Scenario Analysis and the Watershed Futures Planner: Predicting Future Aquatic Conditions in an Intensively Mined Appalachian Watershed

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ABSTRACT

Scenario analysis is a quantitative process for evaluating potential future conditions of aquatic resources under various development/mitigation scenarios. We have constructed an analytical software package entitled the Watershed Futures Planner (WFP), which integrates data management, statistical and process modeling, results summary and visualization, and decision support into a comprehensive analytical tool. The objectives of this study were to describe our overall scenario analysis approach and apply this approach to questions of mine development and watershed restoration within the Coal River, an intensively mined watershed in the mountaintop removal mining region of West Virginia. Application of theWFP in the Coal River watershed produced the following insights: (1) Additional surface mining in the absence of restorative action will likely produce measurable impacts to water quality and biological condition; (2) The greatest benefits to water quality in the future would most likely come from managing the effects of deep mine effluents. These benefits would be overwhelmed, however, in the absence of improved surface mine reclamation if all currently permitted surface mines were mined out; (3) The greatest benefits to biological conditions would most likely come from managing the effects of residential development. In fact, we predict that substantial benefits to biological conditions could be achieved through mitigation of development impacts even if all of the currently permitted mines are mined out. We conclude that potential impacts from future surface mining are manageable, but only when coupled with strategic mitigation of pre-existing impacts caused by other stressors. Application of our scenario analysis approach throughout the central Appalachian region may be used to identify additional opportunities for watershed scale improvements to aquatic conditions in intensively mined watersheds.

INTRODUCTION

Changes in land cover can affect water quality through alteration of flows and introduction of contaminants. These changes have consequences for aquatic resources at a watershed scale (Allan 2004). For example, clearing of forests and large-scale surface mining in small headwater catchments can influence water quality and biological conditions downstream (Lindberg et al. 2011, Merriam et al. 2011). Likewise, residential development activities can dramatically alter stream flows (Kepner et al. 2012), water quality (Utz et al. 2011), and invertebrate assemblages (King et al. 2011) throughout a watershed.

Because landscape change is a wide-ranging problem throughout the US, analytical tools are needed that allow managers to make informed decisions regarding watershed development, conservation, and restoration. Kepner et al. (2012) argue that in order to contribute to the sustainable management of water resources in actively developing watersheds, scientists must more accurately describe and predict how land use decisions today might impact future aquatic ecosystem conditions.

However, complexities of ecosystem functioning and lack of scientific information at relevant spatial scales make it difficult for aquatic resource managers to understand and predict the potential consequences of present-day land use decisions on future conditions of water resources (Kepner et al. 2012). For example, despite several recent studies examining the direct effects of surface mining on downstream ecosystems, our understanding of how mining interacts with other land use activities to affect aquatic conditions remains weak (but see Petty et al. 2010, Merriam et al. 2011). This is an important problem because individual stressors rarely occur in isolation, and consequently, quantitative measures of stressor interactions are needed to improve our ability to predict future watershed conditions in actively developing watersheds (Seitz et al. 2011, Kepner et al. 2012).

Alternative future scenario analysis (henceforth "scenario analysis") is a quantitative process for evaluating potential future conditions of aquatic resources under a range of watershed development scenarios (Mahmoud et al. 2011, Kepner et al. 2012). Scenario analysis can improve the utility of scientific information and increase the transparency of the decision making process. Consequently, scenario analysis has become recognized as a useful tool for solving highly contentious water resource problems; it can provide a better understanding of how and why an alternative future may evolve and the necessary steps that decision makers are required to take in order to adapt to such a future (Kepner et al. 2012).

The mountaintop removal valley fill (MTR-VF) coal mining province of central Appalachia represents a region in which management decisions surrounding land use and aquatic resources are acute and proper action is imperative. Recent research has identified additive effects of multiple surface mines on downstream aquatic resources (Bernhardt et al. 2012, Lindberg et al. 2012). Furthermore, our own research has identified context dependent effects of coal mining on water quality and biological conditions, where impacts of surface mines often depend on the precise spatial location of mines and the presence and extent of pre-existing stressors, such as other surface mines, deep mines, and residential development (Petty et al. 2010, Merriam et al. 2011, Merriam et al., unpublished manuscript).

In this paper, we demonstrate how scenario analysis can be used to better understand how multiple stressors interact to influence aquatic conditions within an intensively mined central Appalachian watershed. Specifically, the objectives of this study are to: (1) describe our overall scenario analysis approach, including: data sources, statistical modeling, GIS modeling and data management, and final scenario assessment and application; and (2) conduct a scenario analysis of mine development and mitigation within the Coal River watershed in south-central West Virginia. We demonstrate how strategic mitigation decisions, when coupled with mine development decisions, can potentially result in improved watershed scale conditions despite expanding impacts from new mine development.

ALTERNATIVE FUTURES SCENARIO ANALYSIS

Scenario Analysis

Formal scenario analysis is a method of using data and models to predict the effects of alternative management actions. Phases of scenario analysis include: (1) Scenario Definition; (2) Scenario Construction; (3) Scenario Analysis; and (4) Scenario Assessment (Liu et al. 2008; Kepner et al. 2012). During scenario development, analysts determine which driving forces to evaluate, the environmental endpoints to assess, and characteristics that will be used to differentiate among scenarios. Scenario construction consists of the actual modeling of environmental response to alternative landscape changes, and outcomes of scenario projections are compared during scenario analysis. Finally, during scenario assessment, alternative scenario outcomes are presented to stakeholders for discussion and final decision making. It is during this phase that socio-economic and institutional constraints must be considered. The purpose of scenario analysis is to identify priority areas within a watershed for restoration and conservation, as well as to highlight the potential value of development techniques that reduce impacts to aquatic resources.

