Technical Progress Report

"Restoring Sustainable Forests on Appalachian Mined Lands for Wood Products, Renewable Energy, Carbon Sequestration, and Other Ecosystem Services"

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ABSTRACT

The overall purpose of this project is to evaluate the biological and economic feasibility of restoring high-quality forests on mined land, and to measure carbon sequestration and wood production benefits that would be achieved from forest restoration procedures. In this quarterly report we present data that show the spatial distribution of carbon in mine soils. Soil carbon data from deep soil pits from grassland minelands located in Ohio, Virginia, and West Virginia were analyzed to determine the vertical distribution and variability of soil organic carbon (SOC) down to a 2-m depth. Regression analyses were used to describe and model the distribution by soil depth of C(wt%), BD_{fines}(g cm^{-3}), and fines(vol%) in mine soils. The volume of excavated mine soil samples was transformed in terms of costs of digging and sampling, including sample collection and preparation, and C(wt%) analysis, in order to determine the maximum cost-effective depth (MCD) for carbon inventorying on the mined sites analyzed. Based on the horizontal variation of SOC(g m^{-2}), we determined the sampling intensity required to achieve a desired accuracy of the amount of sequestered SOC(g m^{-2}) at certain probability levels. The MCD and sampling intensity measurements were used to determine the minimum detectable difference (MDD) of SOC(g m^{-2}) between two consecutive carbon inventories. We also proposed a method to determine the minimum number of years before a future C inventory event is carried out so that the measured SOC(g m^{-2}) differences were greater than MDD. We used geostatistical analyses procedures to determine spatial dependence predictability of surface SOC(g m^{-2}) data on the minelands analyzed. Kriging techniques were used to create surface SOC(g m^{-2}) maps for the sites in Ohio and West Virginia. The average C sequestration rate in the surface soil layer for the Ohio (age 9) sites was estimated at 124 g C m^{-2} yr^{-1}, and it was estimated at 107 g C m^{-2} yr^{-1} for the West Virginia sites (age 4). Because of the young age of the Virginia sites, 0.2 and 1 year old, we came to a decision that C sequestration rates would be inappropriate at this stage of their development, as these soils are expected to change with time.

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INTRODUCTION

Public Law 95-87 mandates that mined land be reclaimed in a fashion that renders the land at least as productive after mining as it was before (Torbert et al. 1995). Research has shown that restored forests on mined lands can be equally as or more productive than the native forests removed by mining (Burger and Zipper 2002). Given that most land surface-mined for coal in the Appalachians was originally forested, forestry is a logical land use for most of the reclaimed mined land in the region (Torbert and Burger 1990). However, since implementation of the SMCRA, fewer forests are being restored in the eastern and midwestern coalfield regions (Burger et al. 1998). In several states, most notably Virginia, the majority of mined land is now being restored to forests. Over 80% of Virginia's mined land has been reclaimed to forested post-mining land uses since 1991. However, regionwide, the majority of mined land that was originally forested is not being reclaimed in a way that favors tree establishment, timber production, carbon sequestration, and long-term forest productivity (Torbert and Burger 1990).

We believe that these reclaimed mined lands are producing timber and sequestering carbon at rates far below their potential for reasons that include poor mine soil quality, inadequate stocking of trees, lack of reforestation incentives, and regulatory disincentives for planting trees on previously forested land (Boyce 1999, Burger and Maxey 1998). A number of these problems can be ameliorated simply through intensive silvicultural management. Through established site preparation techniques such as ripping, weed control, fertilizing, and liming, the quality of a given site can be improved. Other management and silvicultural techniques such as site-species matching, correct planting techniques, employing optimal planting densities, post-planting weed control, and thinning can also improve normal development of forest stands and improve timber production and carbon sequestration.

Similar to the much-debated topic of converting agricultural land to forests, the conversion of reclaimed mined lands to forests carries with it many economic implications. The primary difference between converting agricultural lands to forests and converting reclaimed mined lands to forests is the absence of any obvious extrinsic opportunity cost in the latter scenario; this, of course, assumes that the reclaimed mined land has been abandoned and is not being utilized for any economically beneficial purpose.

A fair amount of research has been conducted regarding the amounts and values of timber produced on reclaimed mined lands. The effect that a carbon market may have on decisions pertaining to the reclamation of mined lands has also been researched. According to previous research, it appears that mined lands are capable of sequestering carbon and producing harvest volumes of equal or greater magnitude to similar non-mined lands. This fact alone, however, does not render afforestation of mined lands economically profitable or feasible in all cases. There is a lack of research pertaining specifically to the conversion of reclaimed mined lands from their current uses to forests and the economic implications of such a land use conversion. Furthermore, the potential for an incentive scheme aimed at promoting the conversion of reclaimed mined lands to forests has yet to be explored in depth.

This study ultimately addresses the potential for increasing carbon sequestration on surface-mined land. The overall research objective of this study is to determine the economic feasibility of carbon sequestration through converting reclaimed mined lands to forests using high-value tree species, and to demonstrate the economic and decision-making implications of an incentive scheme on such a land use conversion.

EXECUTIVE SUMMARY

The purpose of this project is to evaluate the biological and economic feasibility of restoring high-quality forests on abandoned mined land, and to measure carbon sequestration and wood production benefits that would be achieved from forest restoration procedures. The project is based on 14 afforested mined sites varying in age from 20 to 56 years located in a seven-state area of the eastern coalfields (Study 1) (Fig. 1), and a new field study, which is a 3 x 3 factorial in a random complete block design with three replications at each of three locations: Ohio (Fig. 1), West Virginia (Fig. 2), and Virginia (Study 2) (Fig. 2). For Study 2, which is the emphasis of this report, the treatments included three forest types (white pine, hybrid poplar, mixed hardwood) and three silvicultural regimes (competition control, competition control plus tillage, competition control plus tillage plus fertilization). Each individual treatment plot is 0.5 acres. Each block of nine plots is 4.5 acres, and the complete installation at each site is 13.5 acres.

In this quarterly report, we present data that show the spatial distribution of carbon in mine soils. Soil carbon data from deep soil pits from grassland minelands located in Ohio, Virginia, and West Virginia were analyzed to determine the vertical distribution and variability of soil organic carbon (SOC) down to a depth of 2 m. Regression analyses were used to describe and model the distribution by soil depth of C(wt%), BD_{fines}(g cm^{-3}), and fines(vol%) in mine soils. The volume of excavated mine soil samples was transformed in terms of costs of digging and sampling, including sample collection and preparation, and C(wt%) analysis, in order to determine the maximum cost-effective depth (MCD) for carbon inventorying on the mined sites analyzed. Based on the horizontal variation of SOC(g m^{-2}), we determined the sampling intensity required to achieve a desired accuracy of the amount of sequestered SOC(g m^{-2}) at certain probability levels. The MCD and sampling intensity measurements were used to determine the minimum detectable difference (MDD) of SOC(g m^{-2}) between two consecutive carbon inventories. We also proposed a method to determine the minimum number of years before a future C inventory event is carried out so that the measured SOC(g m^{-2}) differences were greater than MDD. We used geostatistical analyses procedures to determine spatial dependence predictability of surface SOC(g m^{-2}) data on the minelands analyzed. Kriging techniques were used to create surface SOC(g m^{-2}) maps for the sites in Ohio and West Virginia. The average C sequestration rate in the surface soil layer for the Ohio (age 9) sites was estimated at 124 g C m^{-2} yr^{-1}, and it was estimated at 107 g C m^{-2} yr^{-1} for the West Virginia sites (age 4). Because of the young age of the Virginia sites, 0.2 and 1 year old, we came to a decision that C sequestration rates would be inappropriate at this stage of their development, as these soils are expected to change with time.

The overall findings in this report support the understanding that establishing C sequestration projects on minelands could be a profitable alternative for mineland reclamation. Due to the inherent variability of soil C(wt%), we suggested that mined sites older than 9 years be selected for C sequestration projects. One of the outcomes from this project is a universal field measurement protocol for minelands that could be applied to any mined land in the eastern United States. Based on our experience and knowledge for site characterization and mapping, horizontal and vertical variability of SOC, and the results for MDD and MCD in mine soils, we have summarized the necessary steps to produce accurate and precise ecosystem C content estimates for minelands of various stages of floristic succession, ranging from abandoned grasslands to shrubland to forestland.

Study 1: Pre-SMCRA Mined Sites Study

14 mined sites (★):
- Forested
  (Hardwoods,
  Conifers,
  Mixed)
- 20 to 55 years old

8 natural sites (★):
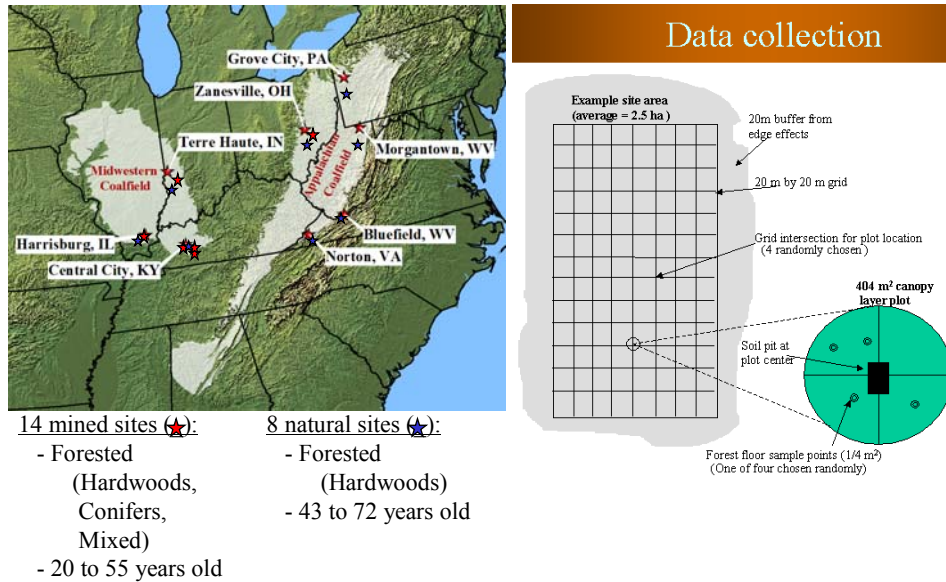- Forested
  (Hardwoods)
- 43 to 72 years old

Figure 1. **Location and layout of experimental sites for Study 1 across a seven-state region.**

Study 2: Post-SMCRA Mined Grasslands Study
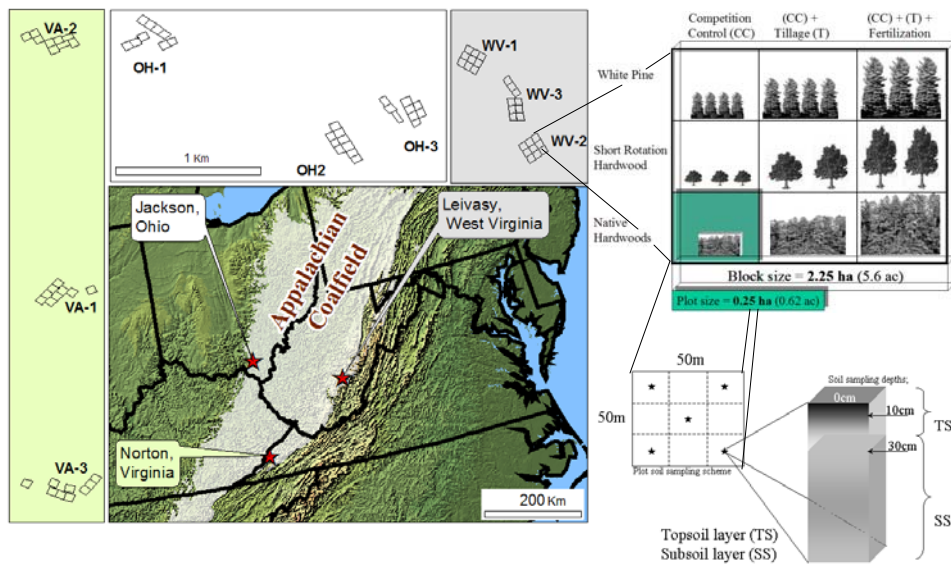
Figure 2. **Location and layout of experimental sites for Study 2 in Ohio, West Virginia, and Virginia.**

TASK 1: Estimate forest productivity and carbon sequestration potential on mined lands supporting abandoned grasslands. (Burger et al.)

Executive Summary

Today, existing at various stages of floristic succession – from abandoned grasslands to brush lands to forestlands – there are millions of hectares of land disturbed by surface mining across the United States. In order for a soil carbon inventory to be economically feasible on minelands, it is desired that at the very least the C credits received for sequestering atmospheric CO_2 in mine soils are enough to recover the costs for measuring and reporting the sequestered C.

Soil carbon data from deep soil pits from grassland minelands located in Ohio, Virginia, and West Virginia were analyzed to determine the vertical distribution and variability of soil organic carbon (SOC) down to a depth of 2 m. Regression analyses were used to describe and model the distribution by soil depth of C(wt%), BD_{fines}(g cm^{-3}), and fines(vol%) in mine soils. The volume of excavated mine soil samples was transformed in terms of costs of digging and sampling, including sample collection and preparation, and C(wt%) analysis, in order to determine the maximum cost-effective depth (MCD) for carbon inventorying on the mined sites analyzed. Based on the horizontal variation of SOC(g m^{-2}) we determined the sampling intensity required to achieve a desired accuracy of the amount of sequestered SOC(g m^{-2}) at certain probability levels. The MCD and sampling intensity measurements were used to determine the minimum detectable difference (MDD) of SOC(g m^{-2}) between two consecutive carbon inventories. We also proposed a method to determine the minimum number of years before a future C inventory event is carried out so that the measured SOC(g m^{-2}) differences were greater than MDD. We used geostatistical analyses procedures to determine spatial dependence predictability of surface SOC(g m^{-2}) data on the minelands analyzed. Kriging techniques were used to create surface SOC(g m^{-2}) maps for the sites in Ohio and West Virginia.

The average C sequestration rate in the surface soil layer for the Ohio (age 9) sites was estimated at 124 g C m^{-2} yr^{-1}, and it was estimated at 107 g C m^{-2} yr^{-1} for the West Virginia sites (age 4). Because of the young age of the Virginia sites, 0.2 and 1 year old, we came to a decision that C sequestration rates would be inappropriate at this stage of their development, as these soils are expected to change with time.

Significant regression models were developed for C(wt%), BD_{fines}(g cm^{-3}), and fines(vol%) by soil depth for the Ohio mine sites, with respective R^2 values of 0.18, 0.24, and 0.28. Similarly, we developed regression models for the distribution of these three variables down the mine soil profiles in Virginia, with respective R^2 values of 0.60, 0.52, and 0.34. Model-fit analyses indicated that the final models for predicting SOC(g m^{-2}) by depth for the mined sites in Ohio and Virginia were of poor fit, with R^2 estimates of 14% and 0%, most likely due to the high variation of C (wt%) by depth. Our results indicated that in one growing season, very little carbon was added to mine soils, evident from the observed low SOC(g m^{-2}) amounts from the soil samples in Virginia (average of 10 g m^{-2}) relative to the 9-year-old sites in Ohio (average of 87 g m^{-2}), which contained an average of 770% more SOC within a 1 cm-thick soil layer at any depth down the soil profile. Due to insufficient data, we did not develop regression models that could describe the amount of sequestered carbon by depth in the sites located in West Virginia.

The results from geostatistical analysis of SOC(g m^{-2}) data for the surface 0-10 cm soil layer indicated that organic carbon was spatially dependent on the sites in Ohio and West

Virginia. The range of heterogeneity was estimated at 576 and 593 m, respectively. The SOC(g m^{-2}) data for West Virginia had better spatial structure (0.764), i.e., higher spatially-dependent predictability, compared to the data for Ohio (0.439), based on the ratio between the spatially-dependent variance and the total variance of the data. The resulting SOC(g m^{-2}) kriging maps indicated that the northernmost plots in the OH1 block in Ohio sequestered the highest amount of soil carbon, ranging from 1,300 to 1,410 g C m^{-2}, and four of the central plots in OH2 contained the lowest SOC(g m^{-2}), ranging from 724 to 825 g C m^{-2}. Similarly, for the sites in West Virginia, the southernmost plots of the WV3 block contained the highest amounts of sequestered SOC(g m^{-2}), ranging from 2,050 to 2,750 g C m^{-2}, and the northernmost three plots of the same block contained the lowest SOC(g m^{-2}), ranging from 60 to 250 g C m^{-2}.

We standardized the amount of cumulative SOC(g m^{-2}) by excavation depth, in order to assign a cost value for analyzing SOC(g m^{-2}), using \$8 cm^{-1} pit^{-1} as base cost estimate for digging, sampling, preparation and analysis of mine soils for SOC(g m^{-2}), and \$127.2 Mg^{-1} C as base profit estimate from C credits. Our results indicated that the profit break-even depth of SOC(g m^{-2}) analysis for C credits, i.e., the maximum cost effective sampling depth, was 18 cm at a sampling intensity of 17 plots ha^{-1} on the OH2 research block. The latter sampling intensity is required for SOC(g m^{-2}) estimation at 15% accuracy and 95% probability levels. Our analysis indicated that more than four-fifths of the total sequestered C will be left unreported below 18 cm depth on the OH2 site. In comparison, due to the lower horizontal variability of the OH1 and OH3 sites in Ohio, the maximum cost-effective depth exceeded 200 cm for SOC estimation at 15% accuracy and 95% probability levels.

The net profit from measuring and reporting SOC for C credits contained in the to 0-25 cm layer on the OH1 and OH3 sites was approximately \$3,000 ha^{-1}, and the net costs were \$620 ha^{-1}. Similarly, the net profits from SOC analysis for the 0-100 cm layer were estimated at approximately \$5,900 ha^{-1} at net costs of \$2,480 ha^{-1}.

We predicted the number of significant years until future C inventory as follows: $T =$ (SOC(g m^{-2})$_{at\ present}$ + 2*(95% CI))/ rate$_{at\ present}$, where 95% CI is the 95% confidence interval of SOC(g m^{-2})$_{at\ present}$ and rate$_{at\ present}$ is the current estimate of the rate of C sequestration. The results showed that approximately 32 years of uninterrupted SOC accumulation within the 0-18cm soil layer on the OH2 mined sites are necessary for the future SOC(g m^{-2}) estimate, SOC$_{at\ [present\ +32]\ years}$, to be significantly larger than the SOC(g m^{-2}) measured at the present time. The MDD for this site for SOC(g m^{-2}) analysis to 18cm was 5,376 g C m^{-2} (equal to 2 * 95% CI).

The overall findings in this report support the understanding that establishing C sequestration projects on minelands could be a profitable alternative for mineland reclamation. Due to the inherent variability of soil C(wt%), we suggested that mined sites older than 9 years be selected for C sequestration projects. One of the outcomes from this project is a universal field measurement protocol for minelands that could be applied to any mined land in the eastern United States. Based on our experience and knowledge for site characterization and mapping, horizontal and vertical variability of SOC, and the results for MDD and MCD in mine soils, we have summarized the necessary steps to produce accurate and precise ecosystem C content estimates for minelands of various stages of floristic succession, ranging from abandoned grasslands to shrubland to forestland.

Experimental

The rate and the extent to which reforested mined land captures and stores atmospheric C as mine soil organic carbon is still largely unknown due to the challenges associated with analytical measurement of SOC and verification of sequestered SOC at the landscape scale. This information is essential to establish a vigorous and effective C market in the United States. The carbon accreditation process, as well as its counterpart, the C sequestration verification procedure, depends on detailed data about the magnitude of minimum detectable difference (MDD) of sequestered SOC and the relative expenses associated with MDD determination for reforestation projects on mined lands.

