Assessment of Regional Forest Health and Stream and Soil Chemistry Using a Multi-Scale Approach and New Methods of Remote Sensing Interpretation in the Catskill Mountains of New York

Final Report 10-28
December 2010

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Assessment of Regional Forest Health and Stream and Soil Chemistry Using a Multi-Scale Approach and New Methods of Remote Sensing Interpretation in the Catskill Mountains of New York

Final Report

Prepared for the

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NOTICE

ABSTRACT AND KEYWORDS

The overall goal of this project has been the development of forest health and sensitivity indicators and baseline maps of potential sensitivity to disturbance for lands within watersheds of the NYC water supply in the Catskill Mountains of New York. The methodologies and data layers created in this effort can now be used to aid management decisions and help determine the extent and magnitude of terrestrial and aquatic responses to acidic deposition. The data products derived from this effort have been produced and documented in such a manner that stakeholders can now use these products for site evaluation as well as to perform more extensive analysis on the suite of readily available geographic information system (GIS) and image-based data products.

The value of a spatially explicit dataset such as this one lies in the ability to test a wide variety of hypotheses or ask specific management related questions of the data and have the answer mapped across 700,000 acres in the Catskills. In this report we take a case study approach to illustrate this flexibility. We discuss three case studies that ask questions ranging from the highly practical *"Where is sugar maple most susceptible to decline?"*; to *"Can we predict and map a key streamwater acidification index without sampling a stream?"*; and finally we create a theoretical index of *"ecosystem health"* using streamwater, soil, and foliar chemistry, forest stress, and nitrogen deposition. Ultimately we hope to see this tool deployed on the web, allowing land managers and scientists to design their own queries based upon criteria and thresholds that are important to them.

The project will facilitate future assessments of forest condition and the creation of more detailed forest sensitivity maps to be made at reduced expense.

Keywords: Nitrogen, calcium, remote sensing, AVIRIS, stream water, nitrogen deposition, foliar chemistry, species classification.

ACKNOWLEDGMENTS

We wish to acknowledge a number of collaborators who have served on this research team. Jennifer Pontius, Lucie Lepine, Jason Siemion, Mary Martin and Pete Murdoch were involved in many aspects of this project, ranging from field sampling to the development of GIS and image data products. Numerous field crewmembers who collected field data over several seasons. Robert Green of the Jet Propulsion Laboratory for the acquisition of AVIRIS data through the NASA funding of the EO-1 Science Validation Team.

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Section 1

INTRODUCTION

The overall goal of this project has been to develop forest stress and sensitivity indicators and "baseline maps of potential sensitivity to disturbance for lands within watersheds of the NYC water supply in the Catskill Mountains of New York (Figure 1). The methodologies and data layers created in this effort can now be used to aid management decisions and help determine the extent and magnitude of terrestrial and aquatic responses to acidic deposition.

The data products derived from this effort have been produced and documented in such a manner that stakeholders can now use these products for site evaluation as well as to perform more extensive analysis on the suite of GIS and image-based data products. The project will allow future assessments of forest condition and more detailed forest sensitivity maps to be made at reduced expense.

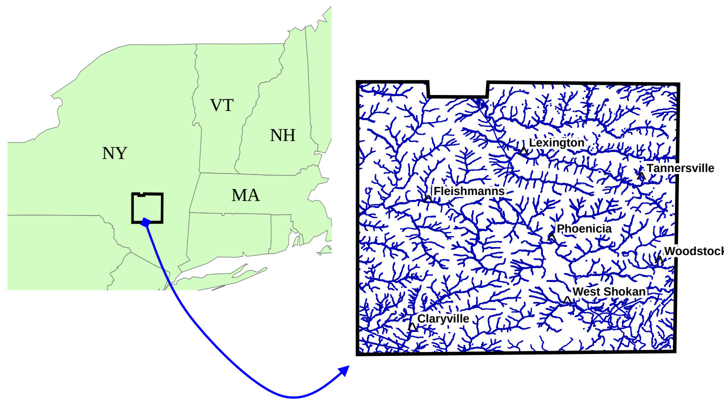

Figure 1. 687,000 acre study area in the Catskill Mountains.

Collaboration between the US Geological Survey (USGS) and the US Forest Service (USFS) has linked field and remote sensing data to produce maps of forest, soil, and surface-water condition in the Catskill Mountain region of New York State. The resulting GIS database highlights forest stands and watersheds sensitive to changes in atmospheric deposition and land use in the Catskill Mountain region. During this collaboration, the USGS and USFS have expanded their capabilities for the development of remote-sensing methods for forest cover and condition making it possible to use the current data analysis as a baseline in assessing future changes in forest health (tree decline) throughout this region at a more detailed resolution than possible through field assessments. The results presented here begin to show the patterns of landscape sensitivity to disturbance (e.g. acid deposition, insect defoliation, logging) within the region, as well as the spatial variability in potential forest and surface water response to decreased or increased levels of acidic deposition and disturbance for the Catskill watersheds.

Ultimately the real value of this project lies in the layering of spatially explicit data, covering a large portion of the Catskills, focusing on important parts of the forested ecosystem and the capability for land managers, environmental conservation groups and scientists to design and ask their own questions, include or exclude variables and set thresholds based on interests and/or expertise. In this report we present a set of static results based upon our own assumptions and questions designed to show the flexibility and utility of this data set.

Section 2

DATA LAYER CREATION

This section discusses the status/quality of the deliverable GIS and image data products. The deliverable data discussed below are provided as spatially explicit data coverages in either raster grid files or vector point/line/polygon files, bundled into a single ARC Project (Table 1) using ArcGIS, Version 9.0 (Environmental Systems Research Institute, Inc., Redlands, CA). These files have been documented with Federal Geographic Data Committee (FGDC) style metadata files, which contain more information on data source/processing/availability than the summary below. These metadata files are attached to the relevant raster and/or vector data coverages in the accompanying ARC Project. In addition to the delivery of these data in the ARC Project format, coverages can be made available via ftp, or a web mapping interface, as well as Web Mapping Service (WMS), which allows for viewing through non-GIS interfaces (i.e. GoogleEarth). The ARC Project suite of data allows for continued analysis and investigation, however we anticipate that there may be an interest in viewing and/or downloading individual components, which can be done through our current web mapping capabilities. Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) imagery is not included with this report, but is a non-proprietary data product which we are free to redistribute to interested parties. We do not include the AVIRIS data here, since data requirements may differ by user. Nevertheless, we can provide the data on request. Contact information for data requests are included in the metadata files.

Table 1. Data layers derived for this project.

