Uncertainty Discounting for Land-Based Carbon Sequestration

By

Man-Keun Kim
Post Doctoral Fellow, Joint Global Change Research Institute
University of Maryland
College Park, MD 20740
man-keun.kim@pnl.gov

Bruce A. McCarl
Regent Professor, Department of Agricultural Economics
Texas A&M University
College Station, TX 77840
mccarl@tamu.edu

And

Tanveer Butt
Visiting Assistant Professor, Department of Agricultural Economics
Texas A&M University
College Station, TX 77840
tanveer@tamu.edu

Uncertainty Discounting for Land-Based Carbon Sequestration

Abstract

The effect of various stochastic factors like weather, fire etc., on the quantity of land based carbon makes the quantity of carbon generated under a project uncertain. When depending on land based carbon credits, entities facing limits on their carbon emissions would be at risk of not meeting their abatement obligations subjecting them to non-compliance penalties. Hence, the quantity of land based carbon credits may need to be discounted to avoid the liability arising from shortfalls. We present a statistics based theoretical approach for estimating the uncertainty discount and discuss the difficulties that might arise in empirical investigations considering the nature of carbon contracts. We suggest the use of proxy variable approach, where historical crop yields across various geographical areas are used to derive uncertainty discount for a multi-year multi-site carbon project. We show that the uncertainty discount is lower for contracts that aggregate land based carbon over a larger space and longer time. We find the uncertainty discount falls in a neighborhood of 5% to 10% for the East Texas region.

Uncertainty Discounting for Land-Based Carbon Sequestration

1. Introduction

Reduction of atmospheric carbon dioxide (CO_2), a major greenhouse gas (GHG), is central to policies that aim to limit atmospheric GHG levels. 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 the attention of policy makers and researchers alike as a strategy for GHG reduction. When implemented, the strategy may lead to the creation of a carbon market where entities sequestering carbon may be able to generate GHG reduction credits that buying emitters can use to offset their emissions (Butt and McCarl, 2004).

Various studies have explored the potential of land-based carbon sequestration strategies such as afforestation, reforestation and other land use changes (Adams *et al*., 1993; Dixon *et al*., 1993; McCarl and Schneider, 2001; Marland and Schlamadinger, 1999; Parks and Hardie, 1995; Plantinga *et al*., 1999; Stavins, 1999; Sampson and Sedjo, 1997;).[1] These studies not only show that a considerable potential for soil based sequestration exists but also that the strategy might achieve GHG reduction targets at a lower cost compared to other alternatives such as developing emission abatement technologies. However, the quantity of land-based carbon sequestration is subject to

[1] There are two major land related sequestration practices that can be employed to offset GHG emissions involve 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 other crop mix, pastureland, or forest establishment.

uncertainty and thus buyers may incorporate uncertainty in their offering prices. This paper presents a confidence interval based uncertainty discount approach motivated by the Canadian (1998) suggestion in the international negotiations and then presents empirical approaches with which it can be used in the context of an investigation of the issue for Eastern Texas.

2. Uncertainty Sources

There are a variety of ways uncertainties arise in regards to the carbon sequestered by sequestration projects. Namely, Birdsey and Heath (1995); and Heath and Smith (2000) argue that the sources of uncertainty include:

- Climate and other factors like pests, fire etc. 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
- Inter-temporal 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 × 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, 2003). 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 trade-off 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. 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 (2002) provide data that indicate the average acre when subjected to a tillage change yields ¼ ton carbon per acre. In contrast, power plants emit larger quantities and may need larger volumes of carbon credits with quantities 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, 2004).

- *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 multi-year contracts with the same group of carbon credit suppliers (Butt and McCarl, 2004). Project commitments spanning over a number of years is 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, 2004). Preserving the carbon sequestered in the soil over time would require multi-year 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 in factors that affect the quantity of carbon sequestered must 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 aspect of the carbon generated under a project is incorporated in estimating the discount.

