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IKONOS imagery for resource management: Tree cover, impervious surfaces, and riparian buffer analyses in the mid-Atlantic region

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Abstract

High-resolution imagery from the IKONOS satellite may be useful for many resource management applications. We assessed the utility of IKONOS imagery for applications in the mid-Atlantic region, including mapping of tree cover, impervious surface areas, and riparian buffer zone variables in relation to stream health ratings. We focused on a 1313-km^2 area in central Maryland using precision-georeferenced IKONOS products. We found the IKONOS imagery to be a valuable resource for these applications, and were able to achieve map accuracies comparable to manual aerial photo interpretation. We were also able to use derived data sets for consistent assessments over areas that would be difficult to accomplish with traditional photographic mapping methods. For example, we found that a stream health rating of excellent required no more than 6% impervious cover in the watershed, and at least 65% tree cover in the riparian zone. A rating of good required less than 10% impervious and 60% tree cover. A number of issues associated with application of the IKONOS data arose, however, including logistics of image acquisition related to phenological and atmospheric conditions, shadowing within canopies and between scene elements, and limited spectral discrimination of cover types. Cost per unit area was also a nontrivial consideration for the image data products we used, but allowed us to provide valuable derived products to agencies in support of their planning and regulatory decision-making processes. We report on both the capabilities and limitations of IKONOS imagery for these varied applications.

Keywords: IKONOS imagery; Resource management; Mid-Atlantic region

1. Introduction

Information on land cover has become an integral part of the environmental and developmental planning process. It has aided in the advancement of more effective land use planning, habitat assessments, and hydrological applications. Historically, land cover and land use information was obtained by a combination of field measurements and aerial photo interpretation. This approach typically required intensive interpretation by expert analysts, and cross validation methods to ensure that analyst interpretations were consistent. Recently, satellite imagery has become available at spatial resolution nearly comparable to aerial photographs, with the added advantage of digital multispectral information more complete even than those provided by digital orthophotographs (DOQs). The platform stability of high-resolution (1–5 m) imagery acquired from Earth-observing satellites provides another advantage to aerial photographs acquired from aircraft, which roll, pitch, and yaw during flight and require corrections for those effects. Because of these advances and advantages, as well as commercial potential, several companies have launched or plan to launch high-resolution satellites in the near future (Stoney, 2001).

High-resolution multispectral imagery has many potential benefits to government organizations, nonprofit agencies, and a wide array of mapping and related commercial ventures (Dial, Bowen, Gerlach, Grodecki, & Oleszczuk, this issue; Sawaya et al., this issue; Tanaka & Toshiro, 2001). Applications of these data can aid and assist the monitoring and management of resource lands, parks, wetlands, and other protected areas, as well assess the effects of natural disasters or complement protective measures in areas

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that have the potential to burn or flood, to name just a few. High spatial resolution imagery is not a panacea for these applications, however, owing to a number of issues that arise with their use. For example, the increased textural information available in fine-resolution imagery allows for improved interpretation based on the shape and texture of ground features, but techniques that have been developed to process and analyze current satellite data, including vegetation indices or multitemporal classification techniques that utilize mid-infrared or thermal channels (e.g., Varlyguin, Wright, Goetz, & Prince, 2001), may not be applicable to the additional information provided by high-resolution satellites. Other issues include difficulties in acquiring consistent sequential acquisition dates, intensive computer processing time and disk space required to store larger image data sets, and considerations of economic efficiencies (Fisher & Goetz, 2001).

The objective of this paper was to assess the practicality of using high-resolution imagery, in this case provided by the IKONOS satellite operated by Space Imaging, for resource management applications in Montgomery County in the mid-Atlantic region of the United States. We sought to utilize the IKONOS imagery as an alternative to air photo interpretation for updating the forested lands map, as well as to map changes that had occurred in land use, particularly residential development and intensification of impervious surface areas. Additional specific goals were to assess the utility of the IKONOS imagery for production of tree cover and impervious surface area maps, and to examine those map products and derivatives, including riparian buffer zone land cover, relative to stream water quality. Related applications include the use of IKONOS to train subpixel algorithms of tree cover and impervious surfaces using coarser resolution imagery (e.g., Landsat). The tree and impervious area maps, when combined, provide an improved ability to meet resource management goals, particularly with respect to comprehensive planning, rural land protection, and goals for improved water quality. We identify and address some of the benefits and limitations of high-resolution imagery for these research applications.