Layer	Source	Notes
	Forest Canopy	
Foliar Ca	Derived from AVIRIS imagery	
Foliar N	Derived from AVIRIS imagery	
Forest Health	Derived from Landsat imagery	
Red Oak	Derived from AVIRIS imagery	Percent basal area
Hemlock	Derived from AVIRIS imagery	Percent basal area
Sugar Maple	Derived from AVIRIS imagery	Percent basal area
	Streams	
ANC	Interpolated from sample points	
Base Cation Surplus	Interpolated from sample points	
Ca	Interpolated from sample points	
Mg	Interpolated from sample points	
Nitrate	Interpolated from sample points	
pH	Interpolated from sample points	
DOC	Interpolated from sample points	
	Soils	
Base Saturation	Inerpolated from sample pits	
Available Ca	Inerpolated from sample pits	
Available Mg	Inerpolated from sample pits	
pH	Inerpolated from sample pits	

REMOTE SENSING DATA

An AVIRIS scene collected in 2001 over 300,000 ha of the Catskill region was used as the primary hyperspectral dataset in this project. The AVIRIS 2001 scene was collected during an Earth Observing-1 (EO-1) Hyperion Science Validation campaign, at which time we also collected extensive foliar chemistry data. The data from this earlier study were processed further to allow us to develop a better and more extensive foliar chemistry image product for this project. For each pixel in the AVIRIS imagery, we were able to estimate percent foliar nitrogen (N(%)) and parts per million Calcium (Ca) (ppm), using a partial least square regression calibration relating field measured foliar chemistry to AVIRIS reflectance spectra (Martin et al., 2008; Smith et al., 2003). Details on the pre-processing of the AVIRIS data (calibration, atmospheric correction, georegistration), and image calibration equations and statistics are contained in the metadata file. Calibration statistics are shown in Table 2, and Figures 2 and 3 are the resulting foliar N and Ca maps.

Table 2. AVIRIS Calibration for canopy-level foliar chemistry.

	Number	Mean (stdev)	Math Treatment	SEC	R^2	SECV	1-VR
Nitrogen	41	2.225 (0.265)	1,2,1,1	0.057	0.954	0.185	0.525
Calcium	40	6136 (2168)	1,2,2,1	886	0.833	1944	0.217

Statistics on dataset composition and results of partial least square regression calibration. Math treatment is specified as [derivative, gap, smooth, smooth], where derivative is the difference between bands separated by the specified gap, with the resulting spectra being the slope of the reflectance spectra. The standard error of calibration (SEC), coefficient of determination (R2), standard error of cross-validation (SECV) and 1-VR (1 minus the ratio of unexplained variance to total variance) are used to characterize equation performance. Cross validation is the prediction on samples not included in the calibration through an iterative leave-one-out, or jackknife technique.

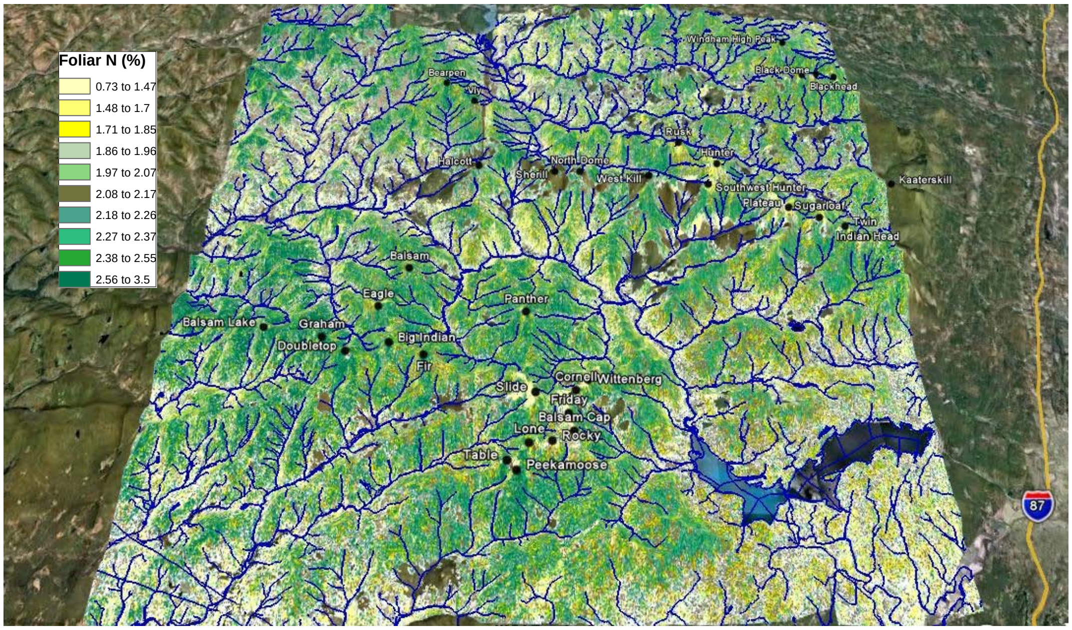

Figure 2. Derived map of Foliar N (%) in the forest canopy. Gaps in the coverage are either non-forested areas or areas where clouds obscured the ground when the imagery was collected.

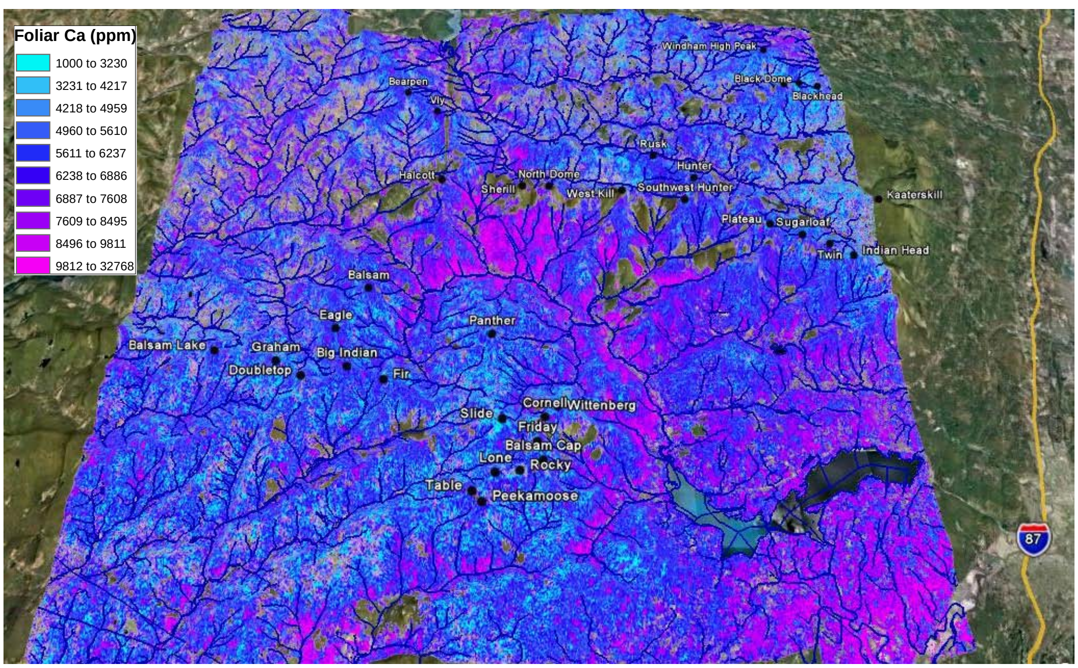

Figure 3. Map of derived foliar Ca (ppm) in the forest canopy. Gaps in the coverage are either non-forested areas or areas where clouds obscured the ground when the imagery was collected.

