MODELING FOREST ECOSYSTEM CHANGES RESULTING FROM SURFACE COAL MINING IN WEST VIRGINIA

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ABSTRACT

The objective of this project is to assess the effects of surface coal mining on forest ecosystem disturbance and restoration in the Coal River Subbasin in southern West Virginia. Our approach is to develop disturbance impact models for this subbasin that will serve as a case study for testing the feasibility of integrating currently available GIS data layers, remote sensing, and existing Forest Inventory and Analaysis program (FIA) data.

Using a set of 30-m-pixel based GIS-based predictor layers (topography, soils and imagery), we developed models that predict total forest carbon for each pixel in the study area. By combining the vegetation change tracker (VCT) year of disturbance outputs with an annual biomass map derived from modeling the FIA data, we will be able to determine biomass losses from mining and estimate potential forest regrowth.

INTRODUCTION

The challenge of mitigating greenhouse gases has resulted in considerable focus being placed on the carbon storage capacities of forests. Trees and other plants naturally remove carbon dioxide (CO_2) from the atmosphere and temporarily convert (sequester) carbon in wood, roots, leaves and the soil. In the Appalachian region of Kentucky, Virginia, Tennessee, and West Virginia, mountaintop removal mining has been prevalent since 1985 (US EPA 2005). This mining technique requires the removal (flattening) of mountain peaks to access the coal layers below. The waste material that is removed is pushed into adjacent valleys (valley fills), burying many headwater streams. Utilization of this mining technique increased with the 1990 amendments to the Clean Air Act, when mining and electric companies focused on extraction of low-sulfur coal to meet the new standards (Fox 1999). At about the same time, larger and more efficient machinery became available for excavation and removal (Szwilski and others, 2001). Between 1985 and 2001, 6,697 valley fills were approved by agencies in these States, and these fills would eventually cover 339 square kilometers (US EPA 2005).

In 2006, 43 percent of all coal extracted from West Virginia came from surface mining, 70 percent of which was mined using mountaintop removal methods (Britton 2007). Not only is forest directly lost, but recent studies have demonstrated that the integrity of the residual forest is significantly altered due to fragmentation and the introduction of edge (Wickham and others, 2007). Conversion of large tracts of interior forest to edge results in a host of ecological changes, both aquatic and terrestrial (SAMAB 1996).

Prior to the 1977 Surface Mining Control and Reclamation Act (SMCRA), most mined land in the Appalachian region was planted with trees. The composition and productivity of the resulting forests are highly variable and spatially irregular due to the physical and chemical properties of the residual mine spoil material (Rodrigue and Burger 2002). SMCRA was enacted to reduce problems with severe erosion, sedimentation, landslides and mass instability caused by pre-SMCRA surface mining (Angel and others 2005). SMCRA regulations require mining companies to post a bond that is sufficient to cover the cost of reclaiming a surface mined site. Because of the 5-year timeframe required to demonstrate successful soil stabilization and vegetation reclamation, many surface mined soils are severely and purposely compacted by machinery and converted to grasslands and shrubs. Native forests have not been successfully restored due to several soil factors: poor aeration, high alkalinity, and reduced water infiltration, in addition to severe compaction (Ashby and others, 1984, Andrews and others, 1998). As a result, millions of hectares of grassland and scrubland, in various successional stages, fragment the otherwise forested mountains and reduce the forest's potential to produce timber and sequester carbon (Burger and Maxey 1998).

The Forestry Reclamation Approach (FRA) is a new approach being tested as a method for reclaiming surface-

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coal-mined land to forest within the guidelines imposed by SMCRA (Burger and others 2005). FRA recommendations are founded on restoring mine-soil quality to increase potential carbon sequestration. Restoration guidelines include the creation of deep soil rooting medium, suitable for planting native ground covers and tree species, to improve ecological values. Post-mining forest restoration is slowly gaining acceptance; about 30 million trees have been planted since 2005 (Personal communication, Patrick Angel, forester/soil scientist, USDI Office of Surface Mining Reclamation and Enforcement, 421 West Highway 80, London, Kentucky 40741). These forests are very young, hence, the future productivity, value, and carbon sequestration potential of these restored forests is still unknown.