2. Study area and data sets

The study area encompasses all of Montgomery County, MD (1313 km^2) (Fig. 1), an area comprised of a mixture of forest and farms interspersed with a range of residential developments and industrial/commercial zones. The county was selected for this research because it seeks to develop improved geospatial information, capabilities, and technologies to assess impacts of environmental change, and a range of resource management decisions. The Maryland National Capital Parks and Planning Commission (M-NCPPC) and the Montgomery Department of Environmental Protection (DEP) are well advanced in their utilization of geographic information systems (GIS) and have been nationally recognized and awarded for their countywide forest preservation and stream protection strategies. The Planning Board of Montgomery County has established master plans for each region to plan future development, and has been at the forefront of many of Maryland's "Smart Growth" programs. One of these includes the "Legacy Open Space" program to fund the purchase of culturally and environmentally unique lands and to "protect the county's surface water supply" (M-NCPPC, 2000). To date, more than 12,000 ha have been protected as parks and open space, at a cost of over US$137 million, and additional acquisitions are planned within a 39,000-ha agricultural preserve. There is a desire by the DEP, M-NCPPC, and others to have these lands connected to other parcels reserved under the counties' parks system and related land conservation programs, providing the county a "green infrastructure" of natural areas to promote recreation opportunities, protect water resources, and maximize biodiversity (Weber & Wolf, 2000). In the 10 years since the last aerial photo-based forest land cover classification, however, there had been considerable residential development and expanded transportation projects, with associated predictions of rapid future rates of land conversion (Jantz, Goetz, & Shelley, in press). These factors provided an impetus for the applications research presented here.

2.1. IKONOS imagery

IKONOS is the first commercially owned satellite providing 1-m resolution panchromatic image data and 4-m multispectral imagery (Dial et al., this issue). The multispectral image data include three visible and one infrared channel (Table 1). Data are collected in 11-bit radiometric resolution and provided in a format compatible with image analysis software. The tile size for each individual scene is 11.3 × 11.3 km. Because of its pointable off-nadir viewing capability, the satellite revisit interval is as little as 3–4 days.

The IKONOS images of Montgomery County (Fig. 2) were obtained through the NASA Scientific Data Purchase, a program designed to make remote sensing data sets available for research and practical applications (Birk, Stanley, & Snyder, this issue). The acquired imagery was equivalent to Space Imaging's Carterra Precision product, which is a "precision-georeferenced" image data product with an absolute horizontal geometric accuracy of 5 m. The NASA Scientific Data Purchase contract specification allowed for mislocation errors of 250 m in standard products (see Helder, Coan, Patrick, & Gaska, this issue), thus a precision product was required for the analyses we wished to conduct. The orthocorrected product we acquired had an RMS error of approximately 1.9 m. Eleven IKONOS image tiles were acquired in six swaths to provide complete coverage of the entire county (Table 2). The nominal cost of the imagery was US$141 km^{-2}. Although the IKONOS platform has a short repeat schedule, a cloud-free image could not be acquired for

