Spatial Decision Support for Assessing Impacts of Atmospheric Sulfur Deposition on Aquatic Ecosystems in the Southern Appalachian Region[1]

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Abstract

We present foundational work on the use of niche modeling to predict continuous surfaces of acid neutralizing capacity (ANC) and base cation weathering (BC_w) within the southern Appalachian Mountain Region of the United States. Predicted ANC and BC_w surfaces are subsequently used to estimate steady-state critical loads (CLs) of atmospheric sulfur deposition. We then present a logic-based model for assessing aquatic environmental effects of sulfur deposition throughout the region based on modeled stream ANC and CL exceedance, and demonstrate application of the logic model in a spatial decision-support system, presenting mapped model results for Great Smoky Mountain National Park. Whereas CLs were uniformly high within the Park area, degree of aquatic impact within watersheds was strongly associated with increasing elevation. The niche and spatial decision support modeling approaches are readily customized for other regions of interest.

1. Introduction

The U.S. Environmental Protection Agency (U.S. EPA) and federal land management agencies are concerned with the current and future health of aquatic ecosystems within the southern Appalachian Mountains. Ecosystem sensitivity to acidification and the potential effects of atmospheric sulfur (S) deposition on surface water quality have been well studied in this region [1,2,3,4,5]. The main sources of atmospherically deposited S are coal-fired electricity generation facilities and industrial air pollution. Sulfur is the primary determinant of precipitation acidity and sulfate (SO_4^{2-}) is the dominant anion associated with acidic streams throughout the southern Appalachian Mountains region [4]. Although a substantial proportion of atmospherically deposited S is retained in watershed soils, sulfate concentration in many mountain streams has increased as a consequence of acidic deposition [6].

Streamwater acid neutralizing capacity (ANC) is a measure that reflects the ability of a watershed to neutralize acidic inputs. As the rate of acidic deposition increases, streamwater ANC can decrease in proportion to the natural re-supply of base cations (BCs) from soils. Lowered ANC reduces stream pH and mobilizes inorganic aluminum (Al) from watershed soils to streams. Both increased hydrogen ion (H^+) and Al concentrations have been shown to be directly toxic to fish, including brook trout (*Salvelinus fontinalis*) [7]. Various ANC thresholds are known associates with biological effects [8], for example, brook trout are sensitive to concentrations below 50 $\mu eq \cdot L^{-1}$, but aquatic insects they feed on are sensitive to concentrations below 100 $\mu eq \cdot L^{-1}$. In general, moderate effects on macroinvertebrate and fish species richness have been associated with ANC concentrations between ~50 and 100 $\mu eq \cdot L^{-1}$ [9, 10]. More substantial effects have been observed at ANC concentrations < 50 $\mu eq \cdot L^{-1}$ [8,9,10].

In this effort, the *critical load* (CL) is the level of atmospheric S deposition above which sensitive ecosystem components are harmed, according to current scientific understanding [11]. Atmospheric S deposition above the CL is termed *exceedance*. CLs of S are often estimated to protect stream resources relative to an ANC threshold that is associated with biological effects.

An important *a priori* consideration when estimating CLs and evaluating impacts to biodiversity is that soils within this region are often derived from parent material that is low in base cations [12]. As a result, many streams draining these watersheds exhibited low-ANC prior to the industrial revolution. It is therefore unreasonable to generate CLs and evaluate effects on species richness using an ANC threshold that cannot be reached in a given stream, even in the absence of anthropogenic sources of S deposition. For this reason, we estimate CLs and overall aquatic ecosystem effects based on ANC thresholds of 50 and 100 $\mu eq \cdot L^{-1}$.

In the following sections, we summarize foundational niche modeling work to predict continuous ANC (in $\mu eq \cdot L^{-1}$) and base cation weathering (BC_w, in $meq \cdot m^{-2} \cdot yr^{-1}$) surfaces within the southern Appalachian Mountains region of the U.S. [13]. ANC is the aquatic chemistry variable that best reflects in-stream acid-base chemistry, stream sensitivity to acidification, and effects of acidity. We use process-model based estimates of BC_w at well-studied stream sites throughout the region, together with other variables representing stream chemistry and watershed characteristics, to generate continuous BC_w surfaces. These values are used with regional estimates of atmospheric BC and S deposition, BC uptake into vegetation, stream discharge, and ANC critical threshold values, to calculate steady-state S CLs and exceedance. We assess aquatic environmental effects of atmospheric S deposition throughout the study region using modeled ANC and CL exceedance in a logic-based model using the Ecosystem Management Decision-Support (EMDS) system [14]. We conclude with discussion of how the EMDS system could be extended to include practical logistical and other considerations for deriving strategic priorities for protection and restoration activities in landscape elements of the southern Appalachian Mountains region.

