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Technical Progress Report

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

Quarterly Report

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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. During the reporting period (October-December 2004) we completed the validation of a forest productivity classification model for mined land. A coefficient of determination (R^2) of 0.68 confirms the model's ability to predict SI based on a selection of mine soil properties. To determine carbon sequestration under different forest management scenarios, a field study was installed as a 3 x 3 factorial in a random complete block design with three replications at each of three locations, Ohio (Figure 1), West Virginia (Figure 2), and Virginia (Figure 3). 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). For hybrid poplar, total plant biomass differences increased significantly with the intensity of silvicultural input. Root, stem, and foliage biomass also increased with the level of silvicultural intensity. Financial feasibility analyses of reforestation on mined lands previously reclaimed to grassland have been completed for conversion to white pine and mixed hardwood species. Examination of potential policy instruments for promoting financial feasibility also have been completed, including lump sum payments at time of conversion, annual payments through the life of the stand, and payments based on carbon sequestration that provide both minimal profitability and fully offset initial reforestation outlays. We have compiled a database containing mine permit information obtained from permitting agencies in Virginia, West Virginia, Pennsylvania, Ohio, and Kentucky. Due to differences and irregularities in permitting procedures between states, we found it necessary to utilize an alternative method to determine mined land acreages in the Appalachian region. We have initiated a proof of concept study, focused in the State of Ohio, to determine the feasibility of using images from the Landsat Thematic Mapper (TM) and/or Enhanced Thematic Mapper Plus (ETM+) to accurately identify mined lands.

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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). Region-wide, 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, 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 (Figure 1), West Virginia (Figure 2), and Virginia (Figure 3). We estimated the carbon stock (kg m^{-2}) on each study site for the surface 0-10 cm, the 0-100 cm mine soil profile, and for a 10-cm-thick layer of topsoil and mine spoil material. Carbon stock values for the 10-cm-thick layer of topsoil and mine spoil material were modeled as a function of their physical and chemical soil properties. We computed the mean carbon stock value (kg C m^{-2}) and the 95% confidence limits of the mean from a set of GIS-based carbon stock maps generated for these study sites. Carbon stock results for the surface 0-10 cm show that the West Virginia mined sites store 26% and 54% more carbon then the surface 0-10 cm mine soil layer in Ohio and Virginia, respectively. Our results show that the variation of the total soil carbon stored in a 10-cm-thick layer of mine soil material across space was greater in the mine spoil (CV of 35% to 81%) compared to the topsoil (CV of 31% to 53%). The GIS-based average carbon stock estimates were more representative for mined lands than the carbon stock computed as the average of collected soil samples.

The treatments imposed on these study sites 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. Based on recent measurements of hybrid poplar, total plant biomass differences increased significantly with the intensity of silvicultural input. Root, stem, and foliage biomass also increased with the level of silvicultural intensity. In our effort to extrapolate our results to mined land regionally, we have compiled a database containing mine permit information obtained from permitting agencies in Virginia, West Virginia, Pennsylvania, Ohio, and Kentucky. Due to differences and irregularities in permitting procedures between states, we found it necessary to utilize an alternative method to determine mined land acreages in the Appalachian region. We have initiated a proof of concept study, focused in the State of Ohio, to determine the feasibility of using images from the Landsat Thematic Mapper (TM) and/or Enhanced Thematic Mapper Plus (ETM+) to accurately identify mined lands. Financial feasibility analyses of reforestation on mined lands previously reclaimed to grassland have been completed for conversion to white pine and mixed hardwood species. Examination of potential policy instruments for promoting financial feasibility also have been completed, including lump sum payments at time of conversion, annual payments through the life of the stand, and payments based on carbon sequestration that provide both minimal profitability and fully offset initial reforestation outlays.

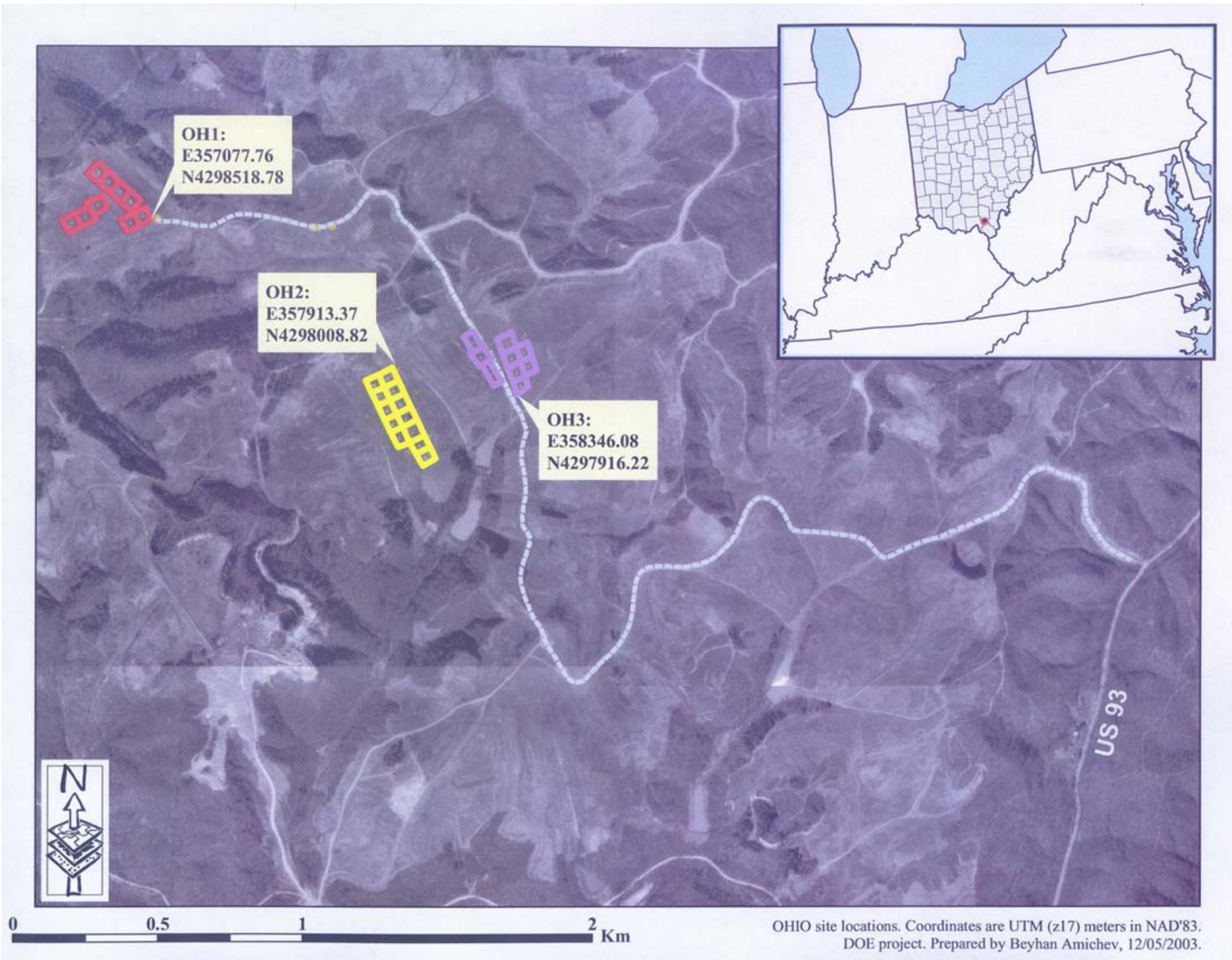

Figure 1. Map of field sites in Lawrence County, Ohio.

