient contracts. In a case study of a major agricultural region in the United States, we confirm that the relative inefficiency of per-hectare contracts varies spatially and increases with the degree of spatial heterogeneity. The results also show that per-hectare contracts are as much as five times more costly than per-tonne contracts—a degree of inefficiency similar to that found in assessments of command-and-control industrial emissions regulations. Measurement costs to implement the per-tonne contracts are found to be positively related to spatial heterogeneity but are estimated to be at least an order of magnitude smaller than the efficiency losses of the per-hectare contract for reasonable error levels. This finding implies that contracting

☆ This research was supported by USDA NRIGCP Grant 00-35400-9144, by NSF Grant BCS-9980225, and by the Montana Agricultural Experiment Station.

*Corresponding author.
E-mail address: jantle@montana.edu (J. Antle).

0095-0696/03/$ - see front matter
doi:10.1016/S0095-0696(02)00038-4

parties could afford to bear a significant cost to implement per-tonne contracts and achieve a lower total cost than would be possible with the less efficient per-hectare contracts.

Keywords: Spatial heterogeneity; Contract design; Soil carbon sequestration; Policy; Efficiency; Measurement costs

1. Introduction

In anticipation of caps being imposed on emissions of greenhouse gases (GHGs) through international agreements such as the Kyoto Protocol of the United Nations Framework Convention on Climate Change, and through domestic policies, various entities have begun working towards the creation of markets for trading of GHG emissions allowances [28]. The Kyoto Protocol provides for GHG trading among industrialized countries, and national governments have begun to establish policies to reduce GHG emissions, including voluntary reductions, command-and-control regulations and market-based incentives.

Countries such as the United States with large areas of crop and forest land have the potential to offset significant amounts of GHG emissions through Carbon (C) sequestration, in above-ground biomass and in soils. Recent research shows US cropland is estimated to have the potential to sequester 75–208 MMTC/year [16], or up to 8% of US emissions.[1] In recent years both Canada and the United States proposed new policies and programs that would pay farmers for adoption of "best management practices" to sequester C in agricultural soils, and the Canadian and US governments began funding research to implement such policies [1,9,36].

Economic research has established that incentive-based approaches to environmental regulation are generally more efficient than command-and-control or design-standard regulations because of the cost differences in implementing emissions reductions across sources of pollutants [31,34], but how much more efficient incentives are depends on accounting for all benefits and costs [20]. Experience with policies for provision of environmental services from agriculture is consistent with the broader environmental regulation literature. Policies that efficiently address the environmental effects of farmers' site-specific management decisions must account for the heterogeneity of bio-physical and economic conditions that characterize agricultural systems [15]. By the same logic, policies such as those presently being proposed in Canada and the US for soil C sequestration, that mandate adoption of specified land use and management practices, are generally inefficient (see [4,5,11,13]). Explanations for the use of inefficient agricultural–environmental policies include: the high cost of information required to measure benefits on a site-specific basis; information asymmetries between government agencies and farm decision makers that result in high implementation costs; distributional effects, and political considerations [37].

Based on prior experience, there would appear to be a prima facie case in favor of policies for GHG emissions reductions working through a cap-and-trade system. It follows that efficient

[1] MMTC = million metric tons C. One metric ton (tonne) of C is equivalent to 3.66 tonnes of CO_2. Changes in land use and management practices that alter rates of change in soil C may also lead to changes in emissions of other GHGs, and these emissions can be accounted for in the overall evaluation of activities to reduce global warming using the concept of global warming potential [27]. Our analysis focuses on CO_2 but the implications of our analysis could be applied equally to an index of global warming potential if suitable data and models were available.

policies for agricultural soil C sequestration would support the participation of farmers in this cap-and-trade system by providing emissions offsets or credits through contracts that pay farmers per tonne[2] of C sequestered, and not through contracts that pay farmers to adopt specified management practices. The recent literature on C sequestration in both forestry and agricultural sectors supports this view. Parks and Hardie [21] use the opportunity costs of foregone agricultural production to show that the least cost policy for sequestering forest C by converting marginal agricultural lands to forested use is associated with bids offered on a per-tonne basis as opposed to a per-acre basis. Pautsch et al. [25] reach a conclusion similar to Parks and Hardie regarding the efficiency of per-tonne versus per-acre payment schemes for sequestering soil C by adopting different tillage practices in the Midwest. However, in an analysis of C sequestration in forests, Stavins [32] suggests that a contract based on tonnes of C sequestered for forest C projects would be prohibitively expensive to implement due to the costs associated with quantifying the amount of C sequestered. Arguably, quantifying soil C may be even more costly than C stored in above-ground biomass, considering that soil C cannot be observed in the ways that biomass can. As yet, there is little research quantifying the costs of implementing the more efficient contracts that would pay per tonne of C sequestered.

The purpose of this paper is to develop methods to investigate the efficiency of alternative types of policies or contracts for C sequestration in cropland soils, taking into account the spatial heterogeneity of agricultural production systems and the costs of implementing efficient contracts. We identify two types of costs associated with implementing soil C contracts, on-farm opportunity costs and measurement costs. In Section 2 we describe per-hectare and per-tonne contracts for soil C, and use a model of farmers' decisions to participate in soil C contracts to derive the on-farm opportunity costs for each type of contract. We also describe a prototype soil C measurement scheme based on statistical sampling methods and show how the costs of implementing these methods can be estimated.

In Section 3 we present an integrated assessment modeling framework, based on coupled site-specific bio-physical simulation models and site-specific economic data and models, that can be used to simulate farmers' decisions to participate in both per-hectare and per-tonne contracts. We use this coupled modeling framework in a case study of the dryland grain production system of the Northern Plains region of the United States. The results of this study are presented in Section 4; Section 5 summarizes our findings.

2. Soil C contracts, efficiency, and measurement costs

2.1. Soil C contracts and farmer decision making

Soil science has established that the amount of soil C at a point in time and space is a function of the bio-physical conditions at the site (soils, topography, and micro-climate) and the land-use history at the site. Typically, past conventional crop production practices caused soil C stock to decline to 50–75% of the amount present in uncultivated soils [35]. In order to increase the stock of C in the soil, a farmer must make appropriate changes in land use and management practices.

[2] Following scientific convention, we use the word tonne to denote 1000 kg.

We let C_j^i denote the soil C stock (tonnes C per hectare) on land unit j that has been managed with production system i. Thus, if a farmer uses a production system i associated with a relatively low equilibrium soil C stock (e.g., conventionally tilled corn, or wheat in a crop-fallow rotation), then the stock of soil C can be increased over time to a new level $C_j^s > C_j^i$ by adopting an alternative system s that is associated with a higher equilibrium level of soil C (e.g., corn produced with reduced tillage, or wheat in a continuous rotation).

The time path between C_j^i and C_j^s is generally nonlinear and may follow a hyperbolic or logistic-shaped trajectory, reaching a saturation point in T years. The data used in this study and from similar analysis (e.g., [14]) show that the path from C_j^i to C_j^s can be approximated as linear. Therefore, we assume that for purposes of implementing soil C contracts, the annual average rate of soil C accumulation per hectare, $\Delta c_j^{is} = (C_j^s - C_j^i)/T$, will be used to estimate the amount of C that a particular change in practices will provide. As we discuss below, a critical issue is the size of the spatial unit over which Δc_j^{is} is either estimated before a contract is agreed to or measured to verify compliance with a contract. Thus, the index j may refer to the spatial unit at which a farmer makes management decisions (i.e., a single field) or to a larger spatial unit at which measurements may be made with a sampling scheme as discussed below. For the application presented below, the data show that a value of $T = 20$ is appropriate.