GROUND CALIBRATION DATA

Table 3. Forest Stress Classes

0-1	Perfect Health
2	Healthy
3	Pre-Visual Decline
4	Early Decline
5	Early/Moderate Decline
6	Moderate Decline
7	Moderate/Severe Decline
8	Severe Decline
9	Death Imminent
10	Dead

During the 2006 and 2007 field season, we established and sampled a network of field plots throughout the Catskills region. These plots were located on New York Department of Environmental Protection (NYDEP) and New York Department of Environmental Conservation (NYDEC) property, and were selected to cover a range of species, health, and site conditions. In addition to basic plot characteristics (plot location, tree positions, basal area), plot health was assessed by common vegetation stress symptoms, including vigor class, transparency, dieback and live crown ratio, as well as incipient stress indicators such as chlorophyll fluorescence indices. All of these field measured variables were normalized by quantiles and averaged to produce the one summary forest stress value predicted in these images (Table 3). For more detail on field sampling methods, see Pontius et al. (2005; 2008).

MAPPING VEGETATION STRESS

Based on an evaluation of available image data for the production of a Catskills-wide forest stress map, we decided to use a Landsat image that was more temporally coincident with our field health measurements than the AVIRIS imagery. Landsat 5 Thematic Mapper (TM), level 1T orthorectified imagery from July 16, 2006 was ordered from the USGS (http://edc.usgs.gov/products/satellite/tm.html) for path 14 row 21, covering the entire study area (Figure 1). The Level 1T Landsat product includes radiometric, geographic and topographic corrections. No further processing was done on this imagery prior to the development of the calibration.

To determine the best spectral indices to determine stress, we created a database calculating a Landsat equivalent to all of the known narrow-band indices that have a known sensitivity to vegetation stress. If for example, the chlorophyll b sensitive index proposed by Datt (1998) calls for (R672nm / R550nm), we calculate a broad band equivalent as Landsat TM5 (Band3 / Band2). By calculating 89 known stress sensitive indices from the wealth of hyperspectral and multi-spectral literature, we then used a stepwise linear regression to identify those indices that best predict forest condition on over 46 calibration plots in the Catskills of New York with a range of species composition, health status and topographic position.

While many of the stress indices were significantly correlated with forest stress, the mixed-stepwise linear regression was limited to a maximum of three terms (for an N of 46), with set limits to enter at 0.05 and to leave at 0.01 to avoid over-fitting (Williams and Norris 2001). The mixed platform tests all possible linear regressions combinations and reports the set producing the lowest standard error of calibration. Variables are entered in the order of greatest significance and retained only if they remain significant as additional variables are added. In order to limit autocorrelation, variables were retained in the final model only if the variance inflation factor was below twenty (Kleinbaum et al., 1998). This ensures stability when the equation is applied to independent data sets. Jackknifed residuals calculated from the predicted residual sums of squares (PRESS) statistic were also used to assess the stability of the final predictive equation as a measure of independent validation accuracy (Kozak and Kozak, 2003).

The final best-fit model included primarily chlorophyll and canopy water content sensitive indices. Validation of the continuous forest stress prediction resulted in an r-square of 0.44 and root mean square error (RMSE) of 0.54. An average jackknifed residual error (0.55 compared to RMSE = 0.54) indicates that we could expect this model to perform similarly on an independent data set. When the continuous forest stress rating is rounded to the nearest integer for class comparison, the model was able to predict forest stress levels for the calibration data with 57% accuracy (10-class system) and an accuracy of 100% to within one class (Figure 4).

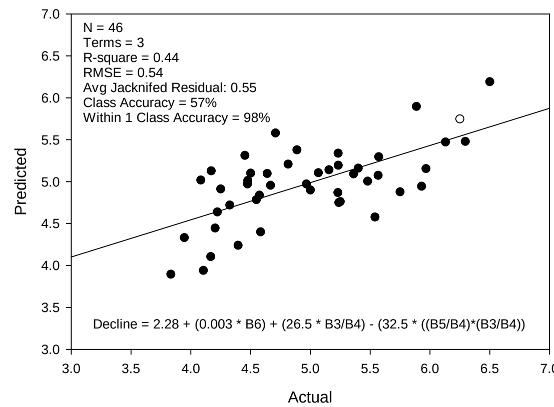

Figure 4. Equation and validation statistics for predicting forest stress.

This equation was applied to the Landsat image (Figure 5), with the values expressed in this coverage representing an assessment of overall vegetation stress on a 0 to 10 continuous scale, where 0 is a perfectly healthy vegetated pixel and 10 is a completely dead vegetated pixel. In order to minimize the inclusion of non-forested pixels, all values greater than 9 (the point at which there is minimal foliage left on a tree and understory occupies almost all the spectral signature) and all values less than 0 have been masked out. These extreme values successfully remove all developed pixels (i.e. roads, buildings, etc). Nevertheless, they still include pixels occupied by shrubs, vegetated wetlands, fields and agriculture. These non-forested, but still vegetated pixels are typically classified between the ranges of 7-9 since they often resemble the mix of bare ground and herbaceous understory seen in declining stands.

Figure 5. Predicted forest stress map. Lower numbers represent better health.

Applied on a pixel by pixel basis, the equation calculates a “stress” value for each pixel regardless of its composition. Therefore, these coverages cannot be considered “stand alone” assessments of forest condition. Please keep in mind that this stress prediction is not stressor, or species specific. It simply describes the range of vegetative health (as characterized by leaf water content, chlorophyll condition and function) across the landscape.

SPECIES MAPPING

Spectral mixture analysis (SMA; Boardman 1994, Boardman et al. 1995) , with a potential advantage of delineating sub-pixel composition, was selected as the method of analysis for this project. This approach is particularly useful for coarser spatial resolution imagery where spectra for a given pixel are characterized by a mix of constituents on the ground (Plourde et al. 2007).

The SMA approach begins with a minimum noise fraction (MNF) transform. Similar to principal components transform, MNF transform (Green et al. 1988, Boardman & Kruse 1994, Bhargava et al. 2000) reduces the dimensionality of hyperspectral reflectance data by reprojecting the data onto vectors that account for the most variability in the spectra, but also includes an additional step that segregates noise from data. In the resulting n-dimensional image, the first few bands include the most information and the latter bands include progressively more noise. After masking pixels that represented non-vegetation (e.g., clouds, bare soil, impervious surfaces, water) from the imagery, we performed MNF transforms. Only the first 20 bands from the MNF transforms were used in subsequent spectral unmixing classification steps.

Of the plots available for the study area, only the most pure samples of each respective species were used as spectral endmembers for SMA image calibration. Endmember spectra were extracted from images for each region by averaging the spectra from the four pixels closest to plot center. In addition, plot data made available through a Memorandum of Understanding with the USDA Forest Service, Forest Inventory and Analysis Program, Northern Research Station allowed us to augment our species spectral endmember dataset. Specifically, spectra from forest inventory and analysis (FIA) plots dominated by sugar maple, hemlock, and oak were extracted from an existing hyperspectral dataset from a prior study in New Hampshire, related to the Catskills image dataset and added to the endmember spectral library for species classification.

Table 4. Accuracy assessment for species fraction classification. Diagonal outlined cells are those instances where the MTMF method characterized the plot within one class of the actual field-measured species fraction based on basal area measurements.