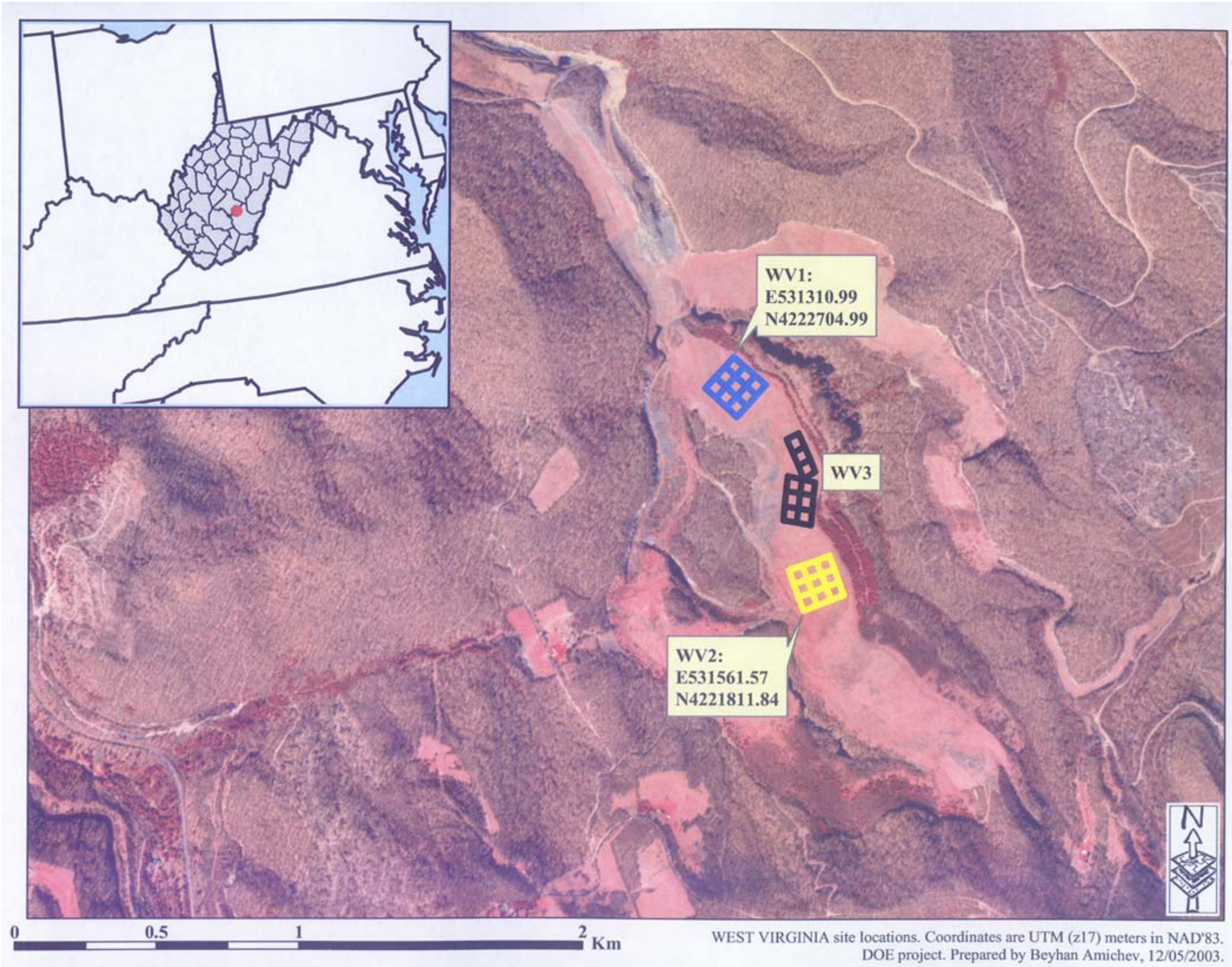

Figure 2. Map of field sites in Nicholas County, West Virginia.

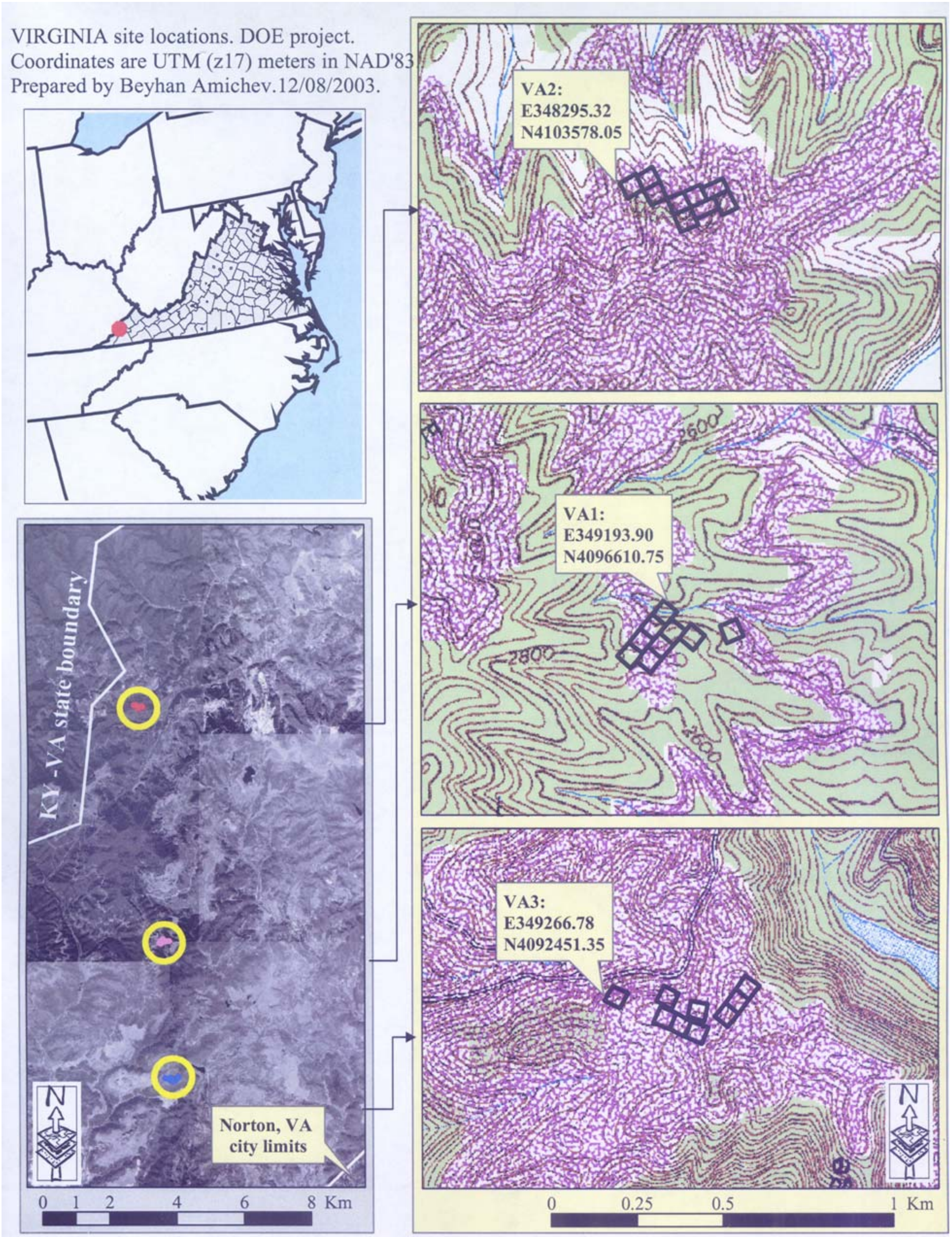

Figure 3. Map of field sites in Wise County, Virginia.

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

Executive Summary

We estimated the carbon stock (kg m^{-2}) on each study site for the surface 0-10 cm, the 0-100 cm mine soil profile, and for a 10-cm-thick layer of topsoil and mine spoil material. Carbon stock values for the 10-cm-thick layer of topsoil and mine spoil material were modeled as a function of their physical and chemical soil properties. We computed the mean carbon stock value (kg C m^{-2}) and the 95% confidence limits of the mean from a set of GIS-based carbon stock maps generated for our study sites. Carbon stock results for the surface 0-10 cm indicate that the West Virginia mined sites store 26% and 54% more carbon then the surface 0-10 cm mine soil layer in Ohio and Virginia, respectively. Our results show that the variation of the total soil carbon stored in a 10-cm-thick layer of mine soil material across space was greater in the mine spoil (CV of 35% to 81%) compared to the topsoil (CV of 31% to 53%). The GIS-based average carbon stock estimates were more representative for mined lands than the carbon stock computed as the average of collected soil samples.

Experimental

Subtask 1.1

Nine study sites were established across three states in the Appalachian coalfields – Virginia, Ohio, and West Virginia. The selection criteria and the locations of these sites have been thoroughly discussed in our previous reports. Six of the study sites, in Ohio and Virginia, were reclaimed with topsoil of average depth of 20 cm (Table 1). There was no topsoil on any of the three West Virginia sites; rather, the black shale and siltstone overburden spoil material was directly seeded to grasses and legumes.

We collected soil samples from the surface and the subsurface soil layers of each plot on our study sites (Figure 4). In Ohio and Virginia we collected (i) 0-10 cm surface soil samples from the topsoil layer and recorded the total observed topsoil depth, and (ii) a 10-cm-thick layer (or >10 cm thick where possible) of the subsurface mine spoil material. In West Virginia we collected 0-10 cm and 10-30 cm samples of the mine spoil material.

On the fine fraction of the soil sample (<2 mm) we measured a wide range of chemical properties, including carbon concentration (gram C/gram soil), carbon-to-nitrogen ratio (CN), nitrogen concentration (gram N/gram soil), pH, and electrical conductivity (EC, mmhos cm^{-1}), which is an indirect measure of the amount of salts in the soil. We made composite samples for the two sampling depth categories, surface and subsurface, by combing and mixing the five respective soil subsamples, as depicted in Figure 4, within each 50 x 50-m plot. On the composite soil sample we determined the physical soil properties of the soil, coarse fragment content estimated as percent of the total soil volume (CFC), soil texture, percent sandstone (SS) and siltstone (SiS) content which were estimated as percent of the total CFC. Lastly, by excavating an approximately 30 x 30 x 30 cm soil pit, we determined the bulk density (BD, g cm^{-3}) of the whole soil within each plot for each depth category. The latter BD measurement was corrected for CFC content in the soil sample assuming 2.65 g cm^{-3} specific gravity of the coarse soil particles to determine the bulk density of the fine fraction of the soil, BD_{Fines}(g cm^{-3}).

Table 1. Total soil carbon stock estimates in the 0-10 cm and 0-100 cm mine soil profiles of nine study sites in Ohio, Virginia, and West Virginia.

