A Vegetation Map for the Catskill Park, NY, Derived from Multi-temporal Landsat Imagery and GIS Data

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Abstract - A map of the vegetation of the Catskill Park, NY, was created using multi-temporal Landsat Thematic Mapper TM data and ancillary spatial data to support ecological studies in Catskill watersheds. The map emphasizes forest types defined by dominant tree species and depicts 24 vegetation classes. Mapping included a series of supervised classifications in a decision tree framework that allowed forest types to be distinguished using spectral characteristics and other environmental relationships (e.g., landscape position, elevation). Traditional contingency table analysis (based on limited ground sampling) suggests overall map accuracy ranging from 28% to 90%, depending on the level of aggregation of the original 24 map classes. Fuzzy accuracy assessment based on the same ground data suggests a 71% level of acceptable classification. The map indicates that maple-dominated forests are predominant in the Catskill region, but that beech and birch-dominated forests become more important at higher elevations. Oak-dominated forests are very important along the eastern side of the Catskills, and conifer-dominated forests are largely restricted to mountaintops and stream bottoms.

Introduction

The largely forested Catskill Mountains of southeastern New York are subject to high rates of atmospheric deposition of pollutants and nutrients due to their high elevation and proximity to sources of urban and industrial pollution in the Midwest and Eastern Seaboard (Weathers et al. 2000). The Catskills include a substantial portion of the 4100 km^2 New York City Water Supply Watershed and provide 90% of the water supply for New York City (New York City Department of Environmental Protection [NYCDEP] 1993). These circumstances, along with basic biogeochemical questions, have stimulated investigations on the Catskills in particular (e.g., Lawrence et al. 2000, Lovett and Rueth 1999, Lovett et al. 2000, Weathers et al. 2000) and the northeastern US in general (e.g., Aber et al. 2003, Ollinger et al. 1993).

The distribution of tree species and the interaction of vegetation and topographic position can strongly influence nutrient deposition rates (Weathers et al. 2000). Additionally, species composition affects nutrient cycling after deposition has occurred (Lovett and Rueth 1999, Lovett et

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al. 2002, Lovett et al. 2004). Nutrient cycling rates in forest floor soil have been shown to be related to tree species composition at the plot scale (Lovett et al. 2004), but a map that distinguishes among dominant deciduous tree species is necessary to answer watershed-scale questions about the influence of vegetation composition on stream chemistry. (Lovett et al. 2004). Existing vegetation maps for the Catskills region such as the National Land Cover Dataset (NLCD) classify forests as deciduous or evergreen, but do not classify forest dominants at the genus or species level. The New York Gap Analysis Project (Laba et al. 2002) mapped statewide vegetation in New York, but did not attempt to split out all deciduous species of interest in the Catskills.

Understanding these factors across geographic space in the Catskills requires a vegetation map that: 1) emphasizes the distribution of dominant tree species, 2) is highly resolved in terms of individual tree species dominance, and 3) has sufficient spatial resolution to capture the fine-grained character of vegetation in this region. The objective of the project described in this paper was to produce such a map, using multitemporal Landsat Thematic Mapper (TM) satellite imagery and other digital data. This paper describes the methods used to create the map, its characteristics, the results of a limited ground-based accuracy assessment, and recommendations for improving similar maps in the future.

From a remote sensing perspective, distinguishing deciduous tree species is a difficult problem for two primary reasons. First and most importantly, spectral signatures of many deciduous forest types are similar during most seasons, making spectral data alone insufficient for mapping. To compensate, data from more than one season can help capture spectral differences between tree species related to timing of phenological changes (e.g., greenup, fall color change, leaf drop; Mickelson et al. 1998, Wolter et al. 1995). The second primary difficulty is that different species frequently occur finely intermixed in space. Thus, satellite pixels are likely to contain more than one species, leading to confusing blends of spectral data for those pixels (Foody 1999). More highly resolved satellite data could help solve this "mixed pixel" problem, but are expensive.

Researchers have used remotely sensed data to discriminate deciduous tree species in general, and northeastern and midwestern U.S. deciduous forests in particular. Eder (1989) used autumn aerial photography to help distinguish deciduous tree species. Bolstadt and Lillesand (1992) combined Landsat data with environmental variables to map forests in Wisconsin, but did not use multitemporal data. Reese et al. (2002) mapped vegetation statewide in Wisconsin using multiseasonal data to improve classification. Other researchers (Bauer et al. 1994, Moore and Bauer 1990, Nelson et al. 1984) have also mapped northern forests with satellite data. In the northeast, Vogelman and Rock (1986) used TM data to characterize forest decline. Schriever and Congalton

(1995) assessed the utility of multiseasonal TM data for forest type mapping in New Hampshire and found that October imagery improved classification accuracy. Several researchers (DeGloria et al. 2001, Laba et al. 2002, Slaymaker et al. 1996) used enhanced and multi-temporal satellite data for regional land cover mapping associated with the USGS Gap Analysis Project. Mickelson et al. (1998) tested multitemporal TM data for mapping forest species in northwestern Connecticut. Foody (1999) explored the concept of fuzzy classification, and suggested that fuzzy concepts are relevant throughout the classification process, especially when mixed pixels are common. The combination of multi-temporal classification, ancillary data, and the species-specific spectral indices described here integrates many of these methods to produce a detailed map of the Catskills.