Species		Fraction	Reference											total
ACSA			0	1-10	11-20	21-30	31-40	41-50	51-60	61-70	71-80	81-90	>90	
		0	4	1										5
		1-10	10	3				1						14
		11-20	1	1	1			1						4
		21-30		2	1		1							4
		31-40	1		1		2			1				5
	Classified	41-50							2	2				4
		51-60							1					1
		61-70							1	1				2
		71-80												
		81-90												
		>90												
		total	16	7	3		3	2	4	4				39
		ASCA within-one-class accuracy: 0.74												
QURU			0	1-10	11-20	21-30	31-40	41-50	51-60	61-70	71-80	81-90	>90	
		0	16											16
		1-10	8	2	1					1				12
		11-20	8											8
		21-30	1											1
		31-40												
	Classified	41-50					1							1
		51-60												
		61-70											1	1
		71-80												
		81-90												
		>90												
		total	33	2	1		1			1			1	39
		QURU within-one-class accuracy: 0.72												
TSCA			0	1-10	11-20	21-30	31-40	41-50	51-60	61-70	71-80	81-90	>90	
		0	4											4
		1-10												
		11-20	2		1									3
		21-30	3									1		4
		31-40	1				1				1			3
	Classified	41-50	1				1		1					3
		51-60	1	1					1	1	1	1	1	7
		61-70								2	1	1	2	6
		71-80						1		1	1	1	1	5
		81-90											1	1
		>90							1	1			1	3
		total	12	1	1		2	1	3	5	4	4	6	39
		TSCA within-one-class accuracy: 0.46												

Once endmembers were identified in each image, SMA was performed with the mixture-tuned matched filtering algorithm in ENVI (v. 4.2) image processing software. Mixture-tuned matched filtering (MTMF; Boardman 1998) detects abundances of user-defined endmembers by “unmixing” the pixels from “background” material. MTMF maximizes the response of the endmember in the MNF image and suppresses the background, thus “matching” the known signature. This unmixing process produced a multiple band image for each region, where each pixel was assigned a matched filter score and an infeasibility. The matched filter score represents how well the pixel spectra match the endmember (e.g., a value between 0 and 1.00, where 1.00 represents a perfect match with the endmember), and the accompanying infeasibility score can be used to reduce the number of false positives. Optimum MTMF results are pixels with high matched filter scores and low infeasibility scores. A stepwise linear

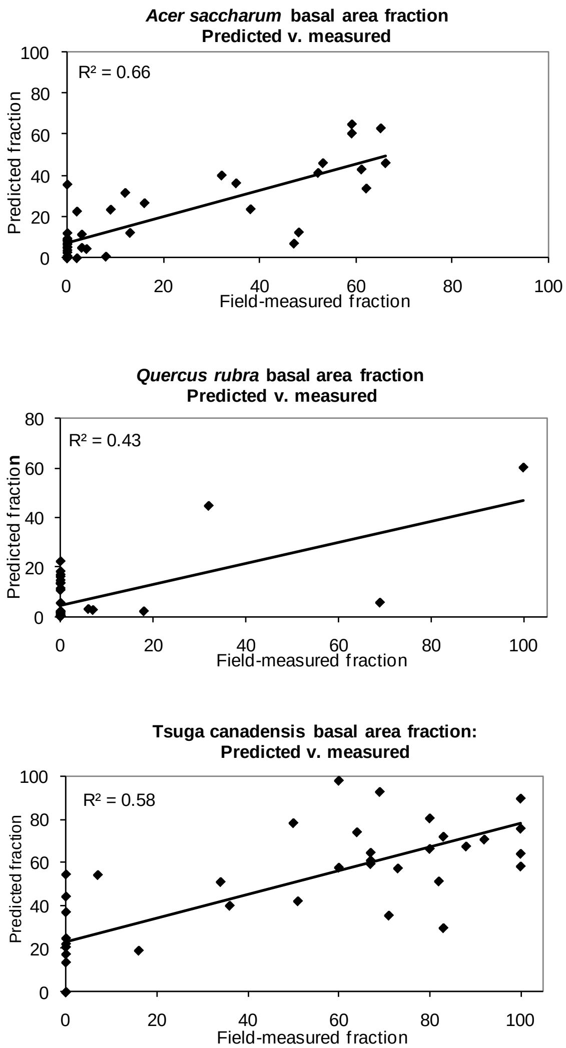

Figure 6. Predicted versus observed validation graphs for maple, oak, and hemlock species maps.

regression was performed using JMP on the MTMF results to determine the optimum combination of matched filter and infeasibility scores for predicting sugar maple, oak and hemlock, using field-measured basal area data for validation. The resulting data product for this project is a series of three raster coverages, one for each species, represented as fraction of species per pixel on a scale of 0-100 (see sugar maple map Figure 7).

Accuracy statistics for the species maps are shown in Table 4. Measured vs. MTMF species fraction is shown in Figure 6.

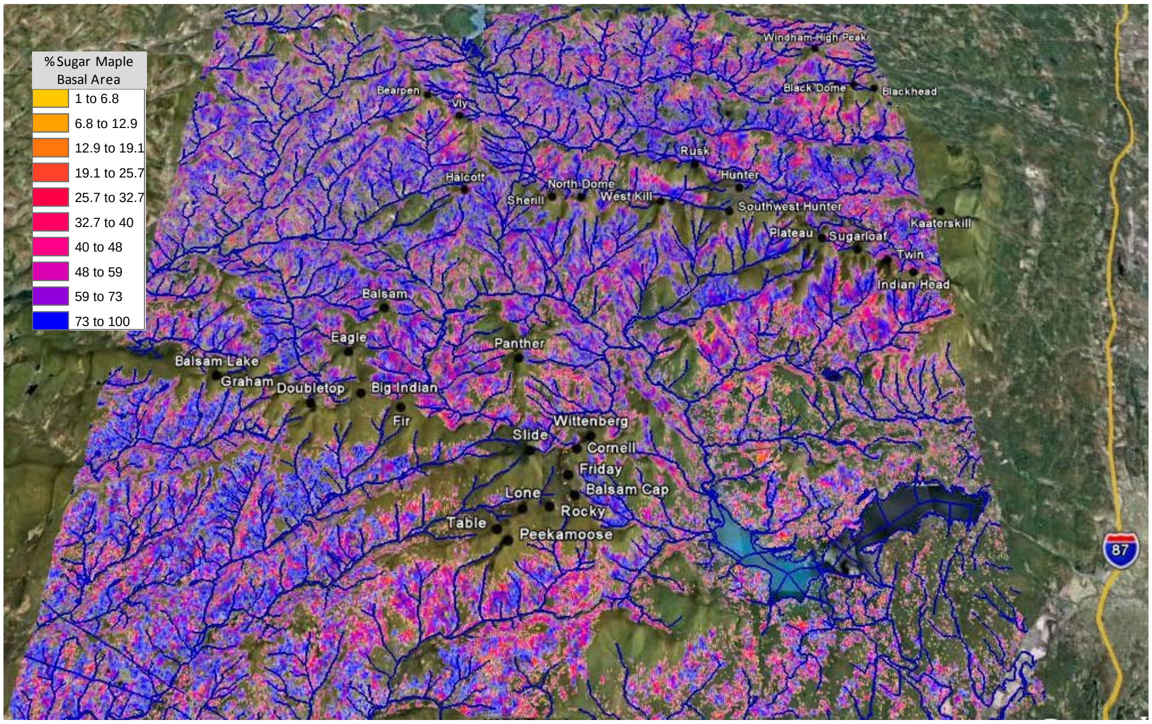

Figure 7. Map of predicted percent sugar maple basal area.