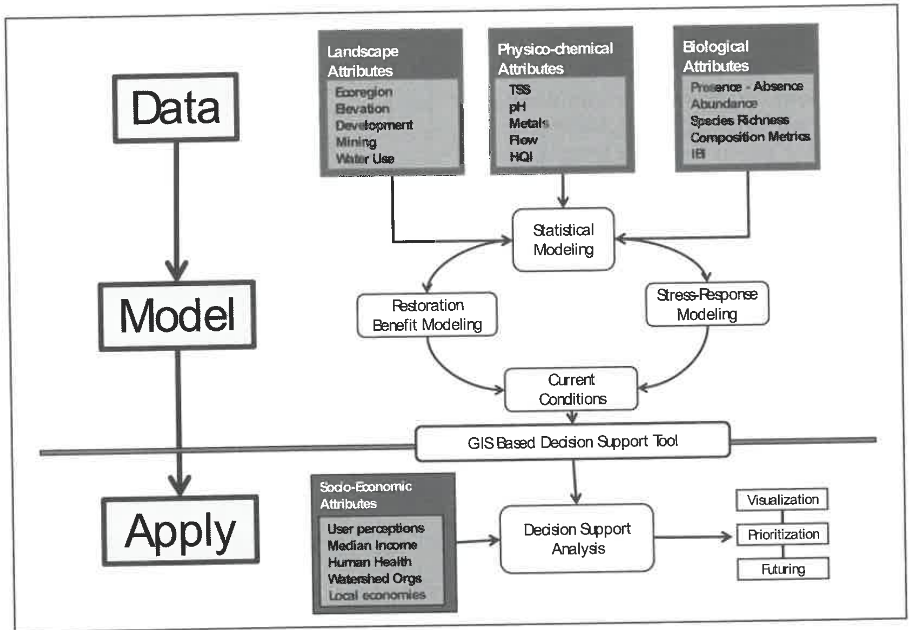

Figure 1. Flow diagram of the overall watershed modeling and scenario analysis process. The Watershed Futures Planner (WFP) is a decision support tool that integrates data, modeling algorithms, mapping tools, and scenario analysis within a GIS-based spatially explicit framework.

Watershed Futures Planner

The Watershed Futures Planner (WFP) is a comprehensive modeling system that our research team has developed over the past ten years as a tool for conducting multi-scale scenario analyses in highly impacted or rapidly developing watersheds (Figure 1) (Petty and Thorne 2005, Strager et al. 2009, 2010, Petty et al. 2010, Merriam et al. 2011). The WFP integrates data along with empirical and process-based models to predict changes in aquatic ecosystem conditions over time that may result from alternative watershed development/restoration scenarios. Outcomes from the WFP are then used by stakeholders to make informed, objective, science-based decisions for watershed restoration and conservation (Figure 1).

The WFP contains a set of analysis tools to enhance decision making for local, state, federal agencies, and stakeholders. The modeling platform integrates spatial data with watershed networks and statistical approaches (Figure 2). Instrumental to the integration is Microsoft .NET architecture with C# utilizing ESRI ArcObjects libraries. The WFP was developed as an independent third party set of software tools that resides on the industry standard GIS proprietary software ESRI ArcGIS Desktop 10.x. The underlying mapping tools in ESRI GIS software with National Hydrography Data allow cumulative watershed calculations. R statistical software was used for performing statistical modeling (e.g., boosted regression trees; BRT) procedures on the GIS watershed data. R software is always evolving and provides a free to use but strong development platform. For the statistical modeling BRT provides a combination of two different algorithms of regression trees (models that relate a response to their predictors by recursive binary splits) and boosting (an adaptive method for combining many simple models to give improved predictive performance). R Scripting language is used to run the BRT models with map libraries for spatial calculations. The integration of the C# .NET watershed models with the statistical package R was performed using an independent execution library rather than functional integration to preserve the integrity of two different languages which helps for future maintenance and updates. This provides limitless options depending on available landscape variables and applicability of boosted regression on the study areas. This modeling platform allows a unique combination of GIS and statistical tools that produce BRT results. The software identifies a set of columns read from a csv file that corresponds with spatial data (GIS Map Attribute table) using Unique ID field to populate resulting data. This data then can be modified using the GIS interface for symbology and other geoprocessing tools.

Data Structure and Modeling Approach

Recent advances in remote sensing and geographic information system (GIS) technologies

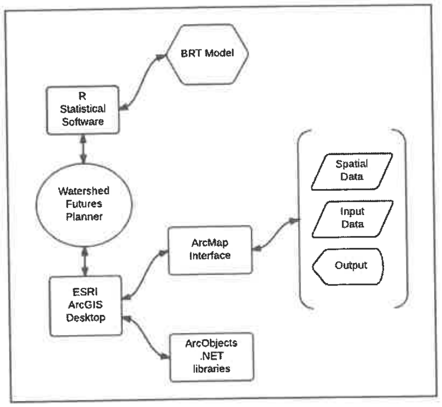

Figure 2. Watershed futures planner software structure

have vastly improved our ability to construct and link high resolution land cover and use data to in-stream conditions (Carlisle et al. 2009). Raster-based land cover and use datasets are typically used to characterize and quantify landscape characteristics upstream of the site of interest. For example, numerous studies have linked degraded aquatic conditions to increases in residential/urban (Utz et al. 2010; King et al. 2011), agricultural (Cuffney et al. 2000; King et al. 2005), and mining-related (Petty et al. 2010; Merriam et al. 2011; Lindberg et al. 2012) land cover. However, ancillary GIS data are often necessary to elucidate cause-effect relationships between land use and altered in-stream condition. Additional anthropogenic features, such as residential and commercial structures (Merriam et al. 2011) and dams (Jones et al. 2001), have been shown to be valuable when modeling and predicting in-stream conditions.