2. Materials and methods

2.1. Study area

The study area spans a broad geographical extent, covering the southern Appalachian Mountains region from northern Georgia to southern Pennsylvania and from eastern Kentucky and Tennessee to central Virginia and western North Carolina (Fig. 1). The region is primarily composed of the Blue Ridge, Ridge and Valley, and Central Appalachian physiographic provinces (Fig. 1), but also includes small portions of the Northern Piedmont, Piedmont, and Western Allegheny Plateau provinces [8, 15].

2.2. Data for niche modeling

Hessburg et al. [13] provide a thorough accounting of the data, methods, and results of the niche modeling effort. Here, we briefly summarize that work and describe how the results were incorporated into an EMDS logic model.

Data on stream water chemistry were supplied from several national and regional databases, including the National Stream Survey, Environmental Monitoring and Assessment Program, Virginia Trout Stream Sensitivity Study (VTSSS), and others [4, 5, 6]. A total of 933 stream ANC sites (Fig. 1) were included in the analyses described here. Water-chemistry data were

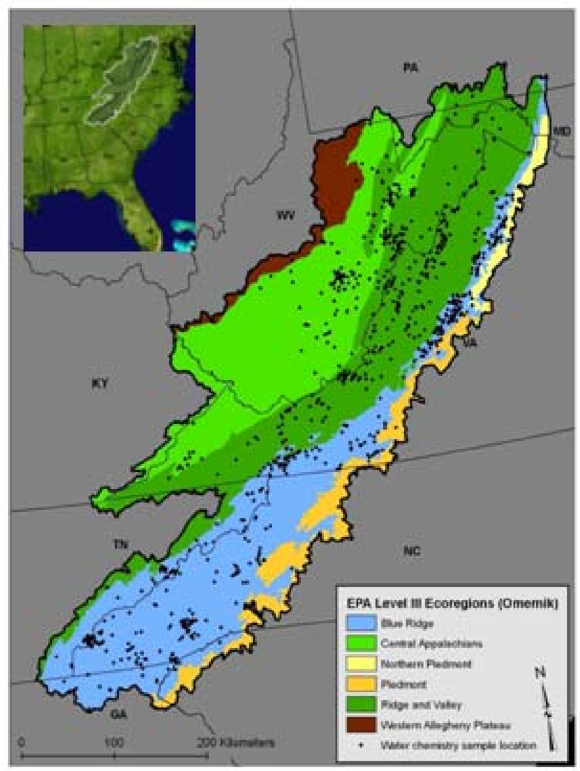

Fig. 1. Study area location and provinces [15].

collected in spring samples between 1986 and 2009. ANC was calculated as the equivalent sum of the base cation concentrations (Ca^{2+}, Mg^{2+}, K^+, Na^+, NH_4^+,) minus the sum of the mineral acid anion concentrations (Cl^-, NO_3^-, SO_4^{2-}). Values for calculated ANC ranged from -109 to 3,889 $\mu eq \cdot L^{-1}$, with a mean of 188.1 ± 414 (SD) $\mu eq \cdot L^{-1}$, and a median of 71.8 $\mu eq \cdot L^{-1}$.

BC_w was estimated with the MAGIC (Model of Acidification of Groundwater Catchments) model for 140 of the 933 sampled water-chemistry sites. MAGIC determines BC_w based on model calibrations which are constrained by measured soil and stream-water chemistry [16]. Previous methods to regionalize MAGIC estimates of BC_w throughout the southern Appalachian Mountains in Virginia and West Virginia are described by McDonnell et al. [17]. A 30m digital elevation model (DEM) was used to create a synthetic stream network from which all ANC sample points were georeferenced within a geographic information system (GIS).

A broad suite of initial predictor variables was chosen to represent potential broad- to fine-scale climatic, lithologic, topo-edaphic, vegetative, land ownership, and sulfur deposition forcing influence on ANC and BC_w. Due to the nature of the hydrologic data used in the study [3], we hypothesized that the influences of predictor variables were proximally and distally important to the sample sites. Consequently, values of predictors from the area contributing to each 30m grid cell were upslope averaged within the study domain, based on methodology described in McDonnell et al. [17]. This process also provided a method for predicting BC_w to all grid cells within the study domain.

Climate and soil variables were developed by Hargrove and Hoffman [18]. Climate variables included both growing season and non-growing season climatic features at 1km resolution. The National Land Cover Dataset [19] was used to quantify the percent aerial cover of major vegetation cover classes. Those used in the current study included the percent cover of coniferous forest, hardwood forest, and all forest types combined. Two additional classes were used that combined mixed coniferous and hardwood forest by weighted average.