SURFACE WATER

Stream water samples were collected during spring sustained high flows each year from 2002 to 2006, and during fall sustained moderate to high flows during the years 2002, 2004, and 2006. The number of streams sampled ranged approximately from 150 to 200. The sampled streams were primarily first order streams that drained basins with over 90 percent forest cover selected randomly to cover the study area. Samples were collected in 500 ml polyethylene bottles and stored on ice until return to the laboratory. The samples were analyzed by ion chromatography for chloride (Cl^-), sulfate (SO_4^{2-}) and nitrate (NO_3^-) by inductively coupled plasma-emission spectrometry for Ca^{2+}, magnesium (Mg^{2+}), silicon dioxide (SiO_2) and total aluminum (Al_{tot}) by flow injection analysis for total monomeric aluminum (Al_{mono}) and organic monomeric aluminum (Al_{org}), by electrode for pH, by a Gran titration for acid neutralizing capacity (ANC) and by ultraviolet oxidation and persulfate oxidation for dissolved organic carbon (DOC) according to methods described in Lawrence et al (1995). Inorganic monomeric aluminum (Al_{im}), the fraction that can be toxic to aquatic biota in high concentrations, was calculated by subtracting Al_{org} from Al_{mono}.

A watershed boundary polygon coverage corresponding to 99 stream sampling locations that were sampled in the spring of each year (2002-2006), was also developed, and is used in the final data analysis where we extract descriptive statistics from the corresponding data products to determine that factors influence stream chemistry.

SOIL

Soil samples were collected from more than 240 forested sites from 2000 to 2006. The samples were collected using a soil knife or similar instrument from the clean wall of hand dug pits from the organic horizon and 0 to 10 cm of the B horizon, and placed into sealed plastic sample bags for transport to the laboratory. Additional samples were collected from deeper sections of the B horizon in selected pits. Soil samples were analyzed for exchangeable acidity, exchangeable aluminum, exchangeable hydrogen, and the percent aluminum acidity by potassium chloride vacuum extraction and titration (Thomas, 1982), exchangeable bases by ammonium chloride vacuum extraction (Blume et al, 1990), calcium, magnesium potassium and sodium concentrations by inductively coupled plasma-emission spectrometry (Lawrence et al, 1995), and pH by electrode (Blume et al, 1990). Soil moisture was determined by the difference of pre and post oven-drying weights; the mineral and organic soils are heated for 24 hours at 110° C and 65° C respectively (Blume et al, 1990). Loss on ignition was calculated by measuring the difference in weight of oven dried soils pre and post complete burning in a muffle furnace at 450°C for 24 hours for both mineral and organic soils.

DATA ANALYSIS

Interpolated maps of stream chemistry (nitrate example shown in Figure 8) and soil chemistry (O horizon exchangeable Ca example shown in Figure 9) were created using the kriging method in the ArcGIS geostatistical analyst at a 50 meter grid cell size. Ordinary kriging with a spherical model was used with input parameters adjusted to better fit the variogram to the data. The stream survey data were split into fall and spring datasets, and then means were calculated for each chemical property for each dataset.   For soil sites with multiple pits per plot, the mean value for the pits at a given site was calculated for each chemical property for each soil depth sampled. The mean values were then used in the interpolation.

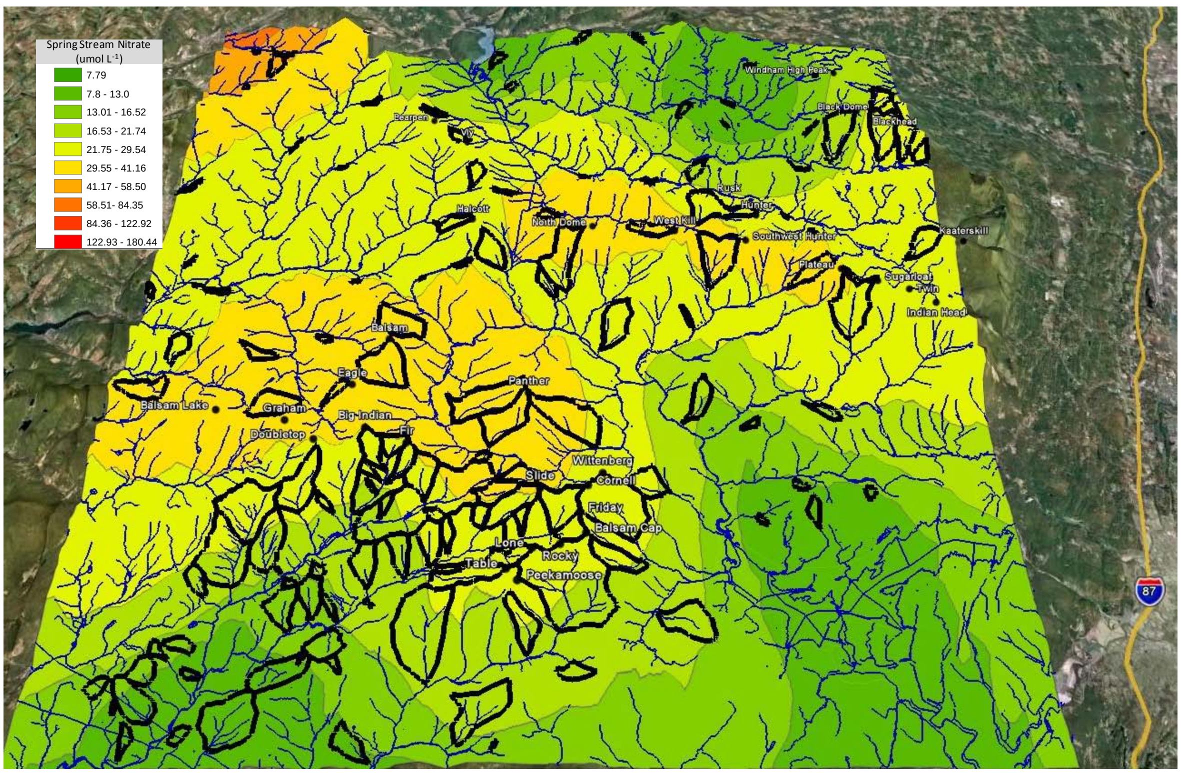

Figure 8. Interpolated map of stream water nitrate from the spring sample periods. Sample watersheds are delineated on the map.