Empirical modeling approaches have proven very effective at modeling in-stream conditions based on statistical relationships with land cover and use data. Studies have related landscape-based indicators to altered in-stream physical and chemical characteristics (Utz et al. 2011), macroinvertebrate (King et al. 2011; Merriam et al. 2011) and fish community structure (Utz et al. 2010), and ecosystem functions (Clapcott et al. 2010).

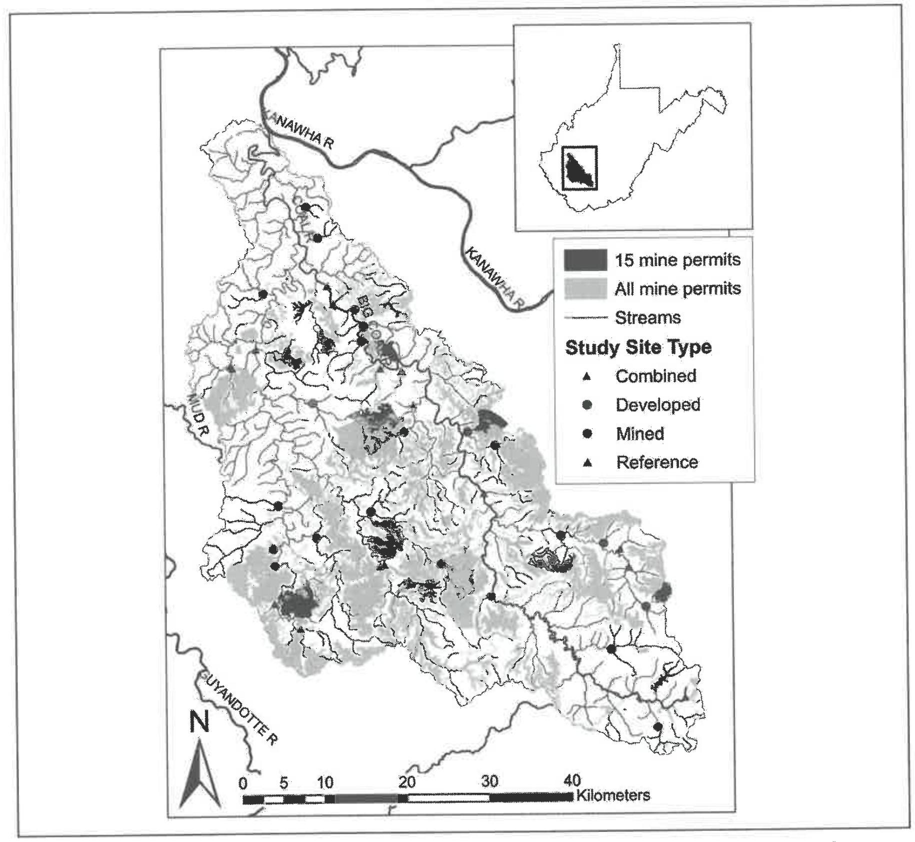

Figure 3. Map of the Coal River watershed illustrated with 1:100,000-scale stream segments, study sites, and surface mining permits. All mine permits and 15 mine permits correspond to alternative future mining scenarios. Stream flow is to the northwest.

Despite these successes, geospatial data have presented statistical problems that complicate traditional linear modeling approaches (i.e., skewed distributions, complex covariance structures, interactions, and nonlinear effects; King et al. 2005). Machine learning techniques, specifically classification and regression tree-based methods (e.g., boosted regression trees; BRT), overcome many of these statistical issues and have been increasingly used to model ecological data sets (Elith et al. 2008; Carlisle et al. 2009). BRT is an extension of classification and regression techniques that attempts to improve model structure and predictive performance by iteratively fitting many simple models from subsets of data and then combining them to offer better estimations of the response (Elith et al. 2008). Moreover, because BRT is a tree-based method, it can handle complicated data (i.e., skewed distributions, non-linearity, and multiple data types) and model complex interactions (Elith et al. 2008; Carlisle et al. 2009).

COAL RIVER SCENARIO ANALYSIS

Study Area

The Coal River is a headwater 8-digit Hydrological Unit Code (HUC) watershed located in south-central West Virginia (WV; Figure 3). The Coal River drains approximately 2307 km^2 and flows northwest until its confluence with the Kanawha River. The study basin is approximately 80% forested. Developed and mining-related cover classes represent the dominant land uses within the study region. Steep topography confines development to narrow floodplains, while coal mining is focused along ridgelines and headwater catchments. Surface mining land use comprises 9% of the total watershed area, and there are >425 underground mine NPDES permits. The low S content of the coal and calcareous nature of surrounding strata result in alkaline mine drainage typified by increased pH, alkalinity, ionic strength (SO_4^{2-}, Ca^{2+} $Mg^{2+}$and HCO^{3-}), and trace elements (Mn and Se; Pond et al. 2008; Lindberg et al. 2011).