We consider two types of contracts for soil C sequestration, per-hectare contracts and per-tonne contracts. The per-hectare contract provides incentive payments to producers for each hectare of land that is switched from a production system associated with a relatively low equilibrium level of soil C to a system associated with a higher equilibrium level of soil C. Thus, the key feature of the per-hectare contract is that the payment per hectare is the same for all land under contract that uses a specified technology (often referred to as a best management practice), regardless of the amount of C that is actually sequestered as a result. Typically, we would expect that per-hectare contracts will require that farmers establish what practices they have used in the past, will specify which practices the farmer must adopt over the duration of the contract, and will specify the payments made for compliance with the terms of the contract. In order to enforce compliance with the contract, land use and management practices specified in the contract will be monitored on a periodic basis.

The per-tonne contract pays farmers a specified price P for each tonne of C that is accumulated and maintained in the soil for the duration of the contract, regardless of what management practices are used. Allowing farmers to choose the most efficient production technology at each site, rather than specifying a best management practice, is the feature that causes the per-tonne contract to be more efficient than the per-hectare contract. To implement per-tonne contracts, it is necessary to quantify the amount of C added to the soil over the duration of the contract, hence it is necessary to establish the baseline amount of C in the soil at the beginning of the contract and the time path of soil C accumulation over the duration of the contract. Because soil C cannot be observed directly, procedures for measuring the baseline levels of soil C and the amount accumulated must be established, as we discuss in detail below. Moreover, because of the typically low annual rates of soil C accumulation, it is only possible to measure soil C changes with a reasonable degree of accuracy at intervals such as 5 years [35]. Therefore, farmers entering into per-tonne soil C contracts face the problem of estimating how much they will earn from the contracts, and buyers of C credits from farmers face a similar challenge of estimating how much soil C they can expect to take credit for.

To resolve this ex ante uncertainty about the amount of soil C that will be produced under a per-tonne contract, we assume that the contracts operate as follows: First, buyers of soil C credits specify a price per tonne of carbon, P, that they are willing to pay (for this discussion we assume this is a constant for the duration of the contract, but this could also be specified to change over time). Second, based on available data (e.g., from independent entities such as a government agency) farmers and buyers agree upon a schedule of expected C accumulation rates $E[\Delta c_j^{is}]$ for all production systems i actually in use and for all feasible production systems s that farmers could adopt. Based on this schedule, farmers choose what practices they will use and receive P dollars for each expected tonne C they produce per time period according to this schedule. Subsequently, measurements are made to estimate actual C rates Δc_j^{is}, and farmers receive additional compensation if $\Delta c_j^{is} > E[\Delta c_j^{is}]$ or refund some of the payments they have received if $\Delta c_j^{is} < E[\Delta c_j^{is}]$.[3]

The efficiency of the per-tonne contracts is likely to depend on the spatial scale at which the measurements Δc_j^{is} are made. If the measurements are made at the same scale as farmers make management decisions (i.e., at the field scale), then the per-tonne contracts are fully efficient in the sense that farmers have an incentive to adopt the most efficient practice on each land unit. However, as we discuss below, measurement could be costly and it may not be feasible to measure C accumulation on each contracted field. Instead, a sampling procedure may be used to estimate the average C accumulation for each practice in a relatively homogeneous agroecozone (farmers' practices also would be monitored in the same manner as in a per-hectare contract to verify that they have used the practice for which they take credit). In this case, the per-tonne contracts can be expected to be somewhat less efficient than when C accumulation is measured at each site, because farmers know they will only get credit for the average measured accumulation for the practice they use. Likewise, because it is only possible to model farmer behavior in an ex ante sense (we can't observe what they actually do in response to prospective policies), we can expect that our estimates of farmers' behavior will tend to understate the true dynamic efficiency of the per-tonne contracts, as is the case with all such modeling exercises [12,31].

We assume that land in a region is heterogeneous with respect to both bio-physical and economic characteristics. To represent bio-physical heterogeneity we introduce a site-specific vector of environmental characteristics $\mathbf{e}_j$, for $j = 1, \ldots, J$ land units in the region. Economic heterogeneity (due to transportation costs, transactions costs and market imperfections) is represented by indexing output prices (p), input prices ($\mathbf{w}$, generally a vector) and capital services $(\mathbf{z})$ by site. The expected profit function for production system i in year t can then be written $\pi_{jt}^i = \pi^i(p_{jt}^i, \mathbf{w}_{jt}^i, \mathbf{e}_j, \mathbf{z}_{jt}^i)$. Changes in management practices from system i to system s may involve both fixed costs (e.g., for the acquisition of new machinery or tools) and variable costs (changes in input use, etc.). In addition, the farmer receives a financial payment for participation in the C contract. In the case of a per-hectare contract, the farmer receives g dollars per hectare per period for adopting a specified practice regardless of how much C is sequestered. In the case of a

[3] In this analysis we maintain the assumption of risk neutrality, but the extension to the case of risk aversion is straightforward.

per-tonne contract, the farmer receives a payment of P dollars per tonne of C sequestered each time period, so if the farmer changes from system i to system s and receives credit for increasing soil C by Δc_j^{is} tonnes per hectare per period, the farmer receives a payment of $P\Delta c_j^{is}$ per hectare per period. Thus, a farmer who enters into a per-hectare or per-tonne contract to switch from system i to system s for T periods earns an expected net present value (NPV) of[4]

$$\mathrm{NPV}_j^{is} = \sum_{t=1}^{T} D_t[\pi^s(p_{jt}^s, \mathbf{w}_{jt}^s, \mathbf{e}_j, \mathbf{z}_{jt}^s) + g_j^{is}] - I^{is}, \tag{1}$$

where $D_t = (1/(1+r))^t$ and r is the annual interest rate, $\pi^s(p_{jt}^s, \mathbf{w}_{jt}^s, \mathbf{e}_j, \mathbf{z}_{jt}^s)$ = net returns for system s in period t, given product price p_{jt}^s, input price vector $\mathbf{w}_{jt}^s$, bio-physical factors $\mathbf{e}_j$, and capital services $\mathbf{z}_{jt}^s$ (\$/ha/year), $g_j^{is} = g$ if a per-hectare contract (\$/ha/year) $= P\Delta c_j^{is}$ if a per-tonne contract (\$/ha/year), I^{is} = fixed cost for changing from system i to system s (\$/ha/year).

If the farmer does not participate in the contract and continues producing with system i, then $g_j^{is} = 0$, $I^{is} = 0$, and the farmer earns a net present value NPV_j^i. The farmer enters the contract if and only if $\mathrm{NPV}_j^{is} > \mathrm{NPV}_j^i$, and does not enter the contract otherwise.

In the special case where expected net returns and P are constant over time, and the fixed cost of changing practices is equal to zero, the condition for entering into a contract can be simplified to $\pi_j^s + g_j^{is} > \pi_j^i$.[5] Rearranging, this equation becomes

$$g_j^{is} > \pi_j^i - \pi_j^s. \tag{2}$$

The expression on the right-hand side is the on-farm opportunity cost for switching to system s from system i, so Eq. (2) shows that the farmer will benefit from the contract when the farm opportunity cost is less than the contract payment per period. The condition for a farmer to participate in a per-hectare contract is simply $g > \pi_j^i - \pi_j^s$, showing that the decision is independent of the amount of C sequestered. In the case of a per-tonne contract, $g_j^{is} = P\Delta c_j^{is}$ and therefore the condition for participation in the contract can be expressed as $P > (\pi_j^i - \pi_j^s)/\Delta c_j^{is}$. Thus, the farmer will participate when the price per-tonne C offered by the contract is greater than the farm opportunity cost per tonne.

As we shall discuss below, implementation of a per-tonne contract is expected to necessitate certain soil C measurements and associated costs. If the farmer is required to pay these costs, then they can be annualized over the life of the contract and added to the cost side of the contract participation decision. These costs would increase the compensation that farmers would have to receive in order to be willing to participate in a C contract. Alternatively, if the buyer has to pay these costs, the net price the buyer would be willing to pay to the farmer will be reduced.

