Disturbance Mapping and Landscape Modeling of Mountaintop Mining Using ArcGIS

Aaron E. Maxwell, Dr. Michael P. Strager, Charlie Yuill, Dr. J. Todd Petty, Eric Merriam, and Christine Mazzarella

Abstract:

Mountaintop removal mining in Appalachia continues to be studied to evaluate its cumulative impact on aquatic and terrestrial systems. Vital to the evaluation is the ability to map disturbance features over large extents. Our approach was to integrate both Geographic Information Systems (GIS) and remote sensing to classify disturbed landscape features for mining, forestry, and construction activities. Spectrally driven analysis of 1 meter spatial resolution aerial imagery combined with landform terrain analysis allowed for accurate classifications. GIS data layers were combined in order to summarize the distribution of disturbance throughout watersheds of interest. Individual watershed variables were accumulated to better map the cumulative impacts spatially throughout the watershed. The approach offers an improvement over traditional approaches that assumed the permitted mine area was the full extent of disturbance. We found on average that 28% of a mine permit was disturbed at any particular time of mining activity.

Introduction

This project investigated mountaintop removal mining with valley fills (MTR/VF) disturbance mapping and the mapping of additional land cover in the Southern Appalachian Coalfields of West Virginia as an input for modeling receiving stream conditions. It was conducted using publically available, 1:10,000 scale National Agriculture Imagery Program (NAIP) orthophotography, which was selected because it was temporally and spatially appropriate for mapping the land cover and disturbance data of interest. Due to compression, reduced spectral resolution, variable illumination, color balance inconsistencies, shadowing, and the high spatial resolution of the data, we did not pursue a purely image classification method. Instead, a combination of user-assisted feature extraction, GIS overlay within ArcMap, and manual digitizing was used to conduct the mapping. The resulting land cover and land use data along with additional GIS data available in the region were summarized relative to 1:24,000 scale catchment areas and used as predictor variables in modeling receiving stream conditions.

MTR/VF is the leading cause of land cover change in central Appalachia, including the Southern Coal Fields of West Virginia (Palmer et al., 2010). Multiple West Virginia watersheds have greater than 10% of their total area disturbed by surface mining as upper elevation forested land cover is converted to barren, grasslands, or scrub/shrub land cover. Reclamation commonly results in grasslands on the topographically altered mountaintops, and in the past such sites have generally shown little or no regrowth of woody vegetation and minimal carbon storage even after 15 years (Palmer et al., 2010). It has been estimated that 1.05 to 1.21 million acres of the landscape has been disturbed by surface mining within the Appalachian region; additionally, at least 500 mountaintops have been altered by MTR/VF mining (Geredien, 2009b).

Mountaintop mining has been shown to have a negative impact on terrestrial and aquatic ecological community health, stream chemistry, surface runoff volumes, and potentially human health (Hitt and Hendryx, 2010; Negley and Eshleman, 2006; Palmer et al., 2010; Phillips, 2004; Petty et al., 2010; Pond, et al., 2008; Wickham et al., 2007). For example, in an EPA (2002) survey of 78 streams affected by surface mining, 73 were found to have selenium concentrations greater than the threshold for toxic bioaccumulation. Paybins et al. (2000) linked declines in biodiversity with degree of mining disturbance in West Virginia. Also, sulfate concentrations have been closely linked to extent of mining in watersheds (Sams and Beer, 2000). Palmer et al. (2010) found significant increases in metal concentrations and decreases in biological health in mine impacted streams. If a model is to be developed that links stream chemistry and biological health to environmental stressors, such as surface mining, accurately describing the landscape stressors are essential to establish a relationship.

Quantifying and mapping MTR/VF mining disturbance has been proven to be challenging. Prior to 2006, estimates of MTR/VF disturbance were often made using permit boundary data; however, it is uncommon for the entire spatial extent of a permitted surface mine to be disturbed at one time (Geredien, 2009a). Surface mining and reclamation extents have also been extracted from Landsat MSS, TM, ETM+, and SPOT data with varying degrees of success (Anderson and Schubert, 1976; Anderson et al., 1977; Campagna, 2007; Irons and Kennard, 1986; Parks et al., 1987; Prakash and

Gupta, 1998; Rathore and Wright, 1993; Townsend et al., 2009; Yuill, 2003). Appalachian Voices (unpublished, 2006) and Geredien (2009a) relied on manual digitizing of disturbance features; as a result, remote sensing and orthophotography interpretation have been investigated for surface mine disturbance mapping. We have expanded on previous work by incorporating feature extraction methods to make use of high spatial resolution imagery.

Methodology:

Orthophotography:

Imagery was obtained through download as compressed MrSid files from the West Virginia GIS Technical Center as county datasets with a compression ratio of 15:1. The most recent color infrared (CIR) orthophotography was collected in late summer 2007. The data were originally published in February of 2008 by the Aerial Photography Field Office of the Farm Service Agency, which is part of the U.S. Department of Agriculture, and this data are currently publically available. The orthophotography has a 1 meter nominal pixel resolution, a scale of 1:10,000, and is rectified to a horizontal accuracy of within +/- 5 meters of reference digital ortho quarter quads from the National Digital Ortho Program.

The most recent true color imagery was collected during leaf-on conditions in 2009, published in October 2009, and made available to the West Virginia GIS Technical Center in January 2010. The true color orthophotography also has a 1 meter nominal pixel resolution, a scale of 1:10,000, and is rectified to a horizontal accuracy of within +/- 5 meters of reference digital ortho quarter quads from the National Digital Ortho

Program. CIR orthophotography was not made available in West Virginia by NAIP in 2009.

Study Area:

The MTR/VF region in West Virginia is shown in Figure 1. This region intersects 17 counties within the state and is estimated as 11,733 km^2 in area. Mapping was conducted throughout this region at a 1 m cell size and on a county-by-county basis. In order to map land cover throughout entire Hydrologic Unit Code (HUC) 8 watersheds, county sets were combined. This paper will specifically make reference to mapping conducted in the Coal River Watershed, a 2,308 km^2 HUC 8 watershed heavily disturbed by surface mining.

Figure 1: MTR/VF region in West Virginia and Coal River Watershed.