Description of the Study Area

The Catskill Mountains occupy a large area in southeastern New York State that includes significant portions of Delaware, Greene, Otsego, Schoharie, Sullivan, and Ulster counties (Fig. 1). The map described in this paper is delimited by the boundary of the Catskill Park,

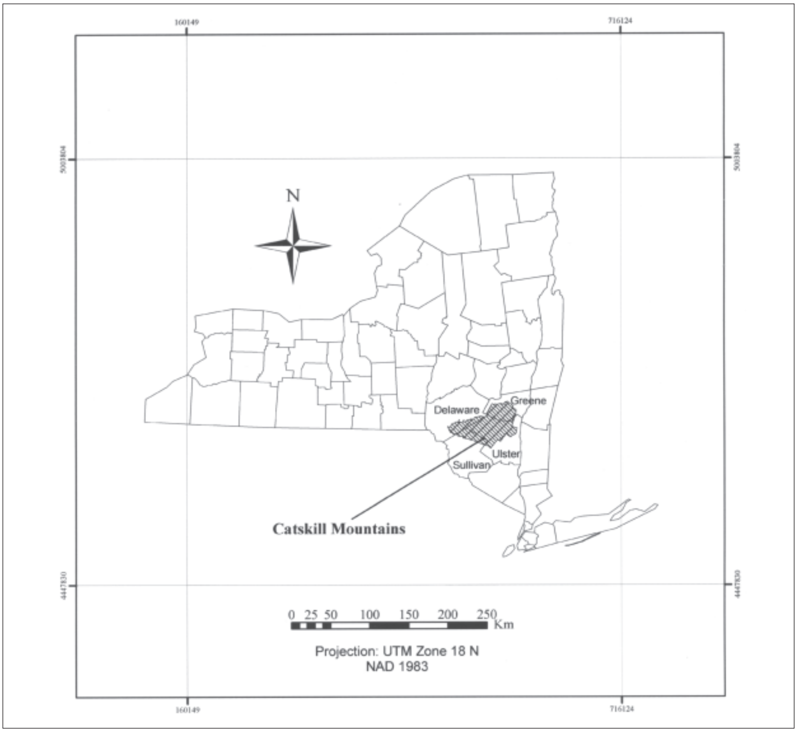

Figure 1. Map of New York State showing county boundaries and the location of the study area.

a preserve occupying 2817 km^2 that is embedded in four of these counties. About 40% of the land within the Catskill Park is part of the New York State Forest Preserve and the rest is privately owned. Forest Preserve lands are protected from logging, road-building, and other kinds of local human disturbance, but most of the Catskill area has been altered by logging, agriculture, and fire since the time of human settlement in the region (McIntosh 1972). Despite these disturbances, some significant tracts of first-growth forest remain (Kudish 2000).

The climate of the Catskills includes cool summers and cold winters, both of which contribute to the popularity of the area for resorts and tourism. Elevations in the park range from 51 to 1219 m, reflecting the rugged character of the Catskills that produces a range of climate conditions across the area. The Slide Mountain weather station (808 m elevation) in the central Catskills reports a mean annual temperature of 4.3 ºC, and annual precipitation of 153 cm with about 20% falling as winter snow (Lovett et al. 2000). Both temperature and precipitation vary substantially with elevation in the Catskills (Kudish 2000).

Lovett et al. (2000) provide a general description of forest vegetation which we summarize here. McIntosh (1972) provides more details. Nomenclature follows Gray (1950). Forests in the Catskills are dominated by mixed oaks at lower elevations (< 500 m), with northern red oak (*Quercus rubra* L.), chestnut oak (*Quercus prinus* L.) and red maple (*Acer rubrum* L.) frequently dominating. Eastern hemlock (*Tsuga canadensis* [L.] Carr) is found in valley bottoms, along streams, and on north-facing slopes, despite extensive harvest of this species to provide bark for a vigorous tanning industry during the early part of the 19th century (McIntosh 1972). Mid-elevation forests (500–1100 m) are dominated by sugar maple (*Acer saccharum* Marsh.), American beech (*Fagus grandifolia* Ehrh.) and yellow birch (*Betula alleghaniensis* Britton). At higher elevations (> 1100 m), balsam fir (*Abies balsamea* (L.) Miller) or red spruce (*Picea rubens* Sarg.), sometimes mixed with paper birch (*Betula papyrifera* Marsh.), often dominate (Lovett et al. 2000). While the forest types described above are typical, other mixtures of deciduous tree species are not uncommon.

Methods

Digital data acquisition

To take advantage of phenological differences between deciduous tree species, we acquired Landsat TM data of the Catskills for four dates capturing pre-green-up, green-up (spring), summer leaf-on, and fall color change. Ideally, satellite data for multi-temporal classification are acquired from a single year, with acquisitions linked to field observation of species-specific phenological change. Unfortunately, this was not possible for this project because of a lack of cloud-free imagery for some target dates and because of the cost of some satellite scenes. Within these constraints, we purchased Landsat TM data (Path/Row = 14/31) for dates capturing the widest possible range of phenological change. These dates included scenes from 28 April 1989 (leaf-off), 9 May 1993 (low elevation greenup), 21 June 1991 (full leaf-on) and 29 October 1986 (oak leaf-on, all other species leaf-off).

All data were geographically and terrain corrected by the U.S. Geological Survey (USGS) and projected into the UTM (Zone 18) projection. TM data have a spatial resolution of 30 m and include 6 reflected spectral bands ranging from visible through infrared wavelengths, and an emitted thermal band. The thermal band was not used for mapping in this project.

Digital elevation models (DEMs) were provided by the USGS with each TM scene acquired from the USGS Multi Resolution Land Characterization (MRLC) Program. These DEMs were registered to the satellite data and are of the same horizontal spatial resolution (30 m). DEM data were used in the classification to help differentiate conifer species.