[4] Plantinga et al. [26] and Stavins [32] discuss discounting C quantities to account for a declining future marginal social value of reducing greenhouse gases. The discounting used here is the conventional discounting of future money values in a present value calculation.

[5] In the application below, the fixed costs of changing practices are in fact zero. In other cases, they will be positive and can be incorporated into the decision accordingly.

2.2. Opportunity costs and efficiency

The marginal opportunity cost of sequestering soil C in each region is constructed by ordering all land units according to farm opportunity cost per tonne of soil C, and then aggregating the quantity of soil C produced at each marginal opportunity cost. Following the theory of the first-best optimal Pigouvian subsidy (e.g., see [4,6,10,29]), it follows that the per-hectare contract design is generally less efficient than the per-tonne contract in the following sense: for each quantity of soil C sequestered in a region, the marginal opportunity cost of the per-hectare contract (MC_H) is greater than or equal to the marginal opportunity cost of the per-tonne contract (MC_T). This divergence between MC_H and MC_T is explained by the spatial heterogeneity in the region. Note that as the payments for participation in C contracts increase, more land would be entered into either type of contract. Therefore, as payments increase, the groups of land units under each type of contract become more similar and the difference between MC_H and MC_T decreases. In the case where only one management practice is used to increase soil C, at the point where all land units participate in contracts, the two marginal cost curves coincide because the marginal opportunity cost for both types of contract must be equal. More generally, when different practices can be used by farmers under the two contracts, the per hectare marginal cost approaches but need not coincide with the per hectare marginal cost. It also follows that in the limiting case of spatial homogeneity the two marginal cost curves coincide at every level of soil C.

This discussion suggests a useful measure of the relative efficiency of the two types of contracts: for a given quantity of carbon, we can interpret the ratio $0 < (MC_T/MC_H) \leqslant 1$ as a measure of the relative efficiency of the per-hectare contract to sequester that amount of C in a given region, where relative efficiency increases as the ratio increases. We can use this measure to quantify the relationship between the relative efficiency of per-hectare contracts and the degree of spatial heterogeneity of the bio-physical and economic characteristics of the land units. We measure spatial heterogeneity using the coefficient of variation of the opportunity cost per tonne of C. This measure embodies the degree of spatial heterogeneity in both bio-physical and economic conditions, since MC_T depends on the spatially varying soil C rates and on economic conditions at each site.

2.3. Costs of measuring soil carbon

Following the contract design outlined in the preceding section, implementation of per-tonne contracts requires measurement of the C accumulation associated with a change in management practices. We assume that both per-hectare and per-tonne contracts will require similar contracting costs for contract negotiation, etc. The key difference between the costs of implementing the two contracts will be the additional costs associated with measuring C accumulation over the duration of the per-tonne contracts. To implement the per-tonne contracts, we assume the following procedure is followed:

1. *Determination of agroecozones* $m = 1, \ldots, A$: These agroecozones are identified using baseline bio-physical data (see Section 3) and are used as the basis for the sampling procedures to quantify C accumulation.

2. *Determination of baseline carbon levels*: Expected baseline C levels $E[C_m^i]$ for the ith production system and mth agroecozone are obtained from existing estimates of soil C from the literature and simulation models such as the Century model (Section 3). The expected average annual rate of C sequestration for a change from system i to system s over T years is then estimated to be $E[\Delta c_m^{is}] = \{E[C_m^s] - E[C_m^i]\}/T$.
3. *To verify compliance with contracts, statistical methods are used to sample land units within each agroecozone for carbon measurements*: The measured baseline C stock for a hectare under the ith system is $C_m^i = E[C_m^i] + v_m^i$ where v_m^i is a random measurement error with zero expectation. The measured C rate for changing from system i to system s over T years is therefore a random variable $\Delta c_m^{is} = (C_m^s - C_m^i)/T$ with mean $E[\Delta c_m^{is}]$ and a variance that is a function of the variances and covariances of the v_m^i.

Several sampling designs can be used to implement step 3, including simple random, stratified and cluster sampling [17,33]. Stratified random sampling has been used to measure C sequestration in forest projects [7,8]. Using a stratified sampling approach, the population of each agroecozone m, defined as all hectares that participate in contracts, can be divided into groups or strata representing the hectares that switch from system i to system s. McConkey and Lindwall [18] and Brown et al. [8] discuss appropriate sampling frequencies for C measurements. The cost per sample can be estimated using data on labor costs, variable input costs, and laboratory costs. A detailed description of the stratified random sampling protocol and data used to derive the measurement costs reported in this paper can be found in Mooney et al. [19]. This protocol shows that the per-tonne measurement costs for implementing a per-tonne contract are

$$M_{\mathrm{T}}(P, \varepsilon, Z) = n(P, \varepsilon, Z)SY/C, \tag{3}$$

where n (sample size) is a function of P (carbon price per tonne), ε (measurement error) and Z (confidence level); S is the cost per sample and Y is the frequency of sampling. In Section 4 we combine these costs with the on-farm opportunity costs to compare efficiency of per-tonne contracts to the efficiency of per-hectare contracts.

3. Integrated assessment model

Our approach utilizes the output of two disciplinary models—a crop ecosystem model and an econometric-process simulation model—to quantify farmers' responses to economic incentives for sequestering soil C on a site-specific basis. This approach integrates spatial heterogeneity in both bio-physical (soil C rates) and economic (land use and management) conditions, and can be used to determine the marginal cost of sequestering C in soil. We use a site-specific econometric-process model to simulate changes in farmers' land use or management in response to economic incentives offered to sequester soil C under per-hectare and per-tonne contracts. We use a crop ecosystem model (Century) to estimate the resulting changes in soil C rates by agroecozone for both contracts.

3.1. Econometric-process model

Econometric-process simulation models were developed to assess the economic and environmental impacts of changes in agricultural production systems [2]. In this approach, site-specific data are used to estimate econometric-production models, and these models are used to parameterize a stochastic simulation model. The simulation model represents the decision-making process of the farmer as a sequence of discrete and continuous land use and input use decisions using the specifications from the econometric-production models. This discrete/continuous structure of the econometric-process model is able to simulate decision making both within and outside the range of observed data in a way that is consistent with economic theory and with site-specific bio-physical constraints and processes. This method provides the capability to simulate the changes in the spatial distribution of land use and cropping practices within a given agroecozone and resulting changes in soil C levels in response to the per-hectare and per-tonne incentives.

Following the earlier notation (Eqs. (1) and (2)), we summarize the formal statement of the farmer's decision problem as follows: within agroecozone m, let $\delta_j^s = 1$ if system s is used on land unit j and let $\delta_j^s = 0$ otherwise, define $\delta_j = \Sigma_s \delta_j^s$. A farmer located in agroecosystem m who used system i up to the present will choose a system in the present periods according to

$$\max_{\{\delta_j^s\}} \Sigma_s \delta_j^s \{\pi_j^s(p_j^s, \mathbf{w}_j^s, \mathbf{e}_j, \mathbf{z}_j^s) + g_m^{is}\} + (1 - \delta_j)\pi_j^i(p_j^i, \mathbf{w}_j^i, \mathbf{e}_j, \mathbf{z}_j^i), \quad j \in m. \tag{4}$$

For the per-hectare contract, $g_m^{is} = g$, so the solution takes the form of the step function

$$\delta_j^{*s} = \delta^s(\mathbf{p}_j, \mathbf{w}_j, \mathbf{e}_j, \mathbf{z}_j, g), \tag{5}$$

where $\mathbf{p}_j$ is a vector of the output prices, and likewise for the other vectors. For the per-tonne contract, $g_m^{is} = P\Delta c_m^{is}$, so letting $\Delta c_m^i = (\Delta c_m^{i1}, \ldots, \Delta c_m^{iA})$ for the $s = 1, \ldots, A$ alternative systems, the solution is

$$\delta_j^{*s} = \delta^s(\mathbf{p}_j, \mathbf{w}_j, \mathbf{e}_j, \mathbf{z}_j, P, \Delta c_m^i), \quad j \in m \tag{5$'$}$$

showing that decisions under a per-tonne contract generally depend on the price of carbon, P, and on the expected carbon rates associated with all of the management options available to the farmer. Using Hotelling's lemma, for the per-hectare contracts the quantity of the sth output on the jth land unit is given by

$$q_j^s = \delta_j^{*s} \partial\pi^s(p_j^s, \mathbf{w}_j^s, \mathbf{e}_j, \mathbf{z}_j^s)/\partial p_j^s = q_j^s(\mathbf{p}_j, \mathbf{w}_j, \mathbf{e}_j, \mathbf{z}_j, g). \tag{6}$$

