Journal of Agricultural and Applied Economics, 41,1(April 2009):1–11

Uncertainty Discounting for Land-Based Carbon Sequestration

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The effect of stochastic factors on soil carbon makes the quantity of carbon generated under a sequestration project uncertain. Hence, the quantity of sequestered carbon may need to be discounted to avoid liability from shortfalls. We present a potentially applicable uncertainty discount and discuss difficulties that might arise in empirical use. We insist that the variance in historical crop yields across geographical areas is used to derive a proxy variance for forming an uncertainty discount for carbon projects. Application of our approach suggests that project level uncertainty discounts would be 15–20% for the East Texas region.

Key Words: carbon seqestration, discount, uncertainty

JEL Classifications: H43, Q54

Reduction of atmospheric carbon dioxide (CO_2), a major greenhouse gas (GHG), is central to addressing the climate change problem and in the formation of policies that aim to limit atmospheric GHG levels (see discussion in IPCC 2007a,b). Land-based carbon sequestration—a process whereby plants and trees, through photosynthesis processes, trap atmospheric CO_2 and fix carbon into soil and plant body mass—has drawn attention as a strategy for GHG reduction. If GHG emissions reductions are pursued, a carbon market may be created as advocated for example in the Kyoto Protocol (UNFCCC) or potential legislation like Lieberman-Warner bill (Lieberman and Warner Bill) where entities sequestering carbon may be able to generate GHG reduction credits that buying emitters can use to offset their emissions (as discussed in Butt and McCarl; Kim and McCarl).

Various studies have explored the potential of land-based carbon sequestration strategies such as afforestation, reforestation and other land use changes (Adams et al.; Parks and Hardie; Plantinga, Maudlin, and Miller; Stavins; McCarl and Schneider; Lewandrowski et al.; USEPA; Lubowski, Plantinga, and Stavins; Antle et al.).[1] These studies not only show considerable potential for soil based sequestration, but also indicate that the strategy might achieve GHG reduction targets at a lower cost compared with other alternatives such as developing emission abatement technologies (see Table 1 for a brief summary of the studies).

From an agricultural producer's point of view, the GHG emission credit price would be a payment that would offset the cost of implementing a carbon sequestration project. The project cost

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The authors thank the editors of this journal as well as three anonymous reviewers for very useful suggestions.

[1] There are two major classes of land related sequestration practices that can be employed to offset GHG emissions involving changes in land management and changes in land use (IPCC 2000). The commonly discussed management changes involve changes in crop mix, tillage systems, nutrients applied, and residue management. Changes in land use involve conversion of croplands to grassland, pasture, or forest uses.

Table 1. Brief Summary of Economic Studies of Carbon Sequestration for U.S.

Study	Activity	Region	Potential (MMTC/year)	Cost of Carbon Sequestration ($/ton)
Adams et al.	Forest plantation	U.S.	640	20–61
Parks and Hardie	Afforestation of crop and pasture land	U.S.	150	5–90
Stavins	Afforestation	U.S. Delta states	7	0–6
		U.S.	518	60–136
Plantinga, Maudlin, and Miller	Afforestation	Maine	2.5	0–250
		South Carolina	14	0–40
		Wisconsin	40	0–85
McCarl and Schneider	Reduced tillage	U.S.	70	10–500
	Afforestation		183	10–500
	Biofuels		156	10–500
Lewandrowksi et al.	Afforestation	U.S.	8.5–133	10–125
	Conservation tillage		1–26.9	10–125
	Change from crops to permanent grass		0	10–125
Lubowski, Plantinga, and Stavins	Afforestation	U.S.	1700	7–275
Antle et al.	Reduced fallow and conservation tillage	Central U.S.	0.9–7.9	10–200

would be any foregone net income arising from altered production plus any added cost to adopt the sequestering practices. The potentially salable quantity of GHGs would equal the net volume sequestered plus any associated net GHG reduction from altered fossil fuel usage, if any. However, as argued in the next section, there also may be *uncertainty* discounts that should be considered. Most previous studies generally ignore uncertainty discount and thus may *overestimate* the salable credits and revenues arising from a carbon sequestration practice. Thus it is important to assess the magnitude of uncertainty discount to formulate the correct economics of a carbon sequestration project. This paper presents a confidence interval based uncertainty discount approach motivated by the Canadian suggestion in the international negotiations and then presents an empirical application in the context of a potential Eastern Texas project.