Soil data were obtained from the Soil Survey Geographic (SSURGO) and the U.S. General Soil Map (STATSGO2) databases. Soil variables included percent clay, soil pH, and soil depth. A five class lithologic classification was used to quantify percent composition of different parent materials across the study domain, based on Sullivan et al. [10]. Identified lithologic classes included siliceous, argillic, felsic, mafic, and carbonate substrates. Mapped surface lithologies were compiled as a composite of state geologic maps (≤ 1:500,000 resolution) provided by the Eastern Mineral Resources Team of the U.S. Geological Survey (USGS).

Total wet + dry S deposition was calculated based on three-year averages of interpolated wet [20] and modeled dry [21] deposition estimates for 2002. Total S deposition was processed with the continuous upslope averaging function.

Three topographic variables were derived directly from the 30m DEM: 1) a topographic wetness index (TWI), represented the propensity of each grid cell to accumulate water, and was defined as the ratio of the upslope contributing area and slope steepness; 2) the surface area ratio (SAR) represented terrain roughness and was computed as the ratio of the sloped surface area of a grid cell divided by the surface area of a flat grid cell; and 3) the flow accumulation area (FAC) was calculated as the total catchment area contributing discharge to each grid cell. Both TWI and SAR were subsequently upslope averaged.

2.3. Niche modeling to predict ANC and BC_w

2.3.1. Predicting ANC. Objectives for ANC predictive modeling were to develop and validate statistical models that best explained observed ANC and BC_w values across the study region. In side-by-side exploratory modeling studies [13], we compared the statistical performance of ordinary least-squares (OLS), logistic regression (logR), geographically-weighted regression (GWR), classification and regression tree (CART), boosted classification-regression tree methods (BCT/BRT) and randomForest (RF) methods. The OLS and logR methods suffered from well-known model overfitting to the data, and RF modeling generally out-performed the remaining methods when considering up to six statistical performance metrics (misclassification rate, Kappa statistic, G-mean, area under the receiver operating curve (AUC), root-mean squared error (RMSE), and model R^2). Hence, we employed RF modeling techniques in subsequent work.

Gatekeeper models [22] are commonly used with ecological and biological count data where zero values dominate the observed data distribution. Gatekeeper models use a two-stage approach. In the first stage, a binomial model predicts a threshold based on a suite of predictor variables, beyond which a defined condition is satisfied. Where satisfied, observations are entered into a zero-truncated Poisson model. In the current study, we used a modeling approach which combined a threshold model to preselect locations that were well buffered (high ANC), and a continuous model that modeled continuous ANC values of the remaining low-ANC sites.

For each 30m grid cell of the study domain (Fig. 1), the predictor variables were entered into the gatekeeper modeling framework. The threshold model predicted the probability that the grid cell had a low ANC value. If the resultant probability value was less than a specified threshold (e.g., 0.5), then the grid cell was considered well-buffered and assigned an arbitrarily large ANC value. If the probability of encountering a low ANC value for a particular grid cell was greater than or equal to the specified threshold, the environmental data (section 2.2) for that grid cell were entered into the continuous model.

There were several steps to building the gatekeeper model for ANC prediction. First, individual components of the modeling framework were assessed. The threshold and continuous models were trained separately to identify the best performing model types. After reducing multi-collinearity, the suite of predictor variables was reduced to the most parsimonious set. Once the best performing predictor set was identified, we built 48 gatekeeper models varying by: (1) the threshold ANC value used to differentiate low from high ANC (150, 200, 250, 300 $\mu eq \cdot L^{-1}$), (2) the probability used to determine low-ANC group membership (0.4, 0.5, 0.6, 0.7), and (3) data resampling to eliminate skewness (i.e., intentionally undersampling low-ANC, oversampling high ANC, or maintaining the imbalanced sample). Gatekeeper model performance was then assessed by identifying the model(s) with the lowest misclassification and RMSE values.

Threshold and continuous models were first trained using a portion of the 933 total ANC sites, and then validated, using the remainder of the ANC data. During model training, we identified the most influential environmental predictors, and evaluated model performance and parsimony to determine the best model. The resulting best model was used to make predictions across the study domain.

RF is an adaptation of CART analysis that uses an ensemble of regression or classification trees to produce robust model predictions. Each individual tree within the ensemble is developed using different subsamples of the data and predictor variables. RF is well adapted to modeling non-linear relationships and does not suffer from some of the known limitations of traditional CART or logistic regression, such as over-fitting.

2.3.2 Predicting BC_w rates. BC_w rates were estimated for 140 of the 933 ANC sites using the MAGIC model [16]. Due to the small sample size and less skewed data distribution, gatekeeper modeling was not used for this analysis. Instead, a continuous RF model was developed.