Variable input demands for the kth input are likewise given by

$$v_{kj}^{*s} = -\delta_j^{*s} \partial\pi^s(p_j^s, \mathbf{w}_j^s, \mathbf{e}_j, \mathbf{z}_j^s)/\partial w_{kj}^s = v_{kj}^s(\mathbf{p}_j, \mathbf{w}_j, \mathbf{e}_j, \mathbf{z}_j, g). \tag{7}$$

For per-tonne contracts, g is replaced in Eqs. (6) and (7) by P and Δc_m^i.

The econometric-process approach combines the econometric-production model represented by the supply and demand functions given in (6) and (7) with the process-based representation of the discrete land-use decision represented by (4) and (5). The model simulates the producer's crop choice, and the related output and costs of production at the field scale over time and space. This simulation structure utilizes the stochastic properties of the econometric models and the sample data, so it provides a statistical representation of the population of land units in the region. The simulations can represent spatial and temporal differences in land use and management, such as crop rotations, that give rise to different economic outcomes across space and time. Moreover, because of the detailed representation of the production system, the econometric-process model can be linked directly to the corresponding simulations of the crop ecosystem model to estimate the impacts of production system choice on soil C.

The econometric-process model, like other spatial econometric models in the literature, can be used to analyze price responses by simulating alternative price or policy scenarios (e.g., [25,26,32]). However, the econometric-process approach departs from most other spatial econometric models used to study land use changes in several respects. First, the econometric-process approach uses site-specific (field-scale) data, so it can be used to simulate changes in the spatial distribution of land use and management in ways that models based on aggregated data and representative agent models cannot do. Second, this approach represents the production process explicitly and therefore can be linked directly to bio-physical crop growth and environmental process models to incorporate bio-physical information such as impacts of soil and climate conditions on crop productivity and soil C.

The econometric-production model described above was estimated using cross-sectional data from a sample of 425 farms and over 1200 fields for the 1995 crop-year that are statistically representative of the USDA's Major Land Resource Areas (MLRAs) in the grain-producing regions of Montana. Log-linear supply functions and cost functions for winter wheat, spring wheat, and barley were estimated using nonlinear three stage least squares with zero-degree homogeneity of the supply function and linear homogeneity of the cost function imposed. The major crops include spring wheat, winter wheat, and barley, and the two principle production systems include crop-fallow or continuous cropping. Crop rotations play a critical role in maintenance of soil quality and productivity, and affect soil C accumulation. The productivity and soil C effects of crop rotations are modeled on a site-specific basis, because their representation requires site-specific data on the history of land use. Data and parameter estimates are described in [2].

3.2. Century crop-ecosystem model and estimated soil C rates by system

The soil C rates used to represent the contract rates were derived from the Century ecosystem model (see [22–24]). Century is a generalized biogeochemical ecosystem model that simulates C, nitrogen and other nutrient dynamics. It includes sub-models for soil biogeochemistry, growth and yield sub-models for crop, grass, forest and savanna vegetation, and simple water and heat balance. The model employs a monthly time step and the main input requirements (in addition to management variables) include monthly precipitation and temperature, soil physical properties (e.g. texture and soil depth) and atmospheric nitrogen inputs.

The three MLRAs represented in the production data were each stratified into two sub-zones (sub-MLRAs), based on high or low precipitation according to historical climate data, giving a total of six sub-MLRAs. Soils and climate data were collected for the six sub-MLRAs. In addition, crop rotation, fertilization and tillage practices are used as inputs into Century. Century calculates average changes in soil C stocks within each sub-MLRA over a 20-year period from winter wheat, spring wheat and barley in addition to grass (the non-crop land use, used for conservation or livestock grazing). For analytical convenience the soil C rates for each change in production system are assumed to be the same within each sub-MLRA, but differ across the sub-MLRAs.

The Century model estimates of the C rates for each sub-MLRA are presented in Table 1. For the five systems considered in our analysis these rates range from 0.06 to 0.68 tonnes per hectare per year (for those changes having positive rates). This range is consistent with summary data compiled by the Intergovernmental Panel on Climate Change for these types of systems and bio-physical conditions [35]. Generally, there is an increase in soil C associated with changes from crop-fallow production systems to permanent grass cover or to continuous cropping systems. There are also changes in soil C possible by changing between grass, spring wheat and winter wheat regardless of rotation.

3.3. Simulation model implementation

To implement the econometric-process simulation model, each field in the data is described by its size, location, and an associated set of location-specific prices paid and received by the farmer. Based on draws from sample distributions estimated from the data, type of tillage, use of crop insurance, and previous crop are selected to initialize the model. The econometric models are simulated to estimate expected output and cost of production, and to then calculate expected returns above short run variable costs of production for each crop alternative or system on each field in each time period.

Each time period has two decision nodes based on the maximization of expected returns: the first is a land-use decision made in the fall regarding planting a winter wheat crop, producing a spring crop, or fallowing the field. If winter wheat is not grown, the model advances to the second decision node, which is a spring land-use decision, where spring wheat, barley, or fallow options

Table 1
Average annual C rates for changes in cropping system, by sub-MLRA (Δc_m^{is})

System change		m = Sub-MLRA					
i = initial system	s = subsequent system	52-high (MT/ha/year)	52-low (MT/ha/year)	53A-high (MT/ha/year)	53A-low (MT/ha/year)	58A-high (MT/ha/year)	58A-low (MT/ha/year)
SF	WF	0.10	0.09	0.09	0.06	0.12	0.15
SF	GR	0.26	0.31	0.30	0.21	0.44	0.29
SF	SR	0.44	0.32	0.33	0.29	0.48	0.36
SF	WR	0.53	0.27	0.38	0.26	0.68	0.49
WF	GR	0.16	0.22	0.21	0.15	0.32	0.15
WF	SR	0.34	0.23	0.24	0.23	0.36	0.22
WF	WR	0.44	0.18	0.29	0.20	0.56	0.34
GR	SR	0.18	0.01	0.03	0.08	0.04	0.07
GR	WR	0.27	−0.04	0.07	0.06	0.24	0.19
SR	WR	0.09	−0.05	0.04	-0.03	0.20	0.12

Note: SF = spring wheat after fallow; WF = winter wheat after fallow; GR = grass; SR = spring wheat following a crop; WR = winter wheat following a crop. Barley is treated in the same way as spring wheat and has the same carbon values.

are selected based on expected returns maximization. For expected returns calculations, it is assumed that if a field is fallowed in the current season then a crop is produced the following season, as is typically the case, with next season's expected returns discounted to the present. Likewise, for calculation of expected returns for crops on fallow, costs of production include the current costs of production plus the previous season's fallow costs compounded to the present. When net returns above variable cost are less than the return to a non-crop use, this alternative land use is selected. This could correspond to idling the land (as opposed to fallow, which means the land is part of an ongoing crop rotation), use of the land for grazing, or putting it in a conserving use. At the end of each crop cycle, the current decisions are saved, and the simulation moves to the beginning of the next crop cycle. The simulation model was calibrated to predict the observed mean frequencies of crops produced in the sample data. For details, see Antle and Capalbo [2].