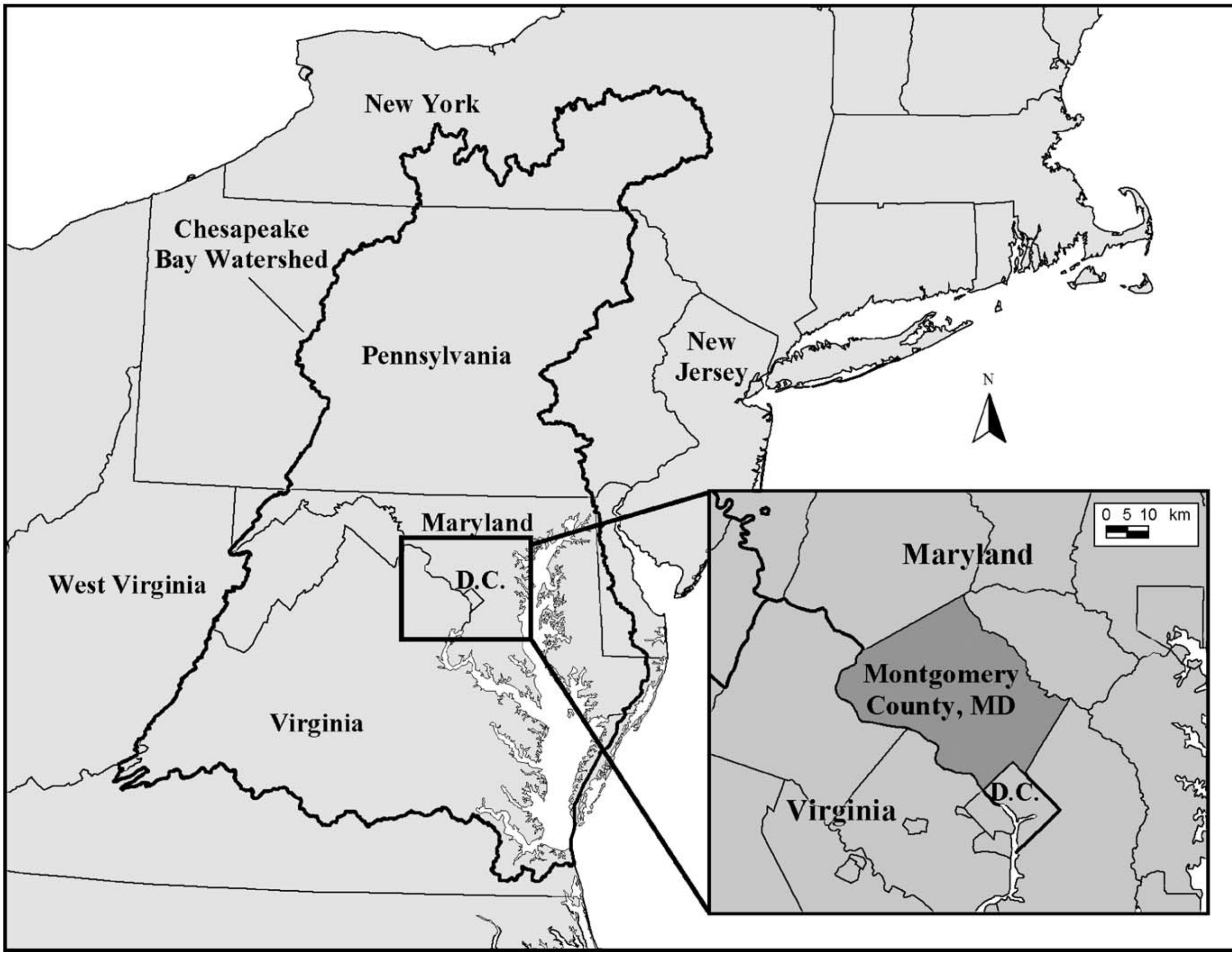

Fig. 1. Study area map of Montgomery County, MD, within the mid-Atlantic region and Chesapeake Bay watershed.

Panel 7 during a 12-month acquisition window. For this panel, a cloud and cloud shadow mask were created manually, through which all processings were filtered. Note that several of the panels were acquired in late spring during leaf-off conditions, while others were acquired in early summer leaf-on conditions (Fig. 2). We also note that the off-nadir view of the county for all panels, in conjunction with the collection azimuth (Table 2), affected the radiance detected at the sensor from the combined atmosphere and surface constituents.

2.2. Planimetric and natural resource data layers

The sole source of reference (i.e., training and validation) data came from planimetric GIS data sets provided by the M-NCPPC. The primary data set for tree cover mapping was a ‘‘natural features’’ database that contained countywide polygon data for forested lands, agricultural lands, and water features. The database was visually interpreted by a commercial vendor contracted by a multiagency consortium, based on use of 1992 aerial photography. The derived forest cover map had a large minimum mapping unit to represent forest areas, rather than individual or small clusters of trees. The agricultural areas contained a wide range of cover types, including row crops, pasture land, fallow fields, and grassy regions.

Additional reference data were provided by the planimetric data of the built environment, which included highly detailed polygons of road and building footprints. This provided the primary data set used for impervious area mapping. Because the planimetric and natural features coverages were developed using photography flown some 10 years ago (1992), changes had occurred in the county up

Table 1
IKONOS spectral band widths specified as full width at half maximum

Band	Spectral wavelength (nm)	
1	445–516	Blue
2	506–595	Green
3	632–698	Red
4	757–853	Near-infrared
Pan	450–900	Panchromatic