Overall Classification Method:

Figure 2 outlines the classification method used to create land cover data. This method relies on user-assisted feature extraction and GIS overlay. First, land cover data was extracted from the 2007 (CIR) and 2009 (true color) NAIP imagery as forested, grasslands, or barren. Scrub/shrub areas were included in the grasslands class. Second, the results were selectively combined as will be described below. Third, in order to differentiate landscape disturbance within mine permits, West Virginia Department of Environmental Protection (WVDEP) surface mine permit boundaries were utilized. Fourth, ancillary water body data from the West Virginia Statewide Addressing and Mapping Board (WVSAMB) were utilized to obtain the open water class. Rogan et al. (2003), Bolstad and Lillesand (1992), and Homer et al. (2004) have documented the use of combining ancillary GIS data with remote sensing data to increase thematic map accuracy and to allow for the mapping of more detailed land cover. This process will be discussed below, and Figure 2 describes the method. The following land cover classes were of interest:

1. Forested
2. Grasslands/Pastureland/Agricultural Land
3. Barren/Developed
4. Forested in Permit (Not Disturbed)
5. Grasslands in Permit (Potentially Reclaimed)
6. Barren in Permit (Potentially Active Mining or Not Yet Reclaimed)
7. Open Water

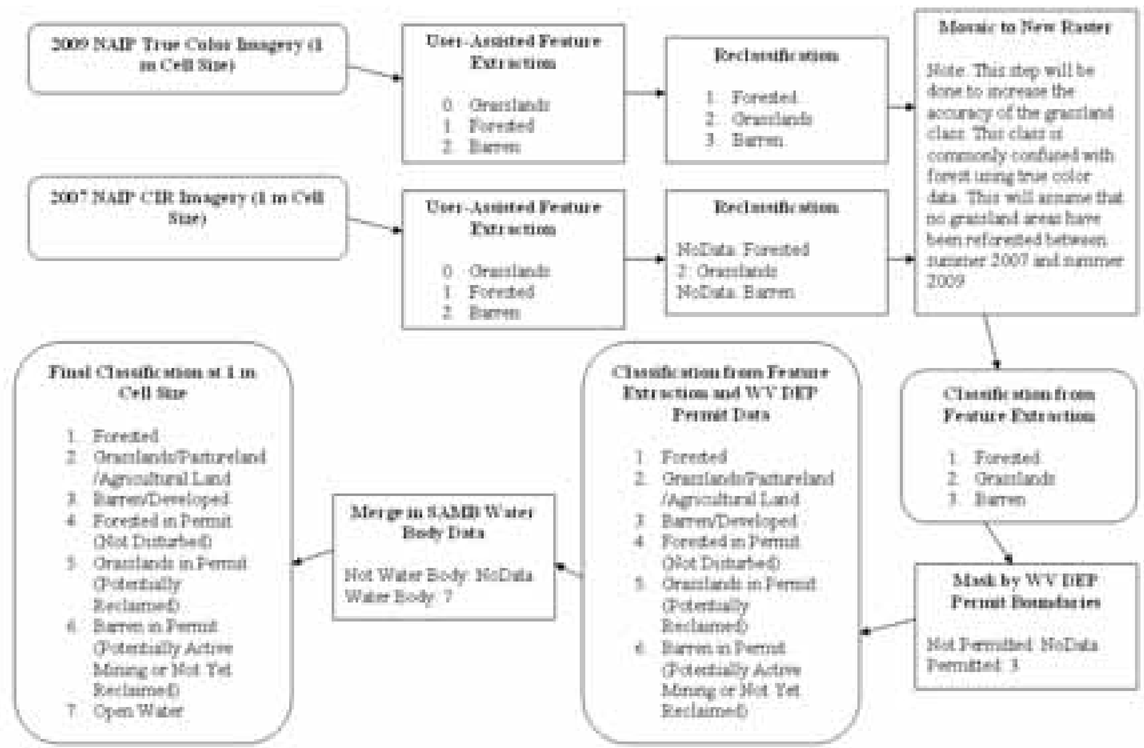

Figure 2: Classification method used.

User-Assisted Feature Extraction:

The software tool Feature Analyst by Visual Learning Systems (VLS) was used within Erdas Imagine to perform the user-assisted feature extractions. Three land cover types were differentiated: forested, grasslands, and barren. In terms of surface mine permit areas, barren areas may represent active mine sites or areas that have not yet been reclaimed. Grasslands within mine permits may represent reclaimed mine lands. Forested areas within mine permits would represent areas that had not yet been disturbed by mining.

The land cover data was extracted from the 2009 and 2007 NAIP orthophotography. Initially, only the 2009 true color data were classified; however, visual interpretation of the results showed that this method often did not capture the entire spatial extent of grassland areas, especially reclaimed mine lands. As a result, the most recently available CIR orthophotography from 2007 was also classified, and the results were combined. This was done to increase the accuracy of the grasslands class and assumed that grasslands had not reverted to forested land cover in the two year period. The barren and forested land cover classes were derived from the 2009 classification, and the grasslands class was derived from a combination of the 2009 and 2007 result to make use of the CIR data.

User-assisted feature extraction uses user-defined knowledge, as training data, to recognize and classify target features in an image (Visual Learning Systems, 2002). Feature Analyst uses machine-learning algorithms and techniques as object recognition to automate feature-recognition from imagery (Visual Learning Systems, 2002). Unlike supervised classification techniques, feature extraction classifies an image using more than just the digital number (DN) or spectral information contained by each pixel. Spatial context information such as spatial association, size, shape, texture, pattern, and shadow are considered (Opitz, 2003). Studies have shown that feature extraction or object-based algorithms are more effective and accurate at extracting information from high resolution imagery than traditional image classification methods, such as supervised classification, because additional image characteristics are considered such as spatial context (Friedl and Brodley, 1997; Harvey et al., 2002; Hong and Zhang, 2006; Kaiser et al., 2004).

As the spatial resolution of an image increases, the spectral variance within a land cover class also increases; as a result, it may not be appropriate to extract thematic data from high resolution aerial imagery using processes developed for coarser resolution satellite imagery (Carleer et al., 2005; Gong et al., 1992). Feature extraction takes into account the spatial context that is available in high resolution imagery, such as NAIP orthophotography. Due to the high spatial resolution and reduced spectral resolution of NAIP orthophotography in comparison to satellite imagery traditionally used to obtain thematic map data, we decided upon Feature Analyst as the classification tool in order to make use of the spatial context information contained in the imagery.