In order for an SOC inventory to be economically feasible, it is desired that at the very least the C credits received for sequestering atmospheric CO_2 in mine soils are enough to recover the costs for measuring and reporting the sequestered SOC. Because of the logistics of soil excavation, i.e., if one is to report C credits below a certain soil depth (assume 50 cm), then first, one must remove the spoil from 0 to 50 cm depth, which unmistakably is associated with certain costs. Undoubtedly, there will be a maximum cost-effective depth (MCD) below which the net monetary value of the sequestered SOC, computed as the difference between gross profit from C credits and the measurement costs of the sequestered SOC, will become negative, and thus undesirable. This is to say that one will pay more money for soil pit excavation, soil sample collection, preparation, and carbon analysis to verify the amount of sequestered SOC below the MCD than the actual net market value of the verified SOC sequestered in the soil.

Therefore, additional information is essential to determine the MCD for mined land and to identify the factors that could allow manipulation of MCD towards gaining more profit from mined land reforestation. Some of the factors that could allow deeper MCD for C analysis, hence additional C credits to report, are the current C price on the carbon market, the variability of SOC within the profile and the variability across the mined landscape, and the respective costs for collecting, preparation, and analysis of soil samples. Provided there is access to efficient mine soil-specific C analysis techniques and more advanced methods and tools for horizontal soil variability analyses, such as geographic information systems (GIS) and geostatistics, landowners will be able to minimize the costs for SOC analysis across the mined landscape and focus the resources available for SOC measurements deeper in the soil profile, where much of the sequestered SOC may be left unreported.

The objectives of this report are: (1) to determine the horizontal and vertical distribution and variability of sequestered C in mine soils; (2) to determine the maximum cost-effective depth (MCD) and the minimum detectable difference (MDD) of soil organic C in C-accreditation analysis for mined land; and (3) to develop a C sequestration measurement protocol for mine soils.

Subtask 1.1

Horizontal and vertical distribution and variability of SOC in mine soils. All composited soil samples and the deep-pit soil samples were analyzed for their C concentration using the 16-step SOC measurement method for mine soils described in our previous report. Soil organic carbon content per soil horizon (or per soil layer) with identified upper and lower boundaries was estimated in g m^{-2} units using total soil carbon concentration measurements corrected for coal content and carbonates, bulk density of the fine earth fraction, percent of the fine earth fraction on a soil volume basis, and horizon depth, as depicted in the equation below:

$$\text{SOC}(g\ m^{-2}) = C(wt\%) * BD_{fines}(g\ cm^{-3}) * Fines(vol\%) * Layer(cm) \qquad \textbf{[Eq.1]}$$

where: $C(wt\%)$ = percent soil organic carbon of the fine soil fraction (fines), less than 2-mm soil

particles, measured on a weight basis = $\dfrac{C_g}{Fines_g} * 100$;

$BD_{fines}(g\ cm^{-3})$ = bulk density of the fines = $\dfrac{Fines_g}{Fines_{cm^3}}$;

$Fines(vol\%)$ = the volumetric fraction of the fines measured as percent of the total

volume of excavated soil sample = $\dfrac{Fines_{cm^3}}{Soil_{cm^3}} * 100$; and

$Layer(cm)$ = soil layer or soil horizon thickness expressed in cm units.

Each variable in Eq.1, except layer(cm), could be associated with certain errors due to the sampling and measurement techniques used. Layer thickness measurements are based on universally available standards for measuring lengths and distances. Assuming that the top and bottom boundaries of a certain soil horizon were clearly observable at a certain sampling location, one could measure its thickness with sufficient accuracy, e.g., +/-0.25 mm (0.5 mm), depending on the type of measurement instruments used, such as a graduated yardstick.

Based on our evaluation of the new C partitioning technique, using the 16-step SOC estimation method, the mean of the measured $C(wt\%)$ in mine soils will be within 16% to 23% of the true SOC. The latter was demonstrated to hold true for mine soils developed from weathered sandstone (SS) or siltstone (SiS) overburden spoil material of up to 10% coal fragment content, by sample weight. Similar evaluation studies for the $BD_{fines}(g\ cm^{-3})$ and fines(vol%) variables could potentially help determine the remaining sources of sampling and measurement errors associated with the final product from Eq.1, the $SOC(g\ m^{-2})$ estimate.

For this project, we estimated $BD_{fines}(g\ cm^{-3})$ and Fines(vol%) from measured $CFC(wt\%)$, $BD_{soil}(g\ cm^{-3})$, and the moisture content of the fines, moisture(%), for our soil samples. The bulk density of the fine earth fraction, $BD_{fines}(g\ cm^{-3})$, was computed as $[[1 - CFC(wt\%)/100]/[1/ BD_{soil}(g\ cm^{-3}) - CFC(wt\%)/(2.65*100)]]/[1 + Moisture(\%)/100]$, where 2.65 g cm^{-3} was the assumed bulk density of SS and SiS coarse rock fragments in minesoils. In addition, the volumetric percent content of the fines, Fines(vol%), was computed as $[100 - BD_{soil}(g\ cm^{-3}) * CFC(wt\%)/2.65]$. The estimated properties for the fine earth fraction of each sample, $BD_{fines}(g\ cm^{-3})$ and Fines(vol%), as well as the measured $C(wt\%)$, were used to estimate the final soil organic carbon content in units of g C m^{-2}, $SOC(g\ m^{-2})$. All measurements were made for mine soil volumes of approximately 1 ft^3 or smaller, dependent on the time and funding allocated to our research sites.

For most rocky and compacted soils, such as mine soils, digging deeper and wider soil pits and sampling large volumes of soil for more complete soil analysis and to achieve accurate measurements of $CFC(wt\%)$ and $BD_{soil}(g\ cm^{-3})$ across the mined landscape can be very costly and laborious. Currently, measurement of $CFC(wt\%)$ in mine soils poses the greatest challenge for C inventorying on mineland when the goal is to produce accurate and precise $SOC(g\ m^{-2})$

estimates across a certain project site. Because of the anthropogenic origin of mine soils, large boulders, often as large as an average-size golf cart, could be randomly distributed below the soil surface across the mined landscape. It is apparent that in order to account for the rock fragments of various sizes in mine soils, one must sample soil volumes that are big enough to contain the largest of soil rock fragments present. Constrained by time and available resources, most mineland researchers collect samples of less than 27,000 cm^3 (approximately 1 ft^3) for studies in mine soils, which is the volume of a 30 x 30 x 30 cm soil pit. This is to say that the results from these studies were based on the assumption that the largest rock fragments on these minelands are of volumes smaller than 1 ft^3. However, failure to test this assumption on a certain mined site could lead to significantly overestimated SOC(g m^{-2}).

Mine soils have coarse fragment contents ranging from 40% to 80% by soil weight. The size of the coarse fragments and their spatial distribution are quite different from those of undisturbed soils. The main reason for this is that the underlying layers of unconsolidated rock were blasted and put on the reclaimed sites at random during surface coal mining operations. Therefore, some parts of the project area may end up with larger coarse fragments that could be of different rock types than others. Unfortunately, there is no established research approach for accurately predicting the distribution, size, and content of mine soil rock fragments.

Techniques that are currently used by mine soil researchers include soil excavation to a predefined depth, such as 30 or 50 cm, and/or predefined volume of mine soil sampling, such as 30 x 30 x 30 cm soil volume. Due to the nature of the mine spoil, it could be impossible to obtain soil samples by hand beyond 30 cm. The latter was the target sampling depth for all shallow pits on our research sites. We assumed that the largest coarse rock fragments on our sites were of volumes equal to or smaller than 27,000 cm^3 and were contained in our excavated 30 x 30 x 30 cm soil samples.

Propagation of uncertainty. Because SOC estimates are most commonly expressed in units that represent a certain area, such as g m^{-2}, kg m^{-2} and Mg ha^{-1}, the results of any SOC quantification analysis include the combined error associated with measuring each individual component in Eq.1. The rules for error propagation described in Harris (2005) were used to produce the 95% confidence limits of individual SOC(g m^{-2}) predictions estimated at 1-cm increments down the mine soil profile for the vertical distribution analysis of SOC(g m^{-2}), and to produce the 95% confidence limits of SOC(g m^{-2}) prediction for the horizontal distribution analysis of soil carbon on minelands. The percent error for SOC(g m^{-2}) was estimated as SQRT[(%εC(wt%))^2+ (%εBD$_{fines}$(g cm^{-3}))^2 + (%εFines(vol%))^2], where %ε represents the percent relative uncertainty of the respective variables. Percent relative uncertainty was estimated by dividing the absolute uncertainty, expressed in the units of the variable such as standard deviation or standard error, by the magnitude of the measurement, times 100, i.e., %ε = [StdErr/Mean]*100.

Statistical analysis and modeling. Statistical procedures for linear regression analysis, PROC REG, and the C(p) model selection method (SAS 2004) were used to create prediction models for C(wt%), BD$_{fines}$(g cm^{-3}), and Fines(vol%) by soil depth. Predictions of individual variables by soil depth and their 95% confidence limits were also estimated and reported. These regression models were used to model the distribution of SOC(g m^{-2}) by soil depth. The latter was further analyzed to determine the MDD of C change on minelands and MCD for C inventorying in mine soils.

Geostatistical analysis on minelands. It is expected that soil properties could vary greatly across the mined landscape and down the mine soil profile. Results from the carbon data analysis and geostatistical data analysis for soil samples from the DOE sites were used to gain a better understanding of the magnitude of the horizontal variability of SOC in mine soils.

Similar to the geostatistical analyses completed by Boruvka and Kozak (2001) and McKenzie and Ryan (1999), we analyzed the SOC(g m^{-2}) data from the composite samples collected from the DOE project sites to the 0-10 cm depth in a GIS in order to determine the spatial dependence of SOC in mine soils. The results from the geostatistical modeling were used for kriging to create SOC(g m^{-2}) prediction maps and to determine whether these data had any spatial dependence predictability. The latter was directly related to the logistics of spoil overburden material mixing, transportation and deposition on mined sites during reclamation (Boruvka and Kozak 2001). Results from the semivariance modeling of the composites SOC(g m^{-2}) estimates were used to evaluate the gain/loss in accuracy of SOC(g m^{-2}) predictions relative to the increase/decrease in sampling intensity for minelands.

Data from the deep soil pits were analyzed to determine the vertical distribution and variability of SOC down to a soil depth of 2 m. Regression analyses were performed in order to describe and model the distribution by soil depth of chemical, C(wt%), and physical properties (bulk density, volumetric content of the fine earth fraction) in mine soils.

Subtask 1.2

MDD of C stocks and MCD for C inventorying on mined land. The concept of minimum detectable difference of carbon stocks measured at two different points in time for a given project site has been the focus of many carbon sequestration studies (Conant et al. 2003, Lilienfein et al. 2003, Zhang and McGrath 2004). Carbon researchers are aware that in order to claim carbon credits, the total sequestered SOC(g m^{-2}) should be significantly (statistically defined) higher than the SOC(g m^{-2}) estimated some 5 to 10 (or more) years ago. In some cases, authors reported statistically insignificant accumulations of SOC even after 30 years under a grassland land-use system (Zhang and McGrath 2004). Others have reported statistically significant accumulations after four years for cultivated lands and forested systems (Conant et al. 2003).

We used the results from the statistical analysis of the carbon data for the DOE project sites, as well as the results for the horizontal variation of SOC, to determine the MDD of C stocks and the suggested time for the next C inventory event for selected sites characterized in this study. In addition, by dividing the total sequestered SOC(g m^{-2}) by the respective reclamation age of each project site, we estimated the relative rate of carbon sequestration on the sites analyzed.

It is evident that within a certain terrestrial system, as soil variability increases, the ability to detect significant changes in SOC using a set number of sampling plots decreases. The latter was demonstrated by Conant et al. (2003), who showed that a greater number of sampling plots is required in forested systems compared to cultivated areas in order to detect a 2 Mg C ha^{-1} carbon stock change over four years.

However, increases in the number of sampling plots for highly variable soils, such as mine soils, could lead to dramatic increase in sampling costs for C verification studies. Hence, the cost-effective depth of soil sampling on mineland could decrease (become shallower) proportionally due to the fact that excavation for soil sampling by depth is a rather tedious and

expensive task, especially in compacted and rocky mine soils.

We used the results from the vertical distribution of SOC on our research sites to estimate the relative decrease in cumulative SOC within a given volume of spoil versus the volume of excavated material. The volume of excavated spoil material used for C analysis was transformed in terms of costs of digging a sampling, including sample collection and preparation, and SOC analysis, in order to determine the maximum cost-effective depth for carbon inventorying on minelands.

Subtask 1.3

Field measurement protocol for carbon inventory on mineland. In order to provide consistency for carbon credit verification and reporting among forested mineland owners, there is a need for comprehensive and practical guidelines for carbon inventory on minelands. We developed a universal field measurement protocol for minelands that could be applied to any mined land in the eastern United States. Based on our experience and knowledge of site characterization and mapping, horizontal and vertical variability of SOC, and the results for MDD and MCD in mine soils, we established the necessary steps to produce accurate and precise ecosystem C content estimates for minelands of various stages of floristic succession, ranging from abandoned grasslands to shrubland to forestland. Our goal was to develop a field measurement protocol in which the mineland owner will find the means to determine the most cost-effective sampling strategies suited for the property in order to determine the amount of sequestered C on the land.

For example, depending on the soil variability of a certain mineland, the landowner would be enabled to compute the maximum cost-effective depth for SOC sampling and analysis on the property as well as the number of sampling soil pits, and the number of vegetation and litter layer sampling plots necessary to achieve certain accuracy and precision levels of the ecosystem carbon estimates. In addition, the field measurement protocol would provide the landowner all the necessary information, or the means to produce such information, in order to determine the time period (in years) between two consecutive carbon inventory events for which C credits could be claimed as the difference between the total ecosystem C sequestered at the end of the inventory period and that sequestered at the beginning of that period.

Results and Discussion

Subtask 1.1

Horizontal and vertical distribution and variability of SOC in mine soils. Soils are three-dimensional landscape features. Although this is a well-known fact, it is not intuitive for the common person to picture the topmost portion of the earth's crust as having variable depth and being characterized with different chemical and physical properties that could vary both horizontally across the landscape and vertically down the soil profile, and that are constantly changed and affected by many factors. The type of vegetation growing on a certain soil, the underlying geology, climate, topography, and time (think millions of years) are all factors that have led to the formation of one type of soil or another across the globe. The implications of all this to carbon sequestration studies for terrestrial ecosystems are that the researchers involved must account for each of the above factors affecting the properties of soils in order to accurately model and predict the amount of sequestered carbon in soils. Another way to get an understanding about the C sequestration potential of different soils is to be able to accurately and precisely measure the

carbon that is currently sequestered in a certain soil in the horizontal and vertical dimensions. Both approaches for predicting sequestered carbon in soils are valid and are widely used among researchers; however, empirical models based on measured data are usually regarded as superior to process-based models. The latter rely on a researcher's complete and thorough understanding and comprehensive and valid modeling of all processes occurring in soils that could affect the amount of sequestered C for different soils. However, empirical models are associated with higher costs. In order to determine the amount of carbon sequestration down the soil profile, a certain soil must be excavated to a desired depth and be sampled and analyzed for C in a cost-effective way so that C sequestration studies can be warranted.

Presented in Figures 1-1 through 1-6 are the vertical distributions of the chemical and physical properties in mine soils that are required for $SOC(g\ m^{-2})$ analysis of the DOE research sites in Ohio, Virginia, and West Virginia. The three variables used in Eq.1, Fines(vol%), $BD_{fines}(g\ cm^{-3})$, and C(wt%), were modeled by depth using standard linear regression analysis techniques, where depth was the independent variable. Significant regression models were developed from the data from the deep soil pits on the Ohio sites for the content of fines (P = 0.1254, Fig. 1a), bulk density of the fines (P = 0.0694, Fig. 1-1b), and C(wt%) (P = 0.0009, Fig. 1-2a). The respective R^2 values for the regression models of the Fines(vol%), $BD_{fines}(g\ cm^{-3})$, and C(wt%) variables were 0.18, 0.24, and 0.28. Similarly, we developed regression models for the distribution of these three variables down the mine soil profiles in Virginia (Figs. 1-3a, 1-3b, and 1-4a). The respective R^2 values for the regression models of the Fines(vol%), $BD_{fines}(g\ cm^{-3})$, and C(wt%) variables were 0.60, 0.52, and 0.34. Due to insufficient data, we were unable to develop prediction models that could be used to describe the amount of carbon sequestration down the mine soil profile for the research sites located in West Virginia (Figs. 1-5 and 1-6).

In Ohio, the content of the fines ranged between 70 and 97% by soil volume, the bulk density of the fines ranged between 0.7 and 1.7 g cm^{-3}, and the C concentration ranged between 0 and 1.9% by soil weight (Figs. 1-1 and 1-2). Soil organic carbon concentration decreased down the mine soil profile following a reciprocal function by depth (x = f(1/y)), but the variation among individual C(wt%) measurements did not permit conclusive inferences about this soil property. The 95% confidence limits of the C(wt%) prediction model indicated that at the lower limit of the predictions there would not be any organic C accumulation beyond a depth of 3 cm. On the other hand, the upper limit of the predictions indicated that there will be at least 1.376 wt% of soil organic carbon at a depth of 200 cm (Fig. 1-2a).

The latter could be regarded as a computational error if one only takes into consideration the fact that root growth is concentrated in the surface soil layers. Because of the excessive compaction of mine soils, root growth is generally restricted to the surface 1 m of the mine soil. However, it could be argued that SOC accumulation in subsurface soil horizons at depths greater than 1 m could be due to the translocation of dissolved SOC down the profile and its adsorption to the surfaces of fine soil particles located in the voids between larger coarse fragments.