The objective of this project is to assess the effects of surface coal mining on forest ecosystem disturbance and simulated restoration in the Coal River Mountain watershed in southern West Virginia. This watershed already has active surface mining. Three new and proposed mountaintop removal mines are projected to produce more than 47 million tons of coal from 2009 through 2025 (WV DEP 2008). Our approach develops disturbance impact models for a sub-watershed that will serve as a case study for testing the feasibility of integrating currently available GIS data layers, remote sensing, and existing data from the USDA Forest Inventory and Analysis (FIA) program. Specifically, we will 1) identify specific areas and ecosystems that have been depleted of carbon stocks; and 2) calculate the reduction relative to a previous condition. This paper presents the methods used to accomplish these two tasks and presents initial results of our biomass modeling efforts. Our ultimate goal is to model the change in carbon stocks from anticipated forest restoration activities using FRA guidelines and make comparisons with the previous condition to determine the long-term effects of the proposed mining on the watershed.

MATERIALS AND METHODS

To identify the year and spatial extent of forest disturbance due to surface mining and to generate maps to estimate the pre- and post- disturbance carbon stocks in these areas, a regression tree predictive modeling approach was employed using Cubist software (www.rulequest.com), which is based on a process created by Quinlan (1992). While the algorithm that Cubist employs is proprietary, generally speaking, regression trees work by using classification trees to classify instances into groups based on values of a set of independent variables and a dependent variable, and then developing regression models that describe the relationship between the dependent and independent variables using the instances contained in each of the classification tree's terminal nodes.

For our regression tree, we used several GIS-based predictor layers as the independent (predictor) variables, and we used total aboveground carbon estimates generated from forest inventory plots as the dependent variables.

INDEPENDENT VARIABLES

Landsat image data were obtained from the US Geological Survey (USGS) Global Visualization Viewer (GLOVIS) data distribution system (http://glovis.usgs.gov), and consisted of a set of annual Landsat 5 scenes collected over path/row 18/34 during the growing season. Image dates (month/day/year) included the following days: 9/17/1984, 9/20/1985, 7/5/1986, 6/6/1987, 6/8/1988, 8/17/1990, 9/21/1991, 6/3/1992, 8/25/1993, 10/15/1994, 8/31/1995, 10/4/1996, 9/5/1997, 8/7/1998, 6/23/1999, 6/9/2000, 10/2/2001, 8/2/2002, 6/2/2003, 6/20/2004, 9/11/2005, 8/13/2006, 9/17/2007, 7/17/2008, and 6/2/2009; suitable data were unavailable for 1989. These scenes were 30-m pixel size and processed by the USGS to Level 1T (terrain corrected) using the Level 1 Product Generation System (USGS 2011) and were further processed using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) software (Masek and others, 2006). LEDAPS software produces atmospherically-corrected, surface reflectance-calibrated imagery that can be used to assess environmental and land cover change (Masek and others, 2006). From the scenes that were available for each year within the growing season, bands 1-5 and 7 of the scene with the greatest cloud-free area were selected.

Other data used for this study are listed in table 1 and included a 10-m elevation dataset obtained from a subset of the National Elevation Dataset (NED) (Gesch and others, 2002), raster elevation derivate datasets created using the NED data, and data from the Soil Survey Geographic (SSURGO) database (NRCS 2011). Also, for each Landsat scene, the disturbance magnitude of the difference Normalized Burn Ratio (dNBR) was created using vegetation change tracker (VCT) software (Huang and others, 2010).

DEPENDENT VARIABLE

Estimates of total aboveground carbon (TAG) were obtained using allometric equations that were applied to data collected by the FIA on the 69 inventory plots found in the portion of the Coal River watershed found within Landsat path/row 18/34 (fig. 1). TAG is calculated as described in Woudenberg and others (2011) and includes the carbon mass of the aboveground portion of live trees with a diameter of 2.5 cm or larger and dead trees with a diameter of 12.7 cm or larger. The FIA data were collected between 2004 and 2008 and consisted of plots with pure stands or hardwoods or conifers.

MODEL DEVELOPMENT

The latitude and longitude of the FIA plots were used to intersect them with the set of predictor data using a GIS, and values for each independent variable were assigned to the TAG value associated with each plot to create the training data for the regression tree modeling. The elevation, elevation derivatives, and SSURGO data were assumed to be temporally constant and these and LEDAPS-calibrated Landsat and VCT Landsat derivatives (dNBR and NDVI) from 2007 were used to build the initial model. Model results were assessed using cross validation (10 percent holdout) statistics: mean absolute error (MAE); relative error (RE), or the ratio of the MAE to the error magnitude that would result from always predicting the mean value; and the correlation coefficient (r) that describes the strength of the relationship between each set of predictions and carbon values from the holdout data. Using a combination of these metrics, correlation matrices, and experience from prior modeling, data reduction was performed automatically and heuristically until a set of independent variables was chosen to produce the final model for 2007 imagery.