4. Spatial heterogeneity and the costs of C sequestration

We now apply the framework described above to an analysis of the costs of sequestering soil C. We use the resulting marginal costs of sequestering soil C to quantify the inefficiency of per-hectare contracts in the dryland grain production systems of the Northern Plains region of the United States, and relate this inefficiency to a measure of spatial heterogeneity. We also apply the methods of Section 2.3 to estimate the measurement costs for implementing per-tonne contracts. These estimates are used to assess which type of contract is most efficient when both farm opportunity costs and contract costs are taken into consideration.

We define per-hectare contracts as a fixed payment per hectare per year for changing from a crop-fallow rotation to a continuous crop rotation. Thus, under the per-hectare contracts, the net returns to system i (crop-fallow rotation) are π_j^i and the returns to system s (continuous rotation) are $\pi_j^s + g$. In the simulations, farmers are offered payments ranging from $g = \$5$ per-hectare per year to $g = \$50$ per hectare per year in \$5 increments for switching from a crop fallow to a continuous rotation. These payments do not vary across sub-MLRAs or across production practices. Under the per-tonne contracts, in agroecozone m the returns for land switched from any system i to any system s are $\pi_j^s + P\Delta c_m^{is}$, where a farmer who formerly used system i may choose any system s that is associated with a higher equilibrium level of soil C. As described in Section 2, in the simulations producers base their decisions on anticipated carbon rates given in Table 1. Model simulations are run for $P = \$10/\text{tonne}$ to \$100/tonne in \$10 increments.

The marginal cost per-tonne C sequestered for each payment level and type of contract in each sub-MLRA is presented in Fig. 1. For the per-hectare contracts, the marginal cost per tonne (MC_H) is found by converting the payment per hectare into an implicit cost per tonne of soil C using the corresponding soil C rates from the Century model. As discussed earlier (Section 2.2), in each area the marginal cost is lower for the per-tonne contracts than the per-hectare contracts; and as the quantity of C increases, the marginal cost curves for the two contracts converge. Within a given sub-MLRA the vertical distance between the marginal cost curves provides an estimate of the relative inefficiency of the per-hectare contracts, excluding measurement costs.

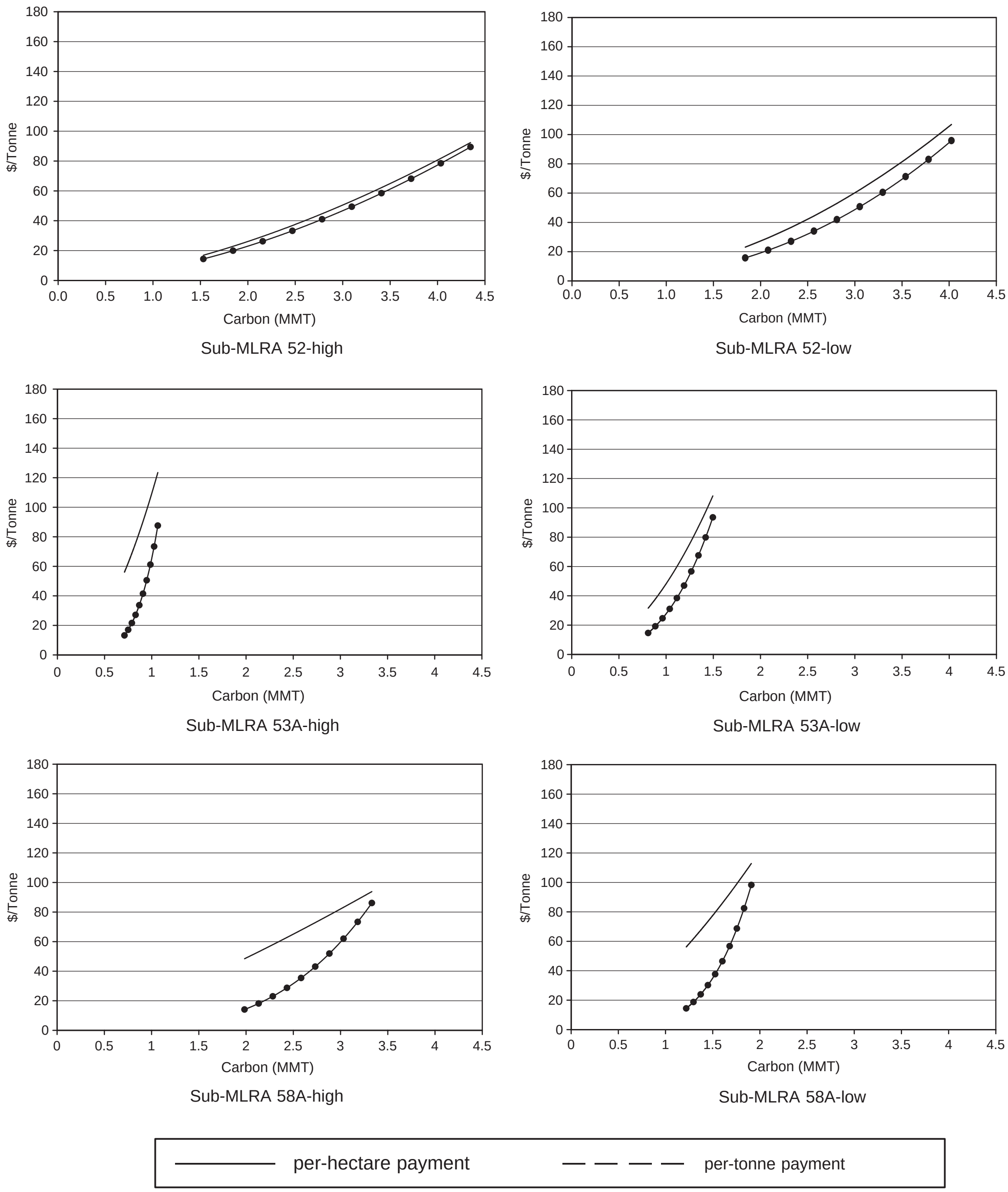

Fig. 1. Marginal cost of per-hectare and per-tonne contracts for C sequestered over 20 years.

Fig. 2 presents a plot of the measure of relative efficiency of the per-hectare contracts (MC_T/MC_H) against the spatial heterogeneity as measured using the coefficient of variation of the opportunity cost per tonne of C, for those fields that are receiving the payment. Within each sub-MLRA, each point corresponds to a different per-hectare payment or carbon price. Fig. 2 shows that there is a negative relationship between payment levels and spatial heterogeneity within each sub-MLRA. As payment levels (or C prices) increase the two marginal cost curves converge in each area, so (MC_T/MC_H) increases and approaches 1.0; and the opportunity costs increase as payment levels (or C prices) increase, reducing the coefficient of variation in opportunity costs. In addition, Fig. 2 shows that the sub-MLRAs with the lowest spatial heterogeneity tend to exhibit the highest relative efficiency of per-hectare contracts. Sub-MLRA 52-high exhibits the highest relative efficiency across the range of payment levels, and this sub-MLRA is associated with lowest levels of spatial heterogeneity. Conversely, areas such as sub-MLRAs 58A-low and 58A-high exhibit much lower relative efficiency and have higher levels of spatial heterogeneity. Thus the empirical results in Fig. 2 confirm the negative relationship between relative efficiency (MC_T/MC_H) of per-hectare contracts and spatial heterogeneity.