Site	Plot	$Carbon_{0\text{-}10\ cm}$ [kg m-2]	Std. $Error_{0\text{-}10\ cm}$ [kg m-2]	No. Samples Topsoil	No. Samples Spoil	Topsoil Depth [cm]	$Carbon_{0\text{-}100\ cm}$ [kg m-2]	Std. $Error_{0\text{-}100cm}$ [kg m-2]	No. Samples
OH	1	2.363	0.1001	45	0	26.2	14.375	1.3114	42
	2	1.995	0.1385	45	0	16.4	13.824	3.4781	44
	3	1.878	0.0928	44	0	19.7	9.421	0.4967	36
	Avg	**2.079**	**0.110**			**20.8**	**12.540**	**1.7620**	
VA	1	1.134	0.0757	44	0	22.0	18.302	1.4546	22
	2	2.275	0.1027	45	0	29.7	21.567	1.3089	33
	3	1.702	0.1486	17	26	8.2	15.254	1.1777	36
	Avg	**1.703**	**0.109**			**20.0**	**18.374**	**1.3137**	
WV	1	2.715	0.1454	0	45	0.0	14.385	0.8778	45
	2	2.125	0.1069	0	45	0.0	9.649	0.3027	45
	3	3.034	0.1370	0	45	0.0	12.685	0.4719	45
	Avg	**2.625**	**0.130**			**0.0**	**12.239**	**0.5508**	

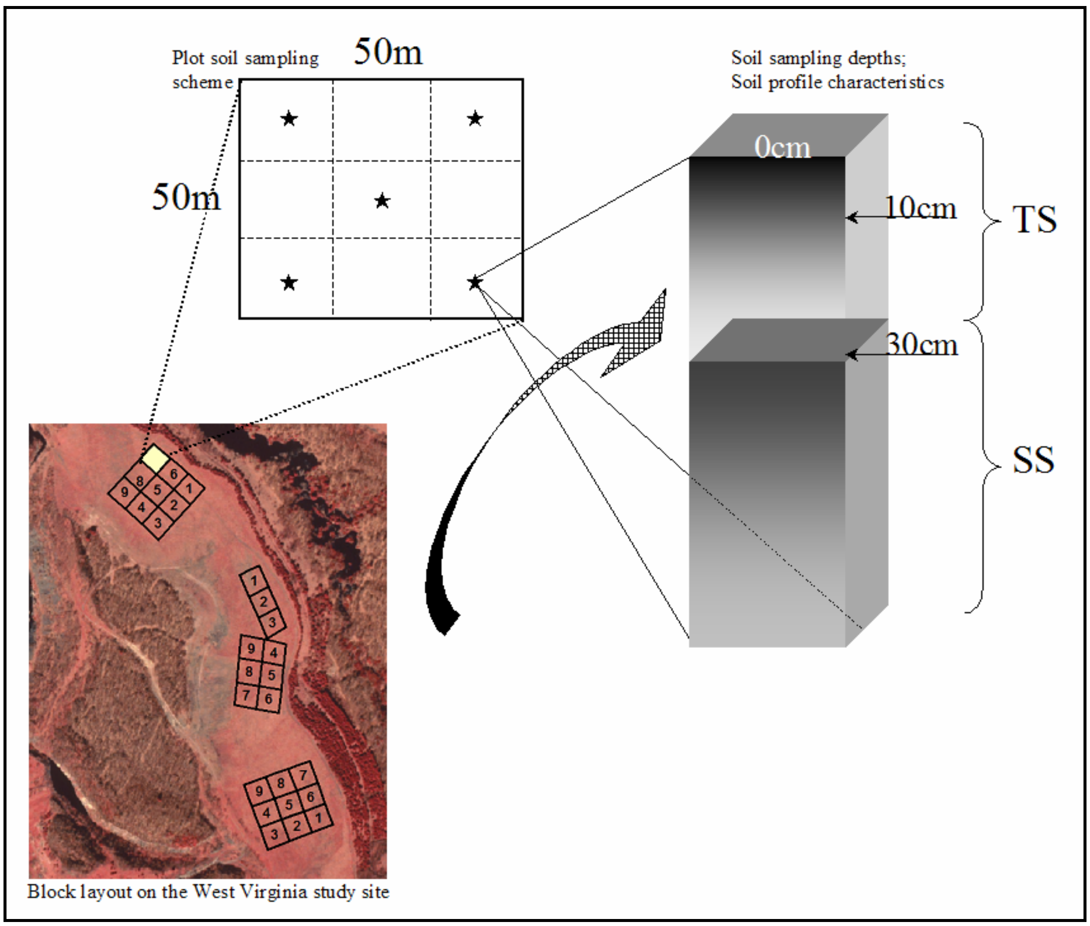

Figure 4. Soil sampling scheme for estimating baseline carbon stock in surface and subsurface layers of a mine soil profile on a hypothetical study site. Usually the surface layer is topsoil (TS) material of varying depths and the subsurface layer (SS) is overburden mine spoil material.

We estimated the carbon stock (kg m^{-2}) on each study site for the surface 0-10 cm, the 0-100 cm mine soil profile, and for a 10-cm-thick layer of topsoil and mine spoil material. Surface and subsurface estimates were computed for a 10-cm-thick layer of topsoil and mine spoil, i.e., for surface topsoil, subsurface topsoil, and for surface spoil and subsurface spoil, in order to investigate the carbon stock variation for soil subsamples obtained from mine soil profiles entirely comprised of topsoil (or mine spoil) material. The 10-cm-thick layer carbon stock estimates we used for statistical analyses to determine the sources of variation in carbon storage in mine soils.

The carbon stock was estimated using the following equation:

$$C(\mathrm{kg\ m^{-2}}) = C(\%) * BD_{Fines}(\mathrm{g\ cm^{-3}}) * \mathrm{Volume_{Fines}}(\%) * LayerDepth(cm) * 1000^{-1} \quad \text{(Eq. 1)}$$

where: *C(kg m^{-2})* = carbon stock, kg, per 1 m^2 area

C(%) = carbon concentration in the fine fraction of the soil, <2mm particles, expressed as percent, i.e. $C_{gram}/Fines_{gram}*100$

$BD_{Fines}(g\ cm^{-3})$ = bulk density of the fine fraction of the soil

$Volume_{Fines}(\%)$ = percent volume of the fine fraction of the soil expressed as percent of the total soil volume, i.e. $Fines_{cm^3}/(Fines_{cm^3}+CFC_{cm^3})*100$

LayerDepth(cm) = depth of the soil layer or soil horizon thickness, expressed in centimeters

1/1000 = unit conversion factor

Subtask 1.2

We identified the sources of variation in carbon stock in the topsoil and mine spoil materials found on our study sites. All analyses were performed on data sets grouped by state location (e.g., all surface topsoil samples in Ohio were grouped in one category and all subsurface topsoil samples in another category, etc.). Carbon stock values for a 10-cm-thick layer of topsoil and mine spoil material were modeled as a function of their physical and chemical soil properties, CN, BD_{Fines}, CFC, pH, EC, SS, and soil texture, using SAS® statistical software package (SAS, 2004). The soil texture was expressed as percent of sand-size (0.05-2 mm) soil particles contained in the fine soil fraction (<2 mm) in order to convert the nominal regressor variable labeled 'soil texture' to a continuous variable labeled 'sand'. For example, there will be approximately 33% sand-size particles in a clay loam soil and the rest of the fine soil fraction will be comprised of silt-size (0.002mm-0.05mm) and clay-size (<0.002mm) particles.

We developed regression models for carbon stock as the response variable and CN, BD_{Fines}, CFC, pH, EC, SS, and sand as the regressor variables. The criteria for selection of the best multiple regression model were those of the Cp selection procedure available in SAS®. All regression models were considered significant at the 10% significance level ($\alpha = 0.1$).

Subtask 1.3

We generated 0-10 cm carbon stock maps for each study site in Virginia. The Virginia study sites were chosen because of the variety of mine landscapes created during site reclamation operations. There were areas of spoil and topsoil that comprised the entire mine soil profile, as well as areas of the typical topsoil-spoil vertical mine soil construction.

The location of all soil subsamples within a 50 x 50m plot was entered into a geographic information system (GIS) of each site in order to (i) uniquely identify each soil sample on the ground and (ii) attempt to relate the estimated carbon stock variation among the individual soil subsamples to their spatial correlation within the site. Soil carbon stock maps were generated using common geostatistical procedures in ArcGIS™ 8.* software (ESRI Inc., Redlands, CA 92373).

Ordinary kriging was used to interpolate the carbon stock value between the subsampling locations. Kriging is a spatial interpolation method that accounts for the autocorrelation between data points and the distance between them, often visualized as a semivariogram graph (ESRI, 2001). As a result, the kriging interpolation procedure produces two surface models, a carbon stock prediction model and a standard error model associated with the carbon stock prediction. Both the prediction and the standard error models were then used to calculate the 95% confidence limits of the carbon stock prediction model within the limits of the study sites.

We computed the mean carbon stock value (kg C m^{-2}) and the 95% confidence limits of the mean from the GIS-based carbon stock maps. The GIS-based mean carbon stock estimate was then compared to the carbon stock computed as the average of collected soil samples.

Results and Discussion

Subtask 1.1

Our carbon stock results for the surface 0-10 cm indicate that the West Virginia mined sites store approximately 26% and 54% more carbon then the surface 0-10 cm mine soil layer in the Ohio and Virginia mined sites, respectively (Table 1). The increased carbon stock in the West Virginia mined sites, where there was no topsoil material, seemed to be in contradiction with a commonly accepted hypothesis that topsoil placement on top of overburden spoil material should lead to increased rates of carbon sequestration by grasses and trees on mined land, thus leading to higher carbon accumulation in mine soils. However, upon investigation of the history of the West Virginia mined site we discovered that this site had been mined in the early 1980's and had been managed as pastureland for a good part of the past 20 years. Although there was no topsoil placed on top of the mixture of dark-colored shale and siltstone overburden material in West Virginia, an average of 2.6 kg m^{-2} of soil carbon had been accumulated in the surface 10 cm of the spoil material, most likely due to the increased grass biomass production enhanced by occasional fertilizer applications and from manure deposition from the intensive cattle-raising farming practices performed on this site (Table 1).

The total carbon estimates for the 0-100 cm mine soil profile show that the Virginia mined sites stored about 33% more soil carbon than the 0-100 cm mine soil profiles in the Ohio and West Virginia mined sites (Table 1). These results led us to believe that there was potentially a different source of soil carbon than plant tissue in the subsurface overburden material in Virginia. The possible carbon sources were (i) carbon from coal particles and (ii) the carbon released from the shale rocks in the overburden material, which we assumed to be negligible.

Researchers in Europe (Braunersreuter and Burghardt, 2002; Rumpel et al., 2003; Rumpel and Knabner, 2003; Rumpel and Knabner, 2002) have reported that the CN ratio of lignite is usually grater than 30 to 35. Assuming that the CN ratio of a typical topsoil material is usually less than 20, one may conclude that there is a great chance for the subsurface spoil material in

Virginia to contain considerable amounts of coal particles comprising the majority of the soil carbon stored within the 0-100 cm mine soil profile (Table 2).