Uncertainty Sources

There are a variety of ways uncertainties arise in regards to the carbon sequestered by sequestration projects. Namely, Birdsey and Heath, as well as and Heath and Smith argue that the sources of uncertainty include:

- Climate and other factors such as pests, fire, and so on that induce annual production variability in the quantity of carbon sequestered at a location;
- Aggregation induced sampling error at a regional scale;
- Carbon pool measurement error; and
- Intertemporal variation in the duration and permanence of carbon sequestered in the future.

Uncertainty in the quantity of carbon sequestered exposes a purchaser of carbon credit to the risk of having the quantity sequestered falling below the claimed level, causing the purchaser to be out of compliance with regulatory limits and having to pay penalties. Under many environmental trading schemes, penalties are imposed for shortfalls. For example, within the US sulfur dioxide (SO_2) trading scheme, the penalty for excess emissions of SO_2 is set at $2000/ton times an annual adjustment factor that translates into an amount which is more than 10 times the observed price of emission rights (Seton's EH&S Compliance

Resource Center). This creates substantial interest on behalf of the purchaser, directed toward ensuring that the potential offset credits acquired can be safely relied upon to exceed the environmental commitments.

The risk of being out of compliance with commitments might lead a purchaser to discount the carbon offset quantity that arises from a project so as to provide additional safety in the face of uncertainty. Economically, the level of such a discount would be based on the tradeoff between the costs of securing additional certainty and the costs of being out of compliance. The form of an uncertainty discount can be based on the standard statistical confidence interval concept where the creditable amount is a reduction from the expected amount based on the standard error of the sequestration amount. While applying the confidence interval concept, one must consider the characteristics of the carbon contract that may have an important bearing on the uncertainty; mainly spatial and temporal aggregation as discussed below:

- *Spatial aggregation*: The biophysical nature of carbon sequestration and the need of potential emitting entities suggest that carbon contracts might involve aggregation of multiple sites generating carbon credits. West and Post show that on average an acre of land when subjected to a tillage change yields about 0.25 tons of carbon per acre per year (equivalently 0.92 tons of CO_2 per acre per year). In contrast, power plants emit larger volumes of CO_2 and may need larger volumes of credits like 10,000 or 100,000 tons of carbon as frequently mentioned at various forums. Thus, a contract for 100,000 tons may require 800 farms of an average farm size of 500 acres (note that the US average farm size is about 440 acres, USDA).
- *Temporal aggregation:* Looking for new sources of carbon credits and signing new contracts involves transaction cost, which is an addition to the price paid for the credits. To keep the overall compliance costs low, it is likely that an emitting entity would sign multiyear contracts with the same group of carbon credit suppliers (Butt and McCarl). Project commitments spanning over a number of years are also expected due to the *impermanence* characteristics of carbon, where the sequestered carbon might revert back to the atmosphere if sequestering practices are discontinued (Kim, McCarl, and Murray). Preserving the carbon sequestered in the soil over time would require multiyear contracts.

Thus, a sequestration contract by a purchaser would arise over a wide spatial area and for a number of years and not from an individual plot or field or farm for just one year. As such, the uncertainty in the cumulative stock of carbon generated at a project level for the entire length of the contract is of relevance when signing a contract. Therefore, when estimating the uncertainty discount, spatial and temporal correlation should be accounted for. In the sections that follow, we first present the confidence interval approach for estimating an uncertainty discount and then discuss how spatial and temporal correlation is incorporated in estimating the discount.