One should also be aware that significant amount of old organic matter, which has not transformed into coal, could be contained within sedimentary rocks such as shales and siltstone. Because the 16-step SOC estimation method is specifically designed to partition the total soil carbon into carbon from coal and carbon from plant material (i.e., recent carbon), the C(wt%) results from this analysis were corrected for the coal content in the soils samples analyzed, but there was no correction applied for the old organic carbon contained within the macerals of shale and SiS rocks.
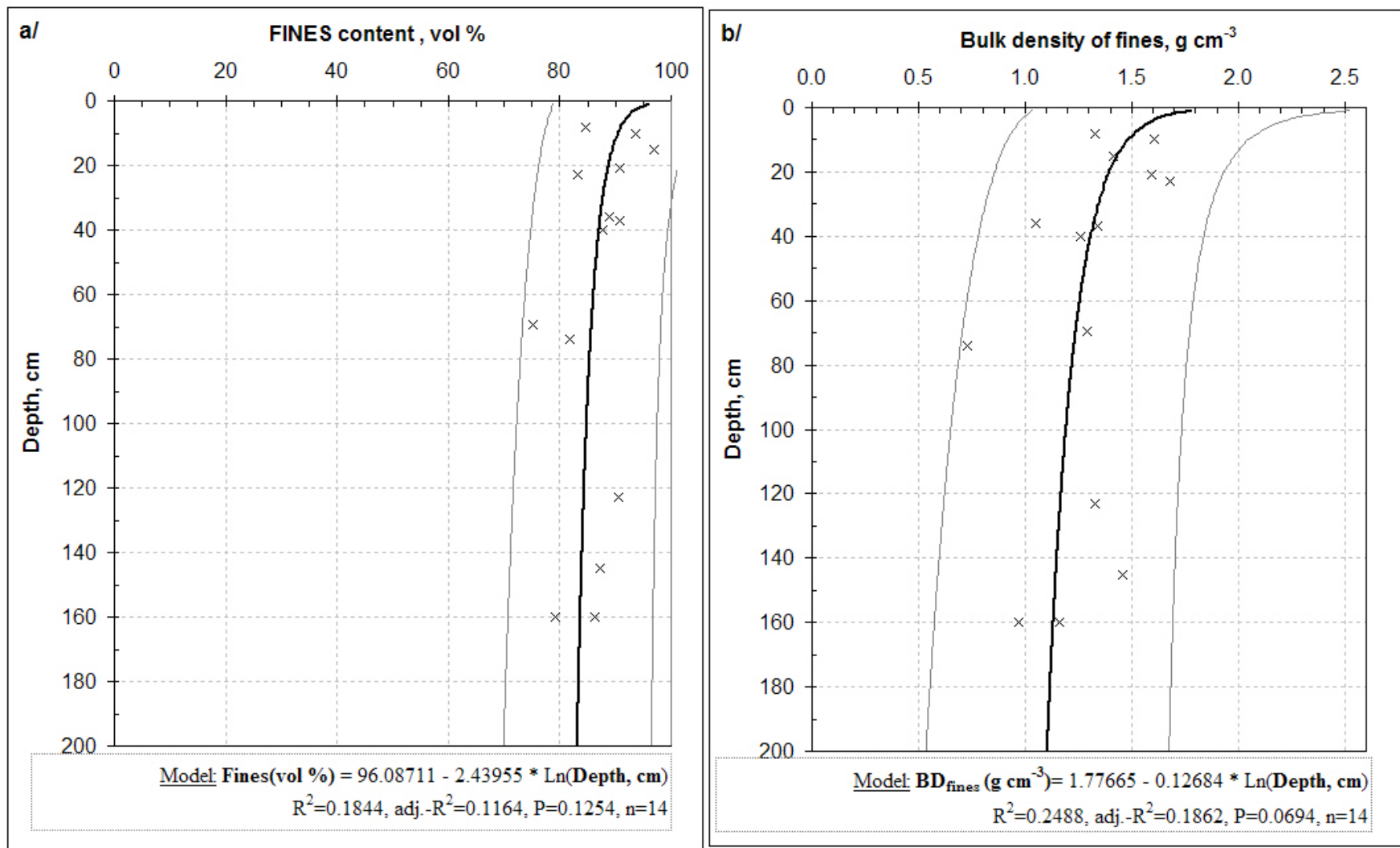
Figure 1-1. Vertical distribution of the content of the fine soil fraction, expressed as volumetric percent (a), and bulk density of the fines (b) down the soil profile of eight deep soil pits excavated on DOE project sites located in Ohio.
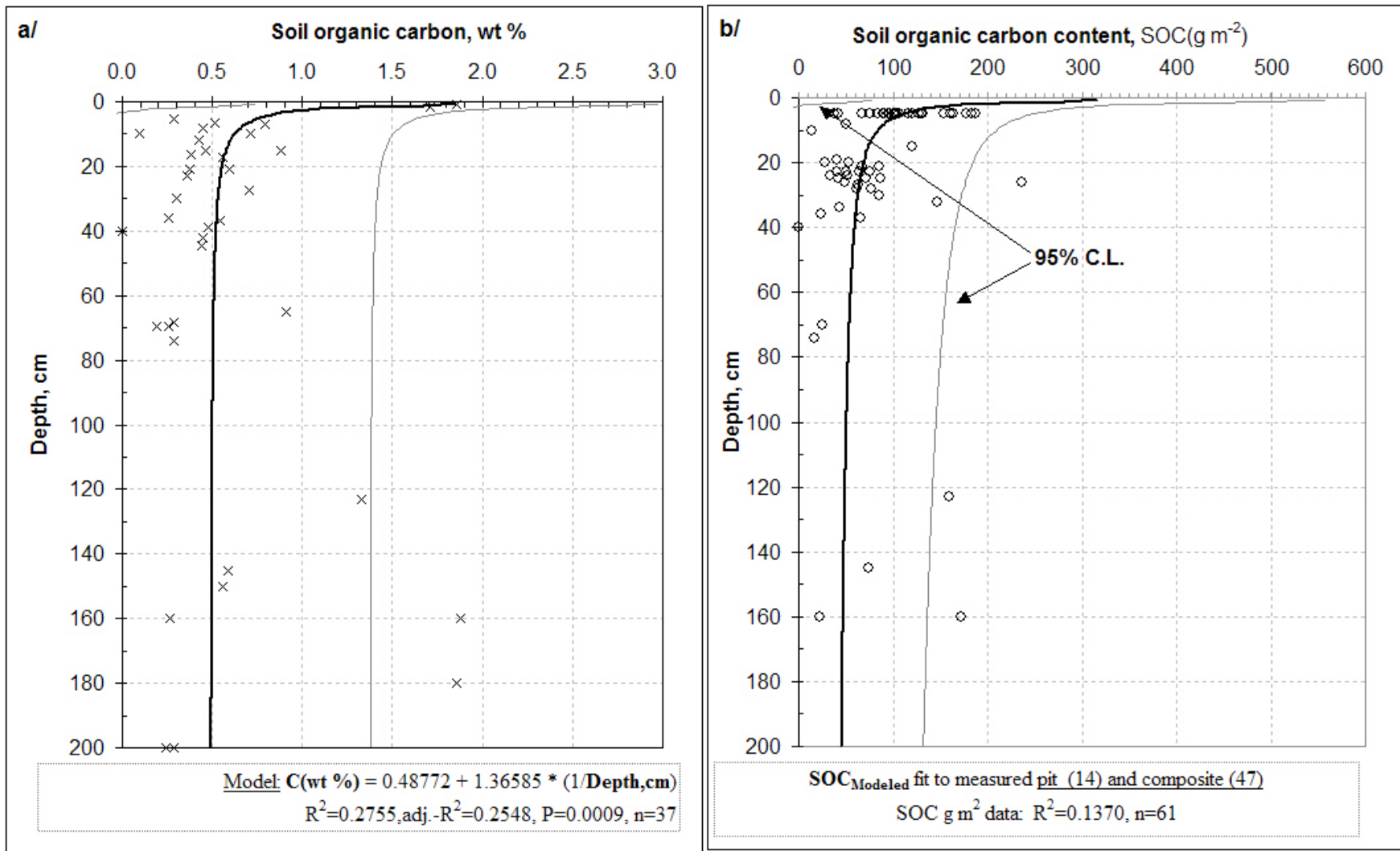
Figure 1-2. Vertical distribution of C(wt%)(a) and the modeled SOC(g m^{-2}) content (b), which was computed in Eq.1, down the soil profile of eight deep soil pits excavated on DOE project sites located in Ohio.
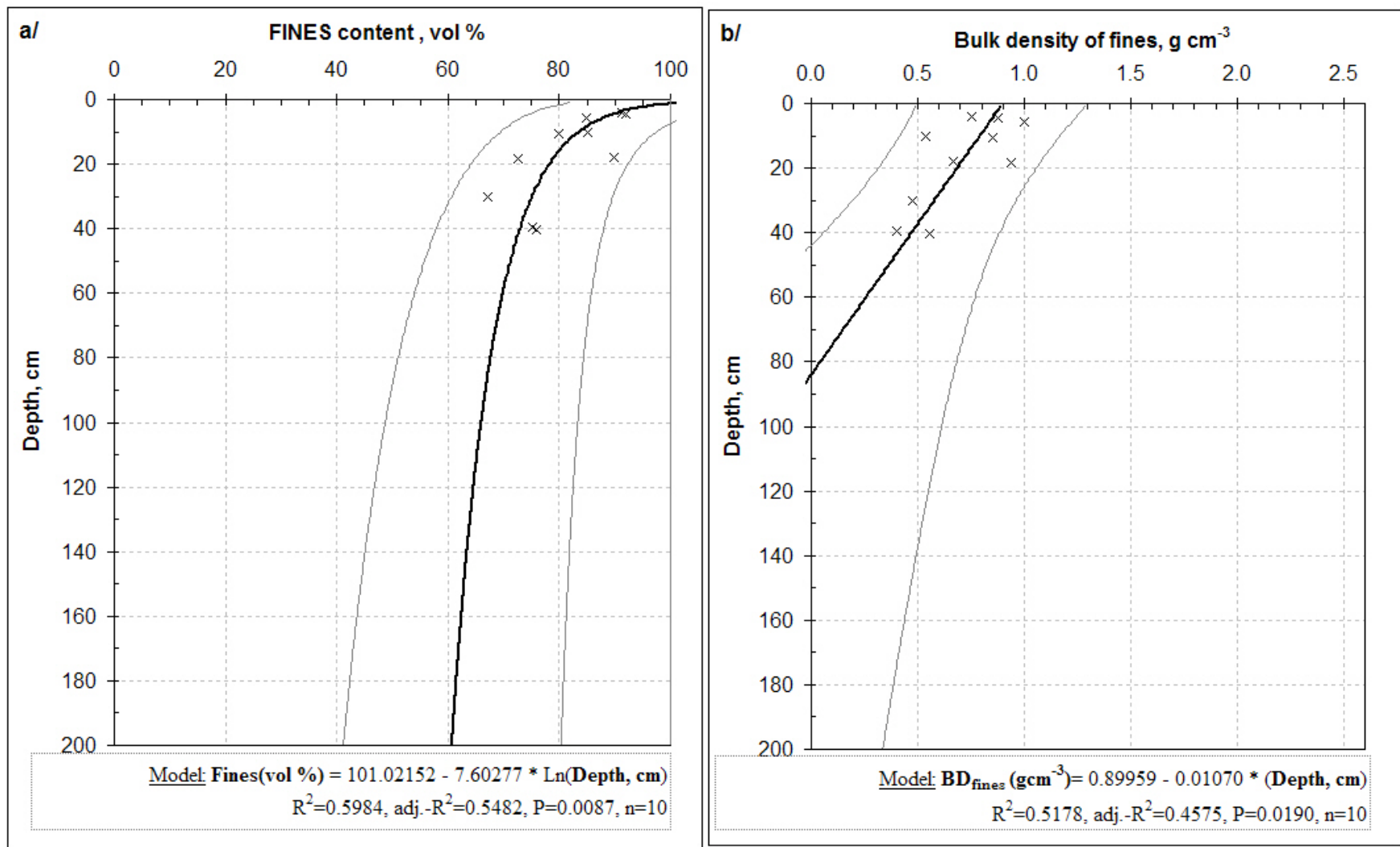
Figure 1-3. Vertical distribution of the content of the fine soil fraction, expressed as volumetric percent (a), and bulk density of the fines (b) down the soil profile of six deep soil pits excavated on DOE project sites located in Virginia.
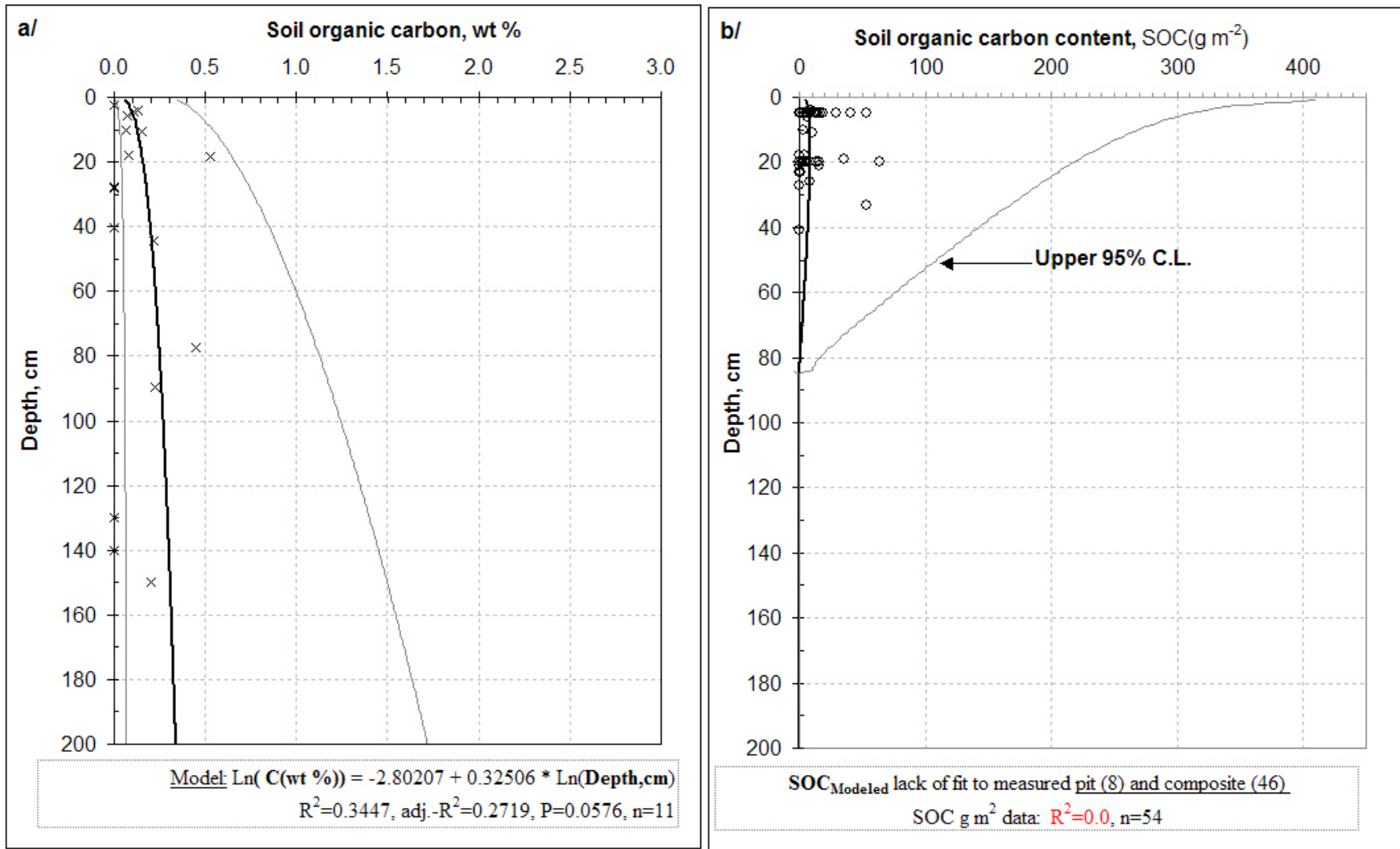
Figure 1-4. Vertical distribution of C(wt%)(a) and the modeled SOC(g m^{-2}) content (b), which was computed in Eq.1, down the soil profile of six deep soil pits excavated on DOE project sites located in Virginia.

a/

FINES content , vol %

b/

Bulk density of fines, g cm^{-3}

Insufficient data for model development n=4.

Insufficient data for model development n=4.

Figure 1-5. **Vertical distribution of the content of the fine soil fraction, expressed as volumetric percent (a), and bulk density of the fines (b) down the soil profile of three deep soil pits excavated on DOE project sites located in West Virginia.**
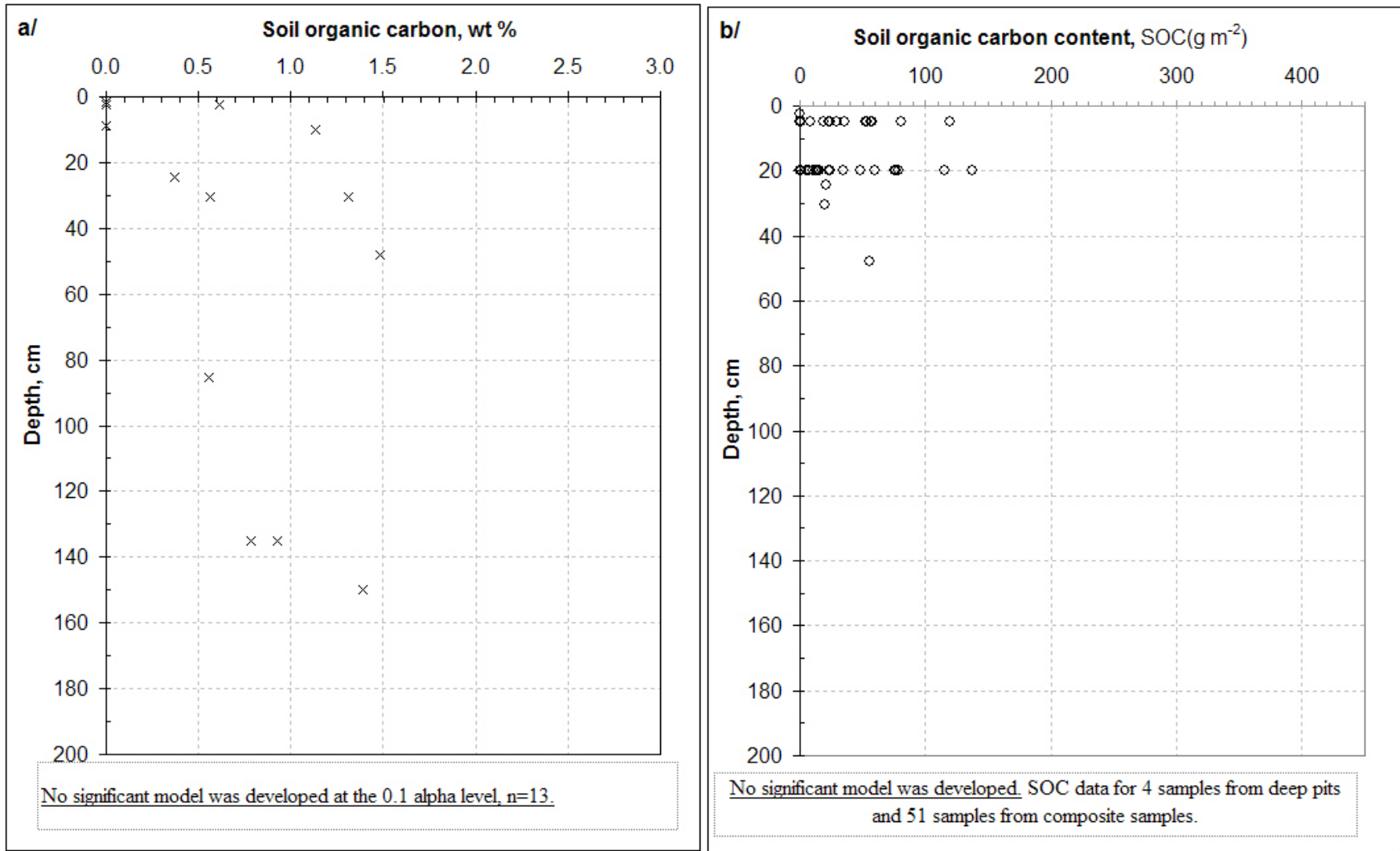
Figure 1-6. Vertical distribution of C(wt%)(a) and the modeled SOC(g m^{-2}) content (b), which was computed in Eq.1, down the soil profile of three deep soil pits excavated on DOE project sites located in West Virginia.

In order to test the hypothesis that at soil depths beyond the maximum observed rooting depth (assume soil depth >1.5 m), measured C(wt%) originated from dissolved C, one should re-visit and measure the C(wt%) at this depth at the same site after a certain period of time long enough to allow significant detectable SOC additions to occur. Only if significant additions were to be observed in the future, then for this site one should have sufficient evidence to prove the tested hypothesis. In practical terms, regarding SOC(g m^{-2}) inventories for C credits on mineland, measurement error due to the old carbon from shales and siltstone spoil materials will be eliminated after subtracting the baseline SOC(g m^{-2}) estimates from future C inventory SOC(g m^{-2}) estimates. This would hold true for most mine soils for which the area analyzed was of similar spoil mixture or better, of the same spoil material, within the boundaries of a delineated mapping strata or polygon of a certain project site. In contrast, coal fragments are often randomly distributed across the mined landscape and down the soil profile and should always be accounted for in SOC(g m^{-2}) analyses on mineland.