Table 2. Average values for eight physical and chemical soil properties of topsoil and overburden spoil materials of two depth categories, surface 0-10 cm and subsurface, from nine mined land study sites. Highlighted rows indicate subsurface layers.

Site	Material Type	Depth Category[1]	C (%) ($C_g/soil_g$*100)	CN (ratio)	BD_{Fines} (g cm^{-3})	CFC (%)	pH	EC (mmho cm^{-1})	SS (%)	Sand (%)	No. Samples
OH	Topsoil[2]	0-10 cm	1.488	12.321	1.458	7.73	5.88	0.100	23.02	41.89	134
		10-[X] cm	0.389	9.140	1.405	12.43	6.32	0.369	4.29	33.00	10
	Spoil	[X]-50 cm	0.819	14.082	1.626	20.10	6.79	0.492	16.99	29.05	124
VA	Topsoil	0-10 cm	1.810	23.018	1.226	39.00	5.97	0.249	63.02	53.36	106
		10-[Y] cm	1.359	24.510	1.227	40.96	5.81	0.349	84.64	56.00	38
	Spoil	0-10 cm	2.122	29.081	1.360	56.57	6.46	0.385	54.23	53.85	28
		[Y]-30 cm	2.410	33.917	1.319	58.65	6.80	0.266	53.42	66.04	95
WV[3]	Spoil	0-10 cm	3.403	12.468	1.137	51.92	6.12	0.214	9.07	70.00	135
		10-30 cm	1.520	13.927	1.137	57.92	6.66	0.105	9.81	61.19	135

[1] [X] and [Y] indicate the total depth of the topsoil layer in Ohio and Virginia study sites, respectively.
[2] Topsoil placed on top of the subsurface spoil material for all sampling locations in Ohio.
[3] There was no topsoil layer in any sampling location in West Virginia.

The variation associated with the surface 0-10 cm carbon stock estimates was similar across all study sites, with an average standard error of the mean equal to 0.116 kg C m^{-2}. However, the variation for the 0-100 cm carbon stock estimates was one order greater magnitude, with a standard error equal to 1.209 kg C m^{-2} (Table 1). The latter could indicate that the variation in total soil carbon increased down the soil profile with no readily discernible trend among the study sites. One possible reason for this could be that fewer subsamples were included in the estimation of the 0-100 cm carbon stock values compared to the 0-10 cm estimates, due to limited CFC and BD data for some subsurface soil profiles (Table 1).

<u>Subtask 1.2</u>

Our results show that the variation of total soil carbon stored in a 10-cm-thick layer of soil material across space was greater in the mine spoil (CV of 35% to 81%) compared to the topsoil (CV of 31% to 53%). The highest carbon stock variation in the mine spoil material was observed in Ohio (CV = 81%), followed by the mine sites in West Virginia (35%). The highest carbon stock variation in the topsoil material was observed in the Virginia mine sites (53%). It was expected that carbon stock variation in the topsoil layer in Virginia would be the highest due to the fact that the Virginia mine sites were reclaimed and seeded to grasses and legumes within the last five years, between 2000 and 2003, compared to the sites in Ohio, which were mined and reclaimed by the early 1990's.

During the many years of physical and chemical weathering of the topsoil in Ohio, most of the topsoil properties have developed towards a common condition allowing for similar plant root growth environment across space. As a result of the similar topsoil conditions, equivalent amounts of carbon had been sequestered and accumulated in these soils across space. We anticipate that the topsoil carbon stock variation across space in the Virginia mine sites will decline as the topsoil continues to weather through the years.

Percent sandstone (SS), CN, and BD_{Fines} explained between 33% and 92% of the variation of topsoil carbon stock (Table 3). Bulk density of the fine soil fraction (BD_{Fines}), CN, CFC, and EC explained between 54% and 91% of the variation of mine spoil carbon stock (Table 3). There was an exponential relationship between carbon stock and the regressor variables for all regression models.

Table 3. Multiple regression models for carbon stock, 10-cm-thick layer (kg m^{-2}), in topsoil and overburden spoil materials of two depth categories as the response variable, and the CN, BD_{Fines}, CFC, pH, EC, SS, and sand physical and chemical soil properties of the respective soil material as the aggressor variables, for nine mined sites in Ohio, Virginia, and West Virginia.

State:	**Ohio**			**Virginia**		**West Virginia**	
Parent Material:	**Spoil**	**Topsoil**	**Topsoil**	**Spoil**	**Topsoil**	**Spoil**	**Spoil**
Depth Category:	***[X]-50 cm***	***0-10 cm***	***10-[X] cm***	***Any***	***Any***	***0-10 cm***	***10-30 cm***
	Model: $\ln(C\_kg\ m^{-2}{}_{10\text{-cm-thick layer}}) = \mathrm{Sum}^{i}_{0}[\mathrm{Regressor}_i * \mathrm{Coefficient}_i]$						
	Regressor variable coefficients in regression models						
Regressors:							
Intercept	-3.71928	-2.13777	+9.24267	-0.64496	-1.91374	-0.31391	-1.73802
CN[1]	+ln(CN)*1.18985	+0.12380	---	+0.04192	+0.05339	+0.07022	+0.09017
BD_{Fines}	+-.36713	+0.91508	-7.03725	+0.56377	+1.04015	+0.64217	+0.62066
CFC	-0.00578	---	---	-0.01830	-0.01828	-0.01280	---
pH	---	---	---	---	+0.22618	---	---
EC	---	---	-0.46630	+1.08987	---	+1.32844	---
SS	---	-0.00219	---	-0.00458	-0.00323	---	---
Sand	---	---	---	---	-0.01311	---	-0.00358
Model Statistics:							
R2	90.87	32.98	92.34	70.26	70.95	53.63	74.23
Adj-R2	90.63	31.43	88.50	68.93	69.57	52.19	73.64
N	122	134	7	118	134	134	135
P-values[2]	$P_{CFC} = 0.0238$	$P_{SS} = 0.0678$	$P_{model} = 0.0059$ $P_{rest} < 0.022$	$P_{BD} = 0.008$	$P_{SS} = 0.0039$ $P_{CFC} = 0.001$	$P_{CFC} = 0.0011$	$P_{sand} = 0.0073$

[1] The CN variable is significant for all regression models without any variable transformation except for the spoil material in Ohio.
[2] P-values for the model and regressor variables were <0.0001 unless otherwise noted.

The carbon stocks increased exponentially as the CN ratio increased in all topsoil and spoil materials of any depth category, in all states (Table 3). This is due to the fact that in soil materials of higher CN ratio (between 15 and 20), the rates of soil organic matter decomposition by the soil microbial communities is somewhat limited compared to a topsoil material from an undisturbed forest with a typical CN of 12. One should be aware that soil CN ratios grater than 20 indicate that there may be a soil condition that is limiting the proper development and functions of the microbial communities that are a significant part of the nutrient cycling in soils. Based on our results, there are no such limiting conditions in any of our study sites (Table 2). However, it is clearly observable that due to the young age of the Virginia mine soils, the microbial communities have not yet fully established and the soil carbon concentration is relatively high (Table 2).

Contrary to our expectations, an increase in BD_{Fines} caused the carbon stock to increase exponentially for all but one mine soil material, the subsurface topsoil in Ohio (Table 3). Upon further investigation one can see that the range of the bulk density of the fine soil fraction for all materials, except for the subsurface topsoil in Ohio, was mostly within the limits required for adequate plant root growth, <1.4 g cm^{-3} (Table 2). Therefore, a slight increase in BD_{Fines} will not limit the carbon sequestration but will greatly increase the surface area of the soil particles that will retain greater amounts of soil organic compounds. On the other hand, for BD_{Fines} greater than 1.4 g cm^{-3}, not only is the plant root growth limited, but the soil solution saturated with organic carbon compounds is isolated from such dense soil layers.

An increase in CFC, SS, or sand in any mine soil material would lead to an exponential decrease in carbon stock in the soil (Table 3). These relationships could be explained in a manner similar to that for BD_{Fines}. As CFC, SS, or sand content increases, the number of sand-size particles and coarse soil fragments increase, leading to greatly reduced soil surface area. As a result, most of the decomposed organic material in soil solution has most likely leached out from the system.

Although the effects of EC on carbon stock in mine soils were somewhat inconsistent (Table 3), our EC measurements on most mine soil materials were less than 0.35 mmhos cm^{-1}, indicating that there is no immediate plant growth-limiting condition (Table 2). However, if EC values increase beyond 0.4 mmhos cm^{-1}, then one could expect a significant decrease in plant growth. Hence, carbon sequestration via plant biomass allocation in the soil will be greatly reduced.

Subtask 1.3

Kriging interpolation techniques were necessary to create continuous carbon stock surfaces that were used to better visualize the total carbon stock distribution across space. Figure 5 is an example of how difficult it is to make any inferences about the spatial allocation of soil carbon stock (kg C m^{-2}) from point data soil carbon measurements. Further spatial analyses are necessary for one to be able to understand the underlying carbon stock variation and to determine the potential causes for the underlying variation (Fig. 5).

Carbon stock maps created with the kriging interpolation procedure could be a source of valuable spatial information about the distribution of soil carbon on mine sites. Point data carbon measurements depicted in Figure 5 were used to create a prediction map and a standard error map for the carbon stock on the study sites in Virginia. Using the prediction and the standard error maps, we generated maps depicting the 95% confidence limits of the carbon stock for the 0-10 cm mine soil layer (Fig. 6).

On the carbon stock maps, one could easily identify the areas (plot by plot) within the study site which have the highest carbon stock in the surface 0-10 cm mine soil profile as well as the areas with the highest spatial variation in soil carbon (Fig. 6). Knowledge about the spatial distribution of carbon stock on mine sites could allow a mine land owner to more efficiently manage the mine land for maximum carbon sequestration by applying different management practices across the mined site dependent on the baseline soil conditions.