3. 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 ($\overline{Q}$), 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:

$$(1) \qquad Q_l = \overline{Q} - z_\alpha \cdot \sigma$$

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 1.96 implies α = 97.5%. However, distribution free assumptions can be used where under Chebychev's inequality a z_α value of 6.32 also implies a 97.5% confidence interval. One can also convert this formula to coefficient of variation (CV) where $CV = \sigma / \overline{Q}$ and the formula for Q_l becomes:

$Q_l = \overline{Q} - z_\alpha \cdot CV \cdot \overline{Q} = \overline{Q}(1 - z_\alpha \cdot CV)$ 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 get it

3.1 Size of α and in turn z_α

The uncertainty discount is tied to the purchaser's preferences and the tradeoffs between assuring additional certainty and exposing one self 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 (1998), 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 (1993), 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 many different distributional assumptions and thus one just needs to develop consistent values of z_α.

3.2 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.*, 2004) or from simulation models. Such estimates typically 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 nature of multi-site multi-year carbon contracts, the CV should be based on carbon generated from multiple sites and multiple years.

Statistically, if all sites were alike and independent with a field level standard deviation of σ and exhibited independent distributions across sites and time where n observations were obtained, then the Central Limit Theorem indicates that the standard deviation for the average amount of carbon from a site would be the standard error at each site divided by square root of the sample size, $\sigma/\sqrt{n}$ (Moore and McCabe, 1993). So, we expect the variance to drop 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.

4. Specifying the CV at the Project Level

Estimating a CV level that accounts for the project level within sites and within years 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 measurement,

(ii) Data from biophysical simulation, or,

(iii) Use of a proxy distribution.

4.1 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 where for example a soil scientist at a recent meeting said that the CV approached one, while the results by West *et al.* (2004; see Figures 1, 2 and 3 that show mean and confidence intervals of soil, and forest carbon sequestration) show CV approaching 0.5.

In addition, given the expected variation in regional conditions it would be highly desirable to have local measurements available for estimating the distribution of carbon generated under a project. However, wide spread local measurements are not currently available. 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.[2]

4.2 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.*, 1994) and EPIC (Izaurralde *et al.*, 2001) simulate changes in soil carbon. Model results can be used to estimate mean

---

[2] 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 current case. 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 and may justify initial uncertainty discounts.

and variance in the quantity of carbon sequestered. 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*., 2004).

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 an 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 CV. 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 overstated if shortfall events at one site are compensated for by excess events elsewhere. Second, important stochastic events like pests, hail, severe winds, diseases etc. 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 (see Richardson *et al*, 2004). However, the granularity of weather stations may still cause a problem as does the omission of localized pest outbreaks, hail damage, wind effects etc.

4.3 Using Crop Yield as a Proxy

While actual field measurements account for the spatial and temporal correlation in the quantity of carbon, the currently available data is 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, 1992). 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 which is highly correlated with yield (such a statement was made by Kimble at The Energy Agriculture Forum, 2004). Thus, we chose to examine the correlation between changes in crop yield and soil carbon to see if crop yield would be an adequate proxy variable.

To do this, we performed biophysical simulations using the EPIC model for the sorghum, rice, and soybeans in Eastern Texas. The results showed a high, statistically significant degree of correlation between changes in crop yields and changes in soil carbon, ranging from 0.7 to 0.9 leading us to conclude we could use the CV for crop yields as a proxy for the CV of carbon.

To use variation in crop yields as a proxy for variation in soil carbon, the variation in crop yields have to be appropriately adjusted because they are not perfectly correlated; measurement errors result when the instrument is not perfectly correlated with the variable of interest (Kennedy, 1992). To show this adjustment, 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 fitting, $\widetilde{Q}_i = a + b \cdot Y_i + \varepsilon_i$, where $\widetilde{Q}_i$ is the quantity of carbon Y is crop yield and ε is the regression error term. Based on this equation, we can derive the relationship between CV_Y *and* CV_Q using the regression based sum of squares:

$$(2) \qquad \sum_i (Q_i - \overline{Q})^2 = \sum_i (a + bY_i + \varepsilon_i - a - b\overline{Y})^2 = b^2 \sum_i (Y_i - \overline{Y})^2 + \sum_i \varepsilon_i^2$$