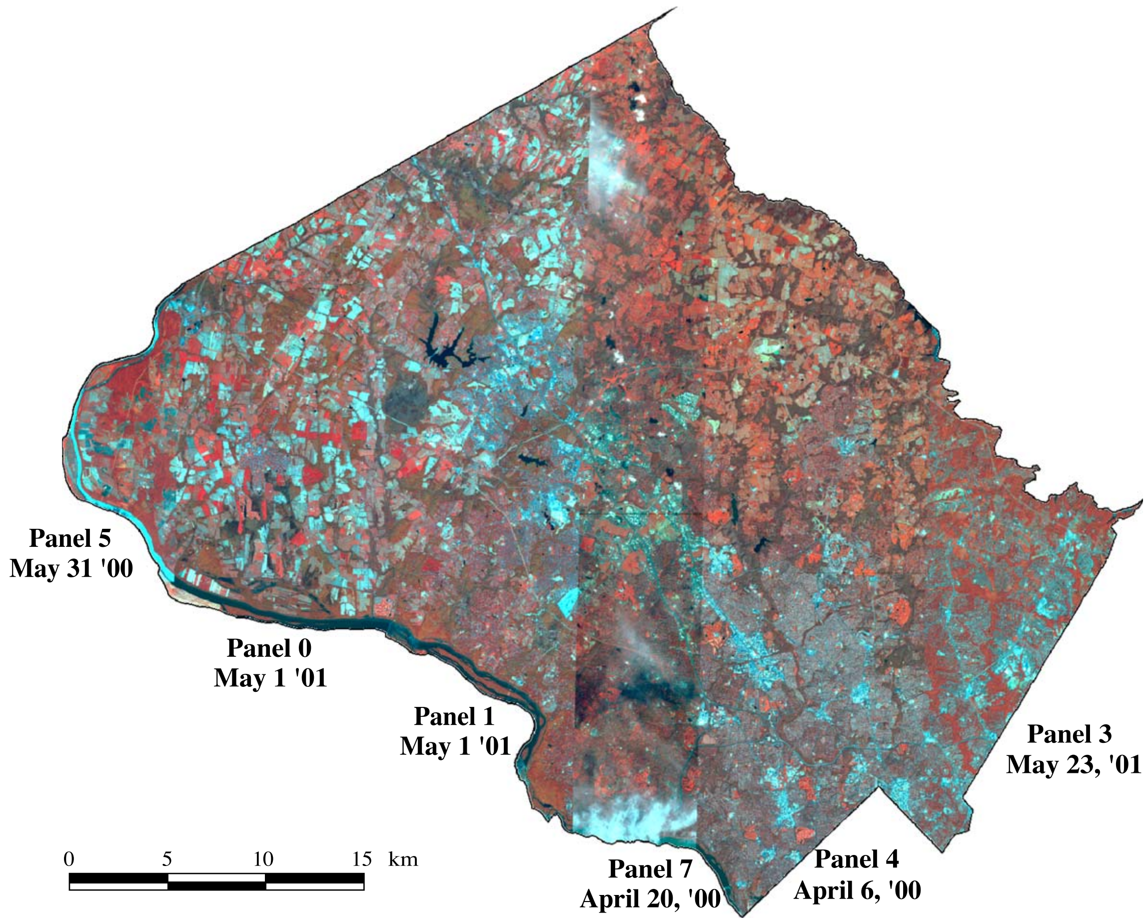

Fig. 2. Location and acquisition dates of IKONOS image panels of the study area. Note the cloud cover remaining in Panel 7 despite a 14-month acquisition window. (Includes material from Space Imaging©.)

to the time of the IKONOS acquisition. This required evaluation of the accuracy of the impervious and natural features coverages, and screening for data sets suitable for algorithm training and map validation.

3. Methods

3.1. IKONOS image preprocessing

The four multispectral IKONOS bands were radiometrically corrected to at-sensor reflectance utilizing the methods outlined by Goetz (1997) and the calibration parameters provided by Space Imaging in the imagery metadata. These corrections to top-of-atmosphere reflectance minimize the errors associated with solar elevation and allow for between-band comparisons of data values.

Table 2
IKONOS acquisition metadata

Panel	Date	Local time	Sun elevation	Sun azimuth	Collection elevation	Collection azimuth
0	5/1/2001	10:59	62.08	143.46	78.25	24.83
1	5/1/2001	11:00	62.16	143.80	88.49	95.46
3	5/23/2001	11:02	67.36	139.09	85.83	276.78
4	4/6/2000	10:35	51.28	139.97	76.46	119.51
5	6/26/2000	10:53	66.98	126.80	79.06	301.54
7	4/20/2000	10:45	57.25	140.47	77.35	349.31

Preliminary supervised and unsupervised forest/nonforest classifications were done using the IKONOS imagery. An unsupervised classification was run using an ISODATA algorithm, specifying 255 clusters, 10 iterations, and a confidence interval of 0.96. The resultant clusters were assigned to three categories (forest, nonforest, or unknown) using manual interpretation of the imagery itself. Clusters assigned to the "unknown" class were located in both the forested and nonforested areas. These were used as a mask to create a new image, which was missing the areas that were earlier assigned to either forest or nonforest. The unsupervised classification was then run again on the revised image, consisting entirely of unknown areas, using the same set of clustering parameters. This process was repeated five times, until it was difficult to identify any new unknown areas. A supervised maximum likelihood classification (MLC) was also developed using visually interpreted training areas for each of four land cover types (tree/forest, agriculture, urban/built, and water). A total of 100 training areas was identified. Classifications produced using these two approaches were assessed for accuracy using 1000 randomly selected samples that were visually interpreted to the appropriate class, of which 100 were visited on the ground to verify the interpretations.

Based on other work using Landsat Thematic Mapper (TM) imagery, we suspect that the modest classification accuracies we found (75–85%) using these classification approaches with IKONOS imagery were due to a combination of leaf-on/leaf-off imagery, limited image spectral bands and spatial–spectral variability within and between image components, as well as limitations in the use of hand-delineated training areas or statistically defined clusters of similar objects. As a result, we decided to take a different approach to the classification, focused on the use of a decision tree classifier and a large number of training samples (described below). We also derived four additional image variables to aid the spectral discrimination process including: (i) Normalized Difference Vegetation Index (NDVI), (ii) Atmospherically Resistant Vegetation Index (ARVI), (iii) NIR/red (simple ratio), and (iv) NIR/blue. The NDVI was added to aid in the discrimination of sediment-laden water from wet fields. ARVI (Kaufman & Tanre, 1992) was included to help remove artifacts within the canopy itself, such as canopy shadow. The simple ratio and NIR/blue ratio were included to aid the discrimination of agricultural fields and shrubs from trees.

3.2. Reference data preprocessing

In the case of tree cover mapping and accuracy assessment, natural features reference data screening was done by overlaying the IKONOS imagery with the reference coverage and by deleting polygons whose cover type did not match. The incorrectly attributed polygons included forested and agricultural areas that had been converted to residential or commercial (developed) land use, as well as forested or agricultural areas that had some development within the polygon to the extent that it could skew the training and validation data. The water polygons were also evaluated for accuracy with errors occurring mostly in farm ponds that had been drained or developed, as well as portions of water bodies occurring in rapids and over rock that were subject to changes associated with flow volume. These screening processes permitted the use of the natural features coverage to develop independent training and cross-validation data sets for the decision tree classifier, and subsequent development of a tree cover map rather than forest cover per se (where forest would imply, e.g., >60% tree cover).