Methods

We quantified local (i.e., for individual stream segments) and cumulative landscape (i.e., all upstream land area) characteristics for all 1:24,000 segment-level watersheds (SLWs) within the Coal River basin (Strager et al. 2009; Merriam et al. 2011). We used spatial analysis functions in ArcView 3.3 (Environmental Systems Research Institute, Redlands, California) in conjunction with flow tables developed by the West Virginia Resources Analysis Center to calculate cumulative measures of all landscape attributes (Strager et al. 2009).

We used 2009 and 2010 National Agriculture Imagery Program (NAIP) orthophotography to map land cover for the study area. NAIP orthophotography was obtained from the Aerial Photography Field Office of the Farm Service Agency and has a 1 meter pixel resolution at a scale of 1:10,000. We used the Feature Analyst software (VLS 2004) to differentiate between open water, forest, grassland/pasture, and barren. We then used the mining-permit boundaries layer developed by the West Virginia Department of Environmental Protection (WVDEP) to differentiate mining-related open water (i.e., slurry impoundments), barren (i.e., active mine lands) and grasslands (i.e., reclaimed mine lands) from non-mining open water, barren (i.e., residential impervious surfaces) and grasslands. We manually digitized valley fill faces and kept their areal extent separate from other reclaimed mine lands. We used national pollution discharge elimination system (NPDES) data obtained from the WVDEP to calculate the cumulative density of all NPDES permits (#/km^2). We also calculated underground mine NPDES permit density to represent deep mine influence. We used the 2003 Statewide Addressing and Mapping Board structures layer in conjunction with information on public service districts to calculate the density of serviced (i.e., connected to public sewage system) and un-serviced residential and commercial structures (#/km^2). We calculated road density (km/km^2) using data created by US Census Bureau, Geography Division. We also calculated the cumulative percentage of coal belonging to the Allegheny and Kanawha formations. Geology data were created by the WV Geological and Economic Survey.

We selected 40 segment-level watersheds as study sites within the Coal River watershed (Figure 3) across a range of influence from residential development and mining (Figure 4). Eleven sites made up a distinct residential gradient (structure density: 5–76 structures/km^2) and had <2% surface mining. Eleven sites were part of a mining gradient (surface mining: 7 to 64%) and a structure density <2 structures/km^2 (Figure 4). We included 2 reference sites with minimal mining and development (<2% surface mining and <2 structures/km^2) (Figure 4) to represent the best possible conditions within the study area and anchor each gradient. The remaining 16 sites, referred to as combined sites, were affected by a combination of residential development and coal mining (Figure 4). Drainage areas ranged from 1–36 km^2, with similar averages among mined, developed, and combined sites (12.5, 12.9, and 11.3 km^2, respectively). All sites were selected to be independent of one another and not linked by flow.

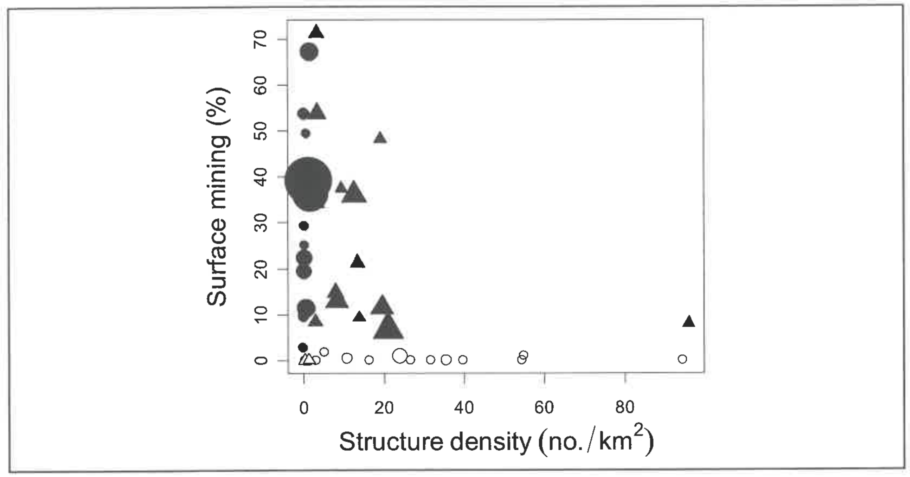

Figure 4. Magnitude of mining and residential development for study sites. Closed circles = mined; open circles = developed; closed triangles = combined; open triangles = reference. Symbol size = # deep mine NPDES permits, with increasing size corresponding to an increasing number of permits.

We visually assessed physical-habitat quality at each site with US Environmental Protection Agency (EPA) rapid visual habitat assessments (RVHA; Barbour et al. 1999). Habitat was assessed during normal baseflow conditions from July 15 to August 15, 2011. We delineated reach lengths as 40× mean stream width, with minimum and maximum reach lengths of 150 and 300 m, respectively. We took water samples during the summer of 2010 (August 9–27). Instantaneous measures of temperature (°C), pH, specific conductance (µS/cm), and dissolved O_2 (mg/L) were obtained with a YSI 650 equipped with a 600XL sonde (Yellow Springs Instruments, Yellow Springs, Ohio) calibrated prior to each sampling date. We collected a 250-mL filtered sample from each site with a Nalgene filtration unit (mixed cellulose ester membrane filter, 0.45-µm pore size). The filtered sample was fixed with nitric acid to a pH <2 and analyzed for Al, Ba, Ca, Cd, Cr, Fe, Mg, Mn, Na, Ni, Se, Zn, and K. We also collected 2 unfiltered samples from each site. The first was fixed with sulfuric acid to a pH <2 and analyzed for NO_3 and NO_2, and total P. The second was analyzed for total and bicarbonate alkalinity, Cl, SO_4, and total dissolved solids. We stored samples at 4°C until analyses were completed at Research Environmental & Industrial Consultants, Inc., Beaver, WV. EPA standard methods were used for all analyses. We took duplicate samples from 10% (n = 4) of sites. One field blank was obtained on each sampling date.