Training Data Collection:

Training data were collected that appropriately represented the classification of interest by manually digitizing training data using the orthophotography as reference within ArcMap; for example, forested training data would include forested areas on all aspects to take into account variable illumination due to topography. Because the imagery was not perfectly color balanced, it was necessary to collect training data across entire county extents to take into account the variability. Separate training data was collected for the CIR and true color imagery. As an example, Table 1 describes the training data collected from the 2009 true color data in Boone County, a county predominately within the Coal River Watershed.

Table 1: Training data from 2009 true color NAIP orthophotography for Boone County.

Class	**Number of Training Polygons**	**Total Training Area**
Grasslands	165	389,935 m^2
Forested	147	4,738,141 m^2
Barren	101	1,045,063 m^2

GIS Overlay:

GIS overlay of ancillary GIS data available for West Virginia was used to refine the land cover classes, and this was conducted in ArcMap. Two ancillary GIS datasets were used to enhance the feature extraction results. First, the results were refined relative to surface mine permit boundaries made available by WVDEP to classify land cover as a result of surface mining. Although there is error associated with the available mine permit polygon data, the researchers accepted this data as definitive boundaries in order differentiate land cover resulting from surface mining. Second, WVSAMB water body polygon data were added to the results to provide an estimate of open water land cover. This data was extracted from 0.6 m cell size, 1:4,800 scale, leaf-off imagery collected in 2003, and the assumption was made that open water land cover had not changed significantly over that time.

Manual Digitizing:

After experimentation with user-assisted feature extraction within the available software and using the available orthophotography, we found that certain features of interest could not be easily extracted. Valley fill faces are an example. In terms of land cover and spatial context, valley fill faces are very similar to other types of reclamation; as a result, they could not be adequately separated from other reclaimed areas. However, an analyst can easily manually digitize these v-shaped, terraced slopes adjacent to mine sites using high resolution aerial imagery. This is a task more suited for manual digitizing. The feature extraction of generalized land cover was augmented with GIS overlay and also manual digitizing.

Features that were manually digitized from the NAIP orthophotography are described in Table 2. Digitizing was conducted at a base scale of 1:10,000 as this was the scale of the NAIP imagery. A 500-by-500 m grid was created across mapping extents, and these grid lines were used to guide the analyst through the imagery during the mapping process within ArcMap. We made a minimum of three passes through the imagery to check digitizing results.

Table 2: Manually digitized features.

Feature	Description
Valley Fill Faces	V-shaped, terraced slopes adjacent to mine sites
Slurry Ponds	Ponds adjacent or within areas of surface mine disturbance/often spectrally dark
Clear Cut Forestry	Forestry with distinct boundaries/deforested areas surrounded by forested land cover/evidence of access roads and landing pads
Construction	Barren exposure induced by construction/predominantly road construction

Summarizing Data:

Once land cover was mapped, the data was summarized relative to 1:24,000 scale catchment areas of which there are 4,229 within the Coal River Watershed. The Tabulate Area function within the Spatial Analyst Extension of ArcMap was utilized to obtain the area of each land cover class within each catchment area. The NHD Analyzer Toolbar, another Arc extension developed by Dr. Sam Lamont and Vishesh Maskey of the West Virginia University Natural Resource Analysis Center, was used to map cumulative disturbance throughout the watershed extent. This process allowed for upstream disturbance to be accumulated to downstream catchments. This resulted in a vector layer of 1:24,000 scale catchments appended with percentage of cumulative upstream land cover and land disturbance that described the cumulative impact of mining disturbance throughout the HUC 8 watershed.

Additional GIS data were summarized for the catchment areas such as National Pollution Discharge Elimination System (NPDES) points and manmade structure point locations. The number of such points upstream from and within each catchment was characterized. Once this land cover data and additional variables were summarized and accumulated relative to 1:24,000 scale catchments, they could be related to field measurements of conductivity and benthic macroinvertebrate populations as predictive variables. This was the primary use of the data. Landscape characteristics were related to receiving stream conditions at the HUC 8 scale.

Results and Discussion:

The land cover data created for the Coal River HUC 8 Watershed using user-assisted feature extraction and GIS overlay are described in Figure 3 and Table 3. Estimated user's accuracies for the three land cover classes obtained through feature extraction ranged from 78% to 99%. Forested and barren land cover were mapped with accuracy, but grasslands, including scrub/shrub land cover, were more difficult to extract and were difficult to distinguish from forest. There is also error associated with the mine permit and water body data utilized though this is difficult to quantify.

As Table 3 describes, 8.7% of the watershed was estimated as forested in mine permits. As a result, if permit boundaries alone were used to estimate the extent of mining disturbance, an overestimate of disturbance would be obtained. Within the Coal

River Watershed, only 18.9% of permitted mine lands were predicted as barren while 31.3% was estimated as grasslands, or potentially reclaimed mine lands. Generally and throughout the Southern Coal Fields of West Virginia, we found on average that 28% of a mine permit was disturbed at any particular time of mining activity. As a result, utilizing available imagery allowed for a more accurate estimate of mining disturbance extents.