Confidence Interval Approach to an Uncertainty Discount

Standard statistical theory prescribes a formula for developing a certainty level of carbon generated (Q_l) as a function of the mean ($\bar{Q}$), standard deviation (σ) and a distribution based multiplier z_α that is a function of the desired level of confidence (α) for Q_l. In statistical terms, we can estimate a lower limit of the quantity of carbon generated for a desired confidence level as shown in equation (1) below:

(1) $$Q_l = \bar{Q} - z_\alpha \cdot \sigma.$$

Such a formula, in a one tailed context, reduces the amount of the uncertain quantity until one reaches a level that exhibits a particular probability level (α) that Q_l or more will be produced. Frequently, this involves a normality assumption where for example a z_α value of 1.64 implies $\alpha = 95\%$.[2] One can also convert

[2] Distribution free assumptions can be used where under Chebyshev's inequality a z_α value of $4.47 = 1/\sqrt{0.05}$ also implies a 95% confidence interval.

this formula to coefficient of variation (CV) where $CV = \ /\bar{Q}$ and the formula for Q_l becomes: $Q_l = \bar{Q} - z_\alpha \cdot CV \cdot \bar{Q} = \bar{Q}(1 - z_\alpha \cdot CV)$ which is the form we will use and uncertainty discount factor would be $z_\alpha \cdot CV$.

Potential use of this formula raises the issues of

- What size of α and in turn z_α would one use.
- How big is CV and how does one develop a CV estimate.

Size of α and in Turn z_α

Generally the uncertainty discount would be tied to buyer preferences and the trade-offs between the costs of assuring additional certainty and the costs of exposing oneself to the risk of shortfall. In the absence of working directly with decision makers, we will use alternative confidence levels 80%, 90%, and 95% that surround the Canadian proposal, which recommends that offsets should be reported with 90% certainty.

The establishment of the z_α level then depends on the adoption of a distributional assumption. We will assume that the total product of the contract is normally distributed. The rationale for the normality assumption arises from the Central Limit Theorem (CLT). The total quantity of carbon credits purchased will be the sum of contributions from many individual sites over a number of years leading to a large number of observations paving the way for the application of CLT. The theorem asserts that the distribution of a sample mean is normally distributed as long as the independence assumption holds or, following Moore and McCabe (pp. 398–402), as long as the sample observations are not too strongly associated. Furthermore, while such an assumption is convenient, it is not essential as the confidence interval approach can be used with alternative distributional assumptions and thus one just needs to develop consistent values of z_α.

Size of CV

The CV is based on the mean and standard deviation. The standard deviation is commonly estimated based on field experiments (see the estimates in West et al.) or from simulation models. Typically, such estimates are summarized in terms of the variation in the annual accumulation rates for a single site, which do not fully incorporate spatial and temporal correlation in factors that affect the quantity of carbon sequestered over multiple sites and multiple years. To be consistent with the likely multisite, multiyear nature of carbon contracts, the CV should be based on carbon generated from multiple sites across multiple years considering spatial and temporal correlation of factors that affect soil carbon.

Statistically, if all sites were alike and independent with a field level standard deviation of (population) σ and exhibited independent distributions across sites and time where n observations were obtained, then the CLT indicates that the standard deviation for the average amount of carbon would be the standard error at each site divided by square root of the sample size, $\sigma/\sqrt{n}$ (Moore and McCabe, p. 398). Therefore, we expect the standard deviation to decrease substantially with aggregation over sites and years, and the same is true for the uncertainty discount.

While our derivation of the contract level CV employs the assumption of independence of quantities of carbon sequestered across sites and time, the assumption is unlikely to hold. Common weather and biophysical characteristics of sites are likely to introduce correlation in the quantity of carbon across sites and over time. The problem of sizing the CV then becomes the problem of estimating the CV across the whole aggregate sample, for which one either needs such data or some way to develop a proxy CV.

Specifying the CV at the Project Level

Estimating a CV level that accounts for the project level spatial and temporal correlations in the quantity of carbon leads to the question of how one can get such an estimate. There might be three possible ways:

(i) Actual field measurements,
(ii) Data from biophysical simulations, or,
(iii) Use of a proxy distribution.

Field Measurement

To obtain the distribution of the quantity of carbon sequestered from field measurements, one can measure carbon stocks at alternative locations and over time. Such measurements involve collecting soil samples and testing the samples for changes in carbon stock over time. Anecdotal experience with such measurements indicates a high CV. Results by West et al. (see Figure 3 in West et al. that shows mean and confidence intervals of annual carbon sequestration after reforestation on agricultural land) approach 0.5.[3]

In addition, given the expected variation in regional conditions it would be highly desirable to have project area measurements available for estimating the distribution of carbon generated under a project. However, there are concerns about field measurement. First, generally it is fair to say that widespread project area measurements are not currently available. The uncertainty discount should be specified before implementing carbon sequestration project, particularly when projects are being set up. Such a pool of measurements may be available several years after the projects have already begun, but estimates are needed to set up contract terms before a project is implemented.[4] Second, field measurement involves monitoring and operational costs which might increase the cost of carbon sequestration. Third, field measurement can be used later in the project to square up for carbon that has been sequestered when the uncertainty has been reduced.