Because the Landsat imagery was calibrated using LEDAPS, we, like Powell and others, (2010), made the assumption that variations in pixel values between corresponding surface reflectance-calibrated images were due to changes in the reflective characteristics of the landscape and not due to differences in the atmosphere or sensor position. We thus applied the regression tree model developed for the 2007 Landsat and ancillary data to the corresponding data for each year of Landsat data between 1984 through 2009 to produce a set of 25 (yearly between 1984 and 2009) maps of carbon estimates for the watershed.

RESULTS AND DISCUSSION

The nonlinear portion of the regression tree process does not have many of the assumptions of linear modeling and is generally effective at choosing the best attributes to use in decision rules from among several potentially collinear variables. However, through a combination of examining cross validation (10 percent holdout) results from Cubist and arbitrary decisions, only 35 of the original variables were used to produce the final model.

The Cubist model output is shown in figure 2. Cubist used 13 exploratory variables. Five variables were important to the classification portion of the Cubist analysis: dNBR, landform, X, Y, and profile curvature. Of these, profile curvature was present in five of the six rules developed, while the remaining four were present in at least half of the rules. Two variables, landform and Y, were only used in the decision process (table 2). Each of the remaining 11 variables was involved infrequently with the linear models for each rule. Only one variable, heatload, was present in half the rules (3 of 6) while the remaining variables were present for only one or two of the six rules generated. In general, coefficients calculated for specific variables during the linear model steps were consistent in sign from rule to rule, i.e, if a coefficient was positive for a variable in one rule it was positive as well in other rules. The actual values plotted against the predicted values have a reasonably linear relationship (fig. 3). The correlation coefficient was 0.89 ($r^2 = 0.79$).

The Cubist model rules (fig.2) were then applied to the aforementioned LEDAPS processed Landsat scenes resulting in TAG estimates maps for nearly all years from 1984-2009. Four of these maps are illustrated in figure 4, where an 8-year interval was used to demonstrate applicability of the model. Rivers and streams clearly appear as white lines within the maps, and irregular patches correspond with areas of disturbance, some of which is already identified as surface coal mining activity. The distinct boundaries that appear in the final map are due to the use of the Easting and Northing in the decision rules. While the existence of these lines creates a visual anomaly, the use of the map is a geospatial dataset that will provide pixel value summaries that serve as estimates. It is recognized that the presence of these discontinuities indicates that additional effort is needed to further refine the predictive models.

CONCLUSIONS

Methodology developed to date demonstrates the feasibility of utilizing a set of GIS predictor layers to generate temporal maps of total aboveground carbon for a watershed containing surface mining activity in West Virginia. This is an important step in the ultimate goal of assessing the amount of carbon stock removed in disturbance events, specifically surface coal mining. Subsequent steps will compare output from the VCT disturbance maps and the predicted TAG maps which will enable temporal removals of carbon stock for the period 1984-2009. Additionally, it is hoped that these later results will have broader applicability to other watersheds containing surface mining activity.

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Table 1—List of datasets assessed for inclusion in Cubist regression tree modeling procedure

Dataset Name	Dataset Description	Source
Forest productivity of yellow poplar	Index of forest productivity	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Forest productivity of red oak	Index of forest productivity	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Forest productivity of white oak	Index of forest productivity	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Site index northern red oak	Index of forest productivity	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Site index white oak	Index of forest productivity	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Site index yellow poplar	Index of forest productivity	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Seedling mortality index	Index of seedling mortality likelihood	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Depth to fragipan layer	Depth to a fragipan restrictive soil layer	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Depth to lithic bedrock	Depth to a lithic bedrock restrictive soil layer	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Depth to paralithic bedrock	Depth to a paralithic restrictive soil layer	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Depth to restrictive layer	Depth to any restrictive layer	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Depth to water table	Depth to the water table	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Liquid limit	Index related to the range of water contents over which a soil exhibits liquidity	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Plasticity index	Index related to range of water content over which a soil exhibits solidity	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Soil organic matter percent	Percent soil organic matter in the top soil layer	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Clay percent	Percent clay content of the surface soil layer	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Sand percent	Percent sand content of the surface soil layer	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Silt percent	Percent silt content of the surface soil layer	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)

Table 1—(Continued) List of datasets assessed for inclusion in Cubist regression tree modeling procedure