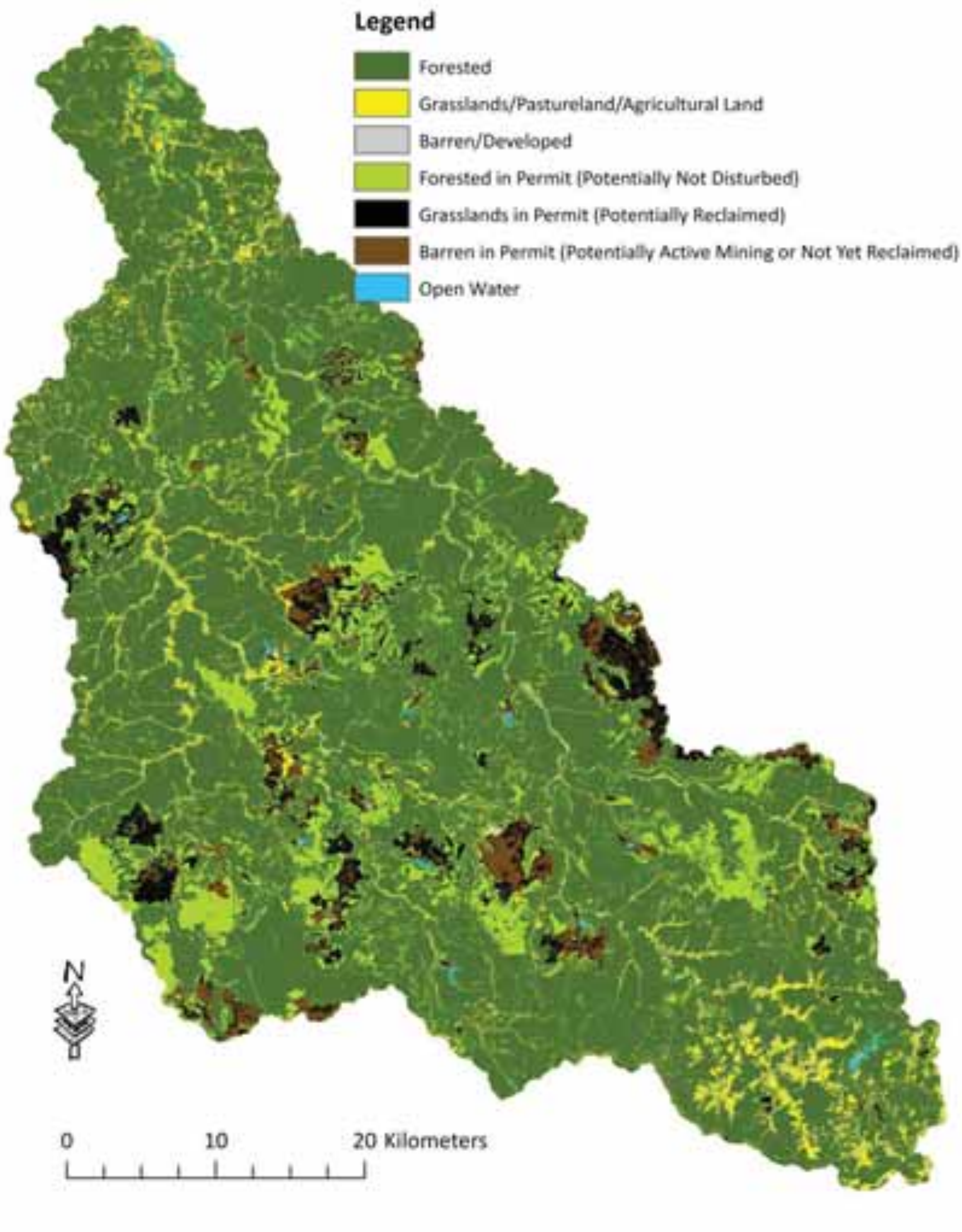

Figure 3: Land cover data for Coal River Watershed.

Table 3: Final land cover data for Coal River Watershed.

Class	Area (km^2)	Percentage of Watershed
Forested	1,684.2 km^2	73.0%
Grasslands/Pastureland/Agricultural Land	164.2 km^2	7.1%
Barren/Developed	41.4 km^2	1.8%
Forested in Permit	200.7 km^2	8.7%
Grasslands in Permit	127.6 km^2	5.5%
Barren in Permit	76.4 km^2	3.3%
Open Water	13.1 km^2	0.6%

An example of a manual digitizing result for valley fill faces is provided in Figure 4. Manual digitizing from the 2009 true color imagery allowed for additional land cover and landscape disturbance features to be mapped that were not spectrally or spatially separable from other land cover types using the software and imagery available. Forestry, construction, valley fill faces, and slurry ponds were manually digitized, and this data provided additional landscape characteristics that could be summarized by 1:24,000 scale catchments.

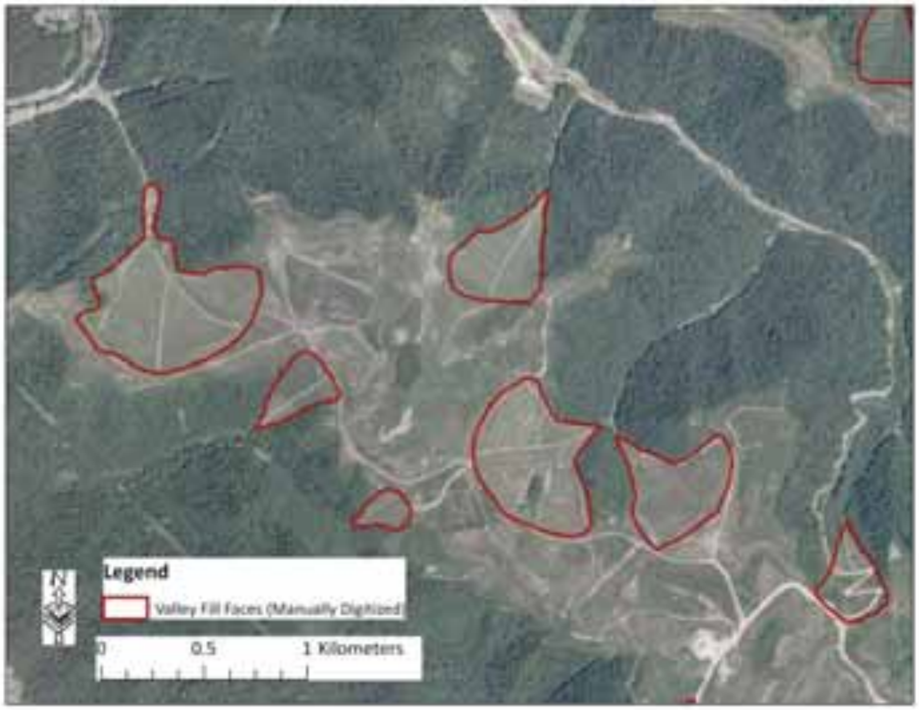

Figure 4: Valley fill faces manually digitized from NAIP imagery.