We sampled benthic macroinvertebrate communities during the summer of 2010 (August 9–27) following procedures established by WV Department of Environmental Protection (WVDEP) Watershed Assessment Program and the USEPA Rapid Bioassessment Protocols for wadeable streams (Barbour et al. 1999; WVDEP 2009). We obtained kick samples (net dimensions 335 × 508 mm with 500-µm mesh) from 4 riffles at each site. We combined organisms and debris from the 4 kick samples into a single composite sample for each site and preserved samples in 95% ethanol. In the laboratory, macroinvertebrates from combined kick samples were subsampled using the 200-count method described by WVDEP (2009). Individuals were enumerated and identified to genus with keys in Merritt and Cummins (2008). We used two benthic macroinvertebrate multimetric indices (MMI) to assess ecological condition at each site. The West Virginia Stream Condition Index (WVSCI; Gerritsen et al. 2000) is a family-level index applied statewide within a single index period. The Genus Level Index of Most Probable Stream Status (GLIMPSS; Pond et al. 2012) is a genus-level index calibrated by region and season. We used GLIMPSS (CF), a version of GLIMPSS not requiring genus-level identification of individuals within the taxa Chironomidae and Oligochaeta. Both WVSCI and GLIMPSS are scored on a scale of 0–100, with scores <68 and <54 being categorized as impaired, respectively. Duplicate samples were obtained and identified from 10% (n = 4) of sites.

Boosted Regression Tree Models

We constructed boosted regression tree (BRT) models to predict current physical (RVHA), chemical (conductivity, TDS, and Se) and biological (WVSCI and GLIMPSS) conditions at the watershed scale. Optimal models were identified by altering tree complexity (number of splits within each tree and degree of interaction; *tc*) and learning rate (contribution of each tree to the growing model; *lr*). A tree complexity of 1 (no interaction among predictor variables) was chosen for all models because predictive performance did not improve with increased depth. Bag fraction (proportion of data randomly selected for each tree) was set at 0.75. We removed redundant variables (r > 0.90) and variables with minimal variation among study sites. We constructed global models with all remaining variables and quantified their relative influences using an out of bag procedure. We assessed predictive performance by calculating mean model deviance (and standard error) and cross- validated (CV) predictive deviance (and standard error) from 10 folds of the data. We then simplified global models using scree plots of predictor relative influences. Simplified models were retained if their CV predictive deviance was better than or equal to that of the global model. We created partial dependency plots to show effects of the 3 most important variables for select models. BRT models were fitted using code provided by Elith et al. (2008).

Alternative Future Scenarios

We used final BRT models to predict current chemical (specific conductance) and biological (GLIMPSS) conditions for all SLWs. We then selected actual surface mine permits from the WVDEP permit boundary dataset to developed 2 future mining scenarios. The first scenario consisted of 15 permits distributed throughout the study basin (Figure 3). The second scenario consisted of all permits (Figure 3). We updated the current landscape for each scenario by converting all land area within the permit boundaries to reclaimed mine land, removing all intersecting vector features, and re-accumulating landscape attributes for all SLWs within the study basin. We also simulated management opportunities under each scenario. We simulated advanced materials handling techniques (i.e., decreased downstream impacts from mines of equivalent size) for new mines by iteratively decreasing the effect size of future surface mines under each scenario by 25, 50, 75, and 100%. In other words, a 100 acre mine constructed with advanced reclamation techniques would be equivalent to a 75, 50, 25, and 0 acre mine constructed with current techniques. We also simulated mitigation of deep mine and development-related impacts by iteratively decreasing their effect size. We compared the length of stream exceeding accepted criteria for specific conductance (500 µS/cm; Pond et al. 2008) and GLIMPSS (54; Pond et al. 2012) for each scenario.

Results

Landscape features associated with residential development were the dominant predictors of RVHA (Table 1, Figure 5). Conversely, surface mining-related land use was the dominant predictor of Se (Table 1). Selenium exhibited sharp increases at low levels of surface mining activity (Figure 5). Specific conductance was strongly influenced by surface mining, deep mining, and development-related land-use (Table 1, Figure 5).

Table 1. Boosted regression tree results for RVHA, specific conductance (SpC), selenium, GLIMPSS, and WVSCI*