Model evaluation was accomplished using out-of-bag estimates of model performance rather than on an independent test set. Out-of-bag samples are the data left out of the development of an individual regression tree within the RF algorithm. Once the entire RF model is developed, the out-of-bag samples are entered back into each tree of the ensemble, new predictions are made from the out-of-bag samples, and validation statistics are calculated (error-rate and RMSE). These model statistics are informative when model validation proceeds in lieu of an independent test dataset, but should still be taken as a liberal estimate of model performance. Model performance was evaluated to balance parsimony with prediction.

2.4. Watershed delineation, calculation of S critical loads and exceedances

Watersheds were delineated based on hydrologically conditioned digital elevation model derivatives from NHDPlus [23]. The minimum contributing area required to generate a headwater watershed was set to a threshold value of 0.5 km^2. Watersheds were delineated according to topographically determined flow routes and stream junctions. We delineated a total of 140,504 watersheds with an average size of approximately 1 km^2.

Sulfur critical loads for each topographically determined watershed were calculated with the Steady-State Water Chemistry model (SSWC) [24]. Model inputs for atmospheric base cation deposition, base cation uptake into vegetation, and the protective ANC flux were calculated in the manner described in [17]. Inputs for BC_w were generated using three different approaches, including: values extracted from the process-based model (MAGIC) calibrations and two sets of statistical predictions using RF (as described above), one based on available water chemistry plus landscape characteristics (n=933) and the other based only on landscape characteristics (n=140,504).

Critical load exceedance was determined by subtracting contemporary estimates of S deposition from the calculated S critical loads. Locations where S deposition was greater than the critical load were considered to be in exceedance. S deposition was determined from CMAQ (Community Multi-scale Air Quality) model estimates of dry atmospheric deposition (12 km) [21] and NADP (National Atmospheric Deposition Program) interpolations of wet atmospheric deposition (375 m) [20].

2.5. Logic to interpret aquatic impacts of S deposition

The first four levels of the logic for assessing aquatic impact of S deposition at a watershed scale are illustrated in Fig. 2. The logic model was implemented with the NetWeaver® (Rules of Thumb, Inc., North East, PA, [25])[2] logic-based modeling system.

Overall *aquatic impact* was assessed in terms of S-deposition *exceedance* and *biological response* with the union (U) operator, indicating that these two premises of *aquatic impact* are being treated as cumulative effects. The first two levels of the logic can be read as “The conclusion that *aquatic impact* is low is true to the degree that its premises (*exceedance* and *biological response*) evaluate as low." *Biological response* also functions as a conclusion with its own sets of premises, but with the premises in this case being combined with the AND operator, indicating that the premises of *biological response* are treated as limiting factors.

With the exception of *fish presence*, topics at the end of each logic path (Fig. 2) represent elementary networks that read and process data, and then interpret results against fuzzy membership functions that return a metric expressing strength of evidence (or degree of support) for a conclusion [25]. For example, the *exceedance* topic computes the ratio of S deposition to

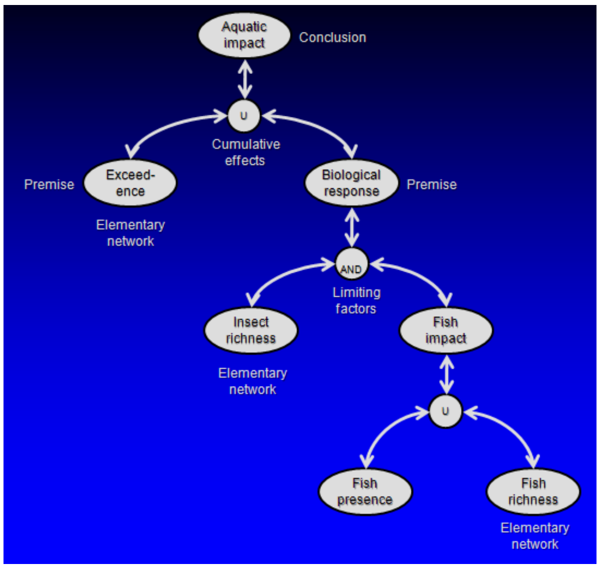

Fig. 2. Logic to assess S impacts. Ovals indicate logic topics, each of which evaluates a proposition. Circles indicate logic operators. See text in section 2.5 for a full explanation of the figure.

the S critical load calculated for a watershed, and then compares the ratio to a fuzzy membership function to test the proposition that the ratio is low (Table 1). As explained in section 2.4, any particular watershed could have up to three associated measures of BC_w: a measure provided by MAGIC, and two measures derived from niche modeling, one based on measured water chemistry plus landscape characteristics and one based on landscape characteristics only. For each watershed, the computation of critical load first tested for the presence of BC_w values from MAGIC and water chemistry (predicted values from niche modeling based only on landscape characteristics were always present), and, when these values were present in the database, they were entered into the computation of a weighted average value for BC_w.