Ground data acquisition

Species composition data were collected in the Catskills by the Institute of Ecosystem Studies (IES) staff during the summers of 1999, 2000, and 2001. These data were the basis for "training sites" used for supervised classification of satellite imagery. Ground data were also collected by IES in 2001 for map accuracy assessment, and were supplemented by data collected by the New York City Department of Environmental Protection (NYCDEP) on their property in the Catskills. The NYCDEP data were collected with the same field methods used by IES personnel. NYCDEP and IES data were combined to create a single larger field data set.

Ground data were collected at 249 sites, located along trails in the Catskills to avoid the difficulties of accessing more remote areas. This along-trail sampling was a compromise between statistical rigor and practical necessity, an unavoidable tradeoff resulting from time and budget constraints. Initially, randomly distributed sites throughout the Catskills were targeted for assessment. Because it soon became apparent that reaching these sites was not logistically practical, we shifted to a trail-based method. We chose 5 trails from different regions of the Catskills that provided elevation ranges characteristic of the topography in their vicinity. For each trail, we divided the elevation range into 10–12 equal intervals. At the midpoint elevation of each interval, we sampled two plots, one on each side of the trail, each at a distance of 150 m from the trail on a line perpendicular to the trail. This provided a stratified sample of the forest at different elevations in a 300-m-wide swath bisected by the trail. Because the sample points were determined prior to sampling, the selection of stands was not biased by subjective considerations in the field, but sampling was biased by the more fundamental choice of sites only along trails. The consequences of this sampling bias are discussed in the map accuracy assessment section to follow. Accuracy assessment data were not used for classification training to maintain their statistical independence.

For training and accuracy assessment, basal area of all trees > 10 cm diameter (breast height) was measured on multiple subplots within a 1-ha plot, using either fixed-area subplots or variable area-sampling with a forester's prism (Avery and Burkhart 1994). The prism method was used for faster sampling in areas where only canopy information was needed, rather than the full assessment of canopy and understory vegetation available from the fixed-plot measurements. Both methods measured all canopy trees, so for the purposes of this study the two methods are equivalent. Total basal area was calculated by species for each plot. Coordinates of plot centers were acquired using Garmin GPS12 and Trimble Pathfinder ProXL GPS equipment, both of which have autonomous positional accuracy of 15 m RMS. Large plots with multiple subplots were used to ensure that plots were larger than the spatial uncertainty introduced by GPS error. Of the 249 total sites visited on the ground, 135 sites representing the range of target classes were selected for training data, and the remaining 114 were set aside for accuracy assessment. Training data were based on ground sampling sites and reconnaissance by the authors in the Catskills.

Landcover classification scheme

Spruce-fir, hemlock, oak, beech, maple, and an "other" class including ash (*Fraxinus* sp.), black cherry (*Prunus serotina* Ehrh.), aspen (*Populus* sp.), and other tree species were initially identified as important for the biogeochemical analysis of Catskills watersheds. Because ground data included quantitative information about species basal area at each training site, we developed a classification system comprised of a more detailed list of forest types (Table 1) as well as three non-forest classes. To test our ability to map subtle differences in types, we maintained the detailed classification during the remote sensing analysis and then lumped types into several levels of aggregation (24, 8, 4, and 3 classes) for accuracy assessment.

For the classification scheme, a species (or species group) is considered dominant if it collectively occupies more basal area in a plot or pixel than any other species (or species group). To be considered a significant component, a species in these pixels must occupy within 25% of the proportion of total basal area of the dominant type. If maple occupies 60% of a pixel, for example, beech must occupy at least 35% of the pixel to be included as a significant subdominant. These definitions recognize species occupying portions of the total tree basal area in each map unit.

Digital classification

The Catskills map was built in stages by performing a series of digital classifications (using ERDAS Imagine version 8.4, Erdas™, Inc., Atlanta, GA) in a decision tree designed to separate particular target classes or groups of classes (Fig. 2). This decision tree approach used TM spectral bands, transformed and enhanced TM data, elevation data, and terrain properties derived from elevation data (e.g., landscape position: ridges, swales, sideslopes, etc.) (Fels and Matson 1996). Each stage of the decision tree evolved from experiments to identify data combinations that best distinguished particular classes (Table 2), and "dead ends" were

Table 1. Land cover classes (with pixel values) in the Catskills map. Type names include the dominant species first with other significant species following. Dominant species occupy the largest amount of basal area at a site. Significant types must occupy within 25% of the basal area occupied by the dominant type.

Class		
#	Name	Description
1	Water	Open water - Lakes, rivers, reservoirs, etc.
2	Non-forest	Grass, bare soil, etc.
3	Human built up	Roads, urban areas, etc.
4	Oak/laurel forest	Relatively pure oak dominated forest with mountain laurel (*Kalmia latifolia* L.) understory
5	Oak forest	Relatively pure oak dominated forest
6	Oak/maple forest	Oak dominated forest with significant maple component
7	Oak/beech or birch or "other" forest	Oak dominated forest with significant beech or birch component
8	Maple forest	Relatively pure maple dominated forest
9	Maple/oak forest	Maple dominated forest with significant oak component
10	Maple/birch forest	Maple dominated forest with significant birch component
11	Maple/beech forest	Maple dominated forest with significant beech component
12	Maple/birch/beech forest	Maple dominated forest with significant birch and beech components
13	Maple/other forest	Maple dominated forest with significant "other" hardwoods present (e.g., ash, cherry, aspen)
14	Birch forest	Relatively pure birch dominated forest
15	Birch/maple or beech or "other" forest	Birch dominated forest with significant maple or beech components
16	Beech forest	Relatively pure beech dominated forest
17	Beech/maple forest	Beech dominated forest with significant maple component
18	Beech/other forest	Beech dominated forest with "other" hardwoods (e.g., ash, cherry, aspen)
19	"Other" forest	Forest dominated by deciduous species not including beech, maple, oak, and birch
20	"Other"/maple forest	Forest dominated by "other" species with significant maple component
21	Spruce/fir forest	Forest dominated by spruce and/or fir species
22	Hemlock/pine forest	Forest dominated by hemlock and/or pine species
24	Spruce/fir/deciduous forest	Forest with a mixture of spruce, fir, and deciduous species
25	Hemlock/pine/deciduous forest	Forest with a mixture of pine, hemlock, and deciduous species