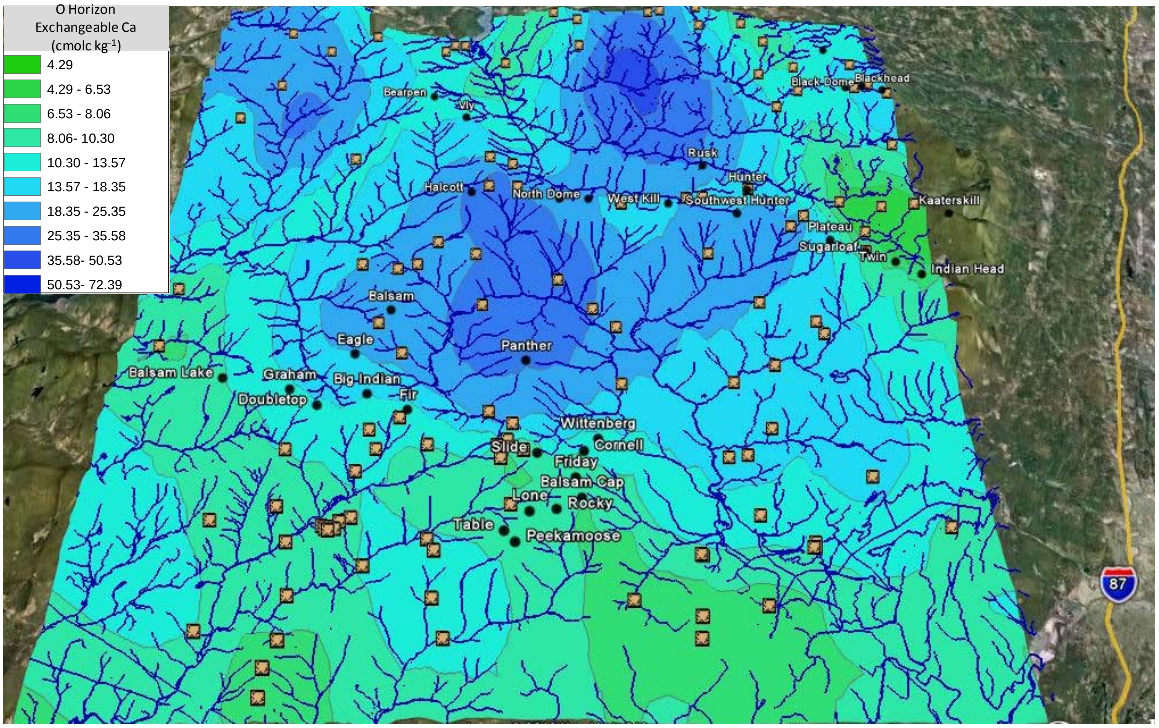

Figure 9. Interpolated map of O horizon exchangeable Ca. Soil sample locations are delineated on the map.

Section 3

DATA SYNTHESIS

The data products developed in the preceding sections were used in the final data synthesis. Within an ARC project, the data was summarized and extracted on two levels. The first analysis dataset was derived by using a point grid overlay to extract underlying data in shape files and image data products. These data were investigated for relationships between soil, streamwater, foliar chemistry, nitrogen deposition and elevation. In a second data analysis approach, data was summarized on the basis of the sample watershed boundaries, allowing the evaluation of soil and foliar chemistry, and species composition with regard to streamwater chemistry.

The value of a spatially explicit dataset such as this lies in the ability to test a wide variety of hypotheses, or ask specific management related questions of the data and have the answer mapped across 700,000 acres in the Catskills. For this final section of the report we take a case study approach to illustrate this flexibility. We discuss three case studies that ask questions ranging from the highly practical *"Where is sugar maple most susceptible to decline?"*; to *"Can we predict and map a key streamwater acidification index without sampling a stream?"*; and finally we create a theoretical index of *"ecosystem health"* using streamwater, soil, and foliar chemistry, forest stress, and nitrogen deposition. Ultimately we hope to see this tool deployed on the web, allowing land managers and scientists to design their own queries based upon criteria and thresholds that are important to them.

A note regarding accuracy

Every map contains errors and these maps are no exception. Wherever possible we have provided some estimate of the accuracy of our predictions using statistics and/or error matrices. When using techniques such as kriging, as we did for the soil and stream water chemistry maps it becomes more difficult to describe an error term for a given map as it is highly dependent on the size of the area for which you are trying to derive a number. The same is true as we begin to combine maps to answer questions about large areas of the landscape. Errors or inaccuracies can propagate and/or cancel each other out as each data layer is added to the model.

For the case studies that follow, quantifying the error in the final maps represents an opportunity for further study. In fact case study 2 is the only one that could be validated now as it does not predict a future outcome. Aside from statistical accuracy of maps such as these, there is what we are calling "Functional Accuracy," which is a representation of the practical value of the map to the person using it. Obviously the functional accuracy of the map may change with the user's goals. Again, designing a way to quantify functional accuracy is a topic for further study and would involve input from users asking specific management questions.

CASE STUDY 1: SUGAR MAPLE SUSCEPTIBILITY TO DECLINE.

Sugar maple (*Acer saccharum*) health and growth in the northeastern and Lake States of the United States and eastern Canada are threatened by multiple factors including disturbance from insect defoliators that have incited periodic declines with accelerated mortality (Gross 1991, Kolb and McCormick 1993, Payette et al. 1996, Horsley et al. 2002). Predisposing stresses include nutrient imbalances that are frequently implicated in sugar maple declines (Mader and Thompson 1969, Bernier and Brazeau 1988, Bernier et al. 1989), while decreased basal area increment (BAI) has been associated with increased soil acidity (Duchesne et al. 2002). Insect defoliation, drought, late spring frosts, and midwinter freeze-thaw cycles frequently have been associated with sugar maple decline (Houston 1999, Horsley et al. 2002). Secondary organisms such as *Armillaria* fungi serve as mortality agents. Studies conducted in 76 stands in northern Pennsylvania, New York, Vermont and New Hampshire identified foliar nutrient (Ca >5500 mg kg^{-1}, Mg > 700 mg kg^{-1}, and Mn < 1900 mg kg^{-1}) and soil thresholds (Ca > 0.2 $cmol_c$ kg^{-1} Mg > 0.05 $cmol_c$ kg^{-1}, Ca:Al molar ratio < 0.03) that enable trees to withstand stresses associated with defoliation and drought, while maintaining healthy crown vigor (Horsley et al. 2000, Bailey et al. 2004, Hallett et al. 2006).

In the Catskills sugar maple decline disease is not a widespread problem, however the region has been impacted by many of the stressors mentioned in the paragraph above. The literature indicates that sugar maple trees with foliar Ca below a threshold of 5500 mg kg^{-1} are more likely to decline when stressed and will have lower growth rates (Long et al., 2009). Let's assume that a land manager would like to assess areas across the landscape for sugar maple decline and that they are only interested in areas with greater than 30% sugar maple basal area (Figure 10, areas mapped in light green). We can further reduce the area to be surveyed by applying our foliar calcium threshold to the new map (using the foliar Ca coverage, Figure 3) resulting in a map showing areas of sugar maple that are predicted to be most susceptible to decline (Figure 10, areas mapped in red). Further parsing of the map can be accomplished by overlaying state land ownership boundaries and focusing on areas only within those boundaries (not shown here but available in the ARC project).