Data inputs for insect richness and fish richness were computed as [9]:

$$\text{insect (EPT) richness} = 13.785 + 0.0241 \cdot ANC - 0.00005 \cdot ANC^2 \quad (1)$$

$$\text{fish richness} = 2.0812 + 0.0598 \cdot ANC - 0.0001 \cdot ANC^2 \quad (2)$$

respectively, and compared to fuzzy membership functions (Table 1) to determine the extent to these premises were satisfied.

Certain computational features were implemented in the logic to facilitate sensitivity analysis and exploration of alternative scenarios. First, with respect to sensitivity analysis, fuzzy membership functions for

Table 1.Thresholds defining fuzzy membership functions for data evaluated by elementary logic topics.

Logic topic	Metric evaluated	Full support	No support
Exceedance	Ratio[a]	1.0	2.0
EPT richness	Proportion of insect families[b]	1.0	0.9
Fish richness	Proportion of fish species[c]	1.0	0.5
Brook Trout presence	Likelihood of presence	1.0	0.5
Sensitive fish presence	Likelihood of presence	1.0	0.5

[a]Ratio of S deposition to S critical load.
[b]Ratio of number of insect families at the predicted ANC to number of families expected at ANC = 100 $\mu eq \cdot L^{-1}$ (see eq 1).
[c]Ratio of number of fish species at the predicted ANC to number of species predicted at ANC = 100 $\mu eq \cdot L^{-1}$ (see eq 2).

evaluating logic topics (Table 1) were not fully specified in NetWeaver. Although the values for full support were hard coded as constants directly into NetWeaver, the values for no support were defined as data inputs to be read from database tables at runtime. Thus, parameters defining fuzzy membership functions are only completed at runtime, and system users can alter database fields, as explained subsequently, to test model sensitivity to parameter choices. In the context of scenario analysis, the calculation of exceedance values requires a specific critical ANC criterion value as a reference condition, which is also supplied from a database table at runtime. Similarly, we designed a scaling factor into the computation of exceedance which can be used to assess the policy implications of reduced sulfur emissions in terms of ecological and biological consequences and their relation to future regulatory standards.

In our original logic design, the topic *fish presence* evaluates two different levels of fish sensitivity. One is based on the relatively insensitive brook trout; another is based on more sensitive species, including various species of dace, darter, and sculpin (Table 1). The model contains placeholders to add additional species as dose/response data become available.

2.6. Spatial decision support with EMDS

EMDS [14] is a modeling building system that is useful for integrating environmental analysis and planning. EMDS provides decision support for landscape level analyses through logic and decision engines integrated with the ArcGIS® (versions 9.2 and 9.3) geographic information system (GIS, Environmental Systems Research Institute, Redlands, CA). Within EMDS, the NetWeaver logic engine evaluates landscape data against a logic model designed in NetWeaver to derive logic based interpretations of complex ecosystem conditions, such as aquatic impacts associated with acidic deposition. A decision engine can then evaluate outcomes from the logic model, along with other feasibility and efficacy data related to potential treatment actions, against a decision model for prioritizing landscape treatment units, built within its development system, Criterium DecisionPlus® (CDP, InfoHarvest, Seattle, WA). CDP models implement the Analytical Hierarchy Process [AHP, 26] and the Simple Multi-Attribute Rating Technique [SMART, 27]. The AHP and SMART utilities allow application developers to clearly reflect their decision criteria, relative weightings among criteria, and to calibrate overall decision-making processes.

The logic model (Fig. 2) was executed in EMDS to provide a spatial assessment of *aquatic impact* for the full extent of the study area (Fig. 1). However, the study area contains >140,000 watersheds, which are far too many to clearly display in the space provided. Consequently, we present representative results for Great Smoky Mountains National Park in NC and TN, an area of significant interest.

As explained in section 2.4, watershed attribute data were associated to a watershed feature class defined on the study domain. Parameters needed to define fuzzy membership functions as well as ANC and deposition scenarios (section 2.5) were stored in a 1-record feature class spanning the spatial extent of the study domain. Within EMDS, one or more layers may participate in the creation of a study area. The present study exemplifies a fairly typical case in which three feature classes participate in the process: 1) a layer of administrative units, one or more features of which define the spatial extent of the study area (e.g., Great Smoky Mountain National Park) and identify features from the other two layers that need to participate in the assessment, 2) a layer that is the primary object of study (e.g., the watersheds), and 3) a layer that contains parameters needed to define fuzzy membership functions and conditions for scenarios (e.g., the ANC reference condition, or adjusted S deposition rate).