encountered that are not described here. Experiments included enhancement of the data (e.g., principal components analysis, Kauth's tasseled cap, image texture) and tests, using Erdas Imagine, of their power to discriminate training classes. For example, we experimented to see if normalizing vegetation indices for elevational effects on phenology would aid in discrimination, but discarded this method because no significant classification improvement was realized. Spectral signatures for classes represented in the ground data were generated for various data enhancements. Data accentuating spectral differences between vegetation classes were used, along with the ground-based training data, to generate a series of supervised classifications. Land cover classes from these supervised classifications were added incrementally to an evolving draft map that eventually became the final map (Fig. 3).

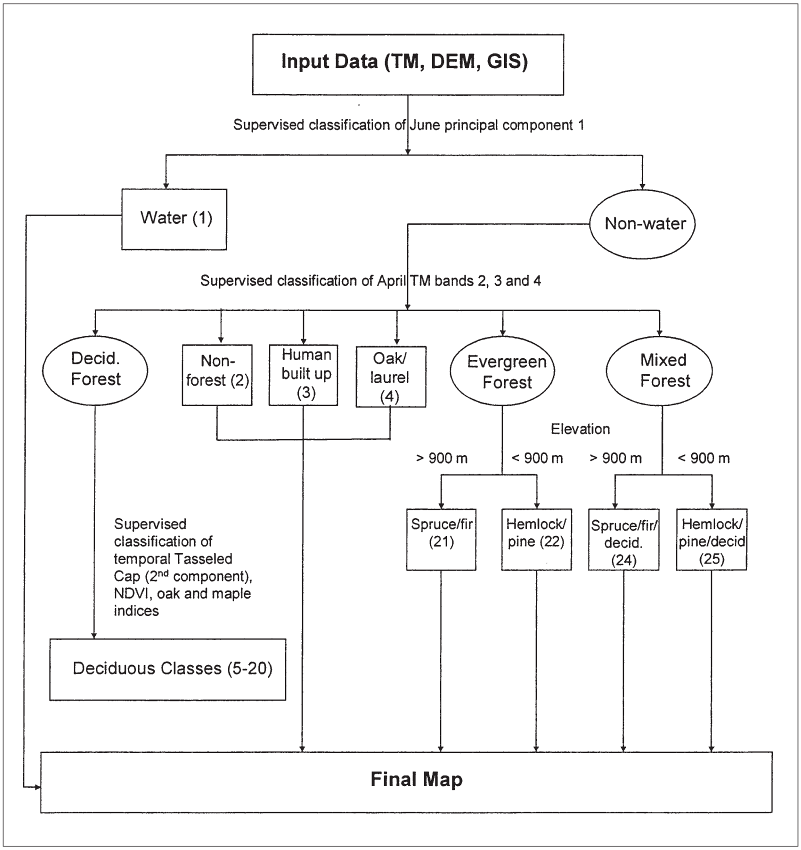

Figure 2. Flowchart showing the processing tree used to create the Catskills vegetation map. Intermediate classes are contained within ovals and final classes within green rectangles. Processing steps and rules are in described in text outside of the boxes and ovals. See text for explanation.

Although most of the decision tree (Fig. 2) is self-explanatory, the branches concerning forest types (evergreen and deciduous) require additional discussion. Evergreen and deciduous species were initially separated from one another using a supervised maximum likelihood classification of the April green, red, and near-infrared (NIR) bands from the satellite data (TM bands 2, 3, and 4 respectively). Data exploration for each group diverged after this, with evergreen species distinguished primarily using elevation data derived from the DEM, and deciduous species distinguished using spectral data enhancements. Classification of

Table 2. Digital data tested for their potential value for separating Catskills vegetation types. Data enhancements that were used to create the map are noted in the "Comments" column and discussed in the text. Images created using each enhancement were compared to training data to identify enhancements that highlighted spectral differences amount the target map classes.

Digital data enhancement	Comments
TM Bands	Explored individual TM bands from each date and across dates. Bands 2, 3, and 4 from the April scene were used to separate deciduous from evergreen, non-forest, and oak/laurel (Fig. 2). Other individual bands were not used.
Normalized Difference Vegetation Index (NDVI)	NDVI was calculated for each scene date and explored for each date and multi-temporally. Multi-temporal NDVI was used (simultaneously with other enhancements) to distinguish deciduous classes (Fig. 2).
Principal Components Analysis (PCA)	PCA was performed for each scene date using the 6 reflective bands. The first principal component (PC1) from the June scene was used to separate water from non-water (Fig. 2).
Tasseled Cap (TC)	Kauth's Tasseled Cap transformation (Kauth and Thomas 1976) was calculated for each date.
Temporal PCA	Principal components were plotted over time using the 4 scene dates.
Temporal TC	Kauth's Tasseled Cap components were plotted across time (for the four dates) to observe temporal patterns. The temporal profile of TC2 was used (simultaneously with other enhancements) to distinguish deciduous types (Fig. 2).
Maple Index	A "maple index" (see text) was devised to enhance the observed characteristics of the temporal reflectance of maple sites. This index was used (simultaneously with other enhancements) to distinguish deciduous types (Fig. 2).
Oak Index	An "oak index" (see text) was devised to enhance the observed characteristics of the temporal reflectance of oak sites. This index was used (simultaneously with other enhancements) to distinguish deciduous types (Fig. 2).
Birch Index	A "birch index" was devised to enhance the observed characteristics of the temporal reflectance of birch sites. This index was not used in the final classification.
Elevation	DEM data were used to split evergreen forest into spruce/fir and hemlock/pine (See rules in Fig. 2).