We estimated the SOC content for 1-cm layer for 0-200 cm depths by multiplying the individual predictions for C(wt%), Fines(vol%), and BD$_{fines}$(g cm^{-3}), from Figures 1-1 and 1-2a, as noted in Eq.1. The 95% confidence limits were estimated using the rules of error propagation described above, and the resulting 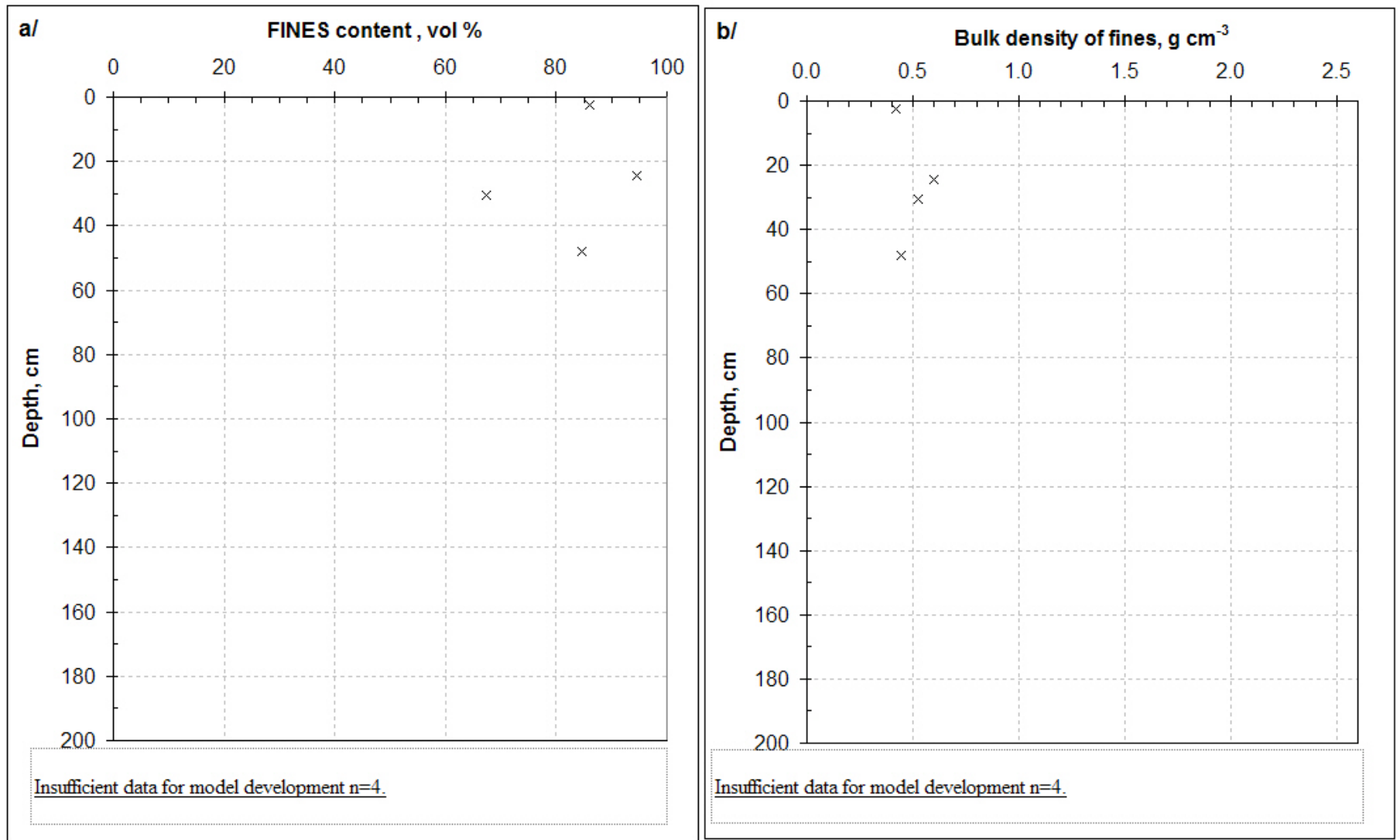predictions were evaluated against the SOC of deep-pit samples, for which all three parameters were measured at the same location in the profile, and SOC(g m^{-2}) of composite samples with estimated average sampling depth within each plot.

In Ohio, the SOC(g m^{-2}) ranged between 0 and 237 g m^{-2} for the data points for which all three variables were measured at the same location within the soil profile. These estimates, along with available SOC data from the composite samples across the landscape, were used to determine the goodness of the SOC model in Figure 1-2b that could be used as the best approximation of the vertical SOC distribution on the mined sites in Ohio. Based on the model-fit analysis, the R^2 of the final SOC(g m^{-2}) model was 14%. This is to say that 86% of the variation of sequestered carbon down the mine soil profile could be explained by a different soil property other than depth, or that additional data are required in order to encapsulate the total variation of SOC for the 0-200 cm soil depth in Ohio.

For the purposes of this work, we used the SOC(g m^{-2}) model for Ohio depicted in Figure 1-2b to determine the maximum cost-effective depth and the minimum detectable difference for carbon inventorying on mineland, which is described in later sections of this text. Note that the former and the latter are critical pieces of information for a cost-effective carbon sequestration analysis on minelands and that both are determined by valid models for SOC(g m^{-2}) content by soil depth.

In Virginia, the content of the fines ranged between 67 and 93% by soil volume, the bulk density of the fines ranged between 0.4 and 1.0 g cm^{-3}, and the C concentration ranged between 0 and 0.5% by soil weight (Figs. 1-3 and 1-4). The estimated SOC content for 1-cm layer at various depths down the profile ranged between 0 and 63 g m^{-2}. Although the individual prediction models for the three input variables for Eq. 1 were of relatively good fit, with R^2 ranging from 34 to 60%, for the SOC and fines models by depth, respectively, the final model for predicting SOC (g m^{-2}) content by depth (Figure 1-4b) had poor fit based on the validation from measured SOC data from composite and deep pit samples in Virginia. The R^2 of the final model was estimated at 0%.

One possible explanation for the poor fit of the SOC prediction model for the sites in Virginia, shown in Figure 1-4b, could be the young ages of these soils. Although the content of

the fines and the bulk density of the fines were predicted with relatively good regression models, because of the low C levels in these young soils and their associated high relative variability by depth, the final SOC(g m^{-2}) prediction model was of poor fit. Our results indicated that in one growing season, very little carbon was added to mine soils, evident from the observed low SOC(g m^{-2}) amounts (average of 10 g m^{-2}) from the composite and deep-pit samples in Virginia relative to the 9-year old sites in Ohio (average of 87 g m^{-2}), which contained an average of 770% more SOC within a 1 cm-thick soil layer (per m^2) at any depth down the soil profile.

One could speculate that most young mine sites would be characterized with low carbon content of a relatively high variability in the vertical and horizontal dimensions which could make it practically impossible to model SOC by depth on mineland of ages between 1 and 9 years, based on our results for the mined sites studied. Therefore, it could be impractical and very costly to inventory the amount of C sequestered in young mine soils, as there would be no suitable data available to recommend a maximum cost-effective depth or a minimum detectable difference for C sequestration projects established on 1- to 9-year-old minelands.

Due to insufficient data, we did not develop regression models that could describe the amount of sequestered carbon down the mine soil profile in the sites located in West Virginia. The data showed that the content of the fines ranged between 67 and 95% by soil volume, the bulk density of the fines ranged between 0.4 and 0.6 g cm^{-3}, and the C concentration ranged between 0 and 1.5% by soil weight (Figures 1-5 and 1-6). The estimated SOC content for a 1-cm layer at various depths down the profile ranged between 0 and 137 g m^{-2}.

The horizontal distribution of SOC(g m^{-2}) content across the mined landscape was determined from the composite samples collected at each plot. Because the mined landscape is a two-dimensional space, as opposed to the one-dimensional soil depth, modeling approaches other than regression models must be used in order to describe the horizontal distribution of SOC(g m^{-2}) on mineland.

If one assumes that all soil samples on the DOE sites were collected independent of each other and were analyzed to produce average SOC(g m^{-2}) estimates, then these results could be used as a surrogate measure of the horizontal distribution of SOC(g m^{-2}). Although results for the mean SOC(g m^{-2}) and the standard error of the mean are the most likely estimates to be reported for C credits, these values contain only a fraction of the information needed to describe the horizontal distribution of sequestered carbon on minelands. This is to say that by producing average SOC(g m^{-2}) estimates, a very important piece of information is omitted – the spatial location of sequestered carbon and the spatial dependence between sampling locations separated by a certain distance. Additionally, if SOC(g m^{-2}) estimates of two sampling locations were dependent upon each other, then some assumptions for statistical analysis may be violated.

Therefore, a modeling approach with spatial capabilities must be used to predict the amount of sequestered carbon across the landscape that will successfully account for spatial dependence between sampling locations. Furthermore, spatial modeling tools, such as the semivariogram, could allow the estimation of SOC(g m^{-2}) between sampling locations across the mined landscape which would be of much greater practical use than a single mean estimate.

There are some advantages to reporting mean SOC(g m^{-2}) estimates for a certain mined site (Table 1-1). The two inferences that could be made from average estimates and their associated variation regarding the carbon sequestration potential of a certain mined site are (i) the relative

ease of comparison of sequestered C between two specific project sites and (ii) the relatively straightforward estimation of the variability of the sequestered carbon at each site.

Table 1-1. Soil organic carbon results for the surface 0-10 cm depth of nine study sites located in Ohio, West Virginia, and Virginia. The results are based on analyses of composite soil samples collected from each 50 x 50-m plot in the three states. Values in parentheses are standard error of the mean.

STATE	Site	N	SOC_{0-10cm} $g\ m^{-2}$	C_{0-10cm} ---------------- wt % ---------------	$Coal\_C_{0-10cm}$
OH	OH1	9	1,254.25 (110.91) [a]	1.070 (0.091)	0.533 (0.106)
	OH2	9	838.57 (122.42) [b]	0.772 (0.142)	0.679 (0.156)
	OH3	9	1,250.90 (125.05) [a]	1.238 (0.128)	0.217 (0.073)
Average		*27*	*1,114.58 (76.60) [A]*	*1.027 (0.078)*	*0.476 (0.075)*
WV	WV1	9	152.26 (68.48) [c]	0.232 (0.099)	3.481 (0.217)
	WV2	9	526.11 (165.70) [c]	0.948 (0.300)	2.180 (0.380)
	WV3	9	601.21 (325.82) [c]	0.707 (0.364)	2.750 (0.443)
Average		*27*	*426.53 (125.17) [C]*	*0.629 (0.165)*	*2.804 (0.225)*
VA	VA1	9	115.64 (28.56) [d]	0.146 (0.036)	0.973 (0.106)
	VA2	9	59.78 (59.49) [d]	0.113 (0.111)	2.188 (0.188)
	VA3	9	269.91 (178.25) [d]	0.376 (0.251)	1.632 (0.316)
Average		*27*	*148.44 (63.32) [D]*	*0.212 (0.091)*	*1.598 (0.156)*

* SOC(g m^{-2}) values within a state followed by the same letter are **not** significantly different at the 0.05 alpha level (PROC GLM in (SAS®),Tukey's HSD means comparison)

Our results indicated that the average amount of sequestered carbon in the 0-10cm layer in the three sites in Ohio was 161% greater than the amount sequestered in West Virginia, and was 653% greater than the C sequestered in Virginia (Table 1-1). Statistical analysis for mean comparison between the sites of each state showed that the average amount of sequestered carbon in the surface 0-10 cm layer was statistically smaller in the OH2 site compared to the other two sites in Ohio, that there was no evidence that the SOC(g m^{-2}) estimates for the sites in West Virginia were significantly different (P = 0.4735), and that there was no evidence that the SOC(g m^{-2}) estimates for the sites in Virginia were significantly different (P = 0.2779) (Table 1-1).

The coefficient of variation (CV% = $^{Std.Dev}/_{Mean}$*100) of sequestered carbon ranged between 27 and 44% in the three Ohio sites, between 94 and 163% for the West Virginia sites, and between 74 and 299% for the Virginia sites. On the one hand, these differences in CV estimates could be the result of the different ages of the respective mine sites, such that as the sites aged, distinct soil horizons developed with discernible better soil structure (Haering et al. 1993) making the mine soil more homogeneous compared to younger sites. On the other hand, as sites aged, higher amounts of C could be sequestered in the soil, the cumulative amount of which could become much greater than the background variation of SOC(g m^{-2}) across the landscape.

Widely available, there are statistical tools for analysis of spatially distributed data such as the amount of sequestered carbon across mined land. Semivariograms are the tools that are commonly used to determine the spatial dependence of a certain soil property across the

landscape (Boruvka and Kozak 2001, Ettema and Wardle 2002, McKenzie and Ryan 1999, Saldana et al. 1998, Zhang and McGrath 2004). The spatial models could be developed from any spatial input data set and could be produced by using automated procedures in ArcGIS® spatial analysis software. Provided there was sufficient data to develop a suitable spatial model, evident from the semivariogram, valid $SOC(g\ m^{-2})$ predictions could be made for all unsampled locations between every two sampling locations that were separated by a distance less than the range. Also, using ordinary kriging procedures the spatial model could be used to create a map of the horizontal distribution of SOC across the landscape. The latter could be of great value and use for planning for future C inventories and for making important land management decisions.

We used the surface $SOC(g\ m^{-2})$ data for 0-10 cm depths for the three sites in Ohio and West Virginia to determine whether sequestered carbon in mine soils was spatially dependent, i.e., to determine whether the SOC for two sampling locations that were spatially close to one other would have more similar SOC estimates compared to sampling locations that were far apart. Ultimately, we attempted to determine whether there was a distance between two sampling locations for our data set beyond which the $SOC(g\ m^{-2})$ measured will no longer be similar. This distance is referred to as the range of heterogeneity beyond which the $SOC(g\ m^{-2})$ estimates of two sampling locations would be independent of one other (Ettema and Wardle 2002).

We assigned the $SOC(g\ m^{-2})$ estimates measured from composite soil samples at the plot level to the center location of their respective plots in Ohio and West Virginia. To achieve normal distribution of the data, and to comply with the normality assumption for geostatistical analysis, the SOC estimates for both data sets were transformed using the natural log transformation prior to spatial modeling. The resulting semivariograms and the SOC prediction maps for the sites in Ohio and West Virginia are depicted in Figures 1-7 and 1-8, respectively. There was insufficient data for spatial modeling of $SOC(g\ m^{-2})$ on the individual sites in Virginia, and the spatial analysis of the combined data for all Virginia sites did not result in suitable semivariogram models, largely because of the great separation distance between the individual research blocks.

The results indicated that $SOC(g\ m^{-2})$ for the surface 0-10 cm soil layer were spatially dependent on the sites in Ohio and West Virginia, and the estimated range was 576 and 593 m, respectively. The $SOC(g\ m^{-2})$ data for West Virginia had better spatial structure, i.e., higher spatially-dependent predictability, compared to the data for Ohio, based on the ratio between the spatially-dependent variance and the total variance of the data. The spatial structure (Ettema and Wardle 2002) for Ohio was estimated at 0.439 (computed as 0.088999/ (0.08999+0.11385)), and for West Virginia it was estimated at 0.764 (computed as 2.8955/ (2.8955+0.89619)) (Figs. 1-7 and 1-8).

The nugget variance, the value of the semivariance at 0-m separation distance, indicated that approximately 56 and 24%, respectively, of the total variation in $SOC(g\ m^{-2})$ for 0-10 cm depth could not be explained by the spatial models developed for the mined sites in Ohio and West Virginia (Fig. 1-7). In order to improve these models additional data is required at higher sampling intensities than the current intensity of four samples per ha for both states (estimated as nine composite samples per 2.25-ha study area). An achievable goal would be to collect sufficient data to improve the above spatial models to desired spatial structures greater than 0.80 that would allow the development of more accurate $SOC(g\ m^{-2})$ prediction maps.

Figure 1-7. **Horizontal distribution of SOC(g m^{-2}) to 10-cm soil depth on the three DOE research sites in Ohio. Semivariogram function indicates spatial dependence of SOC content of sampling locations up to 575 m apart across the mined landscape.**
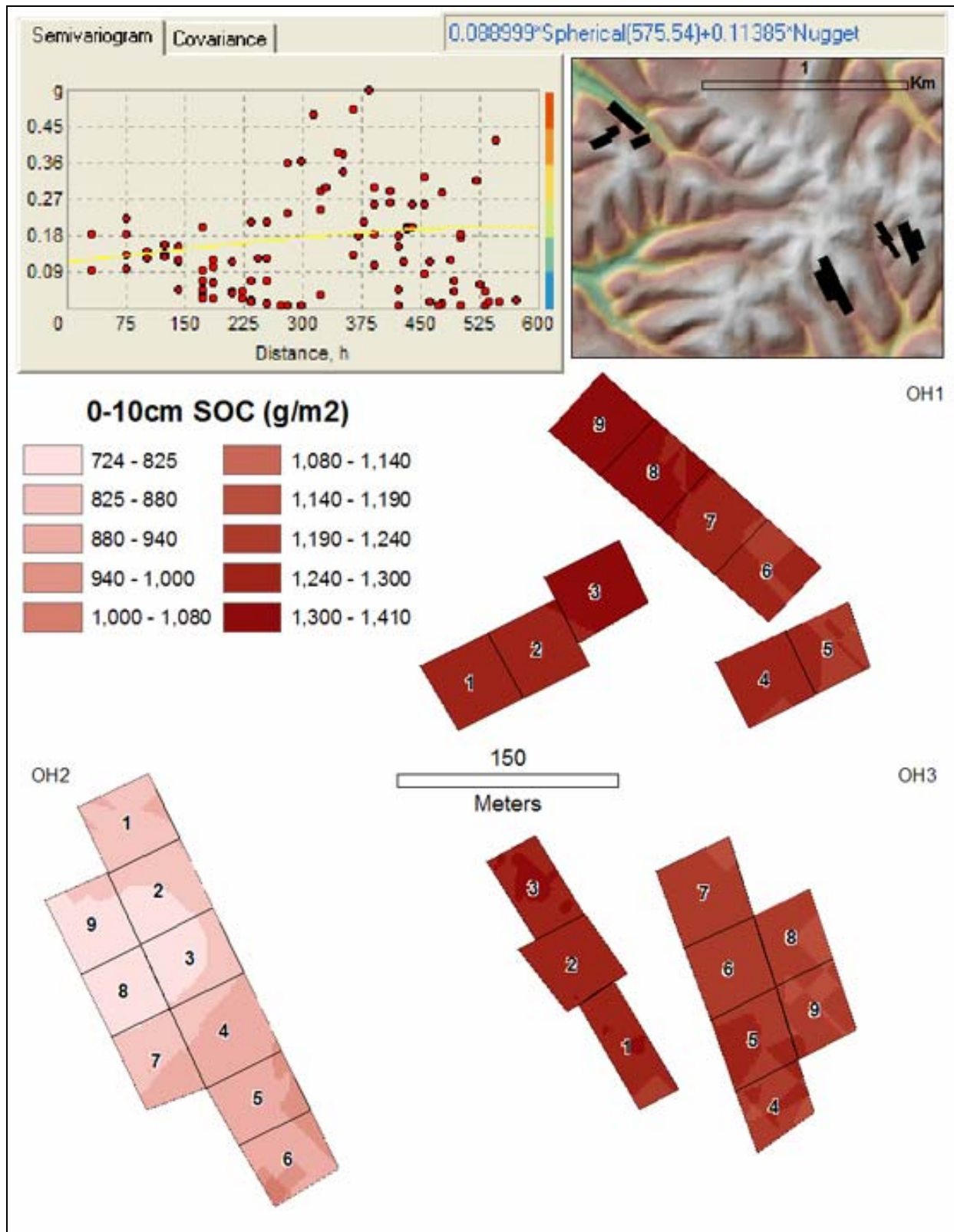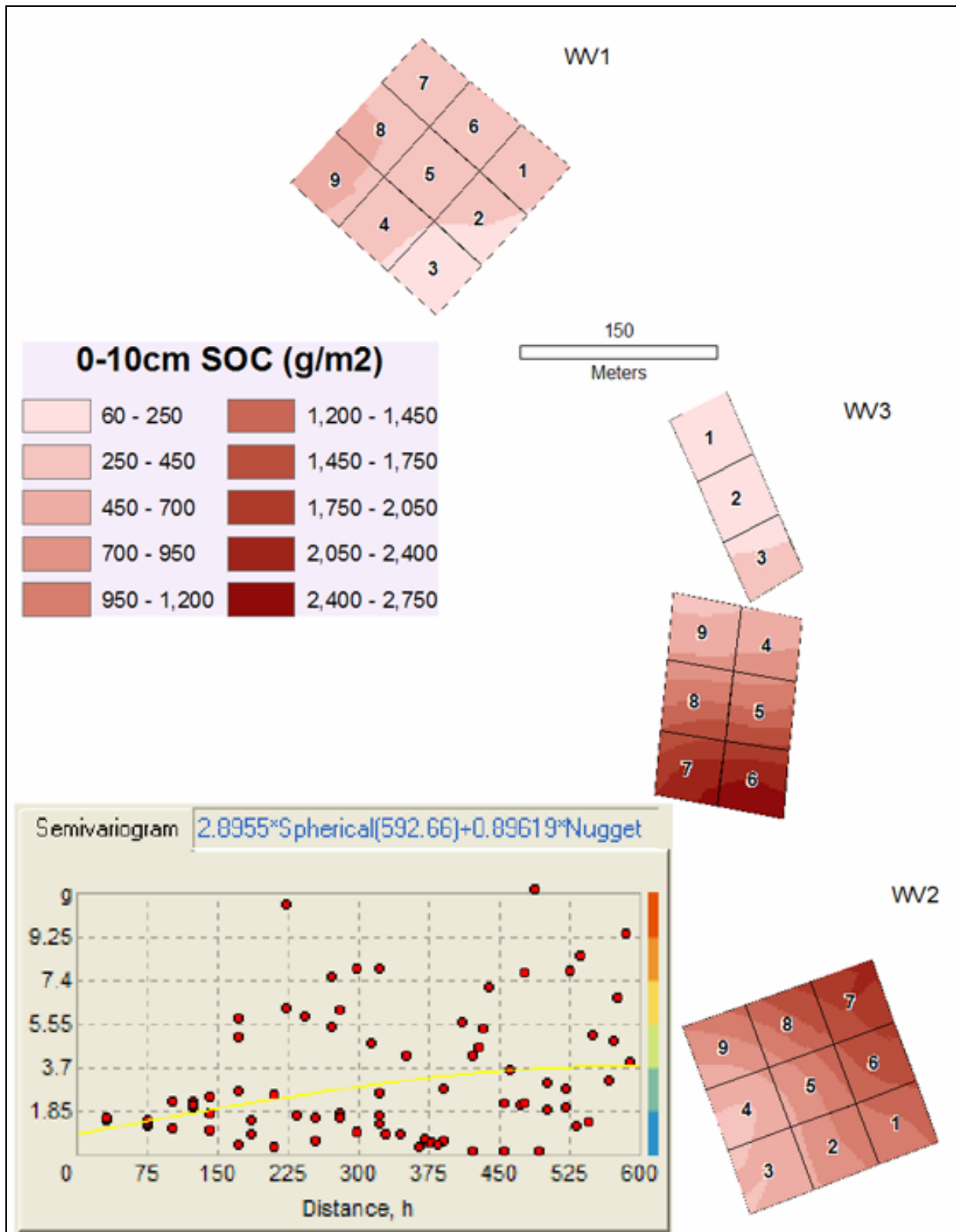
Figure 1-8. Horizontal distribution of SOC(g m⁻²) to 10-cm soil depth on the three DOE research sites in West Virginia. Semivariogram function indicates spatial dependence of SOC content of sampling locations up to 590 m apart across the mined landscape.