Figure 5 described the cumulative percentage of upstream surface mine related disturbance for the Coal River Watershed. This includes barren disturbance or active mining, reclaimed mine lands, valley fills, and slurry ponds. Summarizing and accumulating the data relative to 1:24,000 scale catchment areas allowed the data to be utilized as predictive variables in modeling receiving stream conditions. Although this paper will not specifically discuss the receiving stream modeling in which this data was utilized, it was found that this mapping method provided an adequate representation of the landscape for the modeling purposes.

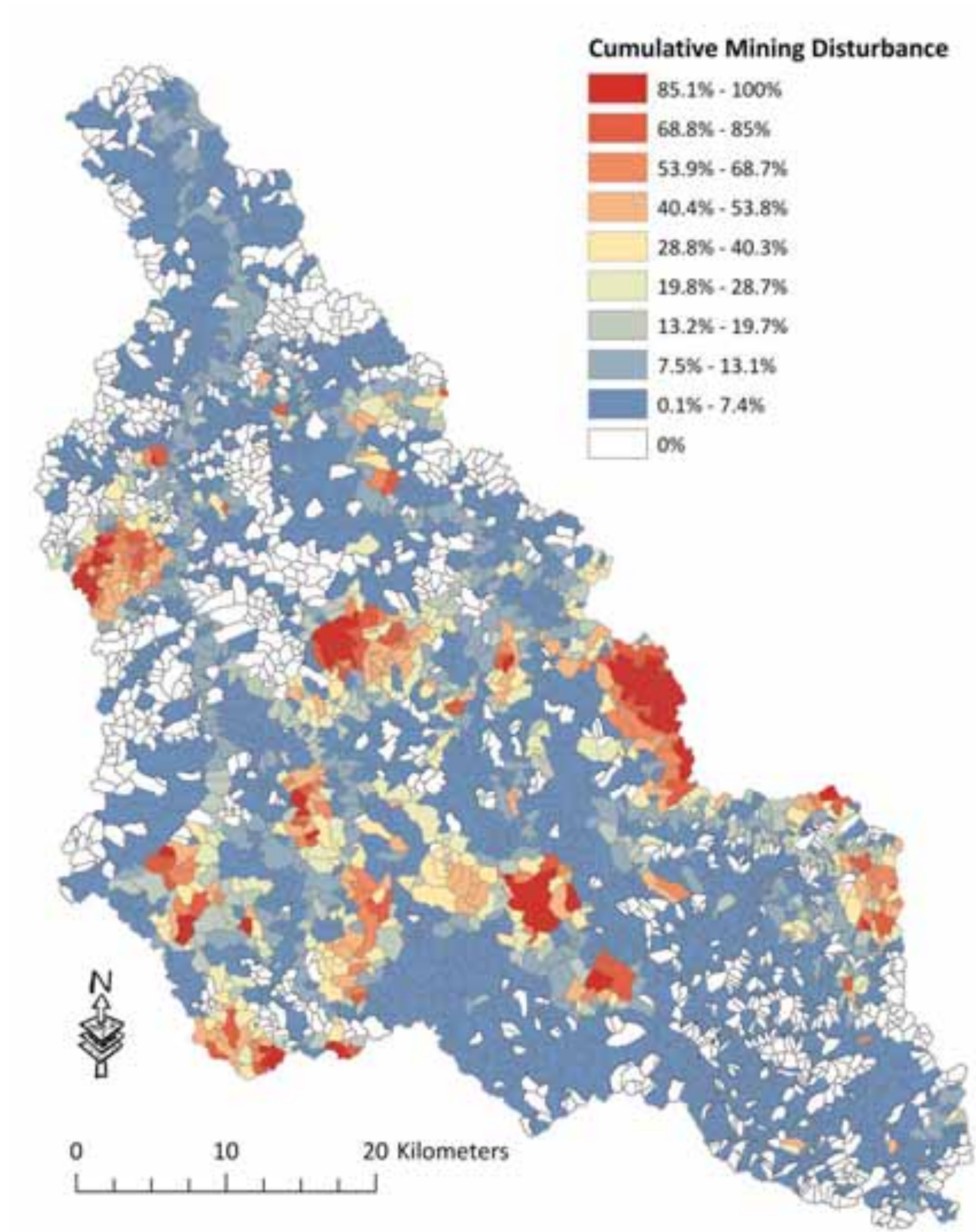

Figure 5: Cumulative mining disturbance in Coal River Watershed.

Conclusion:

NAIP orthophotography provided adequate temporal and spatial resolution to conduct mapping of land cover and landscape disturbance in the Southern Coal Fields of West Virginia; however, obtaining thematic map data from this orthophotography was complicated by compression, reduced spectral resolution, variable illumination, color balance inconsistencies, shadowing, and the high spatial resolution of the data. The researchers found that generalized land cover could be differentiated using user-assisted feature extraction and GIS overlay.

Certain features of interest could not be adequately mapped using user-assisted feature extraction, the available software, and the available orthophotography. One example is valley fill faces, which are easily manually digitized but difficult to separate spectrally and spatially from other reclaimed mine lands. Augmenting feature extraction results with manual digitizing was necessary in this research to obtain all data of interest, and NAIP imagery provided an appropriate mapping scale.

Although NAIP orthophotography is not optimal for extraction thematic map data, adopting a method that utilized user-assisted feature extraction, GIS overlay within ArcMap, and manual digitizing allowed for mapping results that met the needs of the project. Landscape disturbance and additional variables were mapped that could be related to receiving stream conditions at the HUC 8 watershed scale. This method allowed for publically available, high resolution, temporally appropriate data to be utilized to map a landscape that is experiencing accelerated disturbance and change.