The definition of the coefficient of determination (R^2) as in Griffiths, Hill and Judge (1992) is $R^2 = 1 - \frac{\sum \varepsilon_i^2}{\sum (Q_i - \overline{Q})^2}$, which implies

$$(3) \quad \sum \varepsilon_i^2 = \frac{(1 - R^2)}{R^2} b^2 \sum (Y_i - \overline{Y})^2 .$$

Substituting equation (3) into equation (2) yields

$$(4) \qquad \sum_i (Q_i - \overline{Q})^2 = \frac{b^2}{R^2} \sum_i (Y_i - \overline{Y})^2$$

Dividing both sides of equation (4) by (n – 1) and taking the square root we get the definition of s_Q the standard deviation of $\widetilde{Q}$ in terms of s_Y the standard deviation of crop yield:

$$(5) \qquad s_Q = \sqrt{\frac{\sum_i (Q_i - \overline{Q})^2}{(n-1)}} = \sqrt{\frac{b^2}{R^2} \frac{\sum_i (Y_i - \overline{Y})^2}{(n-1)}} = \frac{b}{R} s_Y \,,$$

From equation (5), we can derive the relationship between the CVs by dividing both sides by $\overline{Q} \cdot \overline{Y}$ yielding when a = 0,

$$(6) \qquad \frac{s_Q}{\overline{Q} \cdot \overline{Y}} = \frac{b}{R} \frac{s_Y}{\overline{Q} \cdot \overline{Y}} \qquad \Rightarrow \qquad CV_Q = \frac{CV_Y}{R} \,.$$

Thus, the *CV* for carbon can be estimated using the *CV* for crop yield times the correlation coefficient (R).

5. Empirical CV Estimate

The wide availability of historical crop yield data allows us to investigate the effects of aggregation on crop yield CV and, in turn, on the 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 3 East Texas crops - sorghum, rice, and soybeans from 1990 to 2001 from the Economic Research Service web site http://www.ers.usda.gov/data/psd/.

To examine the effects on the CV of incorporating spatial correlation we computed CVs at the Texas Brazoria County, Texas crop reporting district 9, whole state of Texas and U.S. nationwide basis (Table 1). As expected, aggregation across space reduces the CV_Y. In case of soybeans, the *CV* is 23.1% at the county level, falls to 18.1% at the district level, 15.6% at the state level, and 7% at the national level. Results using EPIC at the site level were in the neighborhood of 60%.

As we also wished to see the effects of multi year agreements on the CV, we computed the 5-year stock of total crop yield. Table 2 contains *CV*s for 5-year moving evaluated at each of the above mentioned regional scales. This shows a substantial further decline in the CV. For example for soybeans, the *CV* falls to 8.7% for the county, 5.4% for the district, 3.9% for the state and 2.5% for the nation. Collectively, the multi-site multi-year variation is much smaller that portends a much smaller uncertainty discount for a multi-site multi-year at the project level.

6. Empirical Uncertainty Discounts

The uncertainty discount from a confidence interval approach is $\delta = z_\alpha \cdot CV_Q$, where CV_Q is the CV of carbon production. We estimate CV_Q based on the CV for yields (CV_Y) via the formula $CV_Q = CV_Y / R$ where *R* is the square root of the coefficient of determination (R^2) from a regression[3]. Using carbon sequestration rates and yield data from EPIC simulations for soybeans, sorghum and rice R averaged 0.75.

[3] The intercept term in regression fitting should be zero (that is, a = 0) to use this formula to find the CV_Q. Most of the regression results show that the intercept term is statistically zero, while the slope is not.

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 4.7%. In turn, dividing by R=0.75 we get a CV of 6.3% resulting in the uncertainty discounts of 10.2% for a 95% confidence level and 7.9% with a 90% confidence level. Collectively, the uncertainty discounts across different crops and confidence levels range from 5.2% to 23.3%.

7. Summary and Conclusion

Land based carbon sequestration might become an important instrument in the US GHG mitigation strategy raising interest among emitting entities needing to offset their GHG emissions. The effect of various stochastic factors like weather, fire etc., on the quantity of carbon makes the quantity of carbon generated under a project uncertain. As a result, purchasers of land based carbon credits would be at risk of not meeting their abatement obligations that might subject them to non-compliance penalties. Hence, the quantity of land based carbon credits may need to be discounted to avoid the liability of shortfalls. This would invoke an uncertainty discount requiring one to estimate the quantity of carbon that could confidently occur, which may also impact the prices paid by the credit purchaser for the quantity of carbon sequestered.