In order to minimize edge pixels, the forest, grass, and water polygons were internally buffered by 20 m (five IKONOS pixels). Areas converted from a natural to a built environment since the creation of the data set were not added to the training data set used for image classification since the existing data included enough samples for the spectral responses of buildings and roads. The planimetric data were rasterized to 4-m pixels utilizing the same pixel footprint as the IKONOS imagery, so that there was exact pixel coregistration. The final reference data set consisted of a coregistered raster file containing forest, crops/grasses, water, buildings, and roads.

Following data quality assessment, the reference data sets were used as the basis for accuracy assessment. Tree cover was assessed using the natural features data set and impervious cover with the planimetric data. A combination of random selection and reserved sample sets was used, as well as independent interpretation of imagery and field visits. These were derived differently for tree and impervious cover, as described below.

3.3. Tree cover mapping

Having the natural features data set available for training the classification algorithm allowed for 1.7 million unique randomly generated samples to be used in a land cover stratification sampling scheme from the training data, and retention of a proportional number of samples in relation to the training data. Of the 1.7 million points, 600,000 were randomly removed from the data set to be used as mutually exclusive validation points. The number of training samples allocated to each panel depended on the respective area of the panel, with the smallest receiving 70,000 and the largest receiving 250,000 samples. The sample size also varied between forests, agricultural lands, water, and urban features. Virtually no urban or suburban trees or grasses were used in the training data because these managed areas have high vegetation indices that create statistical confusion with, for example, deciduous forest spectra.

We used a decision tree classifier, or more specifically a classification tree algorithm, within the statistical software package S-PLUS, developed by Insightful. This univariate decision tree algorithm, based on Breiman, Freidman, Olshend, and Stone (1984), recursively thresholds the training data into increasingly homogeneous partitions using nonparametric rules. Decision trees have become popular for land cover mapping (Friedl & Brodley, 1997; Hansen, Dubayah, & DeFries, 1996; McCauley & Goetz, in press) because the tree output is intuitive, with each IKONOS band or variable threshold listed for each successive partition. The decision tree classifier in S-PLUS works by evaluating individual sample points, so the values of the IKONOS pixels for the original bands, and the derived indices and ratios were used.

Because temporal differences in the IKONOS scene acquisition dates (Table 2) caused type confusion in early classifications, leaf-on and leaf-off imagery required the development of more scene-specific decision trees based on sample points from each individual scene only. To aid in the development of a robust classification, each of the six IKONOS panels was classified individually, and the resulting decision trees were used to classify its respective IKONOS image by applying the threshold breakpoints listed in the classification tree to the eight image variables described above. The panels were then mosaicked back together for the final map of the entire county. An accuracy assessment was completed on the final classification using the data points reserved from the initial sampling of the natural features coverage, without duplication of sample selections.

3.4. Impervious area mapping

The impervious surface mapping was also done using a classification tree approach, but made use of the planimetric map of buildings and roads rather than the natural features database. Upon inspection, it was apparent that the building features had few errors but the transportation features contained numerous errors of omission, particularly parking lots. In order to evaluate the completeness of the data, the county was divided into 689 blocks, each of which consists of many thousands of IKONOS pixels. Each block was checked for errors against recent DOQs and the imagery itself. Areas developed since the creation of the planimetric data were not included in the training data set. Of the 689 original blocks, 197 were deemed sufficient for algorithm development and validation-based tests of spectral discrimination with sample size. Approximately 600,000 data samples (4-m pixels) resulted.

Samples within each block were coded either impervious or nonimpervious based on interpretation of the planimetric data. The sample was then divided into training and validation data sets based on each swath of IKONOS imagery, resulting in about one-fourth (140,366) being reserved for validation. This site-based approach reduced the influence of spatial autocorrelation and artificially high validation statistics. Additional training data were derived for nonimpervious features such as water bodies and wetlands based on the natural features coverage described above.

Predictor variables were chosen based on an analysis of impervious feature signatures and their vegetation indices. As with the tree cover mapping, the set of IKONOS spectral variables used for prediction consisted of the four optical bands, the NDVI, and the simple ratio (NIR/red). Two additional spectral ratios that showed promise in discriminating open soil plots from impervious features were also used (NIR/blue and NIR/green). The spectral information and impervious class for each of these data sets were used to grow impervious surface classification trees. The resulting tree-based algorithms were then applied to the corresponding IKONOS image tile, and thematic accuracy statistics were calculated.

3.5. Stream health analyses

Statistical analyses were performed on the impervious and tree cover maps to determine whether there were statistically significant differences between small watersheds (approximately equivalent to hydrological unit code HUC 14), as rated by water quality experts into one of four possible stream resource condition categories. These were based on countywide baseline stream monitoring data, including pH, dissolved oxygen, and temperature, among others (Van Ness, Brown, Haddaway, Marshall, & Jordahl, 1997). This multiagency effort also assessed a number of biological indicators based on fish and benthic macroinvertebrate surveys, and were used to define an index of biological integrity (IBI) (Stribling, Jessup, White, Boward, & Hurd, 1998). Of the 296 small watersheds in the county, 245 had been analyzed and represented by a categorical stream resource quality rating of excellent, good, fair, or poor. We refer to these as stream health ratings. About one-third of these (93) was indicated as preliminary assessments, which were analyzed as separate categories from the completed assessments.