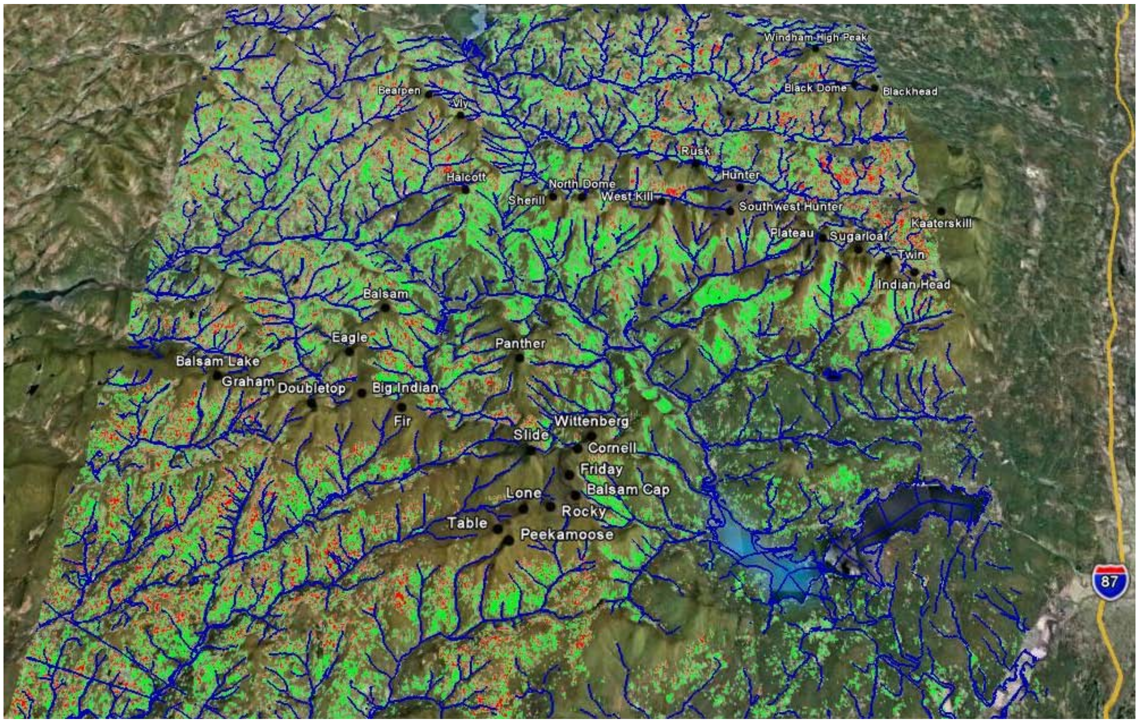

Figure 10. Light green areas are where sugar maple abundance is over 30% basal area. Red areas meet the sugar maple abundance criteria and have foliar Ca below the threshold value of 5500 ppm.

CASE STUDY 2: PREDICTING BASE CATION SURPLUS

The spatially explicit nature of the datasets in this project allows us to examine relationships between variables, such as the streamwater chemistry coming out of a watershed, and relate it to a host of other environmental variables from within that watershed. We delineated a watershed for every stream sampling point (see delineated watersheds in Figure 8) and used GIS tools to extract and average values from each watershed. This allowed us to match watershed soil chemistry, foliar chemistry, species composition and nitrogen deposition data to the stream chemistry variables.

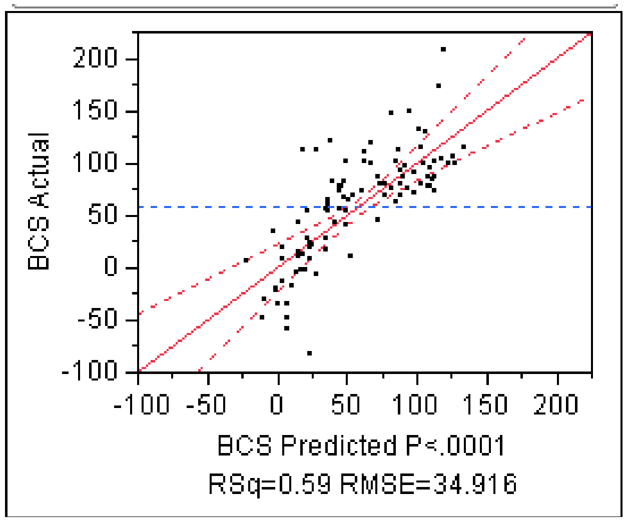

Figure 11. Predicted vs. Observed BCS with regression model statistics.

Base cation surplus (BCS) is a recently developed indicator for measuring stream acidification (Lawrence et al., 2007). A BCS value of less than 0 in streamwater indicates that the soil has become sufficiently acidified by acid rain to enable toxic forms of aluminum to move from the soil to the stream. Stream BCS has been related to the health and diversity of macro invertebrate communities in streams of the Adirondacks (Baldigo et al., 2009). A spatially contiguous map of BCS across the study area could help focus management efforts on those areas that had the highest potential to have a negative impact on water quality.

We conducted a stepwise linear regression analysis to predict BCS across the study area using only non-aquatic dependent variables. Our predictive equation had an R^2 of 0.59 (Figure 11). The equation used species composition, foliar chemistry, and soil chemistry variables to predict BCS (Equation 1).

Equation 1. Regression equation for predicting base cation surplus in stream water.

$$\begin{aligned} BCS = {} & -400.002 + (-0.76308 * \%\,Sugar\ Maple\ Basal\ Area) \\ & + (-.59547 * \%\,Hemlock\ Basal\ Area) + (0.0575 * Foliar\ Ca) \\ & + (315.643 * O\ horizon\ Base\ Saturation) + (-35.6328 * O\ horizon\ Exch.Mg) \\ & + (-136.895 * B\ horizon\ Base\ Saturation) + (135.051 * B\ horizon\ Exch.Mg) \\ & + (83.008 * B\ horizon\ pH) \end{aligned}$$

We applied this equation to the study area in our ARC project and computed a BCS value for every pixel in the study area (Figure 12). Obviously there is not a stream running through every pixel, however this map does give us the ability to aggregate pixels within any watershed in the study area and come up with an average BCS value for that watershed.