	RVHA	ln SpC	ln Selenium	GLIMPSS	WVSCI
# Trees	2150	3300	3750	2800	9850
Learning rate	0.001	0.005	0.001	0.005	0.001
Total Deviance	145.75	0.73	1.77	179.75	134.45
Residual Deviance	99.91	0.06	0.35	24.38	26.80
Variance Explained	31%	92%	80%	86%	80%
CV Deviance (se)	141.11 (18.89)	0.18 (0.06)	0.76 (0.16)	82.47 (14.64)	66.10 (11.29)
CV Deviance Explained	3%	75%	57%	54%	51%
Surface mining land cover variables					
Cumulative reclaimed mine land (%)	.	31.7	19.8	.	.
Cumulative% barren mine land (%)	.	9.1	26.1	.	.
Cumulative% valley fills (%)	.	12.6	43.7	.	.
Underground mining landscape variables					
Cumulative underground mine NPDES permit density (#/km^2)	.	13.0	.	.	.
Human development land cover and use variables					
Cumulative serviced structure density (#/km^2)	11.4	.	.	9.4	.
Cumulative unserviced structure density (#/km^2)	.	.	.	.	.
Cumulative road density (km/km^2)	.	.	.	5.6	14.4
Cumulative grassland and pasture (%)	38.6	14.8	.	21.2	20.0
Cumulative NPDES permit density (#/km^2)	.	.	.	8.2	18.0
Local serviced structure density (#/km^2)	24.0	.	.	4.6	.
Local grassland and pasture (%)	.	.	.	10.8	.
Local barren and developed land cover (%)	.	.	.	9.2	14.8
Natural landscape variables					
Cumulative forest (%)	26.0	18.8	.	31.0	32.8
Local forest (%)	.	.	5.1	.	.
Cumulative Allegheny group coal outcrop (%)	.	.	5.3	.	.

* Relative influences (%) of variables are presented. See methods for description of model statistics. NPDES = national pollution discharge elimination system; ln = natural log transformation.

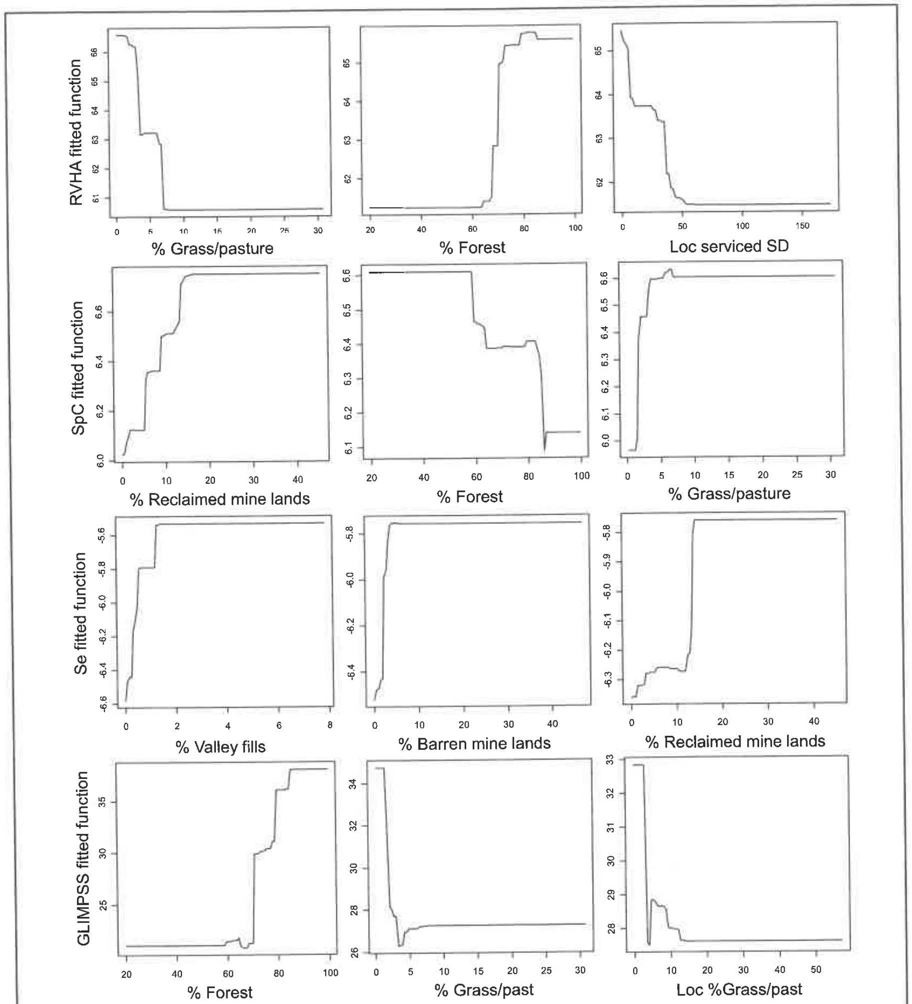

Figure 5. Fitted functional response curves for RVHA, specific conductance, selenium, and GLIMPSS to the three most influential variables in each respective BRT model. Fitted functions represent the marginal response to a given predictor variable, holding all others constant.

Landscape features associated with human development were the strongest predictors of WVSCI and GLIMPSS (Table 1 and Figure 5). BRT explained >80% of the total variation in chemical and biological data (Table 1). Cross validation indicated that models predicting chemical endpoints (57–75% of CV predictive deviance explained) were more certain than those predicting biological condition (51–54%) and habitat quality (3%).