[3] CV is back calculated from the reported carbon management response (CMR) curve in West et al. It may not be comparable to the use of CV in the remainder of the paper because it is calculated from the standard deviation, not from the standard deviation of the mean.

[4] Field measurement might be a practical approach if highly similar projects appear within the same region for which field measurements were available, but this is generally not the case (at least at this point in time). Also, field measurements may be used after the project has been in place to resolve the uncertainty of accumulation but this embodies the risk that the sequestered quantity is found to be less than that claimed quantity and may justify initial uncertainty discounts.

Biophysical Simulation

An alternative to field measurement is biophysical simulation of soil carbon over time. Using data on soil and management characteristics, along with localized temperature and rainfall, biophysical models like CENTURY (Parton et al.) and EPIC (Izaurralde et al.) simulate changes in soil carbon. Model results can be used to estimate mean and variance in the quantity of carbon sequestered. This is illustrated in Kurkalova which investigates the optimal discounting of stochastic carbon sequestration. The variance of change in carbon over time from CENTURY simulation has been used in the sensitivity analysis on measurement costs of carbon sequestration (Mooney et al.).

When simulating changes in soil carbon, the analyst controls management practices (e.g., crop, tillage method, irrigation, fertilizer application, etc.), while the model simulates daily weather from planting to harvesting for a specified number of years. The simulated weather is based on weather parameters derived from historical data for a location relevant to the field for which the simulation is being performed, typically a weather station in the county or a nearby area. The combination of model parameters, management practices, and the daily simulated weather, the biophysical models provide estimates of soil carbon over time, which can be used to estimate mean and variance in the quantity of carbon sequestered.

Such a simulation approach suffers from two potentially critical shortcomings as they relate to the CV for a potential project. First, the simulation of site level weather in biophysical models ignores spatial correlation across multiple sites in a project making an independence assumption. As a result, the fluctuations in soil carbon might be biased if shortfall events at one site are compensated for by excess events elsewhere, or if a high degree of spatial correlation exists. Second, important stochastic events like pests, hail, severe winds, diseases, and so on, that affect crop and the likely carbon production are omitted in biophysical simulations indicating variance may be under estimated.

Spatial correlation across sites can be partially incorporated by allowing the biophysical model to use historical weather as it occurred at all fields and associating the results by year or by somehow correlating the generated weather. However, the granularity of weather stations may still cause a problem as does the omission of localized pest outbreaks, hail damage, wind effects, and so on.

Using Crop Yield as a Proxy

While actual field measurements account for the spatial and temporal correlation in the quantity