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Disturbance Mapping and Landscape Modeling of Mountaintop Mining Using ArcGIS

Natural Resource Analysis Center (NRAC) at West Virginia University

ESRI International Users Conference

July 12, 2011

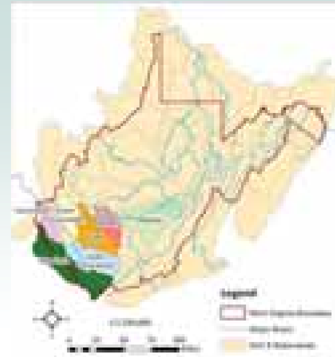
Aaron Maxwell, Dr. Mike Strager , Charlie Yuill, Dr. Todd Petty, Eric Merriam, and Christine Mazzarella

Purpose

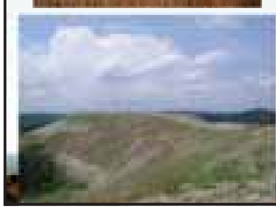
Improve the spatial and temporal mapping accuracy of disturbed landscape features to improve modeling

Use publically available and spatial/temporally appropriate National Agriculture Imagery Program (NAIP) orthophotography to obtain thematic map data

Provide input land cover and disturbance data for environmental modeling



Mountaintop Removal With Valley Fills (MTR/VF)



Creating Land Cover Data From NAIP

Imagery Used

Imagery Source	Imagery Date	Imagery Type	Dominant Use
NAIP Ortho-photography	Summer 2009	True Color	Most Current Extraction of Land Cover
NAIP Ortho-photography	Summer 2007	Color Infrared	Extraction of Grasslands

Data downloaded by county mosaic in MrSID format from West Virginia GIS Technical Center.

- 1 m nominal pixel spacing
- Publically available
- Rectified to a horizontal accuracy of +/- 5 meters of reference digital ortho quarter quads
- 1:10,000 Scale

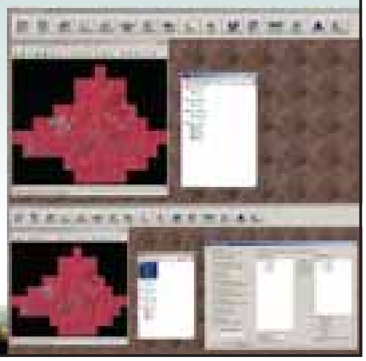
Training Data

- Training data as shape files
- Collected by visual interpretation of the imagery within ArcMap
- Training data should mimic the spatial and spectral variability of the land cover classes

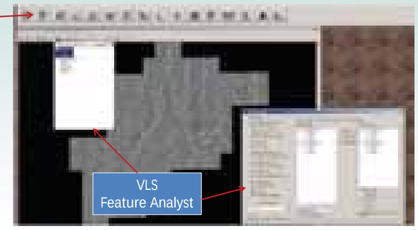
Class	Number of Training Polygons	Total Training Area
Forested	165	389,935 m^2
Grasslands	147	4,738,141 m^2
Barren	101	1,045,063 m^2

User-Assisted Feature Extraction

- Feature Analyst by Visual Learning Systems
- Makes use of spectral and spatial attributes of data
- May need to clean up results by manipulating training data



Visual Learning Systems Feature Analyst for Detection of MTR/VF Disturbance



"Using spectral information and feature characteristics such as spatial association, size, shape, texture, pattern, and shadow in user-identified feature examples, Feature Analyst learns to recognize and classify targeted features in an image."

- Feature Analyst Users Manual

Previous studies have shown that feature extraction tools/algorithms are more effective and accurate at extracting information from aerial imagery than traditional image classification algorithms that only rely on spectral values (Gong et al., 1992; Harvey et al., 2002; Friedl and Brodley, 1997).

What is Feature Extraction?

User-Assisted Feature Extraction uses user-defined knowledge, as training data, to recognize and classify target features in an image. Machine-learning algorithms and techniques serve to automate the feature-recognition process.

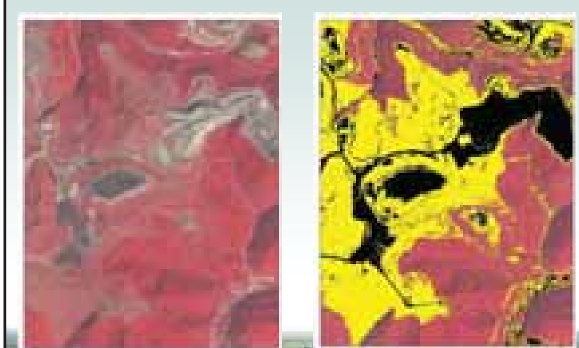
Advantages:

1. Not as labor intensive or time consuming as manual digitization (Blundell and Opitz)
2. More accurate than traditional classification techniques (Gong et al., 1992)

Advantages we have found:

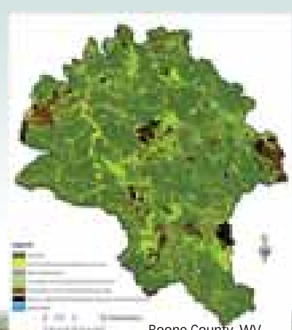
1. Appropriate for imagery scale (1:10,000)
2. Reproducible results

Raw Imagery ------------------------------>Thematic Map Data



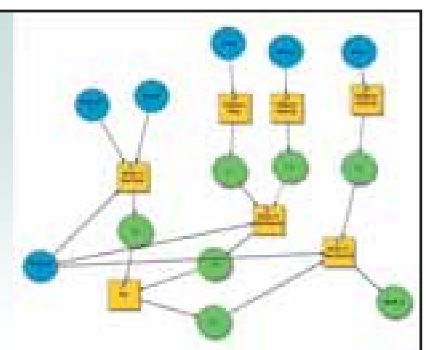
GIS Overlay

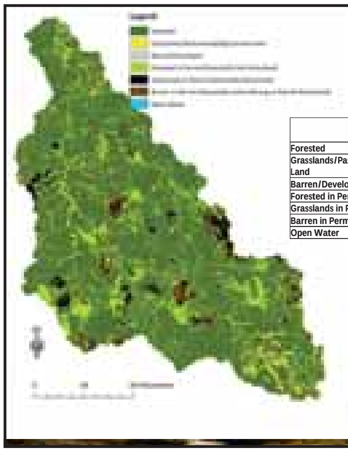
- GIS Overlay is used to combine thematic map data and ancillary GIS data to further distinguish land cover classes
- The adjacent thematic map was produced using the following input data
  - 2009 true color NAIP Imagery
  - 2007 CIR NAIP Imagery
  - Manually digitized training data
  - WVDEP surface mine permits
  - SAMB water body polygons



GIS Overlay Analysis:

- Performed in ArcMap
- Makes use of:
  - Raster Calculator
  - Vector-to-Raster Conversion
  - Mosaic
  - Reclassify
- Manipulate land cover data as integer raster datasets