One of the most important benefits from the geostatistical analyses performed was the ability to locate areas of low and high soil carbon sequestration rates on the sites analyzed, from the SOC(g m^{-2}) maps developed by the ordinary kriging procedure. Our results indicated that the northernmost plots in the OH1 block in Ohio (plot numbers 3, 8, and 9) sequestered the highest amount of soil carbon, ranging from 1,300 to 1,410 g m^{-2}, and four of the central plots in OH2 (plot numbers 2,3, 8, and 9) contained the lowest SOC(g m^{-2}), ranging from 724 to 825 g m^{-2} (Fig. 1-7). Similarly, the southernmost plots of the WV3 block (plot numbers 6 and 7) in West Virginia contained the highest amounts of sequestered SOC(g m^{-2}) on this site, ranging from 2,050 to 2,750 g m^{-2}, and the northernmost three plots of the same block contained the lowest SOC(g m^{-2}), ranging from 60 to 250 g m^{-2} (Fig. 1-8). Despite their spatial proximity, less than 300 m apart, the research plots of the WV3 block had completely different soil properties that resulted in contrasting amounts of sequestered SOC.

If the above research plots were part of a larger mineland carbon sequestration project, then the landowner would know the exact location of the areas of contrasting C sequestration potential, which would allow for a more efficient targeting of different management treatments to the zones of different C sequestration potential on the project area. The cumulative benefits from a targeted land management approach would exceed the costs of preliminary soil sampling and SOC analysis and mapping for mined sites, when the goal is to maximize terrestrial C sequestration. Furthermore, if SOC maps were overlaid with available FSQC maps, then there would be sufficient surveying data that could be used to improve the ground resolution of the original FSQC maps. The combined data could be used to determine the correlation between FSQC and carbon sequestration potential for specific forest management treatments for a certain project area.

A second useful inference that could be made from the semivariograms developed for spatial SOC data sets for minelands is an estimate of the optimal sampling density for C inventories. For example, the semivariogram depicted in Figure 1-8 indicated that at a separation distance of 150 m between sampling locations in West Virginia, equal to a sampling density of approximately 4 plots per 10 ha, the average standard deviation of the mapped SOC estimates (from the kriging map) would be approximately 1.38 g m^{-2} (estimated as the square root of the semivariance at distance 150 m, = SQRT(1.900)) (Fig. 1-8). Similarly, at separating distance of 75 m, equal to sampling intensity of approximately 18 plots per 10 ha, the average standard deviation of the predicted SOC values would be 1.16 (= SQRT(1.344)). These results indicated that a 350% increase in sampling intensity, from 4 to 18 plots per 10 ha, would result in only a 16% decrease in standard deviation of the predicted SOC.

The above example is similar to the argument made by Dollhopf (2000), who discussed the trade-off between increasing sampling intensity and the relative gain in precision of predicted soil properties on minelands. Dollhopf (2000) concluded that geostatistical analyses for minelands should become an important part of the planning for any reclamation task on mined lands. The latter could also be expanded to carbon sequestration projects on mined lands for which accurate and precise SOC estimates are required in order to report and claim C credits.

Until geostatistical analysis methods become the new standard for SOC analysis on mineland, standard statistical methods could be used to determine the optimal sampling intensity for SOC estimation. The sampling intensity could be determined from estimates for the mean and standard deviation of SOC content on mineland using the following equation (Crepin and Johnson 1993):

$$N = \frac{t^2 s^2}{D^2}$$ **[Eq. 2]**

where: t = a number from the *Student's t* table for a chosen level of precision;

$s^2 =$ the variance, which is known beforehand (from preliminary data sampling), or estimated by $s^2 = (R/4)^2$, where R is the estimated range likely to be encountered in sampling (Freese 1962); and

D = the variability that we are willing to accept in mean estimation (in units of the mean)

Depicted in the above equation, one could expect that a greater number of soil samples will be required to achieve a certain accuracy of SOC estimates measured on sites with higher horizontal variation. Consider the variation of the three mined sites in Ohio (Table 1-1). The results indicated that the SOC(g m^{-2}) content measured on the OH2 research block was significantly lower than the estimates for the other two research blocks. The OH2 block was also characterized with the highest CV, 44%, as opposed to 27% for OH1 and 30% for OH3. Using the relationship in Eq. 2, we estimated that 422% more sampling locations would have to be excavated and analyzed on the OH2 block (35 plots ha^{-1}), when compared to OH1 and OH3 (6.7 plots ha^{-1}), in order to determine the SOC(g m^{-2}) for 0-10 cm depth with accuracy level of 10% within the true mean at the 95% probability level (precision) (Fig. 1-9). Similarly, 280 and 135 plots per ha would be the respective sampling intensities for SOC analysis on each of the research blocks in Virginia and West Virginia, in order to achieve 10% accuracy of the mean at the 95% probability level. Needless to say, sampling of such high intensity is impractical and undesired for any carbon sequestration analysis, especially for rocky and compacted mine soils.

Therefore, most researchers would prefer to produce results of lower accuracy and precision in order to be able to determine the sequestered SOC in a cost-effective way. For example, a 57% reduction of the sampling intensity in OH2 would result in 15% reduction of the precision of estimated SOC(g m^{-2}), from 95 to 80%, or would result in approximately 5% reduction in the accuracy level of the estimated SOC(g m^{-2}), from 10 to 15% within the mean, at the original probability level of 95% (Fig. 1-9). However, reduction in the accuracy or precision of SOC estimates could result in a reduced ability to claim the measured carbon for C credits, as these results would have wider confidence limits compared to SOC estimates of higher accuracy and precision levels.

But how low would a sampling intensity be? To provide an answer to the latter question one should be able to determine the maximum cost-effective depth and the minimum number of years one would have to wait to claim C credits from SOC(g m^{-2}) estimates with certain confidence limits. The following paragraphs discuss the procedures that could be used to determine MCD and MDD on mineland, based on selected sampling intensity levels and the current market price of elemental C.
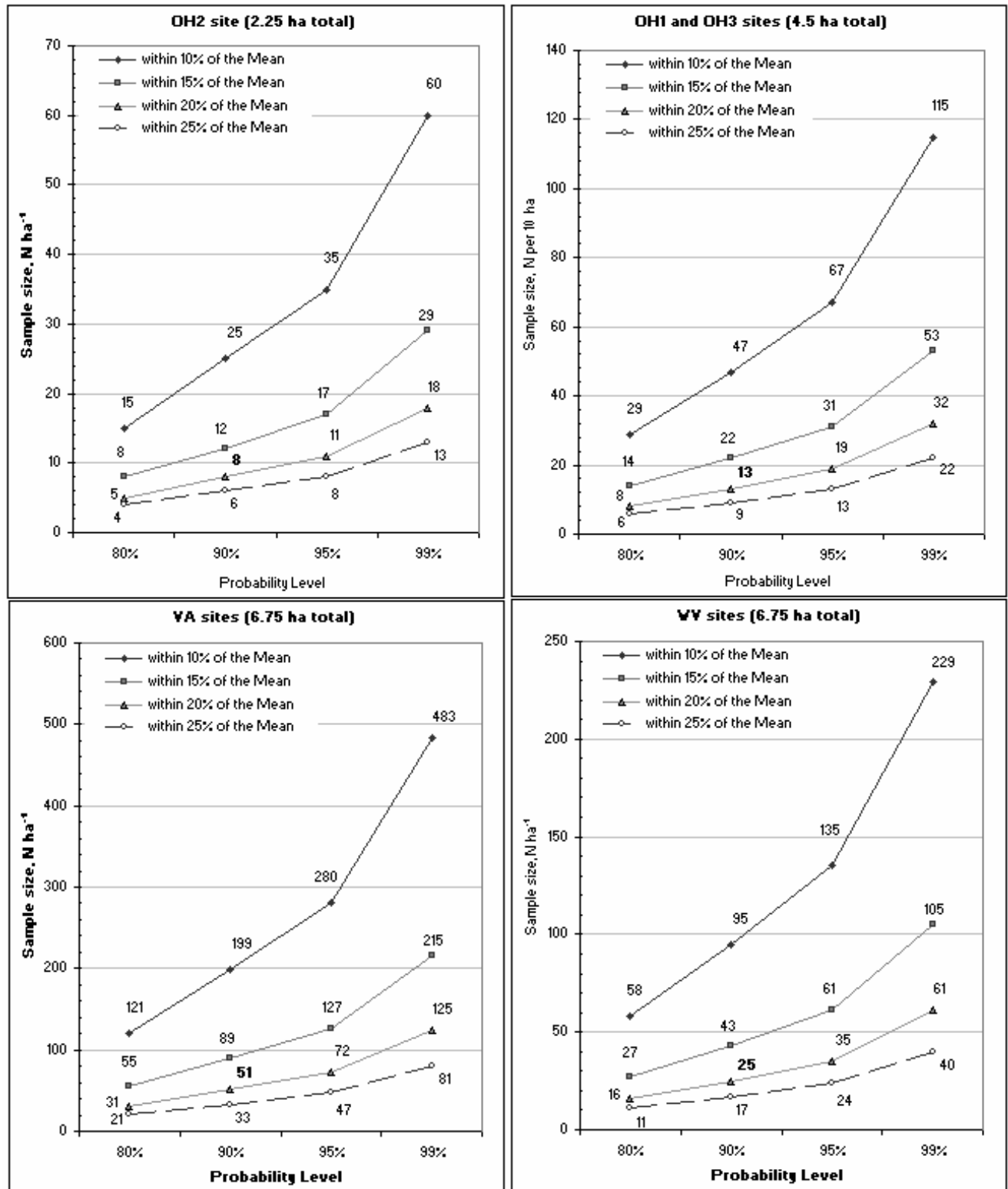
Figure 1-9. Sample size per ha at the 80, 90, 95, and 99% probability levels for SOC(g m^{-2}) determination at four accuracy levels, 10, 15, 20, and 25% from the mean, on mineland in Ohio, West Virginia, and Virginia, when the goal is to claim C credits from sequestered C in minesoils.

Subtask 1.2

   MDD of C stocks and MCD for C inventorying on mined land. A more useful graphical representation of the results for SOC(g m^{-2}) by depth from Figure 1-2b is depicted in Figure 1-10. The cumulative SOC content is presented as percent of the total SOC contained within the 0-200cm soil pedon (Figure 1-10b). The cumulative SOC content versus soil profile depth could be used to determine the maximum cost-effective depth for SOC inventory on mined lands. The results from the mined sites in Ohio indicated that one-third of the total SOC on mined lands was found in the surface 0-47 cm soil layer, while more than two-thirds was located in the 0-120 cm soil profile. It could be argued that any SOC located in lower depth would be of lesser value due to the higher cost of sample collection, especially in compacted and rocky mine soils.

   In an attempt to determine the optimal sampling depth for mined land, one should know not only the variability of SOC down the soil profile, but also the variability across the mined landscape. Assume the following cost scenario: the cost for excavating, sampling (three soil pits), sample preparation, and C analysis for each 5 cm-thick soil layer within the profile costs $40 per pit, and the profit for sequestering atmospheric CO_2 is $127.2 per Mg of elemental C, as indicated by the April 9, 2005, price quote at the European Carbon Market acquired from http://www.pointcarbon.com.

   Upon further analysis, one could estimate that for this cost scenario the total costs for measuring the sequestered SOC(g m^{-2}) within 1 cm soil layer across 1 ha of mineland, at three plots ha^{-1} sampling intensity, is $24 cm^{-1} ha^{-1} (equal to $\dfrac{\$40}{5cm*1pit}*\dfrac{3\,pits}{1ha}$), or $8 cm^{-1} pit^{-1}. Now consider 17 soil pits per ha as the sampling intensity for the OH2 site in Figure 1-9 that is required to produce SOC estimates at 15% accuracy and 95% probability levels. The total cost for OH2 at this sampling intensity would be $136 cm^{-1} ha^{-1} (equal to $\dfrac{\$40}{5cm*1pit}*\dfrac{17\,pits}{1ha}$).

Therefore, in order for a SOC inventory to be feasible below a certain depth, the cost for SOC measurement on this site must be lower than the C credit profit from the measured SOC(g m^{-2}); i.e., the profit-to-cost ratio $(SOC$_{Credit}$)/$(SOC$_{Inventory}$) must be greater than 1 (Table 1-2).

   The data in Table 1-2 depict the computational steps for selected soil depths leading to identification of the maximum cost-effective depth for SOC analysis on mineland. In column *b* depicted are the SOC(g m^{-2}) values for each 1-cm layer within the soil profile while columns *c* and *d*, respectively, depict the cumulative SOC in g C m^{-2} units and as percent of the whole-profile SOC(g m^{-2}), to a profile depth indicated in column *a*. For example, the second data row shows that the SOC for the 9-10 cm soil layer is 83.85 g C m^{-2} and that the cumulative SOC for the 0-10 cm layer is 1.339.08 g C m^{-2}, which represents 11.8% of the total SOC contained within the 0-200cm profile. Note that the data in column b is also presented in Figure 1-10a as the SOC(g m^{-2}) model predictions and the data in column *d* is also presented in Figure 1-10b.

a/

Soil organic carbon content, SOC(g m^{-2})

SOC$_{Modeled}$ fit to measured pit (14) and composite (47)
SOC g m^2 data: R2=0.1370, n=61

b/

Cumulative SOC, [% of total]
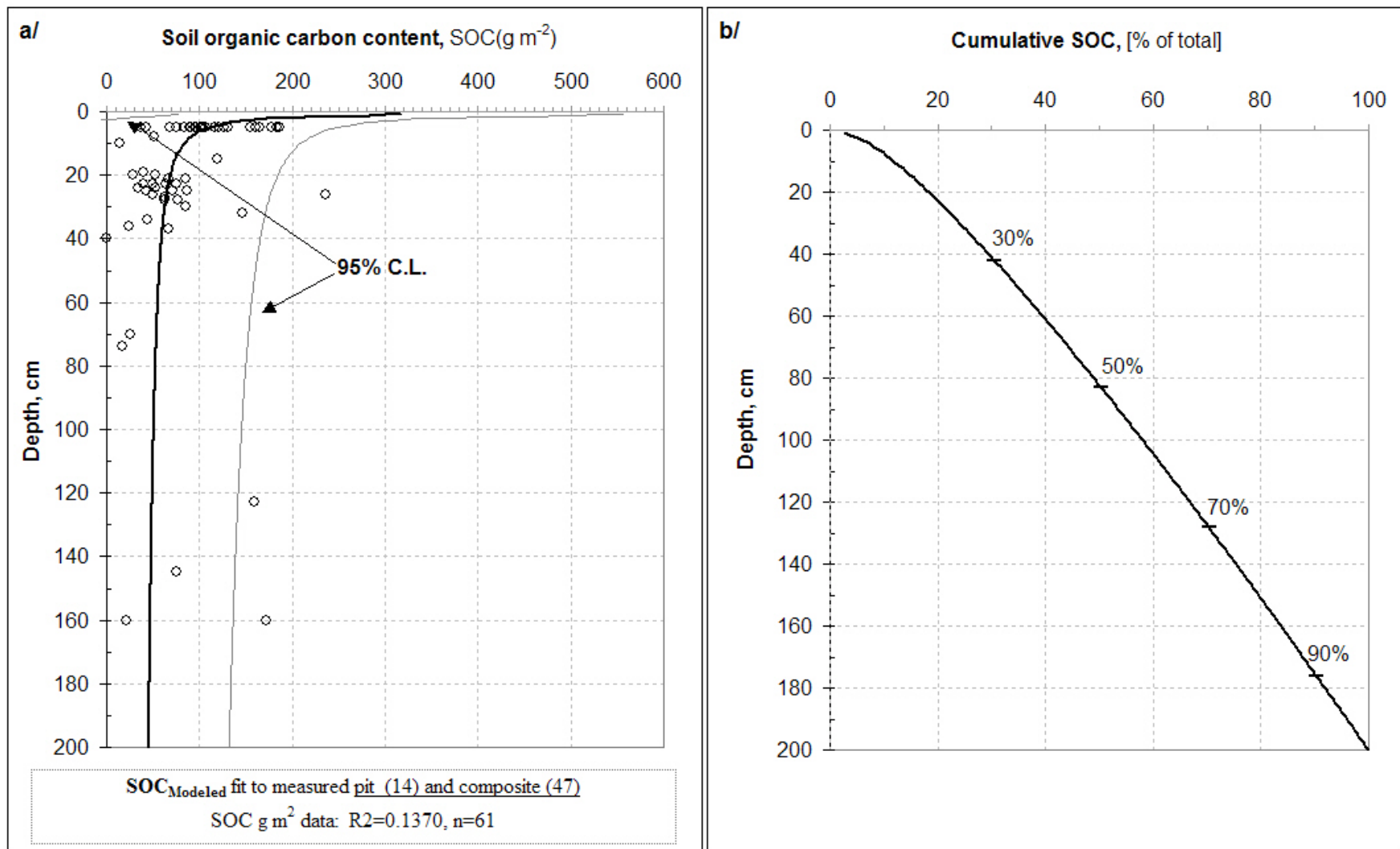
Figure 1-10. Vertical distribution of (a) SOC(g m^{-2}) (estimated from data in Figs. 1-1 and 1-2a using Eq. 1) and (b) its cumulative distribution expressed as percent of the total SOC(g m^{-2}) sequestered down the profile within the 0-200 cm soil pedon of eight deep pits excavated in Virginia. Thicker line indicates the fit of a statistically significant prediction model to the data, marked with circles, and lighter lines show the 95% confidence limits of these predictions.