We examined the amount of tree cover within the entire area of each watershed, as well as within 100-ft riparian buffers (a size determined by independent buffer monitoring and restoration activities) to explore whether there were links to the stream health ratings. The stream buffer was calculated using a hydrology vector layer provided by the county. The amount of impervious surface area within each watershed was also calculated and expressed, as with tree cover, as a proportion of total watershed area.

One-way analysis of variance (ANOVA) was used to assess the relation of each variable to the stream health ratings. Logistic regression was also used to explore the relationship of stream health with the mapped variables (i.e., impervious cover, watershed tree cover, and riparian buffer tree cover). Logistic regression is a nonlinear and nonparametric technique that uses maximum likelihood estimation to predict the odds probability of categorical dependent variables (in this case stream health rating). This is unlike ordinary least squares regression estimation of changes in a numerical dependent variable. The technique also has the advantage of not assuming normal distributions or homoskedastic independent variables (Menard, 1995). It is often used to test binary variables,

Table 3
Comparison of county area classified as tree or nontree using supervised and unsupervised approaches

Classification type	Type	Percent of area
Unsupervised	Tree	44.6
	Nontree	55.4
Supervised	Tree	49.7
	Nontree	50.3

Table 4
Accuracy assessment of supervised and unsupervised classifications

Classification	Overall accuracy	κ statistic	Z statistic
Supervised	0.86	0.72	15.7
Unsupervised	0.83	0.67	13.3

but also can be applied to multinomial dependents with more classes, as in our case with ordinal ratings of stream health.

4. Results

4.1. Tree cover

The extent of the tree cover classifications derived using the supervised and unsupervised approaches is summarized in Table 3. The unsupervised classification provided an estimate of ~5% (67 km^2) more forest than the supervised classification. Accuracy statistics generated for the initial supervised and unsupervised classifications (Table 4) indicate that both classifications were significantly better than random, but the differences between the classified maps, while not statistically significant ($p = 0.07$), were substantial enough to convince us to take a different approach (i.e., decision trees trained with a large sample of reference data).

The tree cover map derived from the decision tree approach (Fig. 3) was spatially detailed and boundaries between scenes are virtually nonexistent, despite the range of dates in the IKONOS acquisitions in both years and seasons. This was due, in large part, to the accuracy of the decision tree algorithm and the abundance of training data. Trees occupied nearly 38% of the county (Table 5). Areas obscured by cloud or cloud shadow, which could not be correctly classified, comprised 7% of the total county area. The original forest classification done ca. 1992, and subsequently manipulated for use as training data for our mapping, depicted just 28% of the county as forested (36,849 ha). The primary reason for the difference was the depiction of a forest/nonforest classification in the natural