We computed the mean carbon stock (kg m^{-2}) and the associated 95% confidence limits for the mean using the GIS-based continuous carbon stock prediction surface by averaging the carbon value of each 0.5 x 0.5m surface grid cell within the site boundaries. The GIS-based average carbon stock values were then compared to the carbon stock computed as the average of collected soil samples.

Considering the fact that the kriging geostatistical procedure uses an important additional piece of information, the spatial location of the analyzed soil samples as well as their proximity to each other, which is in no way accounted for in a simple average computational procedure, we hypothesize that the GIS-based average carbon stock values are more reasonable then the carbon stock values computed as the average of collected soil samples on mined land (Table 4).

Although the mean carbon stock estimates derived from the two estimation methods were very similar the simple average approach produced artificially narrower confidence limits of the mean compared to the GIS average approach, for all mine sites (Table 4). For example, the average carbon stock value for the VA2 study site in Virginia was estimated 2.3 kg m^{-2} by both estimation methods. The 95% confidence limit estimates from the GIS average method indicated that on 95 out of 100 sampling locations on the VA2 study site the carbon stock will be between 0.99 and 3.54 kg C m^{-2} in the surface 0-10cm mine soil (Table 4). Dissimilarly, the simple average approach suggested that on 95 out of 100 sampling locations on the VA2 study site the carbon stock will be between 2.07 and 2.48 kg C m^{-2} (CV=30%). Although it is possible that one could come upon an undisturbed forest site characterized with carbon stock variation of CV equal to 30%, it is highly unlikely this to be the case on mined lands.

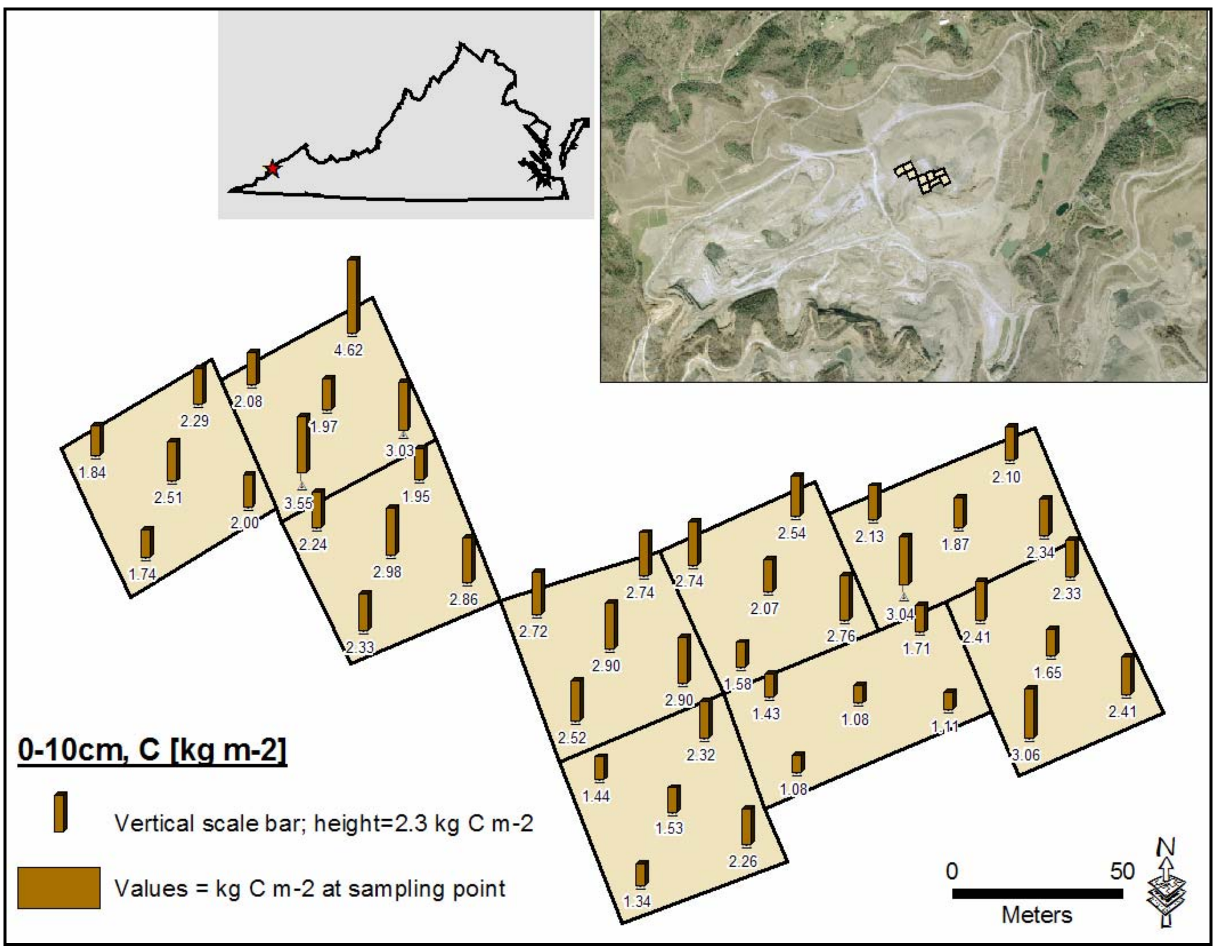

Figure 5. Carbon stock estimates (kg m^{-2}) for the surface 0-10 cm mine soil profile for 45 soil subsamples collected from the VA2 study site located on the Powell River Project mine site in Virginia. Soil subsamples were collected in the summer of 2003.

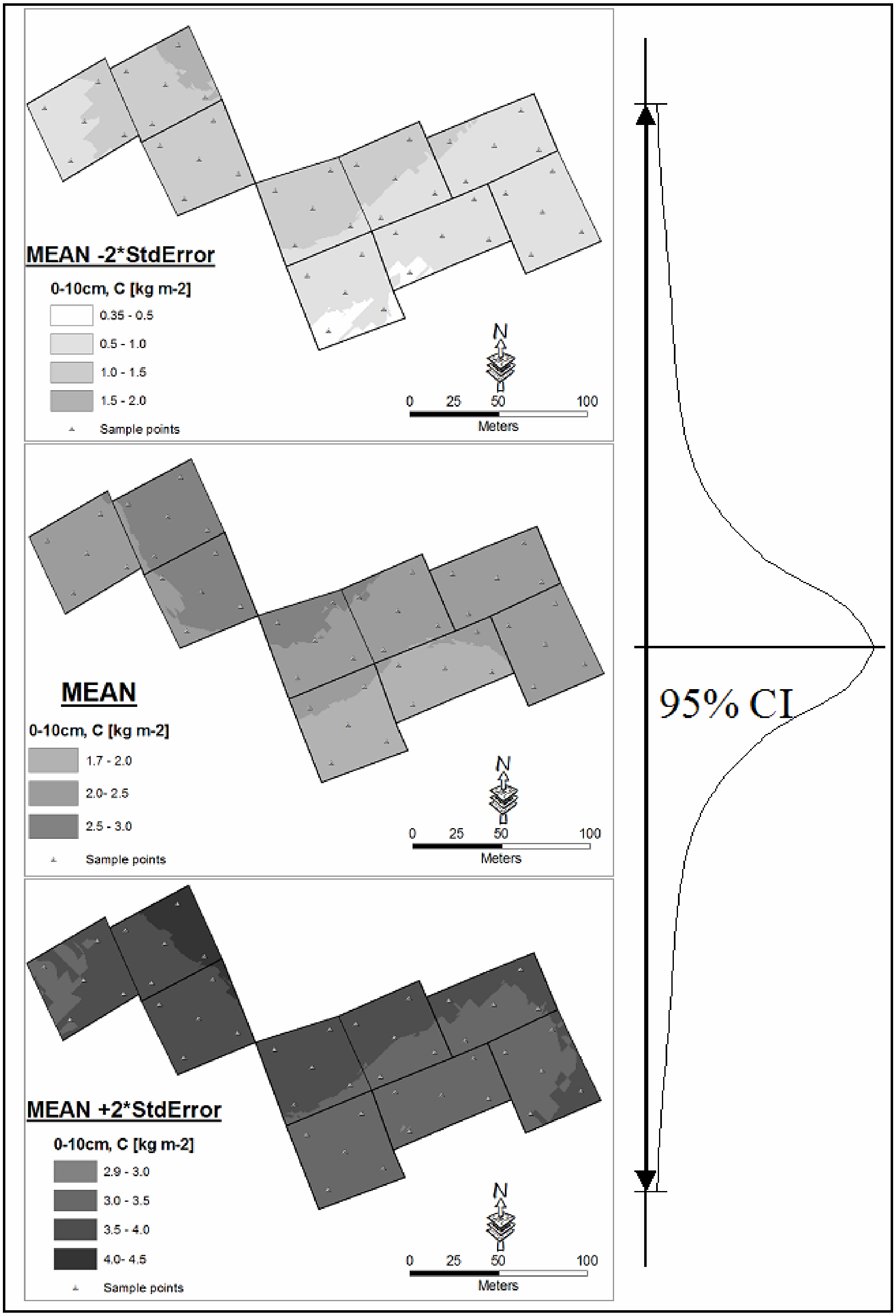

Figure 6. Carbon stock maps (kg m^{-2}) depicting the spatial distribution and the 95% confidence limits of the mean carbon stock in the surface 0-10 cm mine soil for the VA2 study site located on the Powell River Project mine site in Virginia. All maps were generated in ArcGIS™ 8.* software.

Table 4. Mean, lower 95% confidence limit (CL), and upper 95% CL of the mean carbon stock estimates, 0-10 cm, for three Virginia mine sites computed by two methods: (i) Simple average = average of the measured carbon stock for the collected soil samples and (ii) GIS average = average from a GIS-based continuous carbon stock prediction grid surface.