BRT models predicted 1125 km (33%) and 3379 km (98%) of stream as currently exceeding

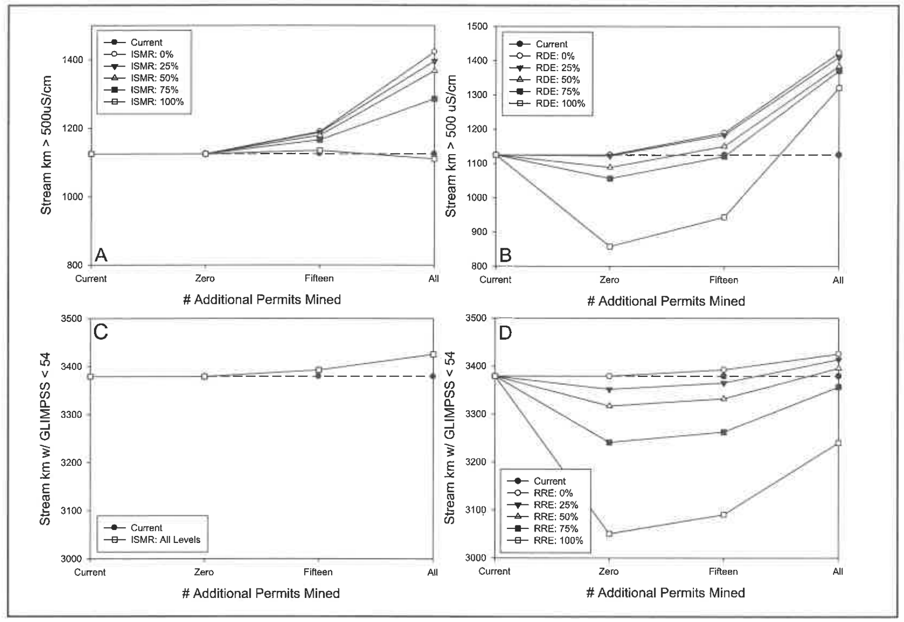

Figure 6. Predicted specific conductance (A and B) and GLIMPSS (C and D) in response to three alternative future mining scenarios (Zero = zero additional surface mining; Fifteen = 15 permit future scenario; All = all permit future scenario) and mitigation activities (ISMR = Increased surface mine reclamation; RDE = reduced deep mine effluents; RRE = Reduced residential effect). Conditions under each scenario are shown relative to conditions under current surface mining, deep mining, and residential land use (Current). Total stream length is 3449 km.

established criteria for specific conductance and GLIMPSS, respectively (Figure 6A, C). In the absence of any mitigation activity, additional mining under the 15 permit scenario resulted in an additional 66 (2%) and 7 km (0.2%) of stream exceeding specific conductance and GLIMPSS criteria, respectively. When all permits were simulated as mined, an additional 299 (9%) and 18 km (0.5%) of stream exceeded specific conductance and GLIMPSS criteria, respectively (Figure 6A, C). Improved surface mine reclamation had no effect on GLIMPSS (Figure 6C). Improved surface mine reclamation practices decreased the length chemically impaired streams under the 15 (0.3–5% of stream length) and all permit (2–22%) scenarios as compared to equal mining under current practices; however, improvement above current conditions did not occur at the watershed-scale (Figure 6A). All levels of decreased deep mine effluent in the current landscape resulted in watershed-scale improvements in the length of stream exceeding 500 µS/cm (0.1–8% of total watershed stream length; Figure 6B). In the 15 mine future scenario, decreasing the effect of deep mining by 75 and 100% resulted in watershed-scale improvements in specific conductance (0.1 and 5% of total watershed stream length, respectively; Figure 6B, Figure 7). The number of streams exceeding 500 µS/cm increased when all permits were mined, regardless of the level of reduced deep mining (Figure 6B). All simulated reductions in residential effect size resulted in watershed-scale improvements in GLIMPSS under both the current (0.8–10% of total watershed stream length) and 15 permit scenario (0.4–8% of total

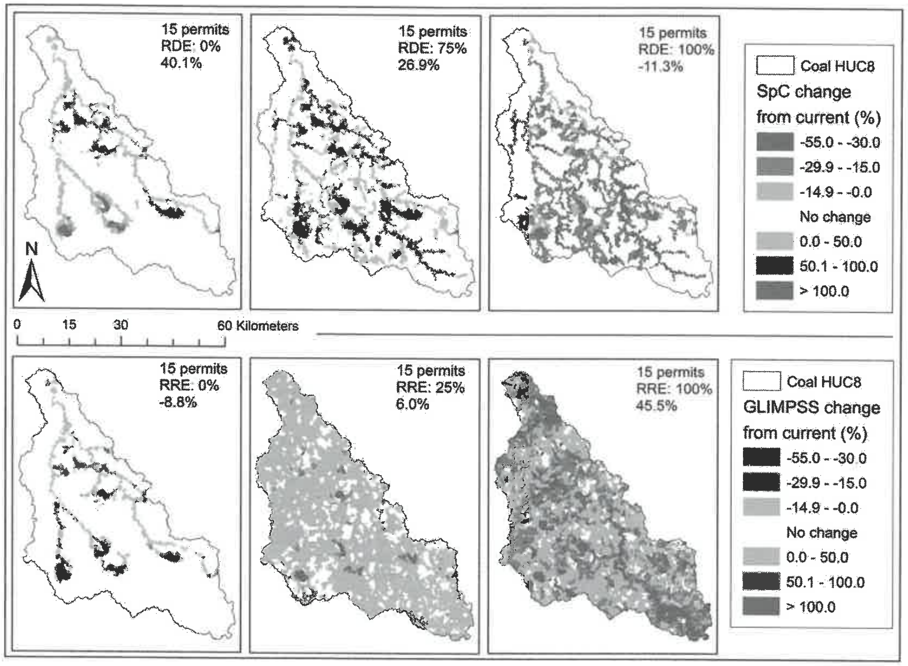

Figure 7. Predicted specific conductance under current landscape conditions (A) and a simulated 100% reduction in deep mine effects (RDME; B) for all mapped stream segments. Predicted GLIMPSS under current landscape conditions (C) and a simulated 100% reduction in residential effect (RRE; D) for all mapped stream segments.

watershed stream length) landscapes (Figure 6D, Figure 7). We predicted watershed-scale improvements in GLIMPSS following simulated mine out of all permits with a 75 (0.6% total watershed stream length) and 100% (4% total watershed stream length) reduction in development-related impacts (Figure 6D).