Dataset Name	Dataset Description	Source
Rock type	Categorical value representing different bedrock types	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Soil pH in water	pH of soil mixed in water	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Cation-exchange capacity (CEC-7)	Cation exchange capacity of the surface soil layer	Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2011)
Elevation	Elevation	Gesch *et al.* (2002)
Filtered elevation range	Elevation range within a 90-m square buffer centered on each pixel	Gesch *et al.* (2002)
Filtered mean elevation	Mean elevation within 90-m square buffer centered on each pixel	Gesch *et al.* (2002)
Filtered mean-minimum elevation range	Mean elevation - minimum elevation within 90-m square buffer centered on each pixel	Gesch *et al.* (2002)
Transformed aspect	Linear transformation of aspect	Roberts and Cooper (1989)
Cosine-transformed aspect-slope	Cos(aspect) X percent slope	Stage (1976)
Sine-transformed aspect-slope	Sin(aspect) X percent slope	Stage (1976)
Relative moisture index	Index of relative amount of moisture available at a site	Parker (1982)
Modified relative moisture index	Variation of relative moisture index	Parker (1982)
Heatload	An index of the relative amount of solar radiation that a site receives	McCune and Keon (2002)
Hillshade	An index of solar radiation a site receives, incorporating shadows and illumination angle	ESRI (2011a)
Bolstad's landform	A landform index	Bolstad and Lillesand (1992)
McNab's landform	A landform index	McNab (1989)
Planform curvature	An index of curvature of the land surface	ESRI (2011b)
Slope curvature	An index of curvature of the land surface	ESRI (2011b)
Profile curvature	An index of curvature of the land surface	ESRI (2011b)
Relative slope position	An index of slope position between valley bottom and ridge top	Unknown; based on ESRI topographic functions
Slope position	Position of the pixel as a percentage between the valley floor and ridgetop.	Unknown; based on ESRI topographic functions
Landform type	A categorical variable representing landform shape and position	Parker (1982)
Surface area : ground area ratio	An index of topographic complexity	Unknown; based on ESRI topographic functions
Topographic roughness index	An index of topographic complexity	Riley *et al*. (1999)
Easting	The value of geographic coordinate in UTM meters	Native ESRI functionality (xmap and ymap environment variables)
Northing	The value of geographic coordinate in UTM meters	Native ESRI functionality (xmap and ymap environment variables)
Easting X Northing	Easting X Northing	Native ESRI functionality (xmap and ymap environment variables)

Table 2— Frequencies of occurence and general coefficient patterns for important variables in Cubist rules

	Decision process	Regression models	Coefficient positive	Coefficient negative
Variable	*No. of rules used in*	*No. of rules used in*	*Number*	*Number*
dNBR	3	2	2	0
Landform	4	0	-	-
X	4	1	1	0
Y*	4	0	-	-
Profile curvature	5	1	0	1
Slope*	0	2	2	0
COS(Aspect) transformation*	0	2	2	0
Relative slope position	0	1	0	1
Landsat band 6	0	2	0	2
Landsat band 4	0	2	2	0
Transformed aspect	0	2	0	2
Heatload	0	3	3	0
Slope position	0	1	0	1

Figure 1—The study site in southern West Virginia, compromised of the portion of the Coal River watershed found within the boundary of Landsat scene 18/34.

```
Rule 1: [7 cases, mean 1759.924, range 0 to 12319.47, est err 4022.683]
 if
        dnbr <= 133
 then
        Total Above Ground Carbon = 1759.924

Rule 2: [6 cases, mean 27173.246, range 11515.6 to 42868.64, est err 15844.396]
 if
        dnbr > 133
        landform in {4, 7, 8}
        profile curvature <= -0.02502192
        x * y > 1.846332e+012
 then
        Total Above Ground Carbon = -241151.452 + 1865 dnbr + 29039 slope * COS(aspect) transformation

Rule 3: [32 cases, mean 49472.605, range 4402.104 to 98225.22, est err 17879.621]
 if
        dnbr > 133
        profile curvature > -0.02502192
 then
        Total Above Ground Carbon = -254641.664 + 0.72 x - 534 relative slope position - 8 landsat band 6 + 2
landsat band 4

Rule 4: [8 cases, mean 65291.813, range 42630.82 to 80570.83, est err 16716.725]
 if
        landform in {3, 6, 9, 10}
        profile curvature <= -0.02502192
        x * y > 1.846332e+012
 then
        Total Above Ground Carbon = -129803.498 + 1086 dnbr - 32917 transformed aspect + 1.9 heatload - 8
landsat band 6
         + 6841 slope * COS(aspect) transformation + 2 landsat band 4

Rule 5: [12 cases, mean 78180.602, range 59397.14 to 121845.6, est err 12838.607]
 if
        landform in {6, 7, 8, 10}
        profile curvature <= -0.02502192
        x * y <= 1.846332e+012
 then
        Total Above Ground Carbon = -15215.85 - 29792 profile curvature - 508 slope position + 3.8 heatload

Rule 6: [4 cases, mean 122093.297, range 100926.2 to 153119.2, est err 11975.873]
 if
        landform in {3, 5, 9}
        profile curvature <= -0.02502192
        x * y <= 1.846332e+012
 then
        Total Above Ground Carbon = -323169.019 - 99972 transformed aspect + 2398 dnbr + 4.7 heatload

Average |error| 10856.566
Relative |error| 0.42
Correlation coefficient 0.89
```