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 of data that may be compatible with multi-site multi-year contracts that are likely to form for land based sequestration. 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 multi-year multi-site 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 multi-site multi-year project would result in a high coefficient of variation (CV); hence, higher uncertainty discount. We adjusted the CV in the quantity of carbon by incorporating common weather and biophysical characteristics, as reflected in the historical crop yields in various geographical areas. We found that the CV in the quantity of carbon reduces substantially as we increase aggregation over space and time. The larger the aggregation over time and space the smaller is likely to be the uncertainty discount as added time and spatial dimension tend to cancel out overall project level variations. Application of our theoretical approach suggests that the project level uncertainty discounts fall in a neighborhood of 5% to 10% for the East Texas region.

8. References

Adams, R., D. Adams, J. Callaway, C. Chang, and B. McCarl. "Sequestering Carbon on Agricultural Land: Social Cost and Impacts on Timber Markets." *Contemporary Policy Issues* 11(1993):76-87.

Butt, T.A., and McCarl, B.A. "On-Farm Carbon Sequestration: Can Farmers Make Money?" *Choices* (Fall 2004):27-31.

Birdsey, R.A., and L.S. Heath. "Carbon Changes in US Forests." In: Joyce, L.A. (Ed.), *Productivity of America's Forests and Climate Change*. General Technical Report RM – 271, USDA Forest Service, Rocky Mountain Forest and Range Experiment Station, Fort Collins, CO, 1995.

Canada. "Methodological Issues, Inventories and Uncertainties." United Nations Framework Convention on Climate Change, Subsidiary Body for Scientific and Technological Advice. Additional submissions by parties to the Ninth Session at Buenos Aires, 2-13 November 1998, Item 4 of the provisional agenda. Other Matters, Approaches to resolving methodological issues related to national communications from Annex I Parties, 1998. Available at http://www.unfccc.de/resource/docs/1998/sbsta/misc06a01.pdf

Dixon, R.K., K.J. Andrasko, F.G. Sussman, M.A. Lavinson, M.C. Trexler, and T.S. Vinson. "Forest Sector Carbon Offset Projects: Near-Term Opportunities to Mitigate Greenhouse Gas Emissions." *Water, Air and Soil Pollution* 70(1993):561-577.

Griffiths, W.E., R.C. Hill and G.G. Judge. *Learning and Practicing Econometrics*. John Wiley & Sons, New York, 1992.

Heath, L.S., and J.E. Smith. "An Assessment of Uncertainty in Forest Carbon Budget Projections." *Environmental Science and Policy* 3(2000):73–82.

Intergovernmental Panel on Climate Change (IPCC), *Land Use, Land-Use Change, and Forestry*, A Special Report of the Intergovernmental Panel on Climate Change, 2000.

Izaurralde, R.C., J.R. Williams, W.B. McGill and N.J. Rosenberg. "Simulating Soul Carbon Dynamics, Erosion and Tillage with EPIC." Paper presented at the First National Conference on Carbon Sequestration organized by the U.S. Department of Energy, Washington DC, May 14 – 17, 2001.

Kennedy, P. *A Guide to Econometrics*. Third Edition, The MIT Press, Cambridge, MA, 1992.

Kim, M. "Economic Investigation of Discount Factors for Agricultural Greenhouse Gas Emission Offsets." PhD Dissertation, Department of Agricultural Economics, Texas A&M University, College Station, TX, 2004.

Kimble, J.M. "Private Communication on Carbon Sequestration and Crop Yield." In the Energy Agriculture Forum in CASMGS, College Station, TX, January, 2004.

Marland, G. and B. Schlamadinger. "The Kyoto protocol Could Make a Difference for the Optimal Forest-Based CO_2 Mitigation Strategy: Some Results from GORCM." *Environmental Science and Policy* 2(1999):111-124.