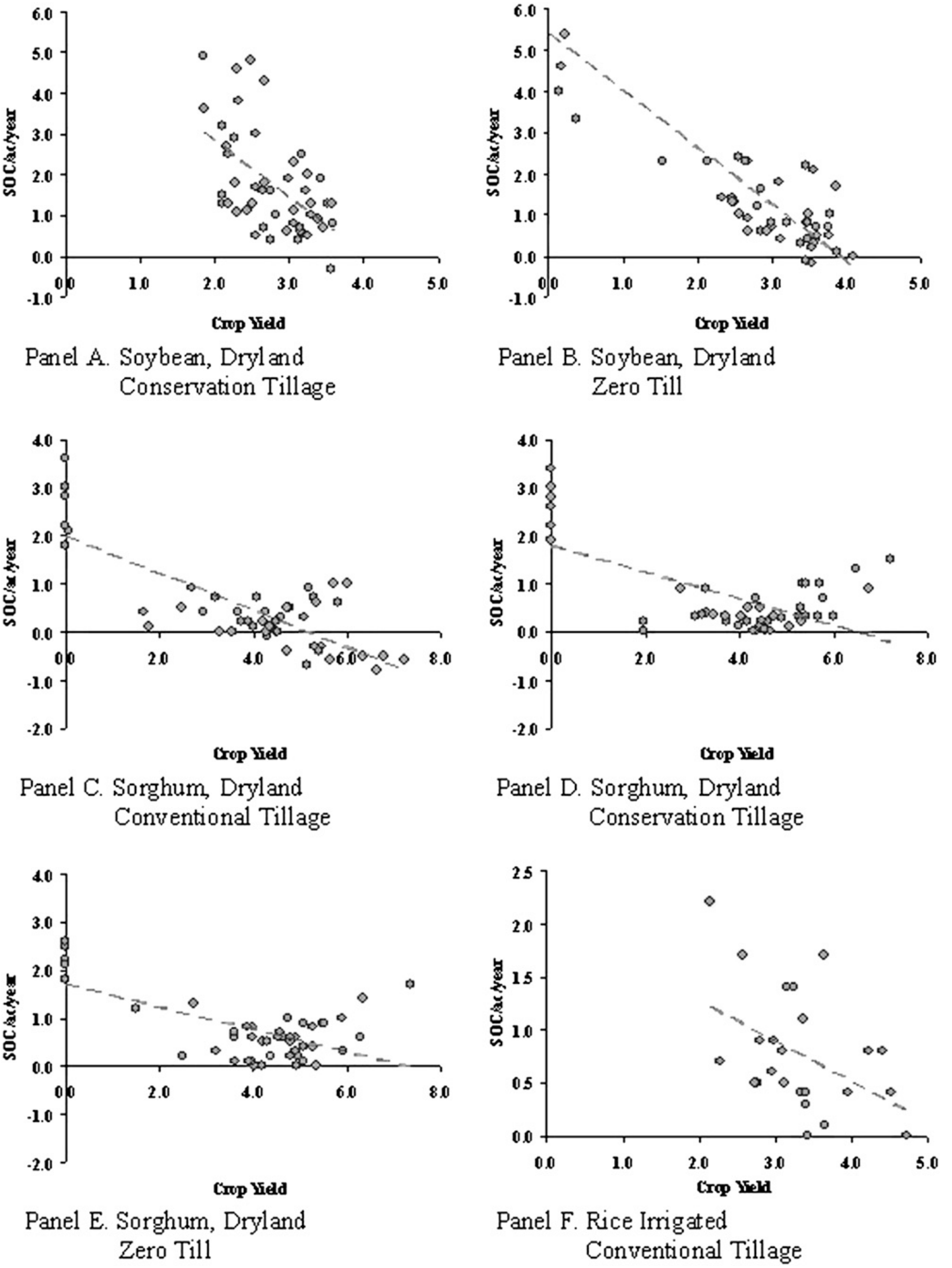

Figure 1. Simulation results for soil carbon vs. crop yield for various cases.

of carbon, the currently available data are inadequate to perform any statistical analysis for derivation of uncertainty discount. In contrast, biophysical models can provide extensive data but ignore spatial and temporal correlation in the quantity of carbon, which is critical to estimating CV at a project level. Another possibility is to use biophysical models to generate average quantity of carbon sequestered, while for estimating the variation use a proxy variable that might account for the variance reducing effects of spatial and temporal correlations in factors that affect the quantities of carbon. The use of a proxy variable is a common practice in the literature when the variable of interest is unobservable (Kennedy, p. 170). The proxy variable, however, must be highly correlated with the variable of interest. In our case, we would need a variable whose variations are highly correlated with variations in the quantity of carbon. Observed crop yields, which do include the spatial and temporal correlation in the biophysical environment simultaneously impacting yield and soil carbon, potentially could fulfill such a need. Soil scientists anecdotally argue that the change in soil carbon is strongly related to the amount of carbon input that, in turn, is determined by the size of the plant on the field that is highly correlated with yield (Kimble). Thomson et al. demonstrate that the simulated EPIC crop yields correspond closely with historical yields, water usage and thus soil carbon. If the correlation between EPIC crop yield and carbon is high we can use crop yield as the proxy variable. Because there is no study about this, we ran numerous EPIC simulations, and computed the correlation coefficient. We found a high degree of correlation with the coefficients ranging from 0.7–0.9 as explained below.