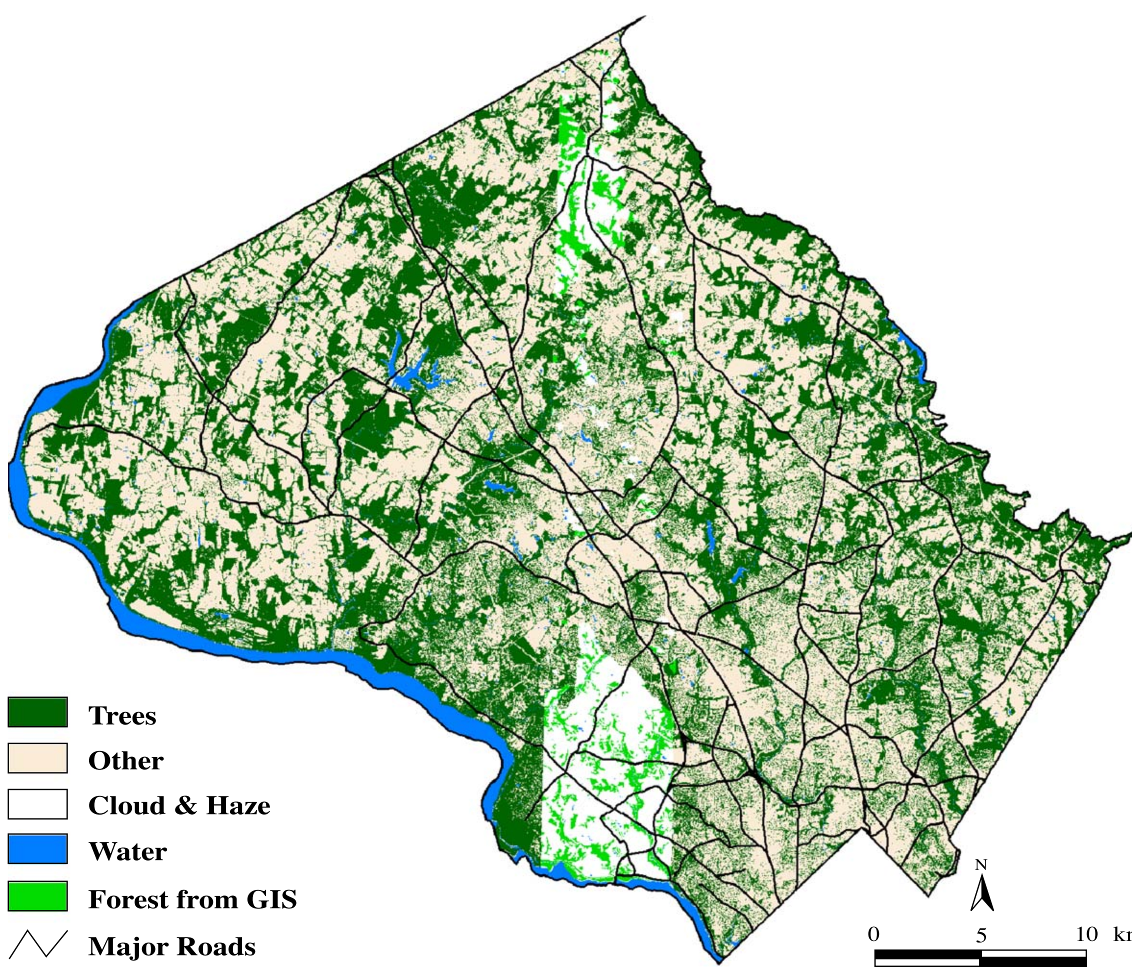

Fig. 3. IKONOS tree cover map of Montgomery County, MD. Note the forest cover data (from natural features GIS coverage; Fig. 4) used in the areas obscured by clouds.

Table 5
Classification of county using decision tree classifier

Classified type	Area (ha)	Percent of county
Tree	49,522	37.7
Nontree	72,268	55.1
Cloud	9478	7.2
Total	131,268	100

features layer, whereas use of IKONOS permitted us to capture, in many cases, individual trees. A subset of the IKONOS tree cover map, along with the reference data (natural features coverage), shows differences between the two mapping approaches (Fig. 4), where tree cover is shown in lighter green compared to the reference forest coverage (darker green). Note the missing trees in the subdivisions and between the links of the golf course in the lower left. It would be possible, if desired, to filter the tree cover map in such a way as to approximate the forest cover map (e.g., by retaining only those areas with at least five of the surrounding eight pixels in a 3×3 window classified as tree).

Accuracy statistics based on the independent 600,000 reference data samples reserved for validation show very high map accuracies, with omission errors of 2.1% and commission errors of 4.1% (Table 6). Overall classification accuracy was 97.3% ($\kappa = 0.95$).