3. Results

3.1. Niche modeling

Comparison of the three threshold models tested in our study indicated that boosted classification tree and RF classification models performed similarly well, whereas logistic regression models consistently underperformed relative to the first two methods.

An objective of niche model building was to balance model parsimony with performance. We chose to include 10 predictor variables in the threshold model, because model performance quickly decreased when fewer than 10 variables were used, and there was little additional improved performance with more than 10 variables, based on RMSE [13]. Top predictors included percent carbonaceous lithology, soil pH, number of droughty days, percent public land, and mean 95% maximum growing season temperature difference, among others.

Validation results for continuous models were similar to those for the threshold model, where RF and boosted classification trees performed well compared to the ordinary least squares model. RMSE values ranged from 36.9-45.1, and R-squared values ranged from 0.4-0.6. RF was chosen for the continuous model. Consistent with the threshold model, ten predictor variables were used in the final continuous model. Top predictor variables in the continuous model were the percentage area in siliceous lithologies, the number of days without precipitation, the amount of dry sulfur deposition, number of droughty days, growing season length, the percent of conifer canopy cover, and soil percent-clay and pH, among others.

We compared validation statistics among all 48 combinations of (1) data rebalancing methods, (2) ANC cutoff values below which sites were considered low ANC, and (3) probability cutoff values resulting from the threshold model. To minimize the number of instances in which a potentially low ANC site was erroneously excluded from the continuous model, we used two evaluation statistics when comparing model performance: the misclassification rate for identifying low ANC sites as well-buffered from the threshold model, and the RMSE from the continuous model. . Both metrics together were used to assess model goodness-of-fit to the testing dataset.

The best performing model (Fig. 3) included the following parameterization: RF model approach for the

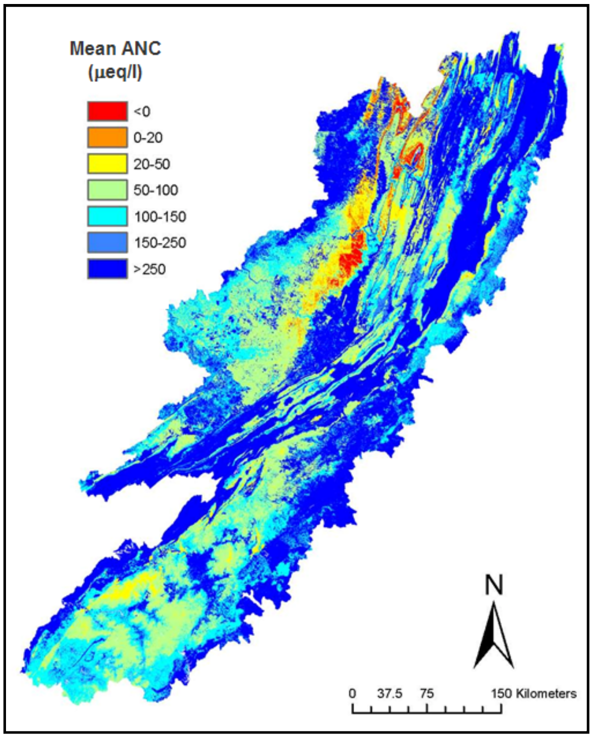

Fig. 3. Mean ANC from 1000 regression trees used to derive the random forest model.

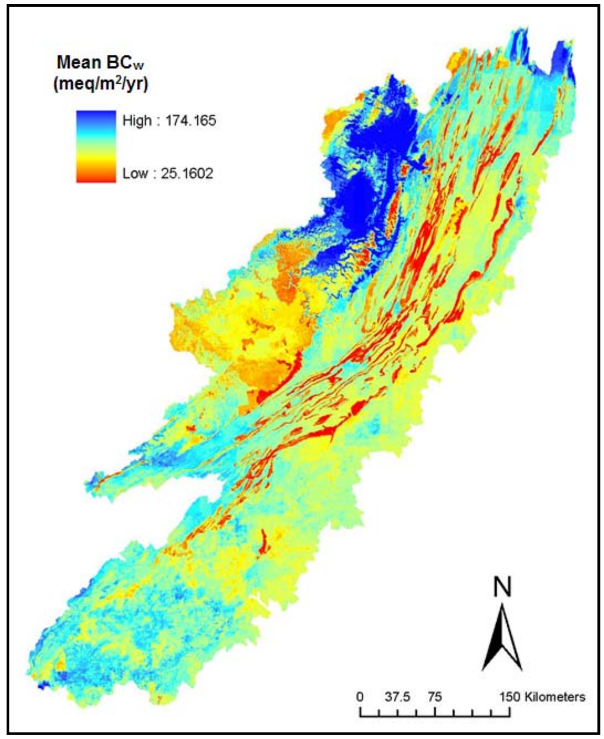

Fig. 4. Mean BC_w from 1000 regression trees used to derive the random forest model.

threshold and continuous models, imbalanced data, 0.7 probability to enter the continuous model, and a 300 $\mu eq \cdot L^{-1}$ ANC threshold. This model had a 5.6% error rate for misclassification of low ANC sites as high, a 9.5% overall error-rate of classification, and a RMSE of 107.5 $\mu eq \cdot L^{-1}$, based on 50 model iterations.