To examine correlation, we performed biophysical simulations using the EPIC model for sorghum, rice, and soybean crops in Eastern Texas over 25 years with historical weather data and computed the correlation between yield and net carbon flux which was calculated as the difference between two successive estimates of carbon inventory (following Smith and Heath, 2001) as follows

$$\text{SOC/ac/year} = \text{SOC}_{t-1} - \text{SOC}_t, \tag{2}$$

where SOC/ac/year is the soil organic carbon per acre per year and SOC_t is the soil organic carbon per acre at time t. Negative SOC/ac/year indicates that sequestration is occurring. The EPIC simulation results we obtained are summarized in Figure 1 Panels A–F which shows different cases arising across crops, land types and tillage types. As shown in Figure 1, there is a high, statistically significant (negative in all the cases) correlation between changes in crop yields and changes in soil carbon, ranging from 0.7 to 0.9. This leads us to conclude we could use the CV for crop yields as the proxy for the CV of quantity of carbon sequestered.

To use the crop yield CV as the proxy for soil carbon CV, the variation in crop yields have to be appropriately adjusted because they are not perfectly correlated; measurement errors result by definition when the instrument is not perfectly correlated with the variable of interest (Kennedy, p. 170). To include such adjustments, we derive a relationship between the coefficient of variation in yields (CV_{Y}) and the coefficient of variation in soil carbon (CV_{Q}) based on a regression fit, $CV_{\text{Q}} = b \cdot CV_{\text{Y}} + \varepsilon_i$. Using the EPIC results, coefficient b is estimated, which is given by

$$\begin{aligned} CV_Q &= 2.138\, CV_Y \\ &\quad\ (12.656) \\ R^2 &= 0.914,\ \text{DW} = 2.21 \end{aligned} \tag{3}$$

where the number in parenthesis is the t-value and the degrees of freedom is 9. Thus, the CV

Table 2. CV for Crop Yield over Space (1995–2005) (Unit: %)

Region	Sorghum	Corn	Rice	Wheat	Upland Cotton	Soybean
Brazoria county, TX	21.47	32.39	13.08	26.25[a]	25.08	27.39
TX Crop Reporting District 9	19.67	27.04	9.71	20.79	21.17	14.01
State of Texas	10.89	9.78	9.35	10.75	20.19	9.32

[a] Several years (1998, 2001, 2002, and 2004).

Table 3. CV for Yield over Time[a] (5 year interval) (Unit: %)

Region	Sorghum	Corn	Rice	Wheat	Upland Cotton	Soybean
Brazoria county, TX	7.30	7.12	6.50		12.21	13.80
TX Crop Reporting District 9	3.48	4.12	6.85	3.94	8.25	5.09
State of Texas	1.36	1.58	6.67	3.17	8.00	4.37

[a] This CV is computed for 5 year moving averages for each crop at each level of aggregation.

for soil carbon is assumed to be 2.138 times larger than the crop yield CV.

Empirical CV Estimates and Uncertainty Discount

The wide availability of historical crop yield data allows us to investigate the effects of aggregation on crop yield CV and, in turn, on soil carbon CV. Yield data are available from various USDA sources at county and higher levels and incorporate temporal and spatial correlation due to weather and localized conditions. We used data for five Eastern Texas crops—sorghum, corn, rice, wheat, and soybeans from 1995 to 2005, drawing those data from the USDA National Agricultural Statistics Service (NASS) Quick Stat Internet site, http://www.nass.usda.gov/.

To examine the effects on the CV of incorporating spatial correlation we computed CVs for a Texas County (Brazoria), a crop reporting district (Texas 9), and the whole state (Table 2). As expected, aggregation across space reduces the CV_Y. In case of soybeans, the CV is 27.4% at the county level, falls to 14.0% at the district level, and 9.3% at the state level. Results using EPIC at the site level averaged about 90% (max 123.1% and min 61.7%).

As we also wished to see the effects of multiyear agreements on the CV_Y, we computed the CV for 5-year moving average yields evaluated at each of the above mentioned regional scales (see Table 3). This shows a further decline in the CV. For example for soybeans, the CV_Y falls to 13.8% for the county, 5.1% for the district, and 4.4% for the state. Collectively, the multisite multiyear variation is much smaller, which portends a much smaller uncertainty discount for a multisite multiyear carbon contract.