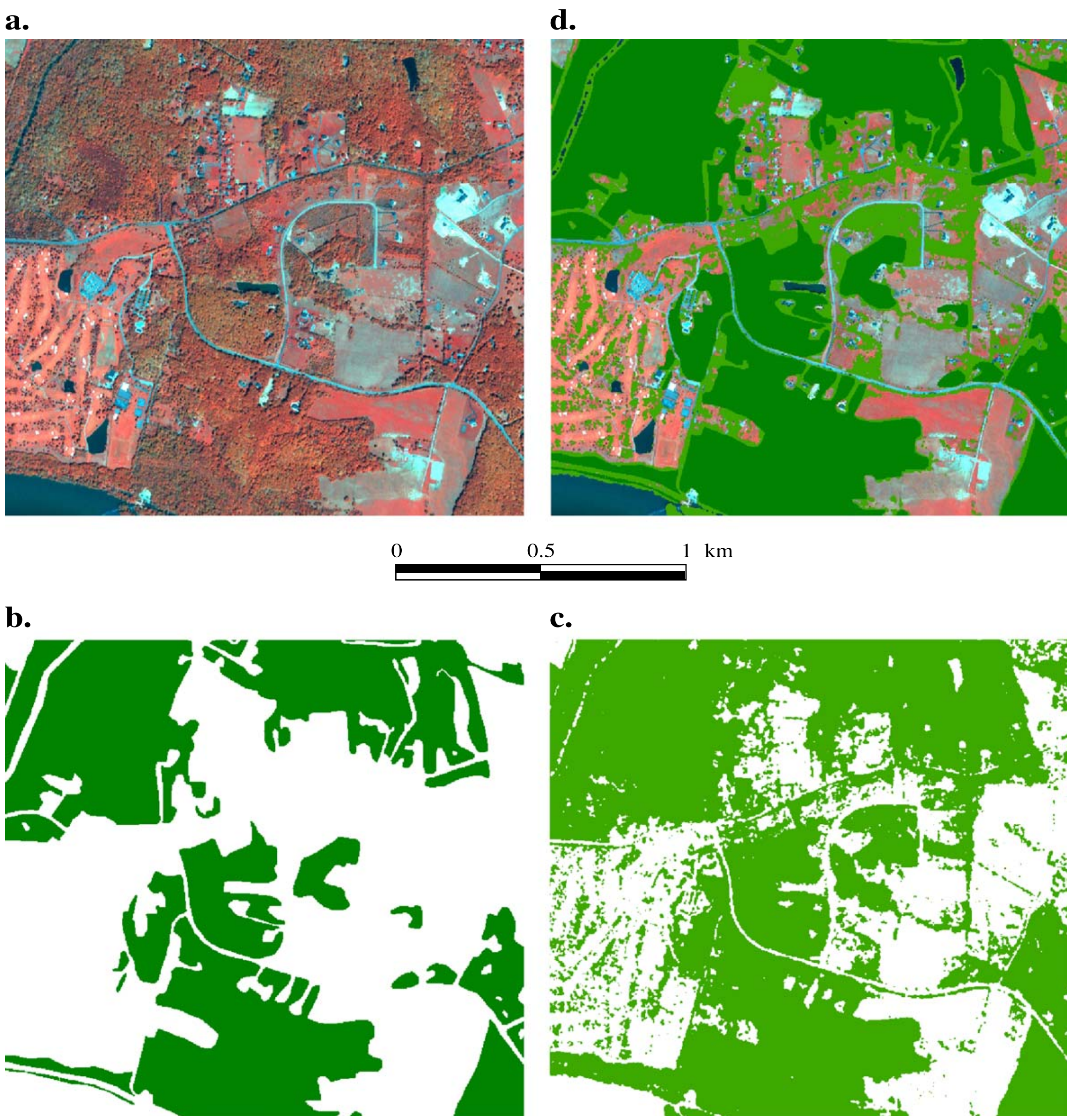

Fig. 4. IKONOS image detail with classification results. (a) IKONOS imagery; (b) 1992 natural features coverage of forest areas; (c) tree cover derived from imagery using a decision tree classifier; and (d) IKONOS image with natural features coverage and derived tree cover maps overlaid. Note the small patches of trees in (c) compared to the forest cover in (b) and the substantial amount of tree cover missing from the forest area coverage (d). (Includes material from Space Imaging©.)

Table 6
Accuracy assessment of tree cover map

	Validation sample (natural features)	Classified (IKONOS)	Number correct	Producer's accuracy	User's accuracy
Tree	212,703	217,224	208,351	98.0	95.9
Nontree	287,297	282,577	278,236	96.9	98.5

4.2. Impervious surfaces

The impervious surface map showed a level of detail sufficient to map individual houses within subdivisions, as well as clearly depicting areas where residential development had occurred since the original planimetric coverage was produced (Fig. 5). This map of impervious areas depicts a wide range of materials, some of which have very different spectral properties (e.g., pavement, concrete, roof tiles, etc.). Other mapping methods based on the use of regression trees, rather than classification trees, permit estimation of imperviousness as a continuous variable (i.e., as a percentage between 0 and 100). We have used the planimetric reference data to train an algorithm of continuous subpixel impervious maps based on Landsat imagery (Smith et al., fourthcoming), but the IKONOS impervious map could be used in place of planimetric data.

Internal accuracy assessment checks are provided by the decision tree software, including estimates of misclassification rates for each intermediate and terminal node, as well as an overall algorithm assessment. Additional checks of misclassification error were done by cross-validating the algorithm using 10% of the data samples in an iterative procedure, cycling through the full data set (after Friedl, Brodley, & Strahler, 1999). Analysis of these accuracy measurements for various tree-growing scenarios strengthened the final algorithm selection and the overall classification accuracies. Independent statistical validation using the 140,366 samples reserved from the image sampling approach demonstrated the ability of the algorithm to discriminate impervious from nonimpervious component materials in the imagery (Table 7). Omission errors in the impervious map were 9.4% and commission errors were 10.8%. Overall classification accuracy was 84.2% ($\kappa = 0.36$). Despite our efforts to screen for mislabeled and omitted features (e.g., driveways and sidewalks) in the planimetric data used for training, some remained present in both the training and

Fig. 5. Impervious surface areas (yellow) for a portion of Montgomery County derived from IKONOS imagery (right) compared to planimetric coverage derived from aerial photographs (left), showing changes in residential development since the area was initially mapped (ca. 1993). IKONOS tree cover (green) is also shown, with the IKONOS panchromatic image as a backdrop. (Includes material from Space Imaging©.)

Table 7
Accuracy assessment of impervious surfaces map

	Validation sample (planimetric)	Classified (IKONOS)	Number correct	Producer's accuracy	User's accuracy
Impervious	108,730	110,466	98,513	90.6	89.2
Nonimpervious	31,636	29,900	19,683	62.2	65.8

validation data samples, which produced somewhat lower accuracy statistics than expected. We believe, based in part on results such as those shown in Fig. 5, that the accuracy of the map is actually higher than that suggested by the interpretation of planimetric data.

4.3. Riparian buffers and stream health

Average tree cover within riparian buffers ranged from as little as 6% to over 98% by watershed, impervious cover within the watersheds ranged from 0% to 43%, and total tree cover (both inside and outside buffers) ranged between 6% and 94%. This range of observations was more than sufficient to detect the sensitivity of the stream health to buffer quality. Differences between watersheds were also visually evident in map comparisons for these same variables (Fig. 6), as well as in the statistics derived for each rating category (Table 8 and Fig. 7). ANOVA showed significant differences between watersheds with different