In the case of BC_w, model performance was similar when 33 to 10 variables were used in modeling; below this, model performance quickly decreased. Out-of-bag RMSE of prediction and R-squared values were 31.5 $meq \cdot m^{-2} \cdot yr^{-1}$, and 0.45, respectively, based on 50 model iterations. The plot of model predictions *versus* observed data indicated that the model performed well, particularly for observed BC_w values below 150 $meq \cdot m^{-2} \cdot yr^{-1}$. Above this value there were relatively few data points to inform the model, which led to poor performance at values above 150 $meq \cdot m^{-2} \cdot yr^{-1}$. The predicted continuous BC_w model in shown in Fig. 4.

3.2. Aquatic impacts of sulfur deposition

Mapped outputs from the logic model (Fig. 5) parallel the original logic structure (Fig. 2). Each map is symbolized in terms of evidence for low impact. A simple way to interpret the maps is that dark blue indicates a good condition (evidence of low impact), while dark red indicates a poor condition (evidence of high impact).

The figure (Fig. 5) displays overall results for the scenario in which the reference ANC for computing *exceedance* has been set to 50 $\mu eq \cdot L^{-1}$. Within Great Smoky Mountains National Park, S critical load *exceedance* is uniformly high, commonly near or above an exceedance ratio (ambient S deposition ÷ S critical load) of 2 (Table 1) even when the ANC reference condition is set to 50 $\mu eq \cdot L^{-1}$. We omit the scenario for an ANC reference of 100 $\mu eq \cdot L^{-1}$ because most of the figure components remain the same, and the resulting changes in *exceedance* and *aquatic impact* are limited to the outer Park fringes. We emphasize, however, that this result is not typical of the full study domain (Fig.1).

Responses in evidence values for *insect richness* and *fish impact* demonstrate much greater heterogeneity compared to that for CL exceedance, with increasing impact generally associated with increasing elevation.

The niche modeling approach used to predict ANC (Fig. 3) and BC_w (Fig. 4) also generates estimates of the standard deviations (SD) of BC_w (Fig. 6) and ANC (Fig. 7), which are plotted against *biological response* and *exceedance*, respectively. Recall that both *insect richness* and *fish richness* (eqs 1 and 2, respectively) are computed as functions of ANC, so the SD of ANC provides useful insight into the predictability of *biological impact*. In particular, note that when biological impact is predicted to be high, the SD of ANC is generally low and conversely (Fig. 6).

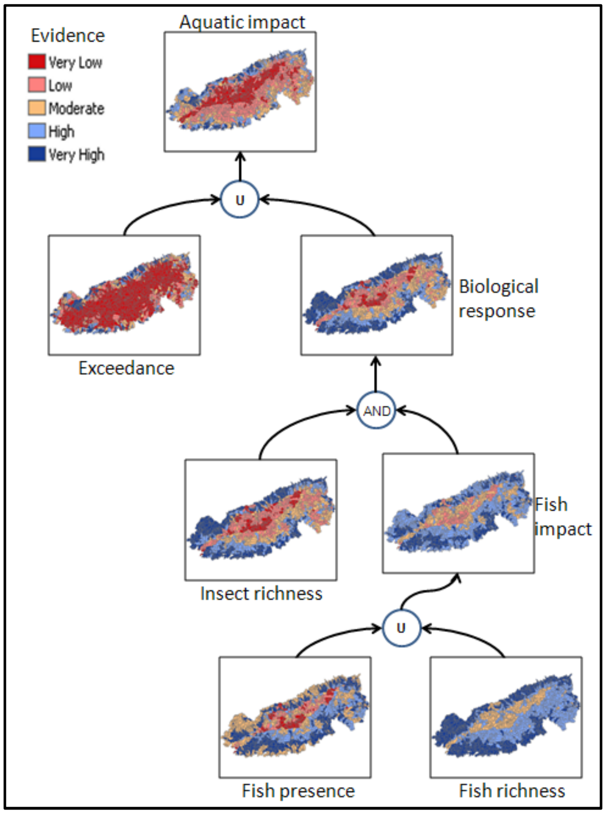

Fig. 5. Aquatic impacts of sulfur deposition in the Great Smoky Mountain National Park, expressed as evidence of low impact.