McCarl, B.A. and U.A. Schneider. “The Cost of Greenhouse Gas Mitigation in U.S. Agriculture and Forestry.” *Science* 294(2001):2481-2482.

Mooney, S., J. Antle, S. Capalbo, and K. Paustian. “Influence of Project Scale and Carbon Variability on the Costs of Measuring Soil Carbon Credits.” *Environmental Management* 33(2004):S252-S263.

Moore, D.S., and G. P. McCabe. *Introduction to the Practice of Statistics*. 2nd Edition, W.H. Freeman and Company, New York, 1993.

Parks, P.J. and I.W. Hardie. “Least-Cost Forest Carbon Reserves: Cost-Effective Subsidies to Convert Marginal Agricultural Land to Forests.” *Land Economics* 71(1995):122-136.

Parton, W.J., D.S. Schimel, D.S. Ojima, and C.V. Cole. “A General Model for Soil Organic Matter Dynamics Sensitivity to Litter Chemistry, Texture and Management.” In R.B. Bryant and R.W. Arnold (eds.), *Quantitative Modeling of Soil Forming Process*. SSSA Special Publication 39, Soil Science Society of America, Madison, WI. 1994.

Plantinga, A.J., T. Mauldin, and D.J. Miller. “An Econometric Analysis of the Cost of Sequestering Carbon in Forest.” *American Journal of Agricultural Economics* 81(1999):812-824.

Richardson, J.W., K. Schumann and P. Feldman, *SIMETAR: Simulation for Excel To Analyze Risk*, Agricultural and Food Policy Center, Department Agricultural Economics, Texas A&M University, College Station, TX, 2004.

Sampson, R.N. and R.A. Sedjo. "Economics of Carbon Sequestration in Forestry: An Overview." *Critical Reviews in Environmental Science and Technology* 27(1997):S1-S8.

Seton's EH&S Compliance Resource Centers. Chapter I – Part 77, *40-CFR Protection of Environment* (2003). Available at http://www.setonresourcecenter.com/40CFR/Docs/wcd0007c/wcd07c1a.asp

Smith, J.E., and L.S. Heath. "Identifying Influences on Model Uncertainty: An Application Using a Forest Carbon Budget Model." *Environmental Management* 27(2001):253–267.

Stavins, R.N. "The Costs of Carbon Sequestration: A Revealed-Preference Approach." *American Economic Review* 89(1999):994-1009.

U.S. Department of Agriculture (USDA), *Farms and Land in Farms*, National Agricultural Statistics Service, 2004. Available at http://usda.mannlib.cornell.edu/reports/nassr/other/zfl-bb/fmno0204.txt

West, T.O. and W.M. Post. "Soil Organic Carbon Sequestration Rates by Tillage and Crop Rotation: A Global Data Analysis." *Soil Science Society of America Journal* 66(2002):1930-1946.

West, T.O, G. Marland, A.W. King, W.M. Post, A.K. Jain, and K. Andrasko. "Carbon Management Response Curves: Estimates of Temporal Soil Carbon Dynamics." *Environmental Management* 33(2004):507-518.

Table 1. CV for Yield Over Space (1990 – 2001) (Unit: %)

Region	Sorghum	Corn	Rice	Wheat	Upland Cotton	Soybean
Brazoria county, TX	21.4	26.3	14.2	N/A	31.1	23.1
TX Crop Reporting District 9	17.0	25.2	7.4*	25.0	23.4	18.1
State of Texas	10.4	11.0	7.5	11.2	9.0	15.6
U.S.	8.8	10.0	5.2	7.1	8.1	7.0

* Rice production area is mainly located in District 9 so that CVs for the state and the agricultural district are very similar.

Table 2. CV for Yield Over Time* (5 year interval) (Unit: %)

Region	Sorghum	Corn	Rice	Wheat	Upland Cotton	Soybean
Brazoria county, TX	5.1	8.6	5.3	N/A	13.9	8.7
TX Crop Reporting District 9	2.9	6.0	2.3	5.7	5.9	5.4
State of Texas	3.3	2.8	2.2	5.2	3.3	3.9
U.S.	1.3	4.6	2.0	4.3	1.5	2.5

* This CV is computed for five year moving averages for each crop at each level of aggregation.