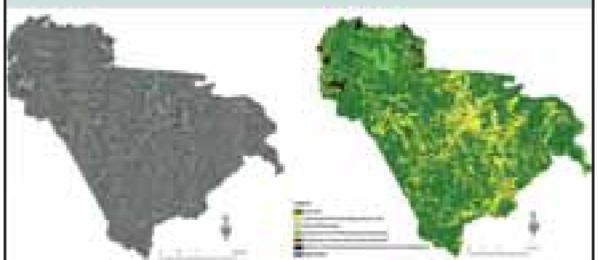




Coal River Watershed

Class	Area (km^2)	Percentage of Watershed
Forested	1,684.2 km^2	73.0%
Grasslands/Pastureland/Agricultural Land	164.2 km^2	7.1%
Barren/Developed	41.4 km^2	1.8%
Forested in Permit	200.7 km^2	8.7%
Grasslands in Permit	127.6 km^2	5.5%
Barren in Permit	76.4 km^2	3.3%
Open Water	13.1 km^2	0.6%

Beckley, WV



Raleigh County, WV

Manual Digitizing in ArcMap

- Certain features of interest were difficult to separate spectrally and spatially from the NAIP imagery
- These features were manually digitized using the imagery and feature extraction results as a guide
- 1:10,000 base digitizing scale, though researchers did digitize at a finer scale

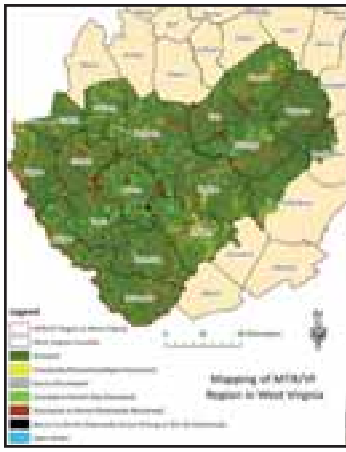
Feature	Description
Valley Fills	V-shaped, terraced slopes adjacent to mine sites
Slurry Ponds	Ponds adjacent or within areas of surface mine disturbance/often spectrally dark
Clear Cut Forestry	Forestry with distinct boundaries/deforested areas surrounded by forested land cover/evidence of access roads and landing pads
Construction	Barren exposure induced by construction/predominantly road construction

Accuracy of Remote Sensing Data

1. Remote sensing error was assessed in Boone County using 600 randomly selected circular areas (15 m radius)
2. Total area: 421,432 m^2
3. Points were randomly selected in Hawth's Tools
4. Majority classification was determined using the Spatial Analyst Extension in ArcMap
5. The majority class was then manually interpreted from the imagery
6. Method takes into account mapping scale and aggregation
7. The K_{hat} Coefficient of Agreement was calculated as 86%

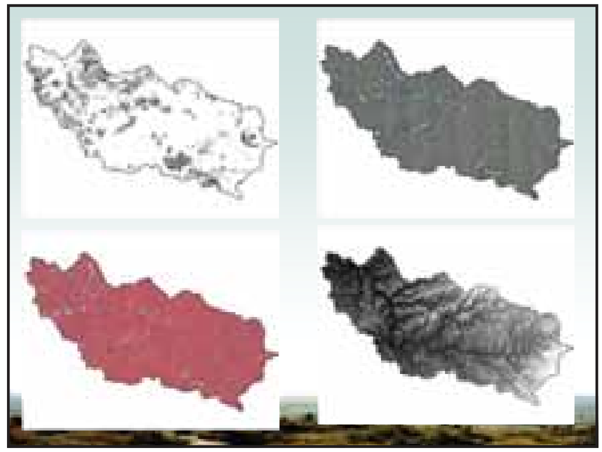
		Reference Data Majority (Pixel Based)				
		Forested	Grasslands	Barren	Row Total	User's Accuracy
Remote Sensing Data	Forested	198	1	1	200	99%
	Grasslands	25	165	10	200	83%
	Barren	3	17	180	200	90%
	Column Total	226	183	191	600	
	Producer's Accuracy	88%	90%	95%		Overall: 91%