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Table 1-2. **Maximum cost-effective depth for soil carbon content inventory for the OH2 study site in Ohio at current C market price equal to $127.2 per Mg of elemental C, and cost of SOC analysis equal to $8 per 1 cm-thick spoil layer per soil pit. Note that 17 soil pits per ha are required to achieve 15% accuracy of the measured SOC(g m^{-2}) at 95% probability level.**

Depth	SOC	Cumulative SOC		SOC standardized by excavation depth	Profit-to-Cost ratio
a	b	c	d	e	f
[cm]	[g m^{-2}]	[g m^{-2}]	[%]	[g m^{-2} cm^{-1}]	---
1	316.43	316.43	2.8	316.43	2.96
10	83.85	1,339.08	11.8	133.91	1.25
17	71.80	1,871.43	16.5	110.08	1.03
18	70.76	1,942.19	17.1	107.90	1.01
19	69.81	2,012.00	17.7	105.89	0.99
20	68.94	2,080.94	18.3	104.05	0.97
30	62.98	2,734.39	24.1	91.15	0.85
40	59.48	3,343.69	29.4	83.59	0.78
50	57.07	3,924.63	34.5	78.49	0.73
60	55.26	4,485.03	39.5	74.75	0.70
70	53.82	5,029.47	44.3	71.85	0.67
80	52.63	5,560.95	48.9	69.51	0.65
90	51.61	6,081.53	53.5	67.57	0.63
100	50.73	6,592.74	58.0	65.93	0.62
110	49.96	7,095.74	62.5	64.51	0.60
120	49.27	7,591.45	66.8	63.26	0.59
130	48.64	8,080.61	71.1	62.16	0.58
140	48.07	8,563.82	75.4	61.17	0.57
150	47.55	9,041.59	79.6	60.28	0.56
160	47.06	9,514.35	83.7	59.46	0.56
170	46.61	9,982.47	87.9	58.72	0.55
180	46.19	10,446.27	91.9	58.03	0.54
190	45.80	10,906.01	96.0	57.40	0.54
200	45.43	11,361.96	100.0	56.81	0.53

Because of the logistics of soil excavation, i.e., before one can collect soil samples from >50-cm soil depths, one must remove the spoil from 0 to 50 cm depth, which unmistakably is associated with certain costs, as mentioned above. A new SOC variable (Table 1-2, column e) was estimated to represent the amount of SOC(g m^{-2}) standardized by excavation depth (column e) = (column c) / (column a). The profit-to-cost ratio in column f is estimated as (column e, g C m^{-2} cm^{-1}) *(1/100) * ($127.2 Mg^{-1} C) / ($136 cm^{-1} ha^{-1}). Note that the division by 100 is used to convert the g m^{-2} units to Mg ha^{-1}, which is necessary for this computational step. Once more, in order for an SOC inventory to be economically feasible, it is desired that at the very least the C credits received for sequestering atmospheric CO_2 are enough to recover the costs for measuring and reporting the sequestered SOC; i.e., the ratio should be greater or equal to 1 (Table 1-2).

The results indicated that the profit break-even depth of SOC analysis for C credits, i.e., maximum cost-effective sampling depth, was 18 cm at a sampling intensity of 17 plots ha^{-1} for SOC(g m^{-2}) estimation at 15% accuracy and 95% probability levels on the OH2 research block (Table 1-2). This is to say that although four-fifths of the total sequestered C is located below 18 cm depth (Figure 1-10b, Table 1-2), one will be losing money if SOC is measured beyond this depth.

In comparison, due to the lower horizontal variability of the OH1 and OH3 sites in Ohio, the maximum cost-effective depth exceeded 200 cm for SOC estimation at 15% accuracy and 95% probability levels (Figure 1-11b). The data depicted in Figure 1-11 could also be used to estimate the net gain from C credits as well as the net cost for SOC analysis. For example, if SOC was analyzed to the 0-25 cm depth on OH1 and OH3 sites, 21% of the total SOC(g m^{-2}) would be reported, 2,386 g C m^{-2} (equal to 0.21*11,362 g m^{-2}) (Figure 1-11b), which equals to gross profits of $3,035 for each hectare of mined land at the current price for elemental carbon of $127.2 Mg^{-1} C. The total cost for measuring and reporting the SOC(g m^{-2}) to 0-25 cm depth on these sites would be $620 ha^{-1} (equal to $8 *3.1 pits ha^{-1}*25cm) at sampling intensity of 3.1 pits ha^{-1} and assumed costs for SOC analysis of $8 pit^{-1} cm^{-1} (Figure 1-11b). Then the net profit for C inventory to 0-25 cm depth on the OH1 and OH3 sites would be approximately $3,000 ha^{-1}. Similarly, SOC analysis to 0-100 cm depth would yield net profit of approximately $5,900 ha^{-1} at net costs of $2,480 ha^{-1}, which would be spent before receiving the profits from C credits for SOC analysis.

Using potential sampling intensity estimates such as the ones presented in Figure 1-9 and the computational steps used to create Table 1-2, one would be able to compute the best economically possible sampling scenario, depending on the financial situation of a given mineland owner. For each chosen sampling intensity, one would be able to compute the net profits from C credits when the SOC(g m^{-2}) are reported to a certain depth, not deeper than the estimated MCD.

One should be cautioned that the above net profit estimates from C credits would only be valid under the assumption that each gram of SOC(g m^{-2}) was sequestered within the time frame of a certain C sequestration project. However, for the sites analyzed, the amounts of SOC(g m^{-2}) reported in Table 1-2 would be regarded as the baseline carbon estimates, which will be subtracted from the SOC(g m^{-2}) amount measured at a future C inventory event at the end of or during the lifetime of a particular C sequestration project. Hence, a very useful piece of information for mineland owners would be the minimum number of years before a future C inventory event is feasible such that the difference (SOC(g m^{-2})$_{future}$ - SOC(g m^{-2})$_{baseline}$) is statistically significant at the 95% probability level. Although SOC is expected to be added to the soil during each year of the C sequestration project, the detectable difference (SOC(g m^{-2})$_{future}$ - SOC(g m^{-2})$_{baseline}$) would not become statistically significant until after a certain period of uninterrupted SOC accumulation, due to the inherent variability of sequestered C in mine soils.
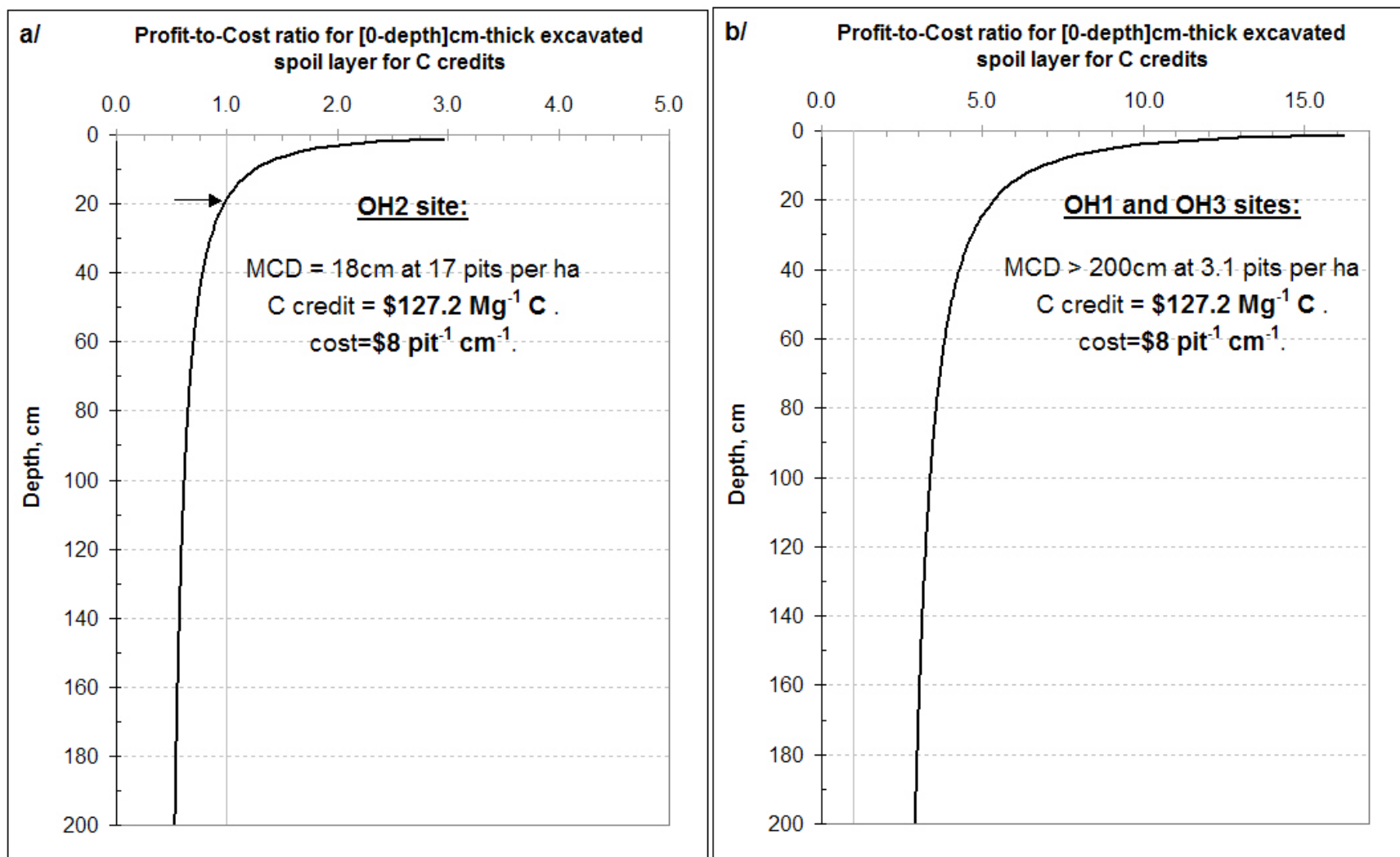
Figure 1-11. Maximum cost-effective depth and profit-to-cost ratio for SOC inventory for three study sites in Ohio at current C market price equal to $127.2 per Mg of elemental C, and cost of SOC analysis equal to $8 per 1 cm-thick spoil layer per soil pit. Note that 17 and 3.1 soil pits per hectare are required to achieve 15% accuracy of the measured SOC(g m^{-2}) at the 95% probability level on the OH2 (a) and the OH1 and OH3 sites (b), respectively.

In Figure 1-12a, we show the graphical representation of the cumulative SOC(g m^{-2}) content and its estimated upper 95% confidence limit distributed down the mine soil profile for the mined sites on Ohio. The mean cumulative SOC(g m^{-2}) estimate can be used to determine the rate of SOC accumulation within a soil layer of thickness [0-depth] cm, where depth ranges from 0-200 cm. For example, the average rate of SOC accumulation on the 9-year-old Ohio sites to a 0-20 cm depth was estimated at 231 g C m^{-2} yr^{-1} (= 2,081 g C m^{-2} / 9 yr) (Table 1-2, Figure 1-12a). Similarly, the rate of SOC accumulation within the entire sampled soil profile, 0-200 cm, was estimated at 1,262 g C m^{-2} yr^{-1} (= 11,362 g C m^{-2} / 9yr). The latter estimates were used to determine the minimum number of years, T (also referred to as "significant" years) of uninterrupted SOC accumulation for any soil layer thickness of [0-depth] cm such that the difference (SOC(g m^{-2})$_{at [present +T] year}$ – SOC(g m^{-2})$_{at present}$) is significant. The latter difference is the minimum detectable difference, MDD.

The number of "significant" years until future C inventory was estimated as the ratio of accumulated SOC(g m^{-2}) to [0-depth] cm soil depth at future year [present +T] and the rate of SOC accumulation (g C m^{-2} yr^{-1}) of the same soil layer thickness measured at present, i.e., $T =$ SOC(g m^{-2})$_{at [present +T] year}$ / rate$_{at present}$. The latter relationship assumes that we know the future SOC$_{at [present +T] years}$.

In reality, one can never measure something that is yet to happen in the future, but we can provide a best approximation for this estimate by making appropriate assumptions. The first assumption we made was that the rate of SOC accumulation will be the same during a period of T years between now and the future inventory event and that this rate will be the rate of SOC accumulation (g C m^{-2} yr^{-1}) measured at present. The second assumption was that the upper 95% confidence interval (95% CI), as opposed to the upper confidence limit (95% CL), of the present SOC(g m^{-2}) estimate, is equal to the lower 95% CI of the future SOC(g m^{-2}) estimate. This is to say that the variation around the mean SOC(g m^{-2}) contents measured at present and in the future will be the same, although the future mean SOC(g m^{-2}) estimate is expected to be greater than that at the present.

A measure of the 95% CI for the Ohio mined sites was obtained from the data presented in Figure 1-12a. Note that the 95% CI is estimated as the difference (95% CL – Mean) for each cumulative SOC(g m^{-2}) to a certain [0-depth] cm depth. For example, the 95% CI to 0-20cm depth was estimated at 2,688 g C m^{-2} (= 4,769 g C m^{-2} – 2,081 g C m^{-2}) (Figure 1-12a).

Based on the above two assumptions, we predicted the number of significant years until future C inventory as follows: $T =$ (SOC(g m^{-2})$_{at present}$ + 2*(95% CI))/ rate$_{at present}$. Estimates for T to 200 cm soil depth for varying thicknesses of SOC analysis for the Ohio sites are presented in Figure 1-12b. The results showed that approximately 32 years of uninterrupted SOC accumulation within the 0-18 cm soil layer on the OH2 mined sites are necessary for the future SOC estimate, SOC$_{at [present +32] years}$ to be significantly larger than the SOC measured at present. Note that 18 cm was the estimated maximum cost-effective depth for the OH2 site (Figure 1-12b) and the minimum detectable difference of SOC(g m^{-2}) stock to the 0-18 cm soil depth was 5,376 g C m^{-2} (equal to 2 * 95% CI). Another way to interpret these data is that any future SOC(g m^{-2}) inventory on the OH2 site, to a MCD of 18 cm, completed earlier than 32 years into the future will yield SOC(g m^{-2}) estimates that would appear to be similar to the SOC(g m^{-2}) measured at present time, i.e., the difference would be smaller than the MDD for this site. Eventually, one would fail to prove that, in fact, the OH2 mined sites had sequestered C in the mine soil, by using standard statistical analysis methods.
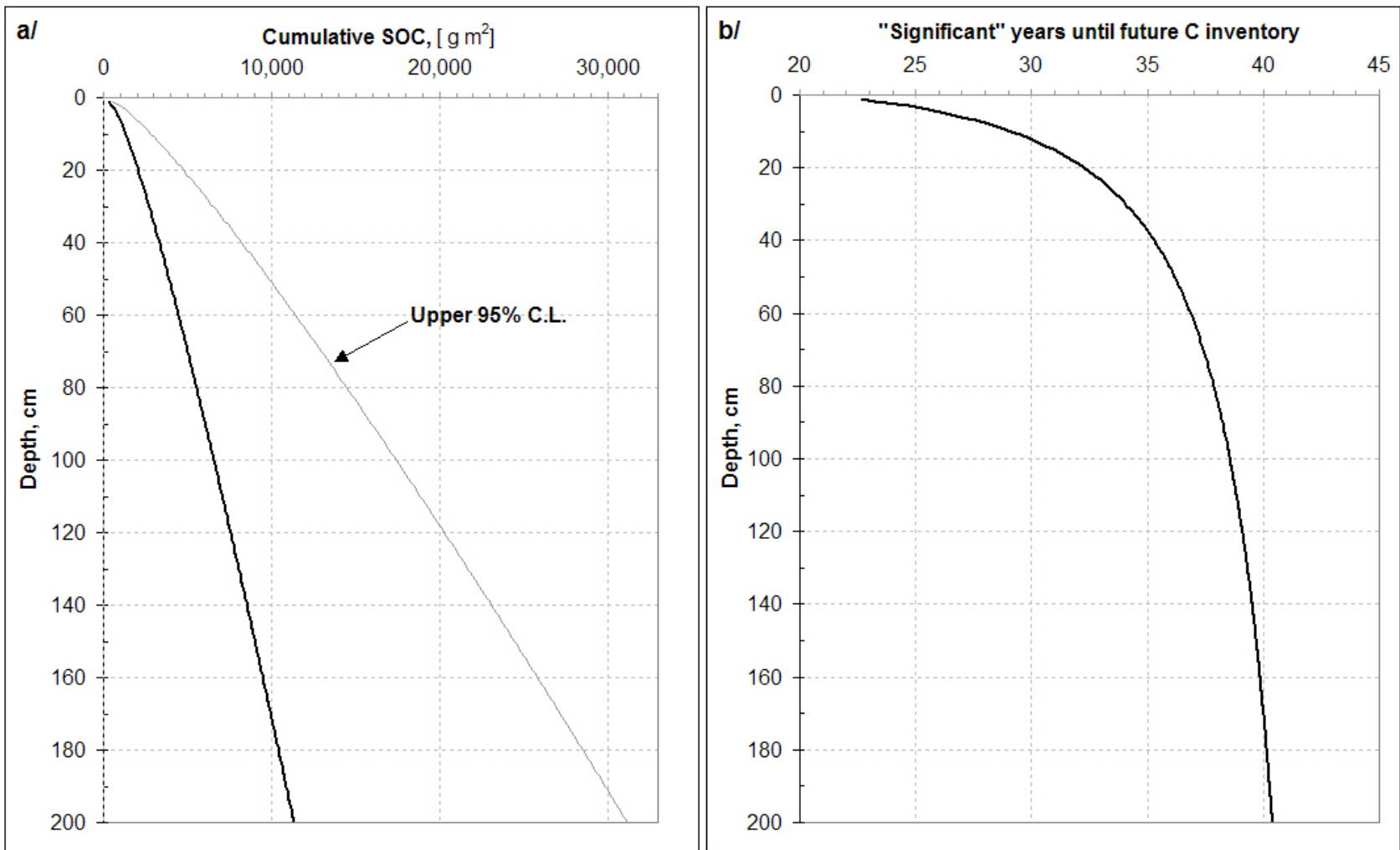
Figure 1-12. The minimum number of years required for cumulative SOC(g m^{-2}) results to a certain depth from two consecutive C inventories on the Ohio study sites to be significantly (in statistical terms) different from each other at the 95% probability level.