The uncertainty discount from a confidence interval approach is $\delta = z_\alpha \cdot CV_Q$, where CV_Q is the CV of soil carbon production. We estimate CV_Q based on the CV for yields (CV_Y) via the formula in equation (3). Based on the large number of farmers that would be needed in a contract and their geographic dispersion we chose to use the 5 year CVs at the district level and we averaged across crops that resulted in a CV of 5.3%. In turn, multiplying CV_Q by 2.138 gives a CV of 11.3% (Table 4), resulting in uncertainty discounts of 18.6% for a 95% confidence level and 14.5% with a 90% confidence level (Table 5). Table 5 shows the uncertainty discounts across different crops and confidence levels ranging from 12.2 to 28.9% with a 95% confidence level and from 9.5 to 22.6% with a 90% confidence level.

Summary and Conclusion

Land based carbon sequestration might become an important instrument in future U.S. GHG mitigation strategies where large emitters could contact with producers to enhance sequestration and in turn offset GHG emissions. The effect of various stochastic factors such as weather, fire, and so on, on the quantity of carbon makes the quantity of carbon generated under a project uncertain. As a result, purchasers of land based

Table 4. CV for Rate of Carbon Sequestered based on Tables 2 and 3 and Eq. (3) (Unit: %)

Region	Sorghum	Corn	Rice	Wheat	Upland Cotton	Soybean
TX Crop Reporting District 9	7.58	8.97	14.91	8.58	17.96	11.08
State of Texas	2.96	3.44	14.52	6.90	17.41	9.51

Table 5. Uncertainty Discount Rates (Unit: %)

Region	Sorghum	Corn	Rice	Wheat	Upland Cotton	Soybean	**Average**
TX Crop Reporting District 9							
95% significance level	12.20	14.45	24.02	13.82	28.93	17.85	**18.55**
TX Crop Reporting District 9							
90% significance level	9.53	11.28	18.75	10.78	22.58	13.93	**14.47**

carbon credits would be at risk for not meeting their abatement obligations that might subject them to noncompliance penalties. Hence, the quantity of land based carbon credits may need to be discounted to avoid the liability of shortfalls. This would involve an uncertainty discount that estimated the quantity of carbon sequestered that one could confidently expect with more than a given level of certainty. This could also be applied by discounting the prices paid by the credit purchaser for the quantity of carbon sequestered and buying more. Also after a project had been in operation for a number of years one could develop improved stock measurements and square up payments for some of the discount applied in the past.

We presented a statistics based theoretical approach for estimating the uncertainty discount, which requires estimating the distribution of the quantity of carbon sequestered. For empirical investigation, however, one faces the difficulty finding variability data compatible with multisite multiyear contracts that would form under a given project. To overcome this difficulty, we suggest the use of proxy variable approach, where historical crop yields across various geographical areas are used to derive uncertainty discount for a multiyear multisite carbon project.

We presented the application of our methodology for East Texas. We found that ignoring spatial and temporal correlation in the quantity of carbon that might be present in a multisite multiyear project would result in a high coefficient of variation (of about 90%); hence, a high uncertainty discount. We adjusted the CV in the quantity of carbon by incorporating the correlations that would occur across farms and time as induced by common weather and other characteristics, using the observations reflected in historical crop yield distributions across time and geography. Such considerations were found to reduce the CV and associated discount substantially. The added time and spatial dimensions tend to reduce the CV by up to 90%. Application of our approach suggests that the project level uncertainty discounts would fall in the neighborhood of 15–20% for the East Texas region.

Finally we should address implications for agencies and stakeholder groups trying to, form rules, facilitate and/or support the use of agricultural soil carbon sequestration programs. We believe the results show the potential for substantial year to year variation in sequestration results and an associated degree of buyer uncertainty and caution. This may be the reason why we observe two phenomena in the existing carbon markets. First, soil carbon has not played a major role internationally with a lot of discussion of issues such as permanence and uncertainty. Second, the Chicago Climate Exchange is paying 0.2–0.6 ton of CO_2 per acre per year (CCX) which is substantially less than West and Post's 0.92 ton of CO_2 per acre per year of average accumulation possibly reflecting an uncertainty discount. We feel the concept of an uncertainty discount should be embraced as it may alleviate the concerns and could make the prospect more profitable than current levels with informal discounts.

[Received December 2007; Accepted September 2008.]

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