Site	Method	Surface 0-10 cm Carbon Stock (kg m^{-2})		
		Mean	Lower 95% CL	Upper 95% CL
VA1	Simple average	1.1336	0.9821	1.2851
	GIS average	1.1330	0.2937	2.0167
VA2	Simple average	2.2739	2.0684	2.4793
	GIS average	2.2633	0.9861	3.5405
VA3	Simple average	1.7024	1.4052	1.9996
	GIS average	1.6718	0.1742	3.4401

Conclusions

Total soil carbon stock on mined land varies greatly across space and down the soil profile. There are many factors that contribute to the spatial variation of soil carbon some of which can be modeled or can be measured indirectly. First, the amount of geogenic carbon in the soil present as microscopic coal particles can be measured with reasonable accuracy. We are currently in the process of developing and evaluating a method that will allow for the partitioning of total soil carbon to pedogenic carbon (C from plant tissue) and geogenic carbon (C from coal).

Second, by using all available information about the distribution of soil carbon in mine soils, i.e., carbon stock variation by soil depth and across space, not only will one produce accurate carbon stock estimates per unit area of mined land, but will also be able to better assess the carbon sequestration potential of land by identifying areas of high to low carbon stock. GIS-based carbon stock maps will serve as a guide for identifying and locating areas of different carbon sequestration potential in the field.

Our statistical analyses indicate that carbon stock is significantly dependent on the physical and chemical properties of mine soils, including CN, BD_{Fines}, CFC, pH, EC, SS, and sand. In the next step of our analyses, we will model the mine soil conditions in time by taking into account the soil improvement effects of the forestry practices implemented on the study sites as part of this research undertaking.

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

Executive Summary

During the reporting period (October-December 2004) we have completed the validation of a forest productivity classification model for white pines on mined land. Using statistical analysis a point system was developed to predict site index (SI) of white pines and classify a site into one of five forest productivity classes. A coefficient of determination (R^2) of 0.68 confirms the model's ability to predict SI. A selected abandoned mine site was mapped using techniques developed in order to test the practicality of the mapping scheme.

Experimental

Validation of the classification model was performed by measuring the growth rate of white pines growing on post-SMCRA abandoned mined land. Fifty-two points were located on lands owned by our research cooperators in southwestern Virginia and southern West Virginia, and ranged from 10 to 18 years old. Soil-site evaluations were performed at these randomly selected points in established pine stands. The nearest two to four trees were measured using the growth intercept model developed by Beck (1971) for white pine. An average of the site index for the surrounding two to four trees was correlated to the site quality rating obtained at each evaluation point by the new classification scheme.

Results and Discussion:

The original model developed is:

$$SI = (pH + EC + slope + aspect + color + CF + texture + rock\ type + density) * WF \qquad (Eq.\ 2)$$

Two of the original 52 data points were thrown out (32 and 33) because they were extreme outliers determined by high dffits. The model was greatly improved with the deletion of these two points. The C(p) selection procedure indicated that a model with only the variables of pH, texture, density, and WF was the best model. These variables were all significant at the 10% level and the vif's indicate that no significant multi-collinearity problems exist.The final coefficient of determination (R^2) value was 0.64. No variables needed transforming and all appear to show a fairly linear relationship. The form of the final model is:

$$SI = ((pH + density + texture) * WF) + 63 \qquad (Eq.\ 3)$$

where SI is in feet.

The correlation coefficients were used to assign the density variable the highest point values and pH the lowest. Following the idea behind the model developed by Torbert et al. (1994), the WF was used as a multiplication factor over the total of the other variables. Variable criteria and point values are reported in Table 5.

The SI is a representation of forest site quality and is used to place a site into one of the five site quality classes: SI >110 = SQC I; SI 95-110 = SQC II; SI 80-94 = SQC III; SI 65-79 = SQC IV; SI <65 = SQC V.

A regression of the SI obtained using the model developed against the measured SI using Beck's (1971) growth intercept model results in an R^2 value of 0.68. This indicates that the point system developed is adequate (Fig. 7).

Table 5. Variable criteria were divided into classes and designated point values. The points were added and then multiplied by the WF.

Classification Model	Forest Site Quality Class[1]				
	I	II	III	IV	V
pH	4.5 - 5.8	4.0 - 4.4 or 5.9 - 6.2	3.5 - 3.9 or 6.3 - 7.0	3.0 - 3.4 or 7.1 - 8.0	<3.0 or >8.0
Texture	SL, SCL	L, SiL	SC, CL, LS	SiCL	SiC, C, S, Si
Density	Very low	Low	Moderate	High	Very high

Need to determine approximate depth to root restricting layer (WF).

- >75 cm depth = WF of 1.0
- 50 - 75 cm depth = WF of 0.9
- 35 - <50 cm depth = WF of 0.8
- >25 - <35 cm depth = WF of 0.7
- 20 - 25 cm depth = WF of 0.6
- 15 - <20 cm depth = WF of 0.5
- 10 - <15 cm depth = WF of 0.4
- <10 cm depth = WF of 0.3

Point Values	I	II	III	IV	V
pH	10	8	6	4	0
Texture	20	16	10	5	0
Density	35	25	10	-5	-10

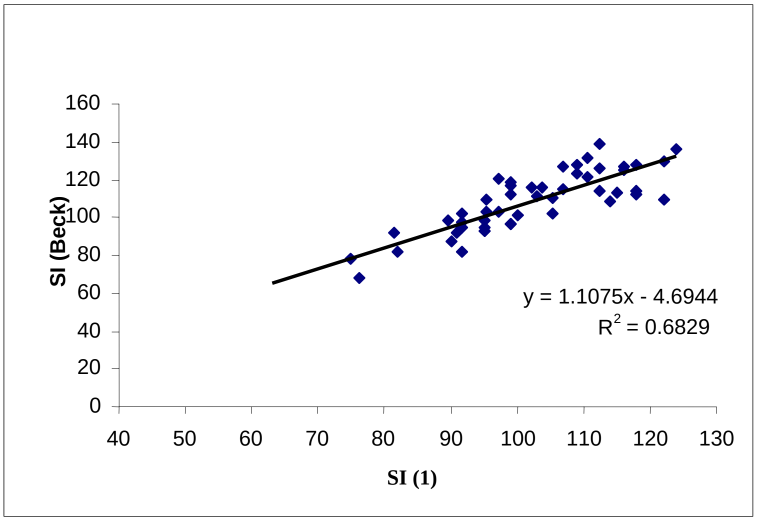

Figure 7. Relationship between white pine site index using a growth intercept model (Beck, 1971), and site index determined by the model developed (Equation 2) using soil classification criteria (Table 5).

An example of using the model is as follows:

After the evaluation of a certain site, a pH value of 6.0, a sandy loam texture, a moderate density level, and a rooting depth of 57 cm were observed. Therefore, ((8 + 20 + 10) * 0.9) + 63) = SI of 97.2 feet, and results in a SQC of II.

The final model obtained seems to be a good predictor of white pine growth on abandoned surface mines. However, some reclamationists may want to plant trees immediately following final reclamation. We believe that the addition of the CF, EC, rock type, and color variables from the original model would be beneficial for sites less than five years old.

Native hardwood tree species may become the intended vegetation on some post-mine sites. The diverse hardwood forest types in the Appalachians can have species that are very different in their optimum growth criteria. This makes modeling for hardwood productivity very difficult. Furthermore, only recently have hardwoods been used in reforestation, and very few sites exist for model validation. However, the productivity model developed for white pine is likely to also represent hardwood productivity.

Conclusion

The model is a reasonably adequate measure of forest site productivity on abandoned mined lands. The mapping of an 80-acre site proved that the classification scheme was a field-practical method. The observation of established vegetation on the site proved to be invaluable for determining map unit boundaries. The use of the model for forest management decisions needs to be further refined and interpreted.

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

Executive Summary

Hybrid poplar (*Populus trichocarpa* L. (Torr. & Gray ex Hook.) x *Populus deltoides* Bartr. ex Marsh.) physiological response to treatments was assessed for trees growing at the research site in Nicholas County, West Virginia, in August and September, 2004. Arrangements have been made to replant research plots at all sites to ensure the long term viability of the study. Additionally, deer exclosures were maintained around research plots in West Virginia and Ohio.

Experimental

Study Design

The study used a randomized complete block design to investigate the effect of three levels of silvicultural treatment on the hybrid poplar clone in question (*Populus trichocarpa* L. (Torr. & Gray ex Hook.) x *Populus deltoides* Bartr. ex Marsh.) at the research site in Nicholas County, West Virginia. This design was replicated three times and the three levels of silvicultural treatment were:

1. Low intensity – weed control only;
2. Medium intensity – weed control plus tillage to alleviate soil compaction; and
3. High intensity – weed control and tillage plus fertilization to amend soil chemical properties.

The post-mining land use at all sites was hayland pasture and supported a dense vegetative cover composed of grasses and legumes. Plot size was 0.25 ha with nine plots in each block and three blocks at each site. Plots were laid out to be as contiguous as possible within each block, while still maintaining uniform soil properties based on the previously mentioned criteria. Slopes in all plots were less than 15%.

The weed control treatment used herbicide to eliminate all existing vegetation. In August 2003 a broadcast treatment of glyphosate herbicide was applied at a rate of 9.35 l ha^{-1}. Following the glyphosate treatment, a pre-emergent herbicide containing pendimethalin was applied after tree planting in April 2004 at a rate of 4.92 l ha^{-1} to control germinating grasses not controlled with the glyphosate. Spot applications of glyphosate were applied in July 2004 to control competition at all study blocks.

The tillage treatment employed was ripping and used a single shank with coulters to create beds. The rips were spaced approximately 3 m apart and the depth of ripping was set between 61 and 91 cm. The plots were tilled prior to planting in April 2004.