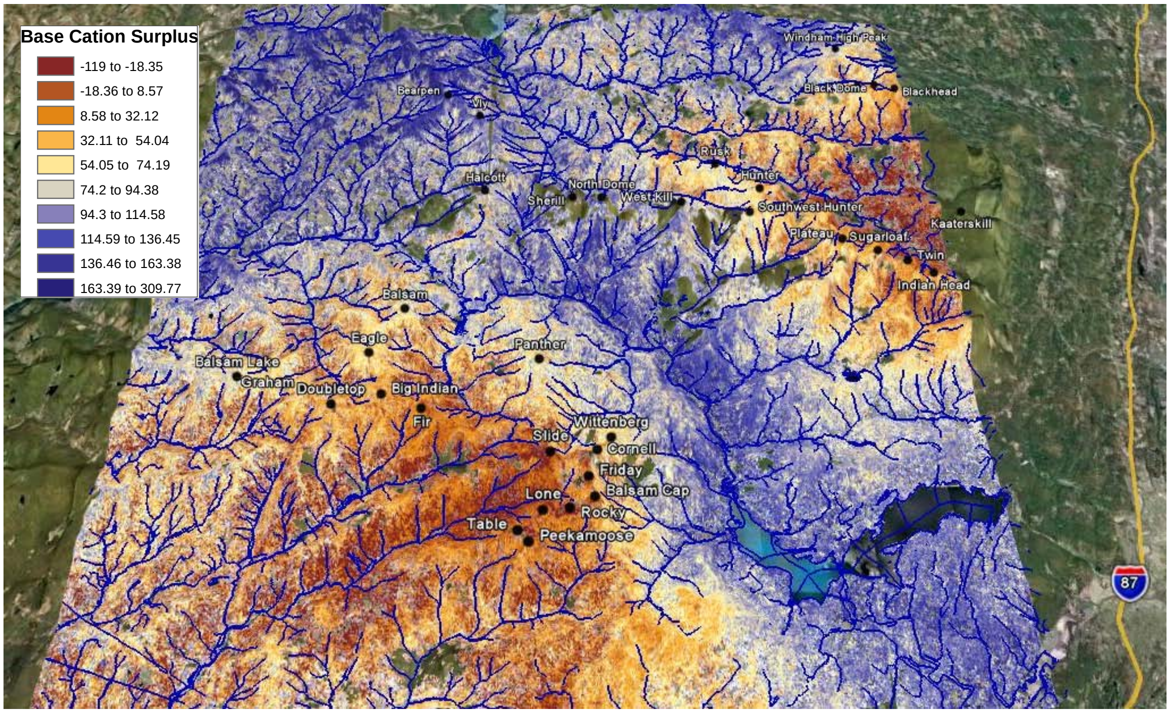

Figure 12. Map of predicted base cation surplus.

CASE STUDY 3: OVERALL ECOSYSTEM HEALTH

Our last case study involves deriving an indicator for overall ecosystem health. This is not a statistically derived model as it is meant to illustrate the potential and flexibility of this unique combination of spatially explicit data and current GIS processing tools at our disposal today. We simply took variables that, as experts in our fields, we felt were important indicators of a healthy ecosystem, and for those data layers we classified them into quantiles using 10 classes. A quantile classification takes into account the distribution of the variable and assigns 10% of the values in the dataset to each class (for a 10 class system). The resulting data set includes values of 1 through 10. This allows us to create equations where each variable has equal influence on the equation. In this example we chose one variable from stream chemistry, soil chemistry, foliar chemistry and added those together, we then subtracted the forest decline status in 2006 and finally we subtracted nitrogen deposition (Equation 2).

Equation 2 Ecosystem sensitivity index equation.

$$\begin{aligned} Ecosystem\ Sensitivity\ Index \\ &= Stream\ Water\ pH + B\ horizon\ Base\ Saturation + Foliar\ Ca \\ &- Forest\ Decline\ Status\ (2006) - \ Nitrogen\ Deposition \end{aligned}$$

The index ranges from -14 to 25 with lower numbers representing areas of the landscape that are more sensitive or vulnerable and higher numbers are where the ecosystem is healthier. Different weightings can be assigned to each variable based upon the relative importance of a given variable. This approach is infinitely flexible, and can be used to create map products with input from groups of experts focusing on nebulous issues such as future ecosystem health or where to focus management efforts to protect water quality, mitigate hemlock loss, or manage sugar maple. Our map shows areas across the study area where we hypothesize that the ecosystem is in poor health (low numbers) or good health (high numbers) relative to other areas on the map.

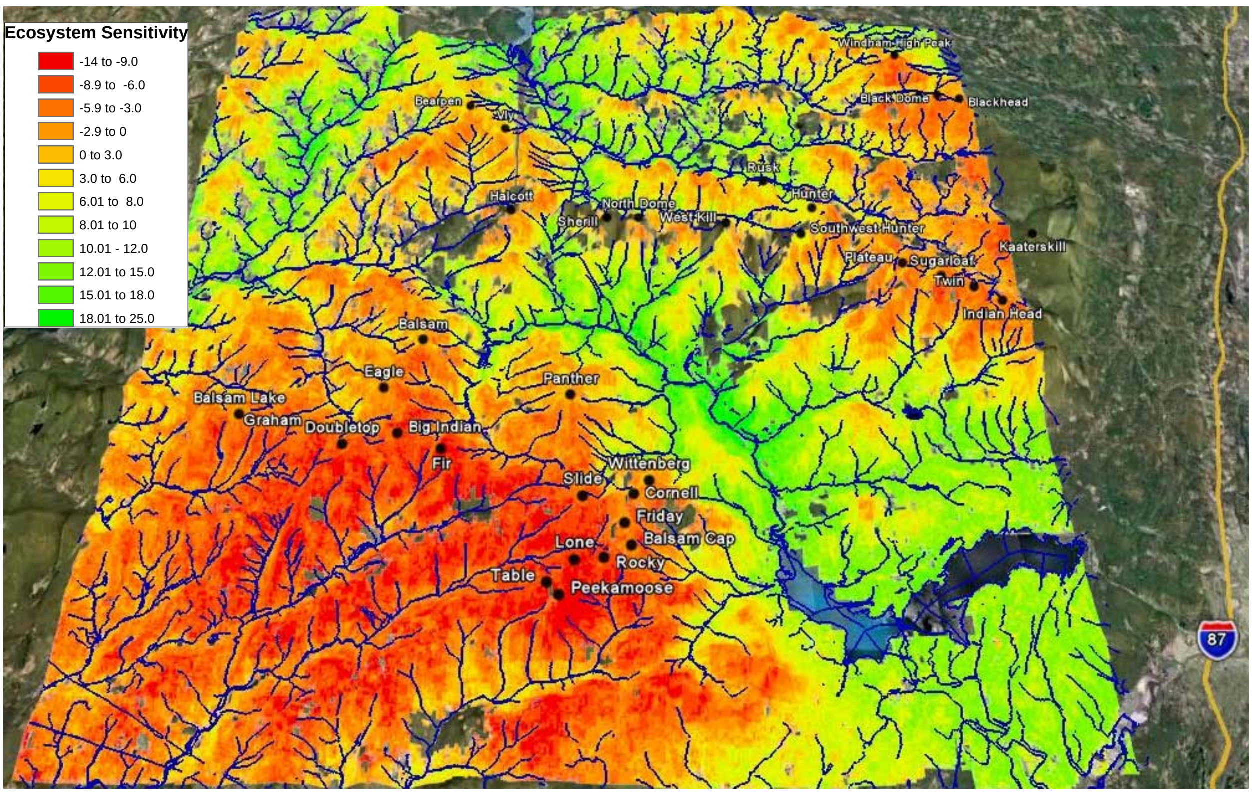

Figure 13. Map of overall ecosystem health. Lower values represent areas of the landscape where ecosystem health may be compromised.

CONCLUSION

We have presented examples that illustrate the flexibility and utility of the data layers compiled in the project and the ARCMAP database that contains the data layers. The strength of this data set lies in the ability to take a question driven approach to understanding ecosystem dynamics across the Catskills based upon user defined assumptions and thresholds, and showing answers in the form of spatially explicit maps that can show patterns across the landscape, allow for queries about total acreage impacted, or even total acreage impacted by ownership. The value of this approach can be enhanced by the addition of other spatially explicit data or data layers that currently exist or can be created.

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