CONCLUSIONS

Scenario analysis coupled with predictive modeling provides an effective way to facilitate the decision making process on highly contentious issues, such as MTR-VF mining. When conducted properly, scenario analysis is transparent and science-based and provides an objective platform for constructive discussion (Kepner et al. 2012). Scenario analysis also provides a straightforward way for scientists to transfer complex information to stakeholders from a variety of backgrounds. However, the value of scenario analysis often is limited by the quality of underlying datasets and models. If data are flawed, then there may be considerable uncertainty in the modeling output. If modeling approaches are weak, then modeling outputs may be unreliable. In many applications, data on aquatic conditions and landscape characteristics may be highly confounded. For example, when aquatic conditions are affected by multiple stressors and the multiple stressors co-vary within the dataset, then it may be impossible to determine the effects of each stressor independently (King et al. 2005).

In this paper, we present the results of a scenario analysis designed to facilitate decisions within the MTR-VF mining region of West Virginia. There are several aspects of this research

that we believe make it a valuable addition to the current debates regarding how best to manage mining impacts. First, stream sampling was designed to minimize the confounding effects of multiple stressors. We know from previous research that surface mining is only one of several possible sources of stress in this region. Other known stressors include deep mining effluents, urban runoff from residential development, and untreated wastewater (Petty et al. 2010, Merriam et al. 2011). We attempted to avoid a confounded dataset by sampling along independent stressor axes as well as within streams affected by multiple stressors simultaneously. Second, models linking landscape characteristics to aquatic conditions were based on landscape data derived from time appropriate aerial photography. Most previous studies are based on stream data collected across many years and landscape data derived from aerial photos that may come several years before or several years after stream sampling. We avoided this problem by analyzing aerial photography from 2009–2010 and linking it to stream data collected in summers of 2010 and 2011. Third, Boosted Regression Trees (BRT) represents the state-of-the-art approach for linking landscape attributes to in-stream conditions. BRT allows for co-varying predictor variables, incorporates interactive effects of multiple stressors, and produces highly precise estimates of stream conditions at the stream segment scale (Elith et al. 2008, Carlisle et al. 2009). Finally, integration of landscape change and BRT modeling within a GIS platform (i.e., the Watershed Futures Planner) enables us to run multiple complex scenarios and produce easily interpreted, visual, and spatially explicit results.

So, what are we able to learn from the scenario analysis of mining in the Coal River watershed? (1) There currently is an extremely high degree of water quality and biological impacts to streams resulting from pre-existing surface mining, deep mining, and residential development. Nearly 1200 km of streams have a conductivity that exceeds a 500 µS/cm benchmark, and nearly 3400 km of streams have a biological condition that is below a critical threshold. (2) Additional surface mining in the absence of restorative action will likely produce measurable additional impacts to water quality and biological condition. Expected response to mining is especially pronounced for specific conductance. Expected negative response of biological condition is relatively low, but only because current conditions are so poor. (3) The greatest benefits to water quality in the future would come from managing the effects of deep mine effluents. These benefits would be overwhelmed, however, in the absence of improved surface mine reclamation if all currently permitted surface mines were mined out. (4) The greatest benefits to biological conditions would come from managing the effects of residential development. In fact, we predict that substantial benefits to biological conditions could be achieved through mitigation of development impacts even if all of the currently permitted mines are mined out. However, full mitigation of development impacts is unlikely. Consequently, improved conditions in the future will require both mitigation and minimization of future mining impacts. (5) Potential impacts from future surface mining are manageable, but only when coupled with strategic mitigation of pre-existing impacts caused by other stressors.

There were several limitations with our analysis that should be addressed. First, we were unable to externally validate the models underlying our scenario analysis. However, internal cross validation procedures underlying the BRT process suggested our models are successfully predicting in-stream chemical and biological conditions. Although these results are specific to the Coal River watershed, it is a continued goal of our research program to construct and validate landscape-based models of in-stream conditions for the entire MTR-VF region. Moreover, the results of our models are consistent with other studies relating land use changes to altered specific conductance (Merriam et al. 2011), selenium (Lindberg et al. 2011), and biological condition (Merriam et al. 2011) in complex mined landscapes. Another limitation of our analysis was the treatment of simulated mitigation and reclamation activities. Iteratively and uniformly decreasing the effect size of surface mining, deep mining, and residential development does not reflect specific practices associated with potential mitigation of anthropogenic activities, such as providing centralized wastewater services to currently under serviced residences. Thus, it is unknown whether actual mitigation and reclamation efforts would result in stream responses similar to those predicted in our analysis. Despite the broad treatment of mitigation and restoration, our scenario analysis successfully identified management needs within the Coal River watershed and provides a framework for studies in other watersheds.

Scenario analysis represents an important step in the management process, but it is not a conclusive step. In order to make progress on recovery in the Coal River watershed, more specific restoration and mitigation plans that target deep mine effluents and stream impacts from poor residential development will be needed. In addition, the Coal River is but a single watershed within a highly impacted region. Scenario analyses for other watersheds will be needed in order to meet water quality management goals for the region.

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