Terrestrial ecosystems could sequester large quantities of atmospheric CO_2 that could be stored in the soil and vegetation biomass for long periods of time. Anderson (1991) estimated average worldwide carbon levels for temperate deciduous forests at 175 Mg C ha^{-1}, with 90 Mg C ha^{-1} in the plant biomass and 85 Mg C ha^{-1} in the soil and litter layer. The average carbon content of forests in the eastern half of the United States was 179 Mg C ha^{-1}, including 81 Mg C ha^{-1} in the forest biomass, 9 Mg C ha^{-1} in the litter layer, and 89 Mg C ha^{-1} in the soil (derived from Turner et al.1995).

It is an obligation of statisticians and environmental scientists to develop SOC measurement and analysis techniques that would allow cost-effective and successful measurement of small accumulations of sequestered C, especially on minelands of higher landscape heterogeneity. Carbon inventories at finer resolution of SOC(g m^{-2}) analysis will allow landowners to be able to claim C credits sooner than the estimated 32 years as shown in the above example, thus providing additional profits that could be used by the landowners to expand the areas of their respective C sequestration projects. Expansion of terrestrial C sequestration projects is one of the provisions of the Kyoto Protocol to combat the negative effects of global warming (COP-UNFCCC1997).

Clearly, there is a need for more efficient C analysis techniques and more advanced methods and tools for horizontal soil variability analyses, such as geographic information systems and geostatistics, in order to minimize the costs for SOC analysis across the landscape and to focus the profits received from C credits to expand the current C sequestration projects. Furthermore, the future involvement of the United States and other nations of the world in a global carbon market, similar to that currently established in Europe, would increase the demand for C credits, thus increasing the price of sequestered SOC. As a result, SOC analyses will become economically feasible to greater soil depths, meaning that more thorough and complete SOC inventories will be possible. Eventually, the greater good following the establishment of such global carbon markets will be the increased interest in establishing ecosystems with high sequestration potential, such as forests, on disturbed land that otherwise exists as abandoned grassland or fallow land.

Subtask 1.3

Field measurement protocol for carbon inventory on mineland. The following sections summarize the necessary steps to determine the ecosystem C stock on minelands located in the Appalachian coalfields, when the goal is to measure and to report C credits. The measurement protocol is presented in the following structure: (A) establishing permanent carbon monitoring plots; (B) baseline carbon stock estimation; (C) periodic carbon content measurement; and (D) reference areas. All recommendations are based on the findings and our observations from the research work carried out on the DOE and Flint Gap project sites, which were described in previous reports.

A. Establishing permanent carbon monitoring plots

A.1. Mineland site quality mapping. Field soil sampling and testing are performed to determine the spatial distribution of mine soil pedons with different site quality revealed in the magnitude of their chemical and physical properties considered most important for tree growth. The parameters of interest that are measured on the field are pH, EC, soil compaction, percent slope, aspect, soil texture, percent coarse fragment content, rock type, and maximum rooting depth.

For each of these soil parameters, sufficiency curves are used to determine the productivity index at each sampled location (Jones, 2005). The relationships between productivity index and forest site quality class as well as the surveying and mapping procedures developed by Jones (Jones, 2005) are used to develop a site quality map of the project area with clearly outlined polygons, or strata, of specific site quality class I through V, I being the best and V being the worst.

For example, using appropriate sets of coefficients indicating the relative importance of the nine field-measured parameters, we tested our current linear model for predicting forest site quality on our research mined sites. The results showed that our field-applicable general model explained 61% of the variation in site quality of minelands ($R^2 = 0.61$), and the white pine-specific site quality model explained 68% (Jones 2005). The final product from the mapping task on the Flint Gap project site was presented in our previous reports for Task 2, where we also described the guidelines used for the field surveying task.

A.2. <u>Determining the number of sampling plots.</u> It is expected that the spatial distribution and the variation in carbon content within the three ecosystem components of grassland mineland, vegetation, litter layer and soil, are different. Hence, the sampling intensities for baseline carbon measurement of the respective ecosystem components on the project site should also be different.

Based on our finding for the DOE project sites, it is recommended that mined sites older than 9 years of age are selected for C sequestration studies. Minelands younger than 9 years exhibited very low soil organic carbon stocks relative to the variability associated with these estimates. It is of reasonable concern that selecting younger mined sites for C sequestration projects could lead to the inability to measure the baseline C stock in mine soils at acceptable accuracy and precision levels, and thus, will lead to the inability to claim C additions to the soil at a future C inventory event.

Our site quality mapping strategy is only intended to be used as a field-applicable means for site characterization and site quality mapping of surface-mined sites. Our model explained 61% of the variation in site quality, and the source of 39% of the variation in site quality was unidentified. The resulting site quality stratification will delineate the mine site area into productivity classes. The premise for site stratification is that the soil carbon content variation, as well as the variation of the other ecosystem components within an individual site quality stratum will be largely a function of the variation in site quality. Once the project site is subdivided into the necessary number of relatively homogenous site quality strata, the variation in carbon content for each ecosystem component (soil, vegetation, and litter layer) is determined, based on additional sampling.

In order to properly determine the horizontal variability of SOC(g m^{-2}) content within mapped site quality strata, shallow soil pits of 0-20 cm depths are excavated at 10 randomly selected locations within randomly selected strata representing each identified FSQC class on the site. Note that 10 shallow pits are excavated for every individual FSQC class identified on the project site, as opposed to sampling a total of 10 sampling locations for the entire project site. The bulk density of fines, content of fines, and C(wt%) are determined by the same methods used for the deep pits. The SOC(g m^{-2}) is estimated using Eq. 1.

The mean and standard deviation for the SOC(g m^{-2}) content from the shallow pits are used to determine the number of shallow pits required to measure the amount of sequestered C on the mined sites for each stratum of a certain FSQC class at desired accuracy and precision levels. The soil sampling intensity is estimated using Eq. 2 for the specific size of each stratum. It is

recommended that the sampling intensity, i.e., the number of sampling plots per stratum, is estimated from the within-stratum carbon content variation at three levels of accuracy of ±10%, 15%, and 20% of the mean, and two levels of precision, 90% ($\alpha = 0.10$) and 95% ($\alpha = 0.05$), using Eq. 2.

Upon completion of the forest site quality mapping task, additional three to five deep pits are excavated down to a 2-m depth in order to characterize the mine soil profile in the vertical dimension. Soil horizons are delineated using standard soil surveying methods and each horizon is analyzed separately for SOC(g m^{-2}) stock. If soil horizons are not readily discernible, then every 5-cm thick soil layer from the 0-200cm depth is sampled and analyzed for SOC content. Bulk density, coarse fragments content, and soil horizon depths are measured by the methods employed by Jones (2005). The bulk density of the fines and the content of the fines are determined by the computational steps described earlier in the text. The carbon concentration, C(wt%), of the soil is determined by the 16-step SOC estimation method, described in detail in Project 1 of this text.

Regression models are developed to model the distribution of BD$_{fines}$(g cm^{-3}), Fines(vol%), and C(wt%) by soil depth. Note that separate models of these three soil properties by soil depth are required for each mapped FSQC class. For example, if the entire project area was mapped to strata of FSQC I and II, then a total of 6 to 10 deep pits should be excavated at representative locations across the site, in order to produce separate final SOC models by depth for strata of the represented FSQC class. The resulting models of SOC(g m^{-2}) by soil depth, created by multiplying the individual predictions for BD$_{fines}$(g cm^{-3}), Fines(vol%), and C(wt%) in Eq. 1, are used to determine the maximum cost-effective depth, the minimum detectable difference, and the number of "significant" years until future SOC inventory for each stratum on the project site, using the computational steps described earlier in the text.

Vegetation and litter layer biomass samples are collected at 10 randomly selected locations within randomly selected strata representing each identified FSQC class on the site. The vegetation biomass at 2 inches above the ground surface is clipped from a square plot of 0.25 m^2. The litter layer biomass is also collected from the same sampling plot for C$_{biom}$(g m^{-2}) content analysis. The estimated mean and standard deviation estimates for C$_{biom}$(g m^{-2}) of vegetation and litter layer biomass are used to determine the sampling intensities of each biomass type at three levels of accuracy, ±10%, 15%, and 20% of the mean, and two levels of precision, 90% ($\alpha = 0.10$) and 95% ($\alpha = 0.05$), using Eq. 2.

The final sampling intensity for each ecosystem component per stratum, of a specific FSQC class, is determined based on a trade-off between desired accuracy and precision of the carbon estimates and cost of performing the field work and laboratory analyses. Due to existing uncertainties as to whether the plots will remain unchanged, undamaged, or intentionally manipulated between carbon inventories, it is recommended that 20% more sampling plots per stratum be located than the number estimated using Eq. 2.

A.3. <u>Locating sampling plots on the field.</u> Sampling plots are randomly distributed within each stratum. A 20 x 20 m grid is laid across the topography of the project site. Grid intersections become the centers of the sampling plots. For each ecosystem component within a certain stratum, the necessary number of sampling plots is selected at random. Plot center locations are marked clearly with pin flags and their location coordinates are recoded with a GPS unit. All plot locations are further secured with rebar, PVC pipes, and flagging tape by the field crew prior

to collecting field data for the first carbon content inventorying event.

These plots are termed permanent sampling plots for carbon measurement and monitoring in future inventories. Equipped with accurate GPS units and by navigating to each plot center's latitude and longitude coordinate, field crews will be able to revisit the project site and perform all necessary measurement and data collection needed to estimate the amount of sequestered carbon for each ecosystem component.

Digital plot coordinates are used to develop a detailed digital database for monitoring forest health conditions, carbon content distribution by ecosystem components, and nutrient availability on the project site. In addition, distinctive marking of these plots will allow for more efficient and more accurate carbon measurement verification by any monitoring agency that would oversee the measurement and reporting of C credits on the site.

B. Baseline carbon stock estimation.

The baseline carbon stock represents the amount of total ecosystem carbon present on the site prior to the implementation of project activities. The difference between the baseline carbon value and the project carbon value is the carbon credit for a mineland reforestation project. Under current site conditions of most mined grasslands, there are three ecosystem components that sequester and/or store carbon. The baseline carbon on minelands is stored in vegetation and litter layer biomass and the mine soil.

B.1. Vegetation. The current vegetation present on grassland mined sites is comprised of various grass and legume species that were sown at the time of site reclamation. Any shrubs and woody vegetation is ignored during this sampling event due to the insignificant amount of carbon contained within them.

The selected number of vegetation sampling plots are randomly located within each stratum and marked with pin-flags. At each vegetation sampling plot, the vegetative cover is collected from a 0.25-m^2 area by clipping all live vegetation biomass above 2 inches from the ground and placing it in paper bags. For strata with vigorous vegetation, a 0.10-m^2 clipping area is recommended in order to fit all sampled vegetation from one sampling plot in one paper bag.

The vegetation samples are dried at 65°C and their weights are measured and recorded. For every tenth randomly selected sample, the vegetation biomass is ground to pass a 1-mm mesh sieve and is analyzed for carbon concentration, C_{biom}(wt%), using an automated carbon-analyzer machine. Using only 10% of all samples for C_{biom}(wt%) estimation is regarded sufficient, as the carbon concentration in vegetation biomass is expected to be consistent across the landscape. The C stocks for the vegetation biomass are calculated as C_{biom}(g m^{-2}) = biomass dry weight (g) * C_{biom}(wt%) /100 * (1/ plot^area m^2), where plot^area m^2 is equal to 0.25 m^2 or 0.10 m^2 depending on the size of the clipped area of each sampling plot.

B.2. Litter layer. Use sampling and measurement procedures for vegetation described above.

B.3. Soils. The number of soil sampling plots is randomly located on each stratum. At each soil-sampling plot, one soil pit is excavated with minimum horizontal dimensions of 30 x 30 cm and the selected cost-effective depth. Standard soil survey techniques are used to obtain horizon depths. Loose samples are collected from each horizon for C(wt%) analysis. Soil bulk density and BD and CFC(wt%) are measured by the methods employed by Jones (2005). Loose soil samples are air-dried and are passed through a 2-mm mesh sieve. Soil carbon concentration is

measured using the 16-step SOC estimation method. Carbon estimates per unit area, $SOC(g\ m^{-2})$, are computed by substituting the measured $C(wt\%)$ content, $BD_{fines}(g\ cm^{-3})$, $CFC(wt\%)$, and horizon depth in Eq. 1.

On many occasions it may be impossible to delineate soil horizons depending on the stage of soil genesis of a specific mineland. This is due to the fact that in most mine soils, greater than 10(25) years are necessary for soil horizons to form. If this is the case and there are no clearly visible soil horizons, then soil samples are collected in 5-cm depth increments to the selected cost-effective depth.

C. Periodic carbon content measurement.

Carbon credits can be reported at any point during the C sequestration project and from any ecosystem component, the C content of which can be measured at desired accuracy and precision levels. Important factors that may be used to determine the optimal time for future C inventories for each ecosystem component are the MDD, estimated for the soil component, and the current market price of elemental C. Claiming C credits is similar to timber harvesting from managed forests. Provided that the ecosystem is sequestering atmospheric CO_2 at its full potential evaluated by forest health, the accumulated ecosystem C can be claimed for C credits at the best financially and logistically possible time during the C sequestration project.

Carbon inventories for the forest and grass vegetation are carried out every five years up until age 15 of the forest stand, and every 10 years thereafter. The soil carbon inventory is carried out no earlier than the number of "significant" years estimated in section A.2. of this protocol.

The sampling intensity, i.e., the number of sampling plots per stratum, is dependent on the variation of site conditions. In future carbon inventories, if there is any indication that the variation in site conditions has been reduced or increased, provided all planned project activities have been implemented correctly, then the sampling intensity per given stratum, or for all strata of a certain FSQC class, could be modified (decreased or increased) such that the required level of accuracy and precision for the final SOC content is still met. A reduced sampling intensity will lead to reduced carbon inventory costs.

The following sampling protocol is designed for carbon measurement and monitoring after all site preparation and tree planting project activities have been implemented on the project site. Sampling is done on all permanently marked sampling plots designated for a specific ecosystem component.

C.1. <u>Vegetation</u>.

C.1.1. Overstory canopy layer. Diameter at breast height (DBH) is measured and recorded by tree species for all trees with DBH greater than 5 cm that are located within a 12-m radius circular area (equal to 452 m^2) from the center of each vegetation sampling plot. Total tree biomass is estimated using biomass equations from the most recent literature. Total forest biomass includes stem wood, stem bark, foliage, treetops, branches, stumps, and coarse roots (Jenkins et al. 2003).

Total forest biomass is converted to kg of C using conversion ratios for different tree species groups (Birdsey 1992). The carbon content results are reported in $g\ m^{-2}$ or in $Mg\ ha^{-1}$ units.

C.1.2. Understory vegetation. Within each overstory measurement plot there are four 2-m radius circular subsampling plots (subsampling plot area equal to 12.5 m^2) used for understory vegetation sampling. The four plots are randomly distributed such that each of the four quadrants of the overstory vegetation sampling plot is sampled.

In order to obtain a good estimate of the carbon sequestered and stored in understory vegetation biomass, all saplings (DBH <5 cm) and shrubs that are less than 1.3 m tall and that fall within or originate from the subsampling plot are clipped and the fallen biomass wet weight is recorded. A composite sample from all four plots is collected and brought to a laboratory for biomass percent moisture and percent carbon determination. Percent moisture is estimated as follows: Moisture % = [wet biomass weight – dry biomass weight (kg)]/ [dry weight (kg)]*100. The composite biomass sample is dried at 65°C, ground, and passed through a 1-mm mesh sieve, and the carbon concentration is measured using an automated carbon analyzer. Carbon content is reported in g m^{-2} or Mg ha^{-1} units and is computed as follows: C_{biom}(Mg ha^{-1}) = (total biomass wet weight (kg)) * C_{biom}(wt%) /100 * (1/ 50.27 m^2) * (1+Moisture%/100) * 10, where 50.27 m^2 is the cumulative area of the four subsampling plots, and 10 is a unit conversion factor to transform biomass content from kg m^{-2} to Mg ha^{-1} units.

Biomass equations are used to compute the total biomass of all saplings and shrubs that have DBH <5 cm but are taller than 1.3m. The total biomass results are converted to carbon content estimates using tree species-specific conversion ratios from the recent literature.

C.1.3. Grasses and legumes. Use sampling procedures described in section B.1. of this protocol.

C.2. Litter layer. Use sampling procedures described in section B.2. of this protocol.

C.4. Soils. Due to the inherent variation of soil properties on minelands, it is likely that a greater number of permanent soil sampling plots may be required compared to the number of vegetation sampling plots. More permanent soil sampling plots, in addition to the permanent vegetation sampling plots, are marked at the intersections of the 20 x 20-m grid, as was previously described. Because of the destructive nature of soil sampling, soil pits are excavated at different 30 x 30-cm horizontal locations around the center of the plot such that the first soil pit is to the north of the plot center, the second is to the east, etc. Assuming that the period between SOC inventories will be no less than 30-60 years, depending on the heterogeneity of each site, soil sampling locations could be re-used after four consecutive inventories, or after approximately 120 years. The following are the specific tasks that can be carried out within each permanent soil sampling plot:

1. Locate permanent soil sampling plots.
   a. Overlay a 20-by-20m grid on the site such that the micro topographic features are accounted for.
   b. Choose at random the necessary number of plots at the grid intersections.
   c. Mark soil pit locations at a distance 30cm from the center of each plot and at a cardinal direction following the order from north – east – south – west.

2. At each soil pit:
   a. The soil pit is dug by hand (where applicable) to a 30 x 30 x MCD cm hole size, where MCD is computed beforehand, as described above.

b. The excavated spoil is placed in heavy-duty paper bags or plastic containers and is transported to a laboratory to determine the total soil weight and the content of coarse fragments) of the excavated soil sample.

c. The volume of the excavated soil is determined using the displacement method by lining the inside of the excavated hole with thin plastic and filling it with lead BB's. The BB's are transferred to a graduated cylinder to determine their volume in cm^3, which will be volume of the excavated soil pit.

d. Soil horizons are delineated (where applicable) using standard soil survey techniques and their depths are measured and recorded.

e. Loose soil samples of approximately 200g soil weight are collected from each soil horizon (where applicable) or from each 5cm-soil layer down soil profile to depth of [MCD]cm and are stored in heavy-duty, plastic-lined soil sampling bags.

3. Loose soil samples are air-dried and are passed through a 2-mm mesh sieve.
   a. Fine soil fraction (<2mm) weight is recorded.
   b. Bulk density and volumetric content of the fine soil fraction are determined.

4. Chemical analysis:
   a. Soil carbon concentration is determined on the fine soil fraction using the 16-step SOC estimation method.
   b. If sufficient funds are available, nutrient content is determined on the <2 mm soil fraction for further site characterization.

5. Data analysis:
   a. SOC($g\ m^{-2}$) is computed using Eq. 1.

D. Reference areas

In order to determine the net carbon sequestration for each forest management treatment used in the reforestation project, a reference measure for the carbon sequestration is necessary. It is recommended that 5% of the total project site area be treated as a reference area to which no-forest management treatments are applied. The reference areas are sampled and analyzed for carbon content in the same way as any other project site stratum.

In order to evaluate the change in carbon sequestration potential of a certain mined land following certain forest management treatments, the net carbon stock of untreated, reference sites is subtracted from the net carbon stock of the treated sites. The reference site(s) are located on the project site to give the carbon sequestration for a "business-as-usual" land management scenario.

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TASK 2: Develop classification and inventory criteria and procedures for mined land. (Galbraith et al.)

This task was completed in September, 2005; all work will be presented in the final report.

TASK 3: Develop reforestation methods and procedures for mined land. (Fox et al.)

This task was completed in September, 2005; all work will be presented in the final report.

TASK 4: Conduct economic analyses of reforestation and forest management activites for carbon sequestration and a variety of forest products and services. (Amacher and Sullivan)

This task was completed in September, 2005; all work will be presented in the final report.