4.1. Carbon measurement costs and contract efficiency

The results in Fig. 2 indicate that the marginal cost per tonne of soil C sequestered under the per-hectare contracts is as much as five times higher than the marginal cost using the per-tonne contracts in some agroecozones. The measure of relative efficiency of per-hectare payments,

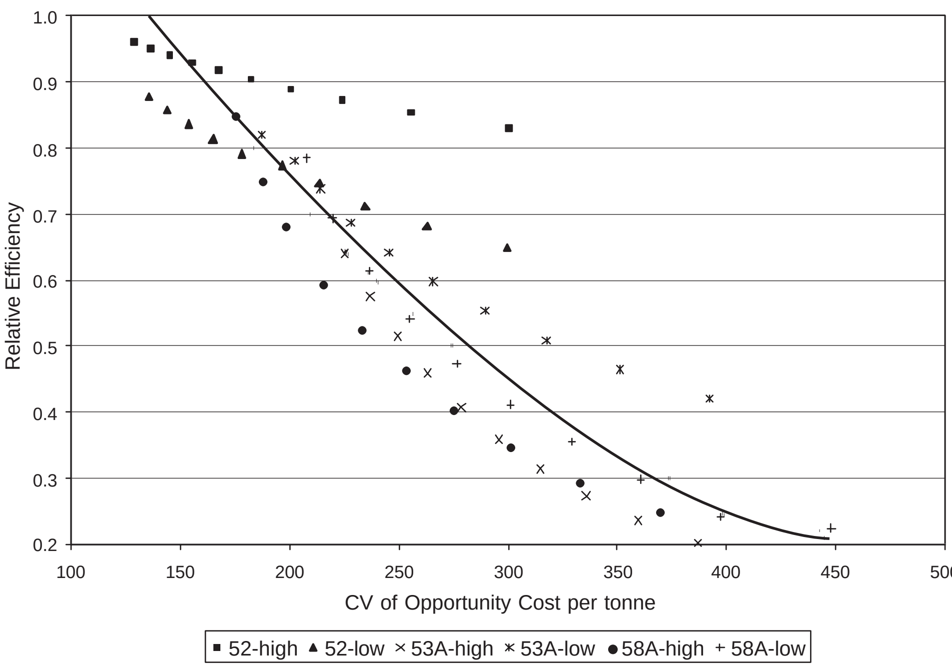

Fig. 2. Relative efficiency (MC_T/MC_H) of per-hectare contracts and spatial heterogeneity of opportunity cost per-tonne C (solid line is trend fitted through all points).

MC_T/MC_H, ranges from 0.2 to 0.95 over the sub-MLRAs (Fig. 2). This finding implies that contracting parties could afford to bear a significant cost to implement the per-tonne contract in terms of measurement costs in the more spatially heterogeneous regions and still achieve a lower total cost per tonne of soil C than would be possible with the per-hectare contract. To assess this possibility more precisely, in this section we compare the measurement costs for implementing the per-tonne contracts, M_T, to the relative efficiency costs of the per-hectare contracts.

Following the procedures presented in Section 2.3, a sampling scheme was developed to estimate measurement costs under a per-tonne contract at C prices ranging from \$10 to \$100 per tonne. The sample sizes within each sub-MLRA required to achieve a 10% sampling error with 95% confidence for a \$30 per-tonne payment are presented in Table 2. Sub-MLRA 52-high requires a sample size that is approximately 0.2% of the contract population compared with the more heterogeneous sub-MLRA 58A-low which needs a corresponding sample size over twice that in percentage terms. Sample size is positively related to the spatial heterogeneity of an area as discussed in [19].

The complete set of assumptions and data sources used to calculate these estimates for n and S are discussed in [19] and are available from the authors. We assume that over the 20-year project lifetime each hectare is sampled four times, first to establish baseline C estimates, twice more for measurement in years 5 and 10 and finally at the conclusion of the contract. The cost for a single sample is estimated at \$16.37, a value similar in magnitude to the costs per sample of approximately \$25 reported by Smith [30] for a project in eastern Oregon.

Table 3 presents the estimates of the measurement costs per tonne based on the \$30 per-tonne payment, for the samples corresponding to 10% and 5% errors and for the contract population of hectares in each sub-MLRA. The latter would correspond to a 0% sampling error and places an upper bound on the magnitude of the measurement costs for the assumed frequency and estimated sample cost S. These costs range from \$0.02 per tonne to a maximum of \$10.60 per tonne. Although not shown in Table 3, cost calculations for payment levels from \$10 to \$100 per tonne bracket those reported in Table 3 and range from about \$0.01 per tonne to \$0.20 per tonne based on the sample size required to achieve a 10% sampling error, and from about \$0.036 to \$1.057 for a 5% sampling error. As the sampling error approaches zero, the costs increase rapidly,

Table 2
Contract population, sample size, and coefficient of variation of soil C rates by sub-MLRA

Sub-MLRA	Contract population (ha)	Sample size (ha)	Weighted mean soil C rate over 20 years (tonnes/ha)[a]	Weighted standard deviation of soil C rates (tonnes/ha)	Coefficient of variation of soil C rates
52-high	277,276	683	8.05	10.72	1.33
52-low	388,611	1630	5.62	11.58	2.06
53A-high	131,646	735	6.23	8.63	1.39
53A-low	197,904	2703	4.90	13.09	2.67
58A-high	271,842	864	8.72	13.07	1.50
58A-low	232,889	1199	5.97	10.56	1.77

[a] Mean change in C rates over 20 years within each stratum, weighted by stratum size.

Table 3
Marginal costs and measurement costs, by Sub-MLRA, for $30 per-tonne payments, 95% confidence

Sub-MLRA	Carbon quantity (MMT)	Marginal cost per-tonne policy ($/tonne)	Sample measurement cost (10% error) ($/tonne)	Sample measurement cost (5% error) ($/tonne)	Population measurement cost (0% error) ($/tonne)	Marginal cost per-hectare policy ($/tonne)
52-high	2.23	30	0.019	0.076	8.150	33.21
52-low	2.58	30	0.046	0.182	9.875	40.52
53A-high	0.92	30	0.057	0.224	9.404	83.69
53A-low	1.00	30	0.175	0.672	12.921	50.20
58A-high	2.54	30	0.023	0.091	7.012	65.56
58A-low	1.44	30	0.054	0.213	10.598	72.96

so that when the full population is measured (a 0% error) costs range from $6 to $18 per tonne [19].

Combining the marginal cost information (Fig. 2) with the measurement cost (M_{T}) data in Table 3 (also see Eq. (3)), it follows that per-tonne contracts are more (less) efficient than per-hectare contracts according to $\mathrm{MC_T} + M_{\mathrm{T}} < (>) \mathrm{MC_H}$. Dividing by $\mathrm{MC_H}$ we obtain

$$M_{\mathrm{T}}/\mathrm{MC_H} < (>) [1 - \mathrm{MC_T}/\mathrm{MC_H}]. \tag{8}$$

To determine the efficient policy, we plot the relative measurement costs to implement per-tonne contracts, $M_{\mathrm{T}}/\mathrm{MC_H}$, and the relative inefficiency cost of the per-hectare contract, $(1 - \mathrm{MC_T}/\mathrm{MC_H})$, as a function of per-tonne payment levels (Fig. 3).

Since $M_{\mathrm{T}}/\mathrm{MC_H}$ is a function of both payment levels and error levels at a given confidence level, there is a relative measurement cost curve for each error level; the curves for 10% sampling error and 0% sampling error are plotted in Fig. 3 for each sub-MLRA (note the 10% error curves are close to the horizontal axis). At each payment level, the vertical distance between the relative measurement costs and the relative inefficiency cost of the per-hectare contract indicates the efficiency of the per-tonne contract. In sub-MLRA 58A-high, for example, at a per-tonne payment level of $30 and for a sampling error of 10%, the per-tonne policy is still approximately 50% more efficient relative to the per-hectare contracts; at a zero sampling error the efficiency of the per-tonne contract over the per-hectare contract decreases to approximately 40%.