deciduous species was the core objective of this project, and the data used to distinguish these species evolved from trial and error using many combinations of spectral data. The final product resulted from a supervised maximum likelihood classification, based on all of the training data, and applied to a 10-band image developed from four data enhancements. These enhancements included: 1) the temporal profile (4 dates) of the 2nd Tasseled Cap (TC) (Kauth and Thomas 1976) component, 2) the temporal Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1973) profile (4 dates), 3) an oak index, and 4) a maple index. By using the temporal profiles of the tasseled cap and the NDVI, we were able to exploit phenological differences in the spectral data.

The final map (Fig. 3) is a combination of the classifications at the end of each branch of the classification tree (Fig. 2). Our approach allowed different components of the map to be separated according to different data combinations that best distinguished them.

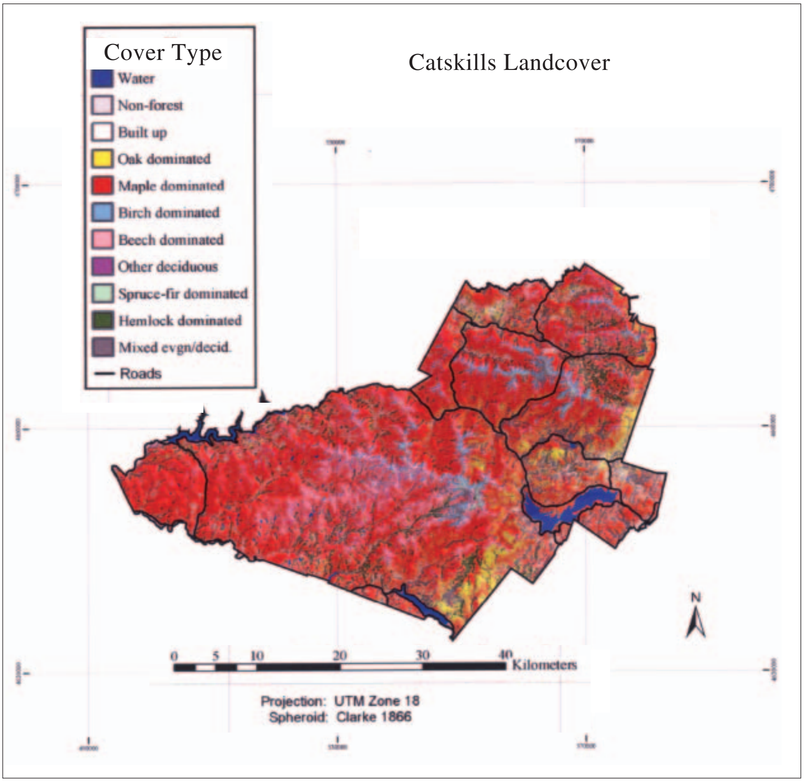

Figure 3. The landcover map of the Catskill Park aggregated to show 7 dominant species groups and 3 non-forest types. Reference grid is in UTM Zone 18 (Clarke 1866) and major roads and shaded relief are included for orientation. The digital map including all 24 mapped classes is available from the authors.

Map accuracy assessment

Thematic map accuracy assessment is based on comparing places on a derived map to reference data, presumed to accurately describe the characteristics of corresponding places on the ground. Map accuracy can be expressed in the context of binary scores (right vs. wrong) for each assessment site, an approach that we call "traditional accuracy assessment" and includes calculation of overall, user's, and producer's accuracy (Congalton and Green 1993). An alternative, called fuzzy accuracy assessment (Gopal and Woodcock 1994), uses a verbal scale (Table 3) defining degrees of error. We calculate a fuzzy accuracy descriptor called the "RIGHT operator" developed by Gopal and Woodcock (1994). This measure counts a mapped pixel as correct if it is considered a "reasonable or acceptable answer" or better for the site as it is described in the ground validation data. To assign scores from Table 3 to mapped pixels at each validation site, we compared the mapped type to the distribution of basal areas by species for that site and summarized these comparisons.

In total, 114 sites were used for accuracy assessment. Sites were located along trails (see description of ground data acquisition above) due to logistical problems with a fully random or stratified random sample. Stehman (2001) notes that budget constraints for ground sampling are common and require balancing statistical rigor with practical limitations when designing sampling strategies. He notes that compromises to the assessment protocol require "reducing precision, restricting the population to which design-based inference applies, introducing assumptions, and allowing greater error in the reference data" (Stehman 2001). For the study described here, along-trail sampling means that our reported map accuracy descriptors can be strictly applied only to the portion of the map along the sampled trails unless we make the assumption that these areas are representative of the entire Catskills Park. While this assumption is likely to be valid due to our selection of trails and elevation zones, we did not formally test it, and the map accuracy described here should be used only as an indicator of the map characteristics.

Table 3. The verbal "correctness" scale and associated codes used for fuzzy accuracy assessment based on the work of Gopal and Woodcock (1994).