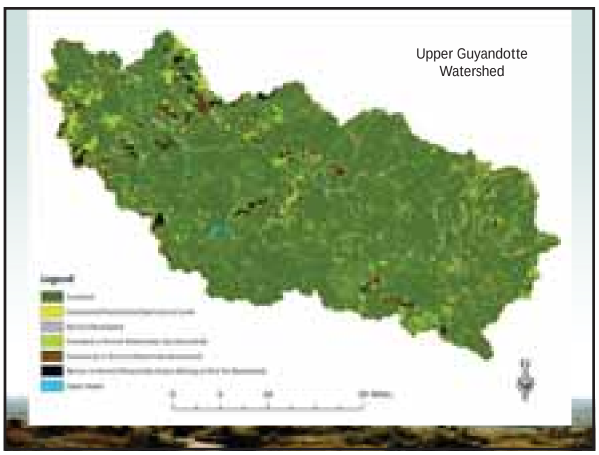
Applying Data for Modeling

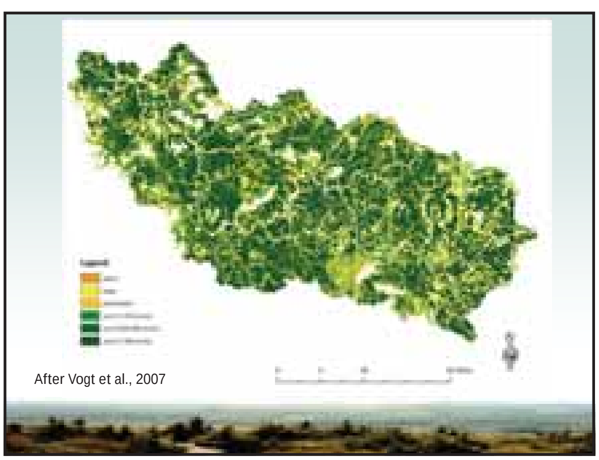


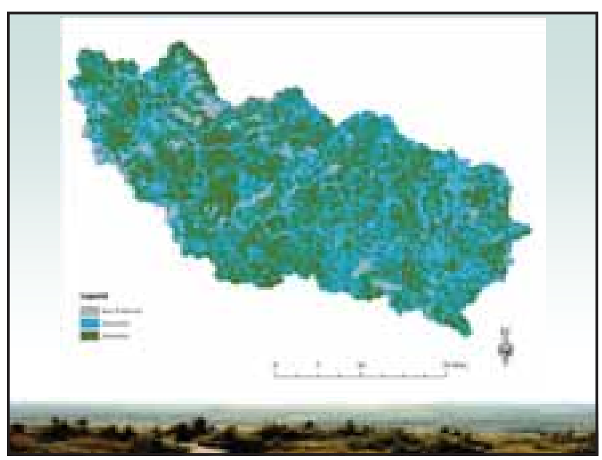
Land Cover Data for MTR/VF Region

1. High resolution forest cover
2. Forest fragmentation (Vogt et al., 2007)
3. Critical forest
   1. Steep Slopes
   2. Riparian Areas
   3. Landform
   4. Headwater Watersheds
   5. Soil Productivity
   6. Contiguous
4. Terrestrial habitat models
   1. Bird community index
   2. Louisiana Waterthrush
   3. Amphibian/Reptile habitat



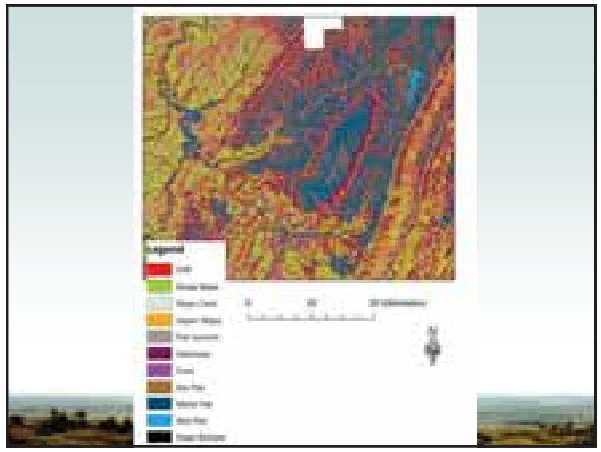


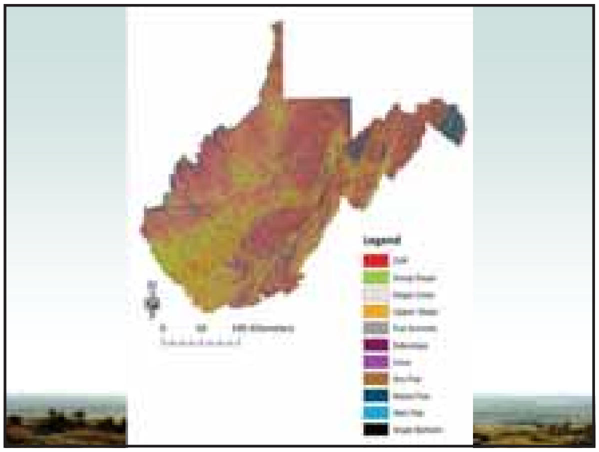




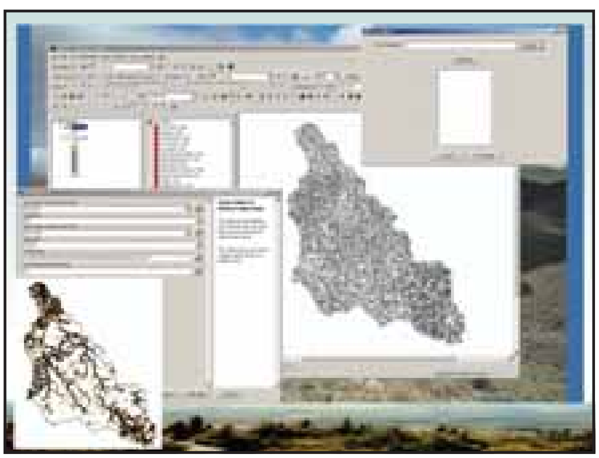
Ecological Land Units

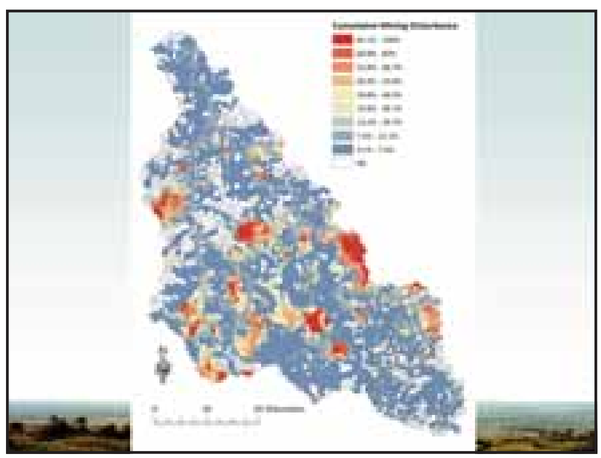
10: Cliff
11: Steep Slope
12: Slope Crest
13: Upper Slope
14: Flat Summit
20: Sideslope
21: Cove
30: Dry Flat
31: Moist Flat
32: Wet Flat
33: Slope Bottom

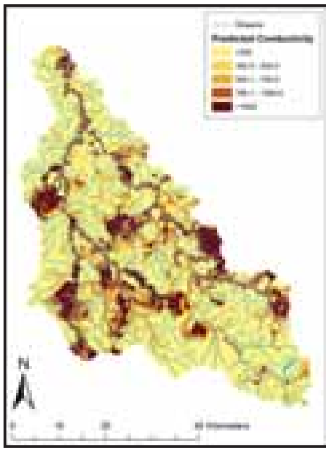




Modeling by 1:24,000 Scale Stream Segments







Current Conditions: Conductivity

Mined sites: $R^2 = 0.84; p < 0.0001$.

	Estimate	R^2
Intercept	3.298	
%SM	1115.97	0.46
NPDES	239.37	0.39

Developed sites: $R^2 = 0.51, p = 0.079$.

	Estimate	R^2
Intercept	115.32	
%SM	1525.07	0.15
200M Structures	4.68	0.13
NPDES	186.21	0.23

Combined sites: R2 = 0.85; $p < 0.0001$

	Estimate	R^2
Intercept	-122.9	
%SM	2028.4	0.76
NPDES	160.3	0.09

•Slide courtesy of Eric Merriam and Dr. Todd Petty

Conclusions