Taken together, Table 3 and Fig. 3 show two key results: first, measurement costs based on a sample size corresponding to a 10% and 5% sampling error and 95% confidence level are at least one order of magnitude smaller than the efficiency cost associated with the per-hectare contract for all sub-MLRAs. Thus, at reasonable error levels, buyers of soil C could afford to implement the per-tonne contract in each sub-MLRA. Second, there is a ‘‘break-even’’ sampling error level at which the per-hectare and per-tonne contracts are equally efficient in each area. In sub-MLRA 52-high where spatial heterogeneity is low and the efficiency loss of the per-hectare contract is low, at an error level near zero it would never pay to invest in measurement costs to implement a per-tonne contract at any payment level. In contrast, in sub-MLRA 52-low where heterogeneity is somewhat greater this break-even error level is equal to zero for a per-tonne C payment of about $60. If the price per tonne of C is less than $60, the sampling error for verifying C would have to increase to make the per-tonne contract be more efficient. In the other sub-MLRAs, where

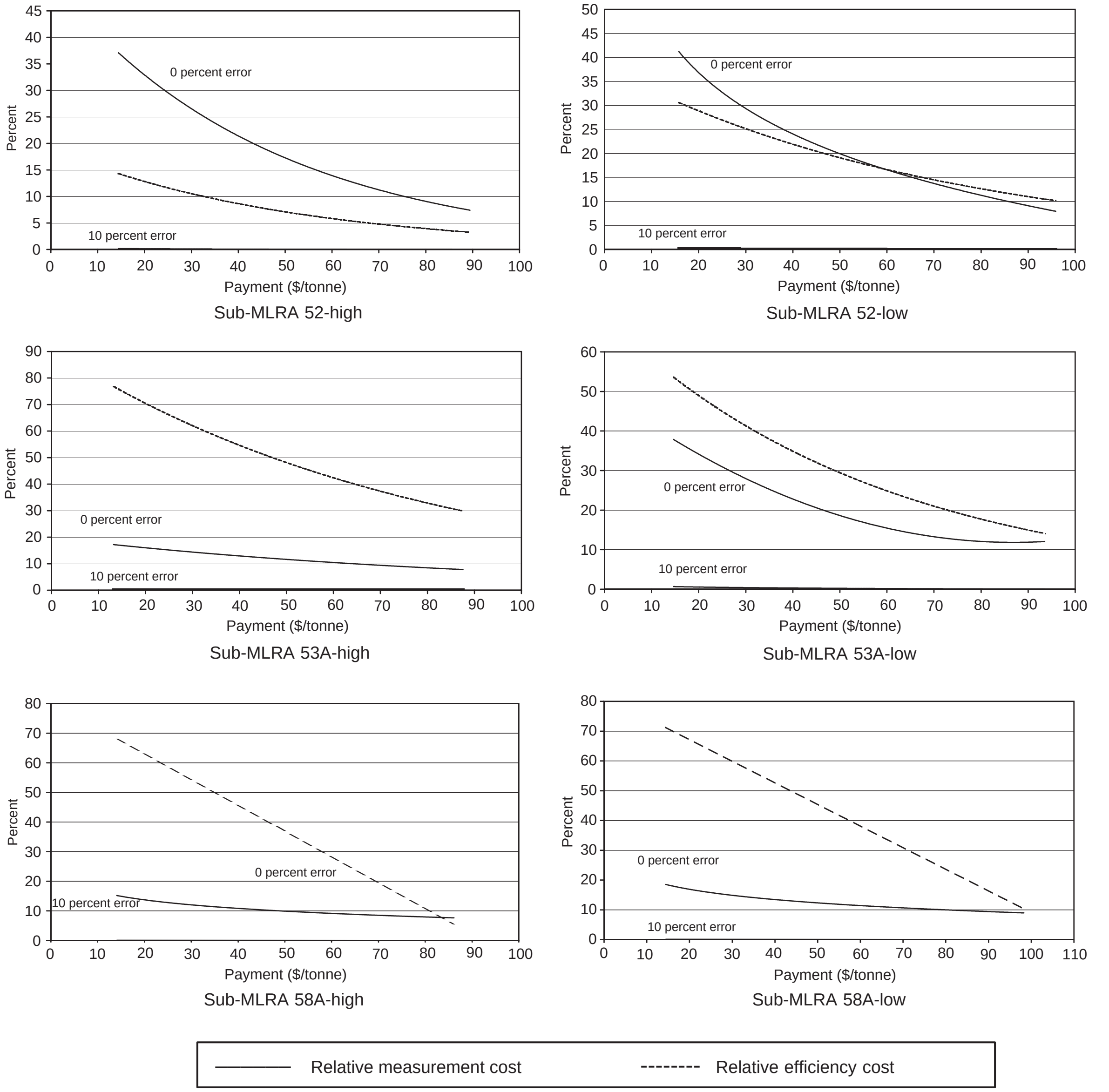

Fig. 3. Relative measurement cost of per-tonne contracts $(M/\mathrm{MC_H})$ and relative efficiency cost of per-hectare contracts $(1 - \mathrm{MC_T}/\mathrm{MC_H})$.

heterogeneity is high, it pays to reduce measurement error to the zero over the range of payments that were simulated up to a payment level of about $85 per tonne. In other sub-MLRAs the break-even error level falls somewhere between 0% and 10%, as demonstrated by the fact that the relative efficiency cost curve falls between the relative measurement cost curves for 0% and 10% sampling errors.

5. Conclusions

The purpose of this paper is to develop methods to investigate the efficiency of alternative types of policies or contracts for C sequestration in cropland soils, taking into account spatial heterogeneity of agricultural production systems and the costs of implementing efficient contracts. We apply those methods in a case study for a major agricultural region in the United States. The case study results confirm that the relative inefficiency of per-hectare contracts varies spatially and increases with the degree of spatial heterogeneity. The results also show that contracts based on adoption of specific production practices are as much as five times more costly than efficient contracts based on payments per tonne of C sequestered—a degree of inefficiency similar to that found in assessments of command-and-control industrial emissions regulations.

Measurement costs to implement the per-tonne contract are estimated to be at least an order of magnitude smaller than the efficiency losses of the per-hectare contract for sampling errors in the range expected to be used in contracts. This finding implies that contracting parties—whether government agencies or participants in a GHG emissions trading system—could afford to bear a significant cost to implement the per-tonne contract and still achieve a lower total cost than would be possible with the less-efficient per-hectare contract.

These findings have several significant implications for the design of contracts for environmental amenities produced by agriculture. First, these results show that a government (or private market) program to sequester soil C and other environmental amenities can achieve efficiency gains, in terms of reductions in farm opportunity cost, through the use of incentive mechanisms that better account for spatial heterogeneity. Second, our analysis shows that both efficiency gains and measurement costs increase with spatial heterogeneity and both factors must be assessed to determine the most efficient contract design. Third, our empirical results indicate that buyers of contracts in a market for tradable emissions credits in the Northern Plains region would have a strong economic incentive to invest in the additional measurement of soil C that would be required to implement spatially explicit contracts. We hypothesize that further research will show that this finding will generalize to other agricultural regions and for other policies associated with GHG mitigation.

In concluding, we note that the specific estimates of the cost of soil C sequestration depend on the soil C rates derived from the Century model. These rates are estimated with some error that is not known. We have shown elsewhere [3] that the marginal costs of soil C sequestration are sensitive to these carbon rates. Therefore, as better estimates of soil C rates become available, or as other changes in the analysis are made (such as the spatial scale) our estimates of soil C sequestration costs will change. In addition, the cost estimates depend on the parameter estimates from our econometric models. Research in progress is investigating the implications of the (known) errors in the econometric model parameters, using Monte Carlo simulation methods.

Finally, we note that this analysis has implications for the optimal size of the spatial unit (what we have called an agroecozone) that is used to define C accumulation rates for soil C contracts. Clearly, as the size of agroecozones decreases and their number increases, the cost of making the measurements needed to establish C rates increases. A useful extension of this research would be to use the relationships we have established between policy design, opportunity cost, contracting costs, and spatial heterogeneity, to assess implications for the optimal spatial scale for the implementation of soil C contracts.

References

[1] Agriculture and Agri-Food Canada, Minister Vanclief Launches Greenhouse Gas Mitigation Program for Canadian Agriculture, http://www.agr.gc.ca/cb/news/2002/n20422ae.html, downloaded April 22, 2002.