Code	Description
5	Absolutely right
4	Good answer
3	Reasonable or acceptable answer
2	Understandable, but wrong
1	Absolutely wrong

Results

Map characteristics

Catskills vegetation is dominated by deciduous tree species, although non-forest and conifer species are a significant component of the landscape. Specifically, non-forest types (including open water) collectively occupy 12.7% of the Catskill Park. Deciduous cover types occupy 71.6% and include maple-dominated types (43.5%), beech-dominated types (10.4%), oak-dominated types (9.4%), and other types (3.6%). Evergreen-dominated types occur in 4.3% of the area and include hemlock (3.6%) and spruce-fir dominated types (0.7%). Mixtures of conifers and deciduous species cover 11.5% of the area (Table 4).

Broad patterns of tree species dominance are evident in the Catskills map (Fig. 3). In general, maple species dominate over much of the Catskills Park. Oak species occupy significant areas in the east, and beech types are prevalent in the south-central portion of the park west of Slide Mountain. Evergreen coniferous trees occur in scattered patches throughout the Catskills, particularly along riparian corridors and at high elevations.

Table 4. Area (km^2) and proportional area (% total) occupied by each of the 24 land cover classes within the boundaries of Catskills Park. Cover codes match the pixel values in the digital map.

Class #	Cover type	Area (km^2)	Area (% total)
1	Water	62.88	2.2
2	Non-forest	130.23	4.6
3	Human built up	164.69	5.9
4	Oak/mountain laurel forest	123.98	4.4
5	Oak forest	27.69	1.0
6	Oak/maple forest	103.67	3.7
7	Oak/beech or birch or “other” forest	8.69	0.3
8	Maple forest	481.10	17.1
9	Maple/oak forest	157.72	5.6
10	Maple/birch forest	85.86	3.1
11	Maple/beech forest	204.60	7.3
12	Maple/birch/beech forest	291.64	10.4
13	Maple/other forest	0.00	0.0
14	Birch forest	122.93	4.4
15	Birch/maple or beech or “other” forest	11.37	0.4
16	Beech forest	23.26	0.8
17	Beech/maple forest	214.87	7.6
18	Beech/other forest	56.82	2.0
19	“Other” forest	0.00	0.0
20	“Other”/maple	102.52	3.6
21	Spruce/fir forest	19.29	0.7
22	Hemlock/pine forest	101.02	3.6
24	Spruce/fir/deciduous forest	24.23	0.9
25	Hemlock/pine/deciduous forest	298.31	10.6

Table 5. Accuracy assessment of vegetation classification with 24 classes. Light gray areas are pixels for which dominant genus is correct, and dark gray areas highlight confusion between maple and beech types. "ND" signifies types for which there were no validation data. Overall, 28% of the reference (ground) vs. mapped vegetation comparisons are perfect matches using this classification. Class numbers refer to the class names referenced in Table 1.

Ref.	Mapped type																									Producer's
type	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	24	25	Total	accuracy
1																									0	ND
2																									0	ND
3																									0	ND
4																									0	ND
5				7										2											9	0.00
6				2																					2	0.00
7				1								1						1							3	0.00
8								5		1															6	0.83
9							1										1								2	0.00
10								1	1	2															4	0.50
11				1											1	1	5								8	0.00
12														1			1						1		3	0.00
13											2						3				1				6	0.00
14												1		3											4	0.75
15								1		1		2		3			1	1							9	0.00
16											1														1	0.00
17														1			3							1	5	0.60
18									1	2				4			2								9	0.00
19						1						2		2			4	1		1					11	0.00
20										1				1			2			1					5	0.20
21																				1	5				6	0.83
22																					1			1	2	0.00
24														1								1		1	3	0.00
25				1				2						1										12	16	0.75
Total	0	0	0	12	0	1	1	9	2	7	3	6	0	19	1	1	22	3	0	3	7	1	1	15	114	
User's accuracy	ND	ND	ND	0	ND	0	0	0.6	0	0.3	0	0	ND	0.2	0	0	0.1	0	ND	0.3	0.7	0	ND	0.8		

Spectral and temporal indices

As part of the remote sensing analysis, we developed oak and maple indices to highlight phenological characteristics of these key species. These enhancements highlighted specific aspects of the spectral response of maple and oak in the Catskills. Maple and oak indices accentuated features of the temporal NDVI and TC2 profiles, respectively. The maple index used the formula:

$$(\text{June NDVI}/\text{May NDVI})/(\text{May NDVI}/\text{April NDVI})$$

Similarly, the oak index was calculated as:

$$(\text{June TC2}/\text{May TC2})/(\text{May TC2}/\text{April TC2})$$

These indices helped significantly for distinguishing oak and maple in particular and deciduous species in general, and may be useful for other mapping efforts in this region.

Table 6. Accuracy assessment of vegetation classification with 8 classes (lumped by dominant genus). Overall, 46% of the reference vs. mapped vegetation comparisons are perfect matches using this classification.

Reference	Mapped type									Producer's
Type	4–7	8–13	14–15	16–18	19–20	21	22	24–25	Total	accuracy
Oak (4–7)	10	1	2	1					14	0.71
Maple (8–13)	2	12	2	11		1		1	29	0.41
Birch (14–15)		5	6	2					13	0.46
Beech (16–18)		4	5	5				1	15	0.33
Other deciduous (19–20)	1	3	3	7	2				16	0.13
Spruce/fir (21)					1	5			6	0.83
Hemlock/pine (22)						1		1	2	0.00
Evergr./deciduous mix (24–25)	1	2	2				1	13	19	0.68
Total	14	27	20	26	3	7	1	16	114	
User's accuracy	0.71	0.44	0.30	0.19	0.67	0.71	0	0.81		

Table 7. Accuracy assessment of vegetation classification with 4 classes. Overall, 84% of the reference vs. mapped vegetation comparisons are perfect matches using this classification.