Fertilizer was applied to the desgnated plots in late May 2004. A banded application of 272 kg ha^{-1} of diammonium phosphate was made along the tree rows. Ninety-one kg ha^{-1} muriate of potash and 20 kg ha^{-1} of a micronutrient mix with an analysis of 1.8 kg ha^{-1} S, 0.2 kg ha^{-1} B, 0.2 kg ha^{-1} Cu, 0.8 kg ha^{-1} Mn, and 4.0 kg ha^{-1} Zn were applied around the base of each seedling.

Tree spacing was fixed for all species at 2.4 x 3.0 m, giving a final planting density of 1,345 trees/ha. Tree planting was done in early April 2004.

Hybrid Poplar Biomass Measurements

Detailed destructive sampling to determine above- and belowground biomass allocation was conducted in the hybrid poplar plots at the site in Nicholas County, West Virginia. Randomly selected trees were harvested in mid-September for plant biomass determinations. Trees were cut off at the ground line and leaves were separated from the stems. The entire root system of each tree was carefully excavated from the soil and washed gently with water to remove soil adhering to the roots. Roots were stored in sealed plastic bags with a moist paper towel for a period of up to four weeks, during which time the roots were separated into coarse (>0.5 mm) and fine (<0.5 mm) root fractions. All tissue samples were dried at 65°C for a minimum of 72 hours and weighed. A subsample was then ground using a Wiley mill to pass a 1-mm screen. In some instances when samples were small, a coffee grinder was used to grind all the the foliage collected.

Hybrid Poplar Tissue Analysis

Tissue samples for foliage, stems, and roots from the sample trees in each plot were composited for nutrient analysis. Total C and N were determined using an Elementar varioMAX CNS analyzer. After dry ashing and digesting with 6*N* HCl, the tissue samples were analyzed using a SpectroFlame Modula Tabletop inductively coupled plasma spectrophotometer to determine elemental concentrations of P, Mg, Ca, and K for all tissue samples and S, B, Cu, Mn, and Zn for foliage samples only.

Hybrid Poplar Moisture Stress Measurements

Seedling water potential was measured using a pressure chamber (PMS Instrument Co. Model 1000 Corvallis, OR) for four consecutive rain-free days (August 16-19, 2004) with the initial measurement having been made the day after a significant rain event. Three trees from each hybrid poplar plot were measured to obtain average water potential for that plot. Measurements were timed so as to measure the water potential of all trees within a plot at the same time during the afternoon (2:30 to 6:30 p.m.) over the course of the four-day period. Water potential readings were taken immediately after the leaf was excised from the tree.

From August 17-19, three randomly spaced soil samples from each plot were collected from the surface 30 cm and stored in a sealed plastic bag for determination of gravimetric moisture content. Soil sampling preceded water potential sampling and was confined to a time period between 12:30 and 2:00 p.m. Individual plots were sampled at the same time each of the three days.

Data Analysis

Hybrid poplar biomass data were analyzed for differences between biomass measures by treatment. Arcsine transformation was used to transform percentage data prior to analysis of variance and any non-normal of heteroscedastic data were transformed using the either the inverse or natural logarithm transformation (Gomez and Gomez 1984). Similarly, data from tissue samples was analyzed for differences between nutrient concentrations by tissue type and non-normal and heteroscedastic data were transformed using the inverse function prior to analysis of variance. Moisture stress data was analyzed as a split-plot design with treatment as the whole plot and date as the split plots for differences between dates and treatments for soil moisture as well as plant water potential.

Mean separation was done using Tukey's HSD with significance set at P<0.05 for all comparisons. If interaction terms were not significant, only main effect means were compared. SAS version 8.2 (SAS Inst. Inc., Cary, NC 2001) was used for all statistical analyses.

Results

Hybrid Poplar Biomass Measurements

Total plant biomass differences increased significantly with the intensity of silvicultural input. Root, stem, and foliage biomass also increased with the level of silvicultural intensity (Fig. 8). The percentage of fine roots (<0.5 mm) was the same for the weed control plus tillage and fertilized treatment (23%), while the weed control only plots had a much higher fine root percentage (54%), which was significantly different from the other two treatments. Additionally, the root-to-shoot ratios were not significantly different between the weed control plus tillage and the fertilized treatments (0.31 and 0.37, respectively), but both were significantly higher than the ratio of the weed control only treatment (0.08).

Hybrid Poplar Moisture Stress Measurements

The treatment by date interaction was not significant for gravimetric soil moisture. There was a statistically significant decrease with each successive day for all treatments. The weed control only and weed control plus tillage treatments were significantly different over all three days of the dry down period (Table 1).

The treatment by date interaction was significant for water potential means. Each treatment increased or remained the same over the first three days of the dry down experiment. No means were statistically significant for the first and third days. The weed control, tillage, and fertilization treatment was significantly different from the other treatments for day two. For the final day, however, the weed control plus tillage treatment continued to increase rapidly (Table 1) and was significantly higher than the weed control only treatment, while the other two treatment means decreased likely as a result of the cloud cover present over the site this particular day.

Hybrid Poplar Tissue Analysis

Foliar nutrient concentrations were significantly higher for N, P, and Mn in the fertilized treatment compared to the other two treatments (Table 2). Foliar K in the fertilized treatment was only significantly different from the weed control plus tillage treatment. There were no differences between treatments for any other nutrients.

For stem tissue, N was the only added nutrient that had a higher mean concentration in the fertilized treatment and this mean was only significantly different from weed control only treatment (Table 2). The concentration of N in the root tissue was significantly higher for the fertilized treatment compared to the weed control plus tillage treatment, but was not significantly different from the weed control only treatment.

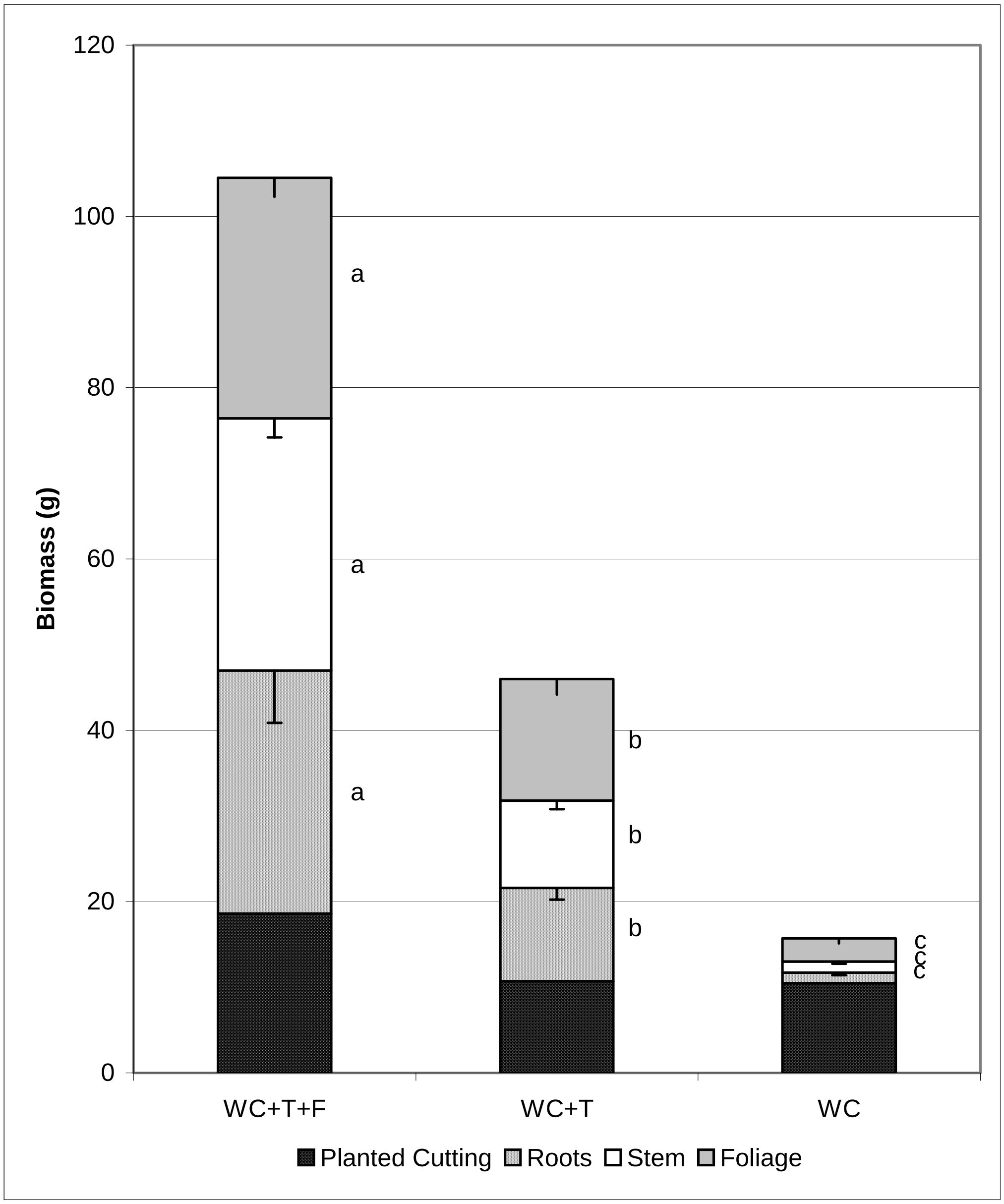

Figure 8. Hybrid poplar biomass by plant part and treatment for study site in Nicholas County, WV. Letters beside segments indicate significant differences at the P < 0.05 level among treatments for that particular segment.

Table 6. Gravimetric soil moisture and water potential for hybrid poplar growing at the research site in Nicholas County, West Virginia.