[2] J.M. Antle, S.M. Capalbo, Econometric-process models for integrated assessment of agricultural production systems, Amer. J. Agric. Econom. 83 (2) (2001) 389–401.

[3] J.M. Antle, S.M. Capalbo, S. Mooney, E.T. Elliott, K.H. Paustian, Sensitivity of carbon sequestration costs to soil carbon rates, Environ. Pollution 116 (3) (2002) 413–422.

[4] J.M. Antle, S. Mooney, Designing efficient policies for agricultural soil carbon sequestration, in: J. Kimble (Ed.), Agriculture Practices and Policies for Carbon Sequestration in Soil, CRC Press LLC, Boca Raton, FL, 2002, pp. 323–336.

[5] B.A. Babcock, P.G. Lakshminarayan, J.J. Wu, D. Zilberman, The economics of a public fund for environmental amenities: a study of CRP contracts, Amer. J. Agric. Econom. 78 (1996) 961–971.

[6] W.J. Baumol, W.E. Oates, The Theory of Environmental Policy, 2nd Edition, Cambridge University Press, Cambridge, MA, 1988.

[7] M. Boscolo, M. Powell, M. Daleney, S. Brown, R. Faris, The cost of inventorying and monitoring carbon: lessons from the Noel Kempff Climate Action Project, J. For. 98 (9) (2000) 24–31.

[8] S. Brown, M. Burnham, M. Delaney, M. Powell, R. Vaca, A. Moreno, Issues and challenges for forest-based carbon-offset projects: a case study of the Noel Kempff Climate Action Project in Bolivia, Mitigation Adapt. Strat. Global Change 5 (1) (2000) 99–121.

[9] Consortium for Agricultural Soils Mitigation of Greenhouse Gases (CASMGS), http://www.casmgs.colostate.edu, 2002.

[10] W.M. Corden, The normative theory of international trade, in: R.W. Jones, P.B. Kenen (Eds.), Handbook of International Economics: Vol. 1, International Trade, North-Holland, Amsterdam, 1984, pp. 63–130.

[11] R.A. Fleming, R.M. Adams, The importance of site-specific information in the design of policies to control pollution, J. Environ. Econom. Management 33 (1997) 347–358.

[12] R.W. Hahn, R.N. Stavins, Economic incentives for environmental protection: integrating theory and practice, Amer. Econom. Rev. 82 (1992) 464–468.

[13] G.E. Helfand, B.W. House, Regulating nonpoint source pollution under heterogeneous conditions, Amer. J. Agric. Econom. 77 (1995) 1024–1032.

[14] J.W. Jones, A.J. Gijsman, W.J. Parton, K.J. Boote, Predicting soil-carbon accretion over space and time: the role of biophysical models in measuring, monitoring and verifying soil organic matter, in: J. Antle, J. Jones, G. Uehara (Eds.), Creating Incentives for Sustainable Agriculture: Defining, Estimating Potential, and Verifying Compliance with Carbon Contracts for Soil Carbon Projects in Developing Countries, Soil Management Collaborative Research Program, University of Hawaii, 2002.

[15] R.E. Just, J.M. Antle, Interactions between agricultural and environmental policy: a conceptual framework, Amer. Econom. Rev. 80 (2) (1990) 197–202.

[16] R. Lal, L.M. Kimble, R.F. Follett, C.V. Cole, The Potential of U.S. Cropland to Sequester C and Mitigate the Greenhouse Effect, Ann Arbor Press, Chelsea, MI, 1998.

[17] C.H. McCall Jr., Sampling and Statistics Handbook for Research, The Iowa State University Press, Ames, IA, 1982.

[18] B. McConkey, W. Lindwall, Measuring soil carbon stocks: a system for quantifying and verifying change in soil carbon stocks due to changes in management practices on agricultural land, Agriculture and Agri-Food Canada, 1999.

[19] S. Mooney, J.M. Antle, S.M. Capalbo, K.H. Paustian, Contracting for soil carbon credits: design and costs of measurement and monitoring, Staff Paper 2002-01, Department of Agricultural Economics and Economics, Montana State University, Bozeman, 2002.

[20] W.E. Oates, P.R. Portney, M. McGartland, The net benefits of incentive-based regulation: a case study of environmental standard setting, Amer. Econom. Rev. 79 (1989) 1233–1242.

[21] P.J. Parks, I.W. Hardie, Least-cost forest carbon reserves: cost-effective subsidies to convert marginal agricultural land to forests, Land Econom. 71 (1) (1995) 122–136.

[22] W.J. Parton, D.S. Schimel, D.S. Ojima, C.V. Cole, A general model for soil organic matter dynamics: sensitivity to litter chemistry, texture and management, in: R.B. Bryant, R.W. Arnold (Eds.), Quantitative Modeling of Soil Forming Processes, SSSA Special Publication No. 39, Soil Science Society of America, Madison, WI, 1994, pp. 147–167.
[23] K. Paustian, E.T. Elliott, L. Hahn, Agroecosystem boundaries and C dynamics with global change in the central United States, FY 1998/1999 Progress Report, National Institute for Global Environmental Change, http://nigec.ucdavis.edu/publications/annual99/greatplains/GPPaustian0.html, 1999.
[24] K. Paustian, E.T. Elliott, G.A. Peterson, K. Killian, Modelling climate, Co_2 and management impacts on soil carbon in semi-arid agroecosystems, Plant Soil 187 (1996) 351–365.
[25] G.R. Pautsch, L.A. Kurkalova, B. Babcock, C.L. Kling, The efficiency of sequestering carbon in agricultural soils, Contemp. Econom. Pol. 19 (2001) 123–124.
[26] A.J. Plantinga, T. Mauldin, D.J. Miller, An econometric analysis of the cost of sequestering carbon in forests, Amer. J. Mgr. Econom. 81 (1999) 812–824.
[27] G.P. Roberts, E.A. Paul, R.R. Harwood, Greenhouse gases in intensive agriculture: contributions of individual gases to the radiative forcing of the atmosphere, Science 289 (2000) 1922–1924.
[28] R. Rosenzweig, M. Varilek, B. Feldman, R. Kuppalli, J. Janssen, The Emerging International Greenhouse Gas Market, Pew Center for Global Climate Change, Arlington, VA, 2002.
[29] A. Sandmo, Optimal taxation in the presence of externalities, Swed. J. Econom. 77 (1975) 86–98.
[30] G.R. Smith, Case study of cost versus accuracy when measuring carbon stock in a terrestrial ecosystem, in: J.M. Kimble, R. Lal, R.F. Follett (Eds.), Agriculture Practices and Policies for Carbon Sequestration in Soil, CRC Press LLC, Boca Raton, FL, 2002, pp. 183–192.
[31] R.N. Stavins, What can we learn from the grand policy experiment? Lessons from SO_2 allowance trading, J. Econom. Perspect. 12 (1998) 69–88.
[32] R.N. Stavins, The costs of carbon sequestration: a revealed-preference approach, Amer. Econom. Rev. 89 (1999) 994–1009.
[33] S.K. Thompson, Sampling, Wiley, New York, 1992.
[34] T.H. Tietenberg, Economic instruments for environmental regulation, Oxford Rev. Econom. Pol. 6 (1) (1990) 17–33.
[35] R.T. Watson, I.R. Noble, B. Bolin, N.H. Ravindranath, D.J. Verardo, D.J. Dokken, Land use, land-use change, and forestry, A Special Report of the IPCC, Cambridge University Press, Cambridge, England, 2000.
[36] White House, Global Climate Change Policy Book, http://www.whitehouse.gov/news/releases/2002/02/climate-change.html, downloaded February 15, 2002.
[37] J. Wu, W.G. Boggess, The optimal allocation of conservation funds, J. Environ. Econom. Management 38 (1999) 302–321.