TASK 5: Determine the potential of large-scale SMCRA grassland restoration to sequester carbon and create other societal benefits. (Zipper and McGrath)

Executive Summary

Many reclaimed coal-surface mine sites in the eastern United States are not in productive use. Reforestation of these lands could provide benefits, including timber production and carbon sequestration. Currently, little information is available on the characteristics and extent of the land resource base created under SMCRA. Our objective was to determine the suitability of eastern U.S. coal mined lands for reforestation. Study sites in four eastern states were selected randomly from agency permitting records. Sampling points on 25 sites were selected using a randomization procedure. At each sampling point, soil properties affecting reforestation potentials were measured. This report presents preliminary results.

Introduction

Society has an interest in assuring that lands disturbed by coal surface mining are restored to productive use, and U.S. federal law requires it. The Surface Mining Control and Reclamation Act (SMCRA) requires lands that coal mine operators "restore the land affected to a condition capable of supporting the uses which it was capable of supporting before mining, or higher and better uses of which there is a reasonable likelihood" [Section 515 b(2)]. This requirement is commonly interpreted as stating that all lands mined for coal must be restored to an "equal or better" land use than that which preceded mining.

In the eastern United States, the vast majority of lands mined for coal are forested prior to mining. Most of these lands are reclaimed to support non-intensive land uses such as wildlife habitat, unmanaged forest, and hay production or livestock grazing ("hayland-pasture"), and sites reclaimed to a hayland-pasture post-mining land use are often abandoned from that use. Thus, the suitability of the soils created by mining operations for biologically productive forests is both an environmental policy issue and a natural resource management concern. Therefore, our goal is to determine the suitability of reclaimed coal mined lands in the eastern USA for forests.

Experimental

Twenty mine permits each in Kentucky, Ohio, Virginia, and West Virginia were selected from permitting databases maintained by state agencies for sampling using a randomized procedure where individual permits were weighted by acreage. An effort was made to identify and contact landowners so as to obtain site access permissions. For sites where access permission could not be obtained but knowledgeable parties communicated opportunities to access nearby sites with similar characteristics, these sites were sampled as substitutes for the original sites. Sampling locations were located on each site using a randomization procedure.

Six mine sites were sampled in Ohio, Kentucky, and Virginia, and seven mines were sampled in West Virginia (Figure 5-1). The 25 sites yielded 225 sample locations (Table 5-1). A variety of soil and vegetation analyses were conducted, including rooting depth by methods developed by Jones (2005) for minesoil application using a screw auger to penetrate the soil until refusal; bulk density and particle size analyses of the soil-sized fractions of the top 30 cm; and pH for samples taken from 0-10 and 10-30 cm depths. Bulk density analyses were derived from whole-soil samples removed from approximately 30 x 30 x 30-cm holes. Additional analyses were also performed, as reported in the December 2005 Quarterly Report.

Forest productivity "sufficiency curves" developed by Jones et al. (2005) were used to determine sufficiency levels for each soil measurement at each sampling location and a forest site productivity index was determined for each sampling location, also using Jones et al. (2005).

Sufficiency values are assigned to soil parameters at each sampling location on a 0-1 scale, with 0.0 indicating poor forest site quality and 1.0 indicating superior quality. These values are combined to calculate a productivity index using the following equation:

$$PI = 0.44*SBD + 0.28 * SRD + 0.20\, STX + 0.08\, SPH$$

where:

    PI = productivity index;
  SBD = bulk density sufficiency;
  SRD = rooting depth sufficiency;
  STX = soil texture sufficiency;
  SPH = soil pH sufficiency.

Mean sufficiency values for each parameter and a mean productivity index were calculated for each mine site. Productivity indices are interpreted as representing forest site quality classes I (PI< 40, "poor") through V (PI > 85, "excellent") based on Jones et al. (2005). Mean values were calculated for each state from the mine site means.
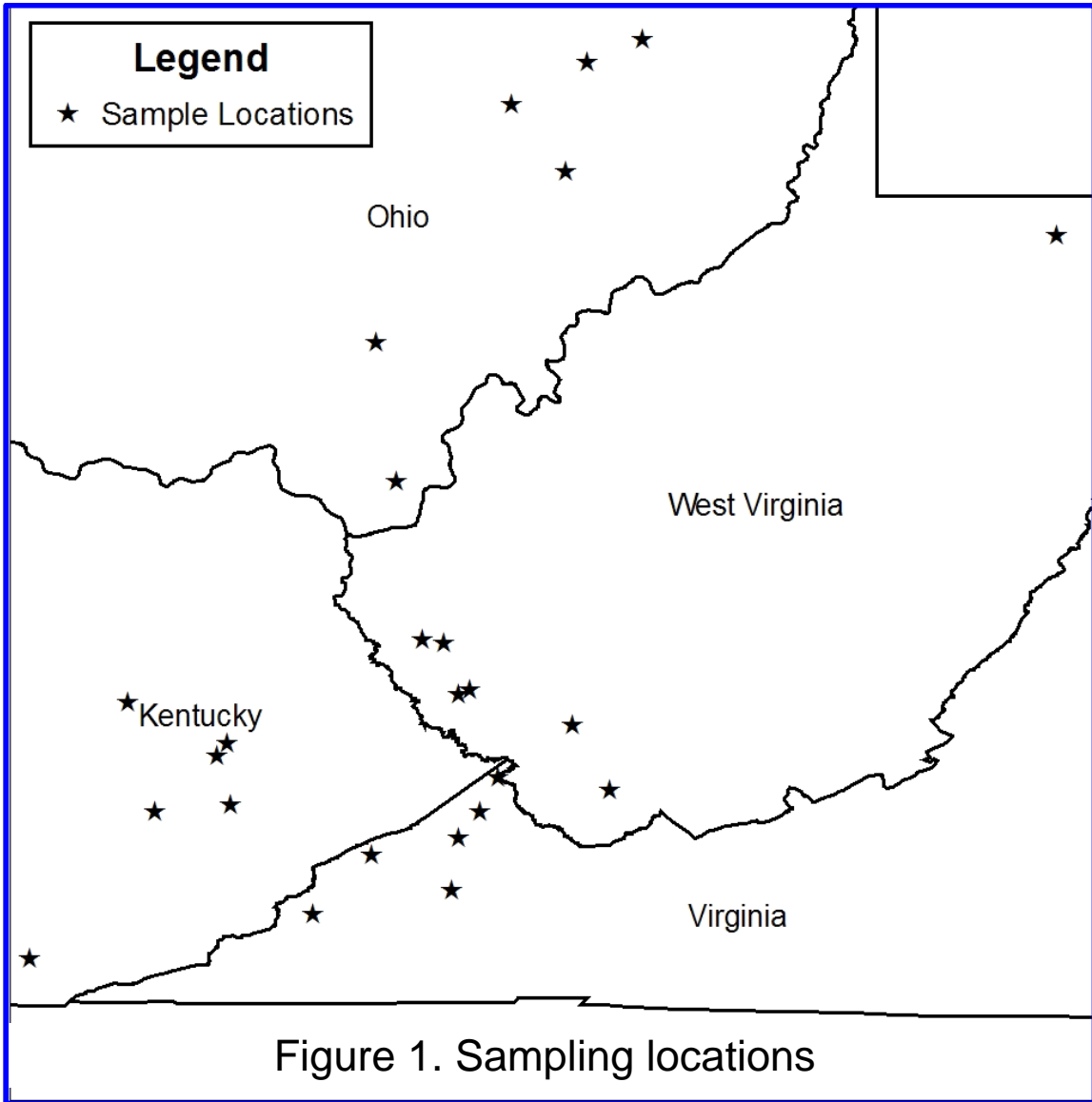
Legend

★ Sample Locations

Ohio

West Virginia

Kentucky

Virginia

Figure 1. Sampling locations

Figure 5-1. Sampling locations.

Table 5-1. Mean value of selected soil properties at the 25 mine sites.

State	Site	Sample Count	EC*	Coarse Fragments (%)	Bulk Density (g/cc)	Rooting Depth (cm)	Silt+Clay (% of soil fraction)	pH
KY	1	5	0.44	48.17	0.9	30	64%	4.44
KY	2	10	0.13	50.13	1.0	32	62%	5.73
KY	3	10	0.11	48.97	1.154	14	55%	6.77
KY	4	10	0.11	49.33	1.2	29	73%	6.00
KY	5	3	0.11	48.65	1.0	30	48%	5.06
KY	6	10	0.34	40.02	1.4	29	71%	5.63
OH	1	10	0.15	35.22	0.9	32	83%	7.08
OH	2	9	0.12	44.53	1.2	34	75%	6.54
OH	3	10	0.10	33.12	1.4	36	64%	6.11
OH	4	10	0.16	20.50	1.472	31	79%	7.71
OH	5	9	0.13	32.28	1.248	37	66%	6.04
OH	6	6	0.12	38.53	1.2	29	72%	5.52
VA	1	8	0.08	36.62	1.2	38	39%	5.13
VA	2	9	0.09	47.55	1.0	38	58%	4.85
VA	3	10	0.09	43.45	1.023	40	54%	5.15
VA	4	10	0.15	48.64	1.1	27	62%	6.29
VA	5	10	0.15	49.11	1.5	35	64%	6.15
VA	6	10	0.17	41.74	1.222	24	77%	6.58
WV	1	10	0.11	39.74	1.5	30	46%	5.39
WV	2	9	0.11	45.01	1.141	22	59%	5.43
WV	3	10	0.11	56.56	1.080	24	68%	6.44
WV	4	8	0.09	50.54	1.1	23	40%	4.93
WV	5	9	0.13	52.07	1.4	27	36%	5.81
WV	6	10	0.08	52.04	1.284	33	57%	5.30
WV	7	10	0.10	56.06	1.238	20	62%	5.87

* Estimated 1:5equivalent (see text).

Results

Mean values, by state and overall, of soil parameters are reported in Table 5-1; sufficiency values for sites located in each state are represented in Figure 5-2; and productivity indices for sites within each state are represented in Figure 5-3.

One complication with the procedures utilized concerns electrical conductivity (EC). EC measurements were conducted by the Virginia Tech Soil Testing Laboratory at a 1:2 soil:water ratio, but Jones' sufficiency values are based on 1:5 soil:water ratio EC values. Therefore, the equivalent 1:5 EC equivalent values (Table 5-1) were derived using the method of Chen et al. (2000) from the 1:2 soil:water measured values; the Chen et al. (2000) method is based on analyses conducted in Florida natural soils. Thus, these values should be considered as preliminary estimates of 1:5 soil:water EC equivalents.

Sufficiency and forest site productivity for individual sites are represented in Figures 5-2 and 5-3. Using this method of analysis, the majority of the sites sampled have productivity indices that correspond with site quality class IV ("good"). Considerable variation was found to occur among the sampled sites.
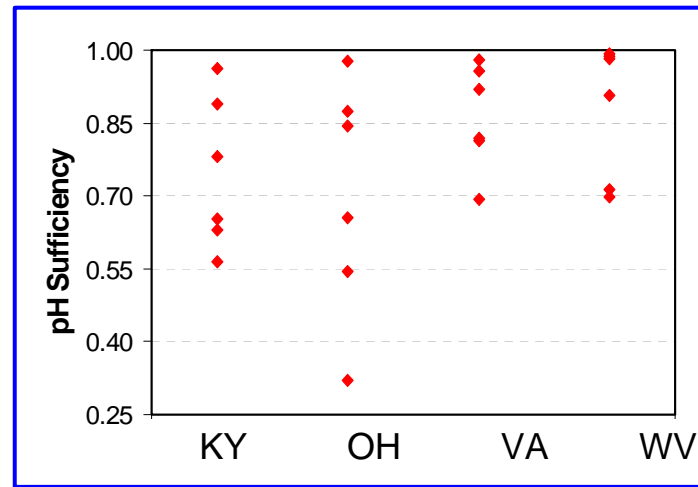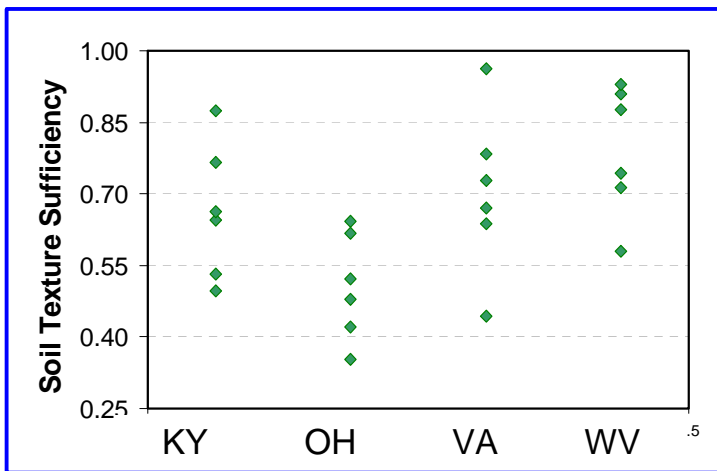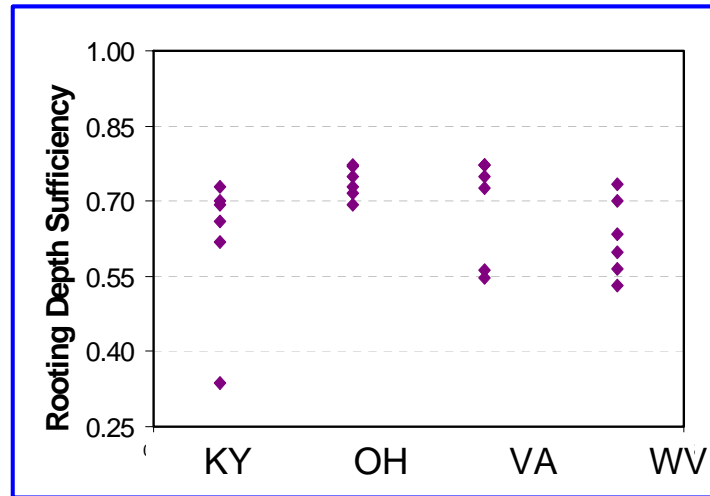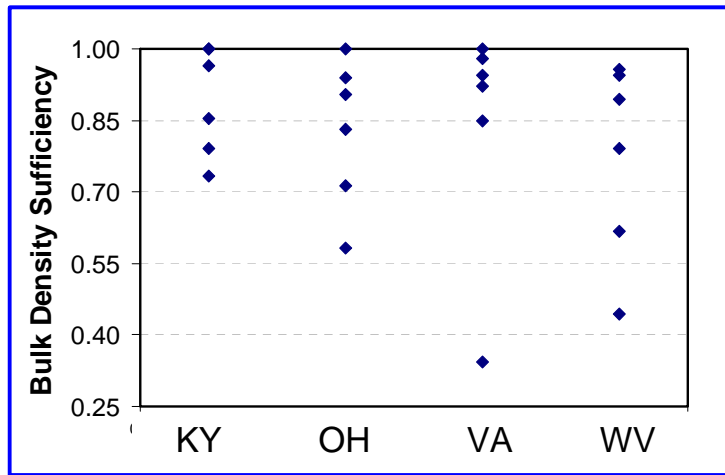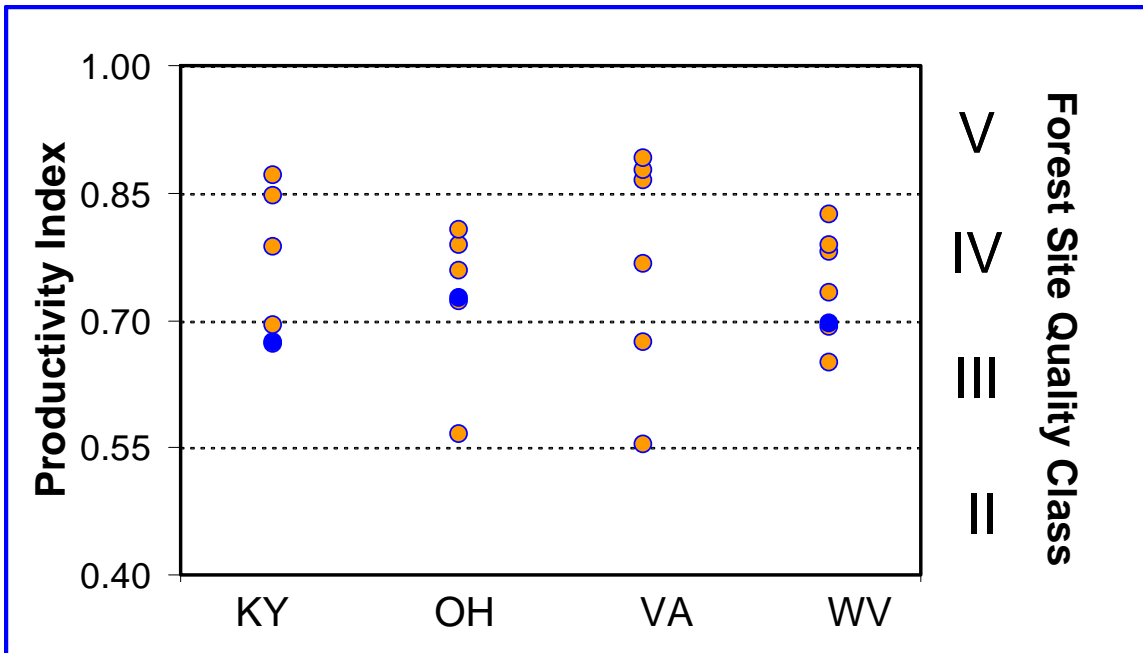
Figure 5-2. Mean sufficiency levels for 25 mine sites in four states.

Figure 5-3. Mean forest productivity index (PI) for sampling sites in four states (left axis), and equivalent site quality classes (right axis). Darkened symbols represent coincident PI values (overlying symbols).

Analysis and Interpretation

These are preliminary data that have not yet been thoroughly reviewed and scrutinized. Therefore, no firm conclusions are drawn. We are somewhat skeptical of the utility of the Jones et al. (2005) method for determining rooting depth and its utility for characterizing forest site quality. Therefore, other approaches will be applied to interpret these data for forest site quality (Andrews et al. 1998, Rodrigue and Burger 2004, Showalter et al. 2006, Torbert et al. 1998).

Acknowledgments

These data were presented at the 2006 National Meeting of the American Society of Mining and Reclamation (McGrath et al. 2006).

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PROJECT TIMETABLE

	Planned		Completed									

Year:	2002	2003				2004				2005		
Quarter:	4th	1st	2nd	3rd	4th	1st	2nd	3rd	4th	1st	2nd	3rd
Task 1												
Subtask 1.1	Baseline Carbon Sequestration Potential											
Subtask 1.2	Mine Soil Productivity											
Subtask 1.3					Carbon Sequestration by Forest Practice							
Subtask 1.4					Accounting Procedures							
Task 2												
Subtask 2.1	Classification Criteria											
Subtask 2.2				GIS Mapping								
Subtask 2.3				Test Remote Sensing								
Subtask 2.4					Experimental Plots							
Subtask 2.5						Soil Analyses						
Subtask 2.6											Validate classification criteria	
Task 3												
Subtask 3.1	Locate sites											
Subtask 3.2				Establish experiment								
Subtask 3.3					Silvicultural recommendations							
Subtask 3.4					Reforestation costs							
Subtask 3.5					Evaluate survival and growth							
Subtask 3.6					Estimate growth potential							
Subtask 3.7						Estimate timber & carbon value						
Task 4												
Subtask 4.1	Economic feasibility											
Subtask 4.2				Evaluation								
Subtask 4.3						Government policies						
Task 5												
Subtask 5.1			Identify SMCRA grassland									
Subtask 5.2				Use characteristics of permits								
Subtask 5.3					Soil properties by permit							
Subtask 5.4					Est. quantity grassland							
Subtask 5.5					Est. C sequ. by site quality class							
Subtask 5.6											Est. C seq. by policy scenario	