Treatment	Aug. 16	Aug. 17	Aug. 18	Aug. 19	Treatment Average
	---------- Gravimetric Soil Moisture (kg kg^{-1}) ----------				
WC	---	0.16	0.15	0.12	0.14 x[1]
WC+T	---	0.14	0.13	0.12	0.13 y
WC+T+F	---	0.15	0.12	0.12	0.13 xy
Date average	---	0.15 a[1]	0.13 b	0.12 c	0.13
	------------------ Water Potential (MPa) ------------------				
WC	-1.30 a x	-1.66 b x	-1.89 b x	-1.62 ab x	-1.62
WC+T	-1.32 a x	-1.72 ab x	-1.90 bc x	-2.30 c y	-1.81
WC+T+F	-1.17 a x	-1.97 b y	-1.97 b x	-1.78 b xy	-1.72
Date average	-1.26	-1.78	-1.92	-1.90	-1.72

[1] a, b, c: values within rows with the same letter are not significantly different at P < 0.05.
[2] x, y, z: values within columns with the same letter are not significantly different at P < 0.5

Table 7. Macro- and micronutrient concentrations by tissue type and treatment for hybrid poplar growing at the research site in Nicholas County, West Virginia.

Tissue Type and Treatment	Macronutrients (g kg^{-1})					Micronutrients (mg kg^{-1})				
	N	Ca	K	Mg	P	S	Zn	B	Cu	Mn
Foliage:										
WC	0.24 a[1]	12.14 a	14.19 a	4.60 a	1.98 a	3.92 a	84.30 a	30.04 a	8.95 a	161.17 a
WC+T	0.26 a	12.26 a	15.89 ab	4.86 a	1.93 a	4.82 a	92.21 a	26.61 a	9.71 a	134.44 a
WC+T+F	0.33 b	11.95 a	17.28 b	5.11 a	2.32 b	4.42 a	84.94 a	46.98 a	10.92 a	309.97 b
Stem:										
WC	0.07 a	1.37 a	2.76 a	0.51 a	0.37 a					
WC+T	0.07 ab	1.25 a	2.14 a	0.51 a	0.24 a					
WC+T+F	0.08 b	0.98 a	1.71 a	0.41 a	0.25 a					
Root:										
WC	0.09 ab	6.30 a	8.68 a	1.80 a	1.06 a					
WC+T	0.08 a	7.28 a	10.65 a	1.79 a	0.95 a					
WC+T+F	0.11 b	7.55 a	10.63 a	2.01 a	1.21 a					

[1] For a given plant part, different letters within a column indicate significant differences at P < 0.05.

Discussion and Conclusion:

None to date. Data analysis has just been finished.

References:

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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)

Executive Summary

Literature regarding forest taxes has been examined and the landowner decision model has been extended to include additional government policy instruments that can be used to promote reforestation of reclaimed mine lands, which will serve as the framework to examine these instruments empirically. A manuscript that describes our analysis, results, and conclusions to date has been written and submitted to *Resources Policy* to be peer-reviewed for publication. In addition, a presentation of results was made at the Ohio Department of Mineral Resource Management Applied Research Conference 2004, on December 8.

Experimental

Financial feasibility analyses of reforestation on mined lands previously reclaimed to grassland have been completed for conversion to white pine and mixed hardwood species. Examination of potential policy instruments for promoting financial feasibility also have been completed, including lump sum payments at time of conversion, annual payments through the life of the stand, and payments based on carbon sequestration that provide both minimal profitability and fully offset initial reforestation outlays. Task 4 work during the October-December 2004 reporting period has focused on extending the basic landowner decision framework to incorporate relevant tax instruments that could be used to improve financial feasibility of reforestation on mined sites.

Previous Task 4 work has been based on a landowner decision framework that compares the utility of reforesting reclaimed mine sites with the utility of leaving the site as grassland, where utility functions recognized both revenue and non-revenue. Again the indirect utility function associate with forestry can be written as:

$$V(r,I,L_f) = V[r(L_f),I] + \phi(L_f) \qquad \text{(Eq. 4)}$$

where *V(.)* is indirect utility, which represents maximized landowner welfare when decisions are made optimally, *r* is the revenue generated from the property (which could be considered land rents, and consequently include the market value of the land), *I* is exogenous landowner income, Φ measures amenity benefits derived from owning the land, and L_f is the condition of the land after reforestation (i.e., resulting from the combination of site quality and regeneration intensity), and discounted revenues and amenity benefits from forestry are:

$$r(L_f) = \frac{pQ_f(t)e^{-it} - c_f e^{-it}}{(1-e^{-it})} - c_0 + \int_0^{\infty} a[L_f(z)]e^{-iz}dz \qquad \text{(Eq. 5)}$$

and

$$\phi(L_f) = \int_0^{\infty} b[L_f(z)]e^{-iz}dz \qquad \text{(Eq. 6)}$$

where *p* is the unit price of timber, $Q_f(t)$ is the volume of timber produced from reforested land at age *t* (rotation length), c_f is regular reforestation costs after timber harvest, c_0 is initial reforestation costs incurred when converting grassland into forest, *i* is the interest rate, *a(.)* are annual revenues generated from the land (perhaps grazing or hunting leases), *b(.)* are amenity benefits derived from owning land each year, z is a variable of integration representing time periods $1\ldots\infty$, and $L_f(z)$ is forested land condition at each point in time.

Reforestation adjustments to forestry-specific taxes may provide policymakers an opportunity to improve the financial viability of reforestation on mined sites. Relevant taxes issues identified in literature (e.g., Bailey et al. 1999, Haney et al. 2001, and Bishop and Greene 2004) include (1) a deduction of the first $10,000 of reforestation expenses against current income, (2) an allowed 8-year amortization of expenses over the $10,000 limit (versus capitalizing those expenses against harvest income), and (3) yield taxes paid at harvest, which alter Equation 5 collectively as follows:

$$\begin{aligned} r(L_f) &= \frac{pQ_f(t)e^{-2it} - c_f e^{-it}}{(1-e^{-it})} + (1+y)(1-k(I,h))pQ_f(t)e^{-it} \\ &- (1-r(I,h))(1-x(I,h))c_0 + \int_0^\infty a[L_f(z)]e^{-iz}dz \end{aligned} \qquad \text{(Eq. 7)}$$

where y is a yield tax adjustment that could increase after-tax revenue at harvest, k is an expense capitalization adjustment that represents an after-tax reduction in revenue at harvest, r is a reforestation deduction adjustment that reduces after-tax costs, and x is the amortization adjustment that also reduces after-tax costs.[1] To avoid unnecessary clutter, this formulation depicts p, c_f, and c_0 as after-tax prices and costs. Therefore, tax adjustments shown in Equation 7 represent changes from current tax rules that could be used to encourage reforestation of mined sites. Also note that tax rate adjustments $k(.)$, $r(.)$, and $x(.)$ are a function of overall landowner income (which of course alters marginal tax rates) and land holding size.[2]

As presented in Equation 7, only first-rotation tax incentives are identified, reflecting a focus on incentives to encourage reforestation of mined sites, and not general forest tax treatment in subsequent rotations. Incorporation of these tax considerations provides a framework for exploring potential tax-based incentive schemes.

Results and Discussion

No new results were obtained during the October-December 2004 reporting period.

Conclusion

No new conclusions were reached during the October-December 2004 reporting period.

References

Bailey, P.D., H.L. Haney, D.S. Callihan, and J.L. Green. 1999. Income Tax Considerations for Forest Landowners in the South. *Journal of Forestry* 97(4):10-15.

Bishop, L. M., and J. L. Greene. 2004. Tax tips for forest landowners for the 2004 tax year. Cooperative Forestry: Technology Update. USDA For. Serv. Manage. Bull. R8-MB-121.

Haney, Jr., H. L., W. C. Siegel, W. L. Hoover, and J. L. Greene. 2001. Forest Landowners' Guide to the Federal Income Tax. Ag. Hndbk. No. 718. USDA For. Serv., Washington, DC. 177p.

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[1] Expensing reforestation costs involves amortization of those costs over a 8-year period, and hence our representation in Equation 7 at a single point in time is a simplification for illustration purposes only.

[2] The reforestation deduction currently applies only to the first $10,000 of costs, regardless of total acreage, with the remainder of expenses being amortized over the first eight years of the rotation or capitalized against harvest income. Hence on a proportional basis the adjustment will be smaller for land owners with larger holdings.

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

Executive Summary

We have compiled a database containing mine permit information obtained from permitting agencies in Virginia, West Virginia, Pennsylvania, Ohio, and Kentucky. Due to differences and irregularities in permitting procedures between states we found it necessary to utilize an alternative method to determine mined land acreages in the Appalachian region. We have initiated a proof of concept study, focused in the State of Ohio, to determine the feasibility of using images from the Landsat Thematic Mapper (TM) and/or Enhanced Thematic Mapper Plus (ETM+) to accurately identify mined lands.

Experimental

Landsat images from path 18, row 32 for each year and season from 1999 through 2004 were obtained. After inspecting the available images, it was determined that images from the spring would be best suited for this study. Currently we are in the process of performing a supervised classification of the images to identify mined areas. We intend to use the spectral characteristics, spatial trends, and temporal changes in land cover to identify areas that have been mined and reclaimed to non-forest land uses. We have obtained and refined a spatial dataset from the Ohio Department of Natural Resources, Division of Mineral Resources, and the Ohio Department of Administrative Services, Office of Information Services, which identifies the boundaries of permitted surface mines in the study area. We are using this dataset to select training sites for the spectral classification and to provide for an accuracy assessment after completion of the image classification stage.

Results and Discussion

No results have been generated at this time.

Conclusions

Currently, an accurate, consolidated dataset that identifies and locates reclaimed surface coal mines in the Appalachian region does not exist. If successful, the current study will provide such a spatial dataset. Production of this dataset is critical to achieve the overall objective of this task: "to determine the potential of large-scale post-SMCRA grassland restoration to sequester atmospheric carbon." Moreover, this dataset will likely support policy decision-making, resource management, and research efforts related to coal mining well beyond the current project.

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 sequ. by policy scenario	