Reference	Mapped types					Producer's
type	4–7	8–20	21–22	24–25	Total	accuracy
Oak (4–7)	10	4			14	0.71
Other deciduous (8–20)	3	67	1	2	73	0.92
Evergreen (21–22)		1	6	1	8	0.75
Evergreen/deciduous mix (24–25)	1	4	1	13	19	0.68
Total	14	76	8	16	114	
User's accuracy	0.71	0.88	0.75	0.81		

Map accuracy assessment

We present results of both "traditional" map accuracy assessment and "fuzzy" accuracy assessment. For this paper, we include contingency tables summarizing the traditional approach (Tables 5–8), a summary of the fuzzy assessment (Table 9), and a brief discussion of both

Table 8. Accuracy assessment of vegetation classification with 3 classes. Overall, 90% of the reference vs. mapped vegetation comparisons are perfect matches using this classification.

Reference type	Mapped type 4–20	Mapped type 21–22	Mapped type 24–25	Total	Producer's accuracy
Deciduous (4–20)	84	1	2	87	0.97
Evergreen (21–22)	1	6	1	8	0.75
Evergreen/deciduous mix (24–25)	5	1	13	19	0.68
Total	90	8	16	114	
User's accuracy	0.93	0.75	0.81		

Table 9. Fuzzy accuracy (RIGHT operator) summarized for individual mapped cover types, and overall fuzzy accuracy for the Catskills land cover map. The percent correct for each mapped cover type is the proportion of validation sites for which the comparison of mapped type to validation site yielded a score of 3 or greater on the verbal scale presented in Table 3. Overall fuzzy accuracy is the total number of scores greater than 3 divided by the total number of validation sites (114). ND is No Data: mapped cover type has no validation sites.

Class number	Cover type	Percent correct
1	Water	ND
2	Non-forest	ND
3	Human built up	ND
4	Oak/laurel forest	83.33
5	Oak forest	ND
6	Oak/maple forest	0.00
7	Oak/beech or birch or "other" forest	0.00
8	Maple forest	88.89
9	Maple/oak forest	0.00
10	Maple/birch forest	71.43
11	Maple/beech forest	33.33
12	Maple/birch/beech forest	66.66
13	Maple/other forest	ND
14	Birch forest	73.68
15	Birch/maple or beech or "other" forest	0.00
16	Beech forest	0.00
17	Beech/maple forest	68.18
18	Beech/other forest	33.33
19	"Other" forest	ND
20	"Other"/maple	66.66
21	Spruce/fir forest	85.71
22	Hemlock/pine forest	100.00
24	Spruce/fir deciduous forest	0.00
25	Hemlock/pine deciduous forest	93.33
	Overall fuzzy accuracy	71.05

approaches. The relatively small number of sites compared to the number of mapped classes and the lack of an unbiased sample limit the power of the assessment, but we feel that the results offer valuable information about the map.

Traditional accuracy assessment

Tables 5–8 present four contingency tables (error matrices) summarizing the traditional accuracy assessment of the Catskills map, beginning with the primary vegetation classification with 24 cover types and proceeding to increasingly simplified classifications derived by lumping cover types from the primary classification. In the contingency table for the full 24-class vegetation classification, two types of mismatches (errors in the traditional assessment) are highlighted (Table 5). In the lightly shaded rectangles, the match is not perfect but species dominance is mapped correctly. Examples of correctly mapped species dominance include maple-dominated forest with a strong beech component that was mapped as maple-dominated forest with a strong birch component. The two darkly shaded areas indicate a different type of mismatch, in which there is confusion between maple vs. beech-dominated forest (unfortunately, these forest types have contrasting biogeochemical cycling properties of ecological importance [Lovett et al. 2004]).

The overall map accuracy is 28% for the classification with all 24 classes (Table 5), 46% when types are lumped by dominant genus into 8 classes (Fig. 3, Table 6), 84% when the only deciduous classes are oak and non-oak for a total of 4 classes (Table 7), and 90% when there are just 3 classes (deciduous, evergreen, and mixed) (Table 8).

It is important to note that many of the types in the map classification (e.g., non-forest) had no validation sites associated with them. These types are indicated by no data (ND) in the contingency tables and their mapped accuracy cannot be determined. Many other types have small sample sizes, and our confidence in the accuracy estimates is consequently low.

Fuzzy accuracy assessment

Fuzzy assessment required the assignment of verbal descriptions (Table 3) of the level of agreement between mapped and reference sites. If the mapped dominant type matched the dominant type and subdominant types at the ground reference site, the site was considered a perfect match (5). If the mapped type was not a perfect match but captured the mix of tree species at a site, the site was rated as a good (4) or acceptable (3) match depending on the mix of species and dominants mapped vs. those actually found at the site. Several points from this analysis need emphasis. First, accuracies calculated using the fuzzy "RIGHT" criterion are significantly higher than accuracies based on a binary "right/wrong" criterion. This higher accuracy is expected since the fuzzy criterion allows a pixel to be counted as correct even when the match is not perfect. Fuzzy accuracy assessment complements traditional accuracy assessment and, in a sense, quantifies important aspects of the off-diagonal elements in the traditional contingency tables (Tables 5–8) that were described above. Secondly, overall map accuracy using this criterion is about 71%. While this level of accuracy is comparable to other remotely sensed maps in eastern deciduous forests (e.g., Mickelson et al. 1998), it might be improved with other sensors or more intensive ground surveys. Third, even by this criterion, beech and maple confusion is evident and represents the most significant confusion in the map.