Figure 2—Cubist output modeling total aboveground carbon.

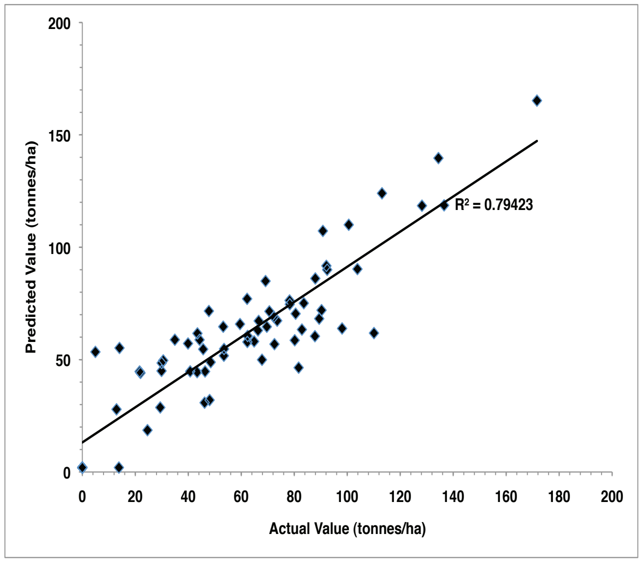

Figure 3—Cubist total aboveground carbon predictive values vs. the actual total aboveground carbon values.

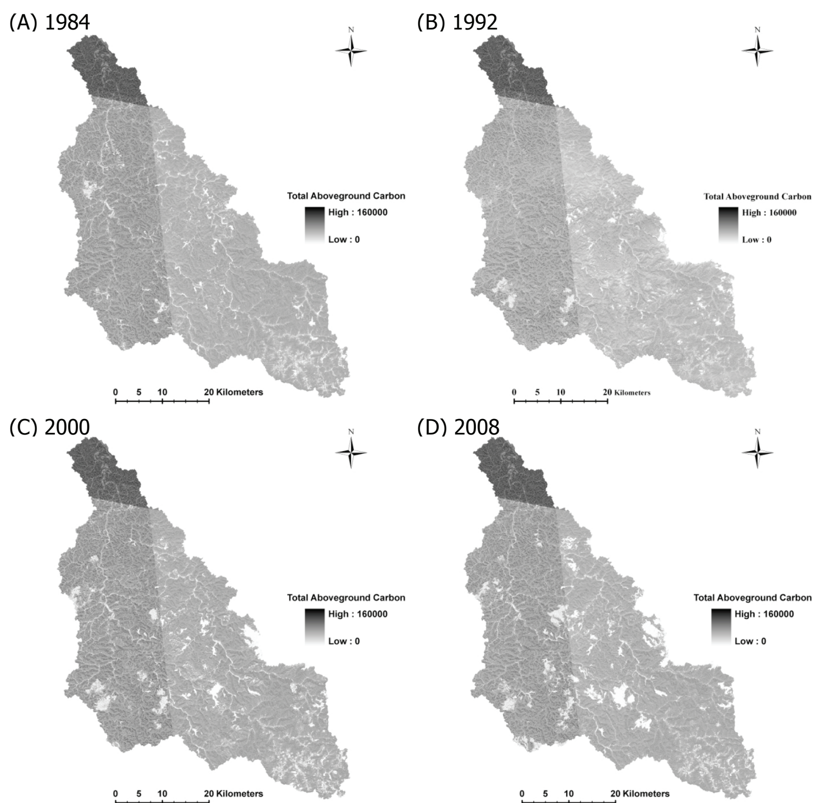

Figure 4—Prediction maps for total aboveground carbon. Selected maps were produced at 8-year intervals.