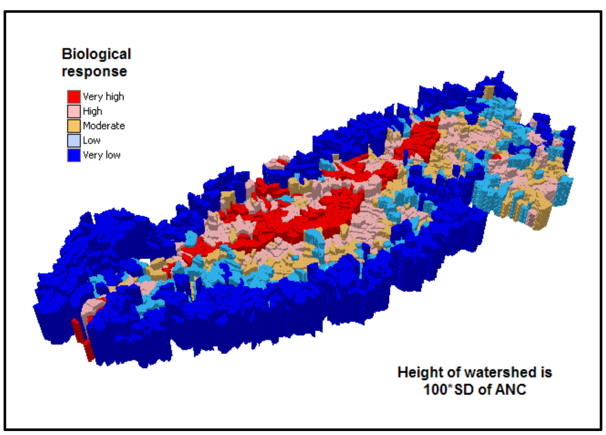

Fig. 6. Standard deviation of predicted ANC in relation to spatial evaluation of biological impact.

The relationship between the SD of BC_w and high exceedance is analogous (Fig. 7). However, in this case, the figure only provides a partial explanation, because BC_w, though it may be the most important term, is only one of five terms that go into the calculation of critical load. Unfortunately, error estimates for other terms in the critical load calculation are not readily available.

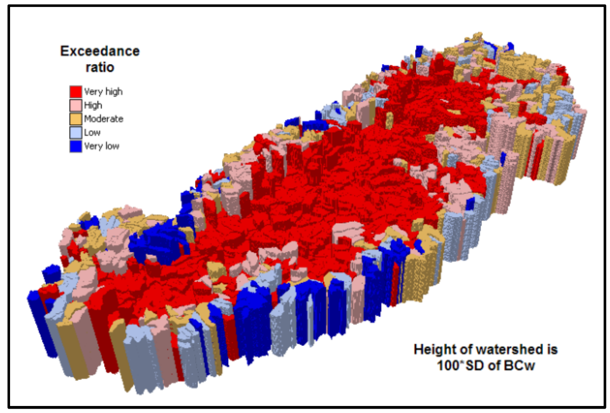

Fig. 7. Standard deviation of predicted BC_w in relation to spatial evaluation of exceedance.

4. Discussion

The study reported here provides a logic-based interpretation and synthesis of data related to aquatic impacts associated with S deposition in the southern Appalachian Mountains region. The four unique elementary topics (Fig. 2) combine two contrasting perspectives: *exceedance* represents both a potential regulatory and a long-term impact perspective; *insect richness*, *fish richness*, and *fish presence* represent shorter term perspectives on more or less current biological responses of major ecosystem components. The overall model of *aquatic impact* is a synthesis of these contrasting perspectives.

In any study of *aquatic impacts* associated with S deposition, logic-based map products (Fig. 5) provide synoptic views of the spatial assessment, in which the logic processing steps leading to the final synthesis can be communicated in an intuitive way. The EMDS system also implements a more surgical approach (not presented here), in which a user can drill into the derivation of model results for individual spatial features via a graphic interface to the logic engine. This latter capability is useful for verifying model behavior in the developmental stages of a project.

Due to space limitations, we have not presented modeling results related to sensitivity or scenario analysis. However, we emphasize that the implementation of the logic was designed with these capabilities in mind. For example, users of this model can perform model sensitivity analysis by testing the influence of changing the parameter values used to define fuzzy membership functions, or they can evaluate effects of alternative scenarios for reducing S emissions, or assess S critical loads based on alternative critical ANC criterion reference conditions.

Finally, in describing EMDS (section 2.6), we alluded to decision models as optional components of EMDS applications. Although a decision model has yet to be designed for the current application, we conclude by considering how such a model can usefully extend the current application with additional functionality.

Logic and decision models in EMDS are intended to complement one another. A logic model focuses on the state of the system, whereas a decision model focuses on what can be done about the state of the system. Logistical issues are not pertinent to the first part, but they are important to the second. An important consequence of separating the overall modeling problem into two complementary models is that each model is rendered conceptually simpler. The logic model evaluates the status of the topics under evaluation, in our case, *aquatic impact* of S deposition (Fig. 2). The decision model considers the status of *aquatic impact* of each watershed, but can also place it in a management context that further informs decision-making, considering, for example, practical issues of the feasibility and efficacy of management choices associated with selecting specific watersheds for protection and restoration.

5. End notes

[1]This research was funded by the U.S. Environmental Protection Agency under interagency agreement DW-12-92250101-0.

[2]The use of trade or firm names in this publication is for reader information and does not imply endorsement by the U.S. Department of Agriculture of any product or service.

6. References

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