Discussion

Classification of forest types using multi-temporal Landsat TM images offers an alternative to traditional, single-image classification methods and may allow discrimination of more deciduous forest types in some situations (Mickelson et al. 1998). Detailed treatment of deciduous species dominance is critical for biogeochemical modeling and may also be useful for animal habitat studies, hydrologic modeling, and monitoring changes in the Catskills park through time.

Oak-dominated forests can be distinguished from northern hardwood forests (dominated by beech, birch, and maple) with good accuracy using this technique, and this distinction is quite important for ecological studies such as the biogeochemical modeling for which this map was developed. The ability to distinguish accurately between oak vs. non-oak types is particularly noteworthy and valuable because oak-dominated forest types are biogeochemically unique in the Catskills area (Lewis and Likens 2000, Lovett et al. 2002, Lovett et al. 2004). Oaks are valuable because they are harvested for timber and because they produce copious crops of acorns, which are an important part of the diet of many wildlife species (Burns and Honkala 1990). In addition, oak forests appear to inhibit the process of nitrate formation in the soil, thus reducing nitrate loss to stream water (Lewis and Likens 2000, Lovett et al. 2002, Lovett et al. 2004). Excess nitrate has been implicated in the acidification of surface waters in the Catskills (Murdoch and Stoddard 1992) and elsewhere (Aber et al. 2003).

The map reveals an interesting geographic distribution of forest types in the Catskills. The dominance of maple types concurs with the vegetation analysis of McIntosh (1972). At higher elevation, beech and birch assume dominance over maple, and the tops of the highest peaks of the Catskills can be distinguished by their spruce-fir vegetation on the map (Fig. 3). The oak-dominated forests of the eastern Catskills may be a result of disturbance, including both cutting and burning, by Native Americans and, later, Europeans from the heavily-populated Hudson

River Valley to the east (Kudish 2000). The central Catskills, which for the most part have only been selectively logged, have very few oaks (Kudish 2000).

The classification accuracy was quite low (28%) for the full 24-category cover type map using traditional accuracy assessment. However, when the acceptance criteria were relaxed in the fuzzy accuracy assessment, the map accuracy was an acceptable 71%. Bauer et al. (1994) achieved classification accuracy up to 75% in Minnesota using a less detailed list of classes. Schriever and Congalton (1995) reported 74% overall map accuracy using multitemporal data for forest mapping in New Hampshire. Laba et al. (2001) reported overall map accuracy from 42% to 74% depending on the level of aggregation of types in New York. Reese et al. (2002) report 70–84% accuracy for forest species in a statewide map of Wisconsin. For this study, we present the results of both traditional and fuzzy assessments of the map because consideration of both methods provides a more informative assessment for map users who may use the map data for different applications.

The limited ability to distinguish beech- and maple-dominated forest types is an important shortcoming of this map because an exotic disease complex (beech bark disease) is currently having a severe effect on beech trees in this area, and maples are the species most likely to benefit from the demise of the beech (Griffin et al. in press, Houston 1994). Better resolution of beech and maple forests would be an obvious improvement, and we offer some suggestions on how future efforts could enhance the ability of remote sensing to distinguish forest types.

Spectral limitations

Observed spectral differences between target tree species in the Catskills were subtle in terms of the limited spectral resolution of the TM instrument. These differences vary over time due to differences in occurrences of phenological changes across species and elevation ranges, a circumstance that was exploited using multi-temporal data for this study. Even so, we were often frustrated by very small distinctions in spectral response combined with difficulties untangling species mixtures within TM pixels (see below). Use of data offering higher spectral resolution than the TM, in our opinion, would be the most likely way to improve the current map. Higher spectral resolution would require either acquisition of new data from instruments like the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) or the recently launched Hyperion satellite-borne hyperspectral instrument, or more data acquisitions across time to capture a better sample of phenological change.

Spatial resolution

Catskills vegetation, as described by field data collected for this study and by other researchers (e.g., McIntosh 1972, McIntosh and

Hurley 1964) is often mixed at the 30-m Landsat TM spatial resolution, with various target tree species intermingled within the same pixel. This problem, especially in the context of similar spectral characteristics of target tree species, adds to the difficulty of adequately separating and mapping the distribution of dominant species.

Map error resulting from confusion due to mixing within TM pixels might be improved in future efforts using several approaches. First, sensors offering higher spatial resolution are currently available (e.g., Space Imaging IKONOS or Digital Globe Quickbird) and in some cases also offer sufficient spectral and temporal resolution (return time) to be promising. Second, data manipulation known as "pixel unmixing" (e.g., Smith et al. 1990) may allow solving of within-pixel confusion. Foody (1999) suggests that fuzzy methods may be fruitful for situations where mixed pixels are common if the methods are applied at all stages of the analysis, from collection of training data to accuracy assessment.

Ground data

Remote sensing studies are nearly always limited by the availability of high-quality ground data. The ground data for this study were of high quality, but low quantity. Better spatial distribution would improve the development and assessment of the classification model. Substantial additional field sampling requiring an expensive, time-consuming effort would be required to improve accuracy estimates. Ground data for future mapping efforts would ideally be optimized for the sensors used and correspond with the timing of satellite data acquisitions.

Conclusions

The map of the Catskill Park presented in this paper in its most refined form depicts 24 landcover types, with an overall fuzzy accuracy of 71%. Traditional map accuracy at this level of refinement is low (28%), and map accuracy increases as forest types are aggregated hierarchically. Oaks are particularly well separated from other types but confusion remains between beech- and maple-dominated forest. Despite some weaknesses, this digital map is a step forward in the spatial representation of Catskills' vegetation and should serve as a valuable resource for ecological studies, and perhaps recreational and other uses in this area. The digital version of the map is available from the authors on request. Future efforts that use additional image dates and/or more spectrally and spatially resolved data may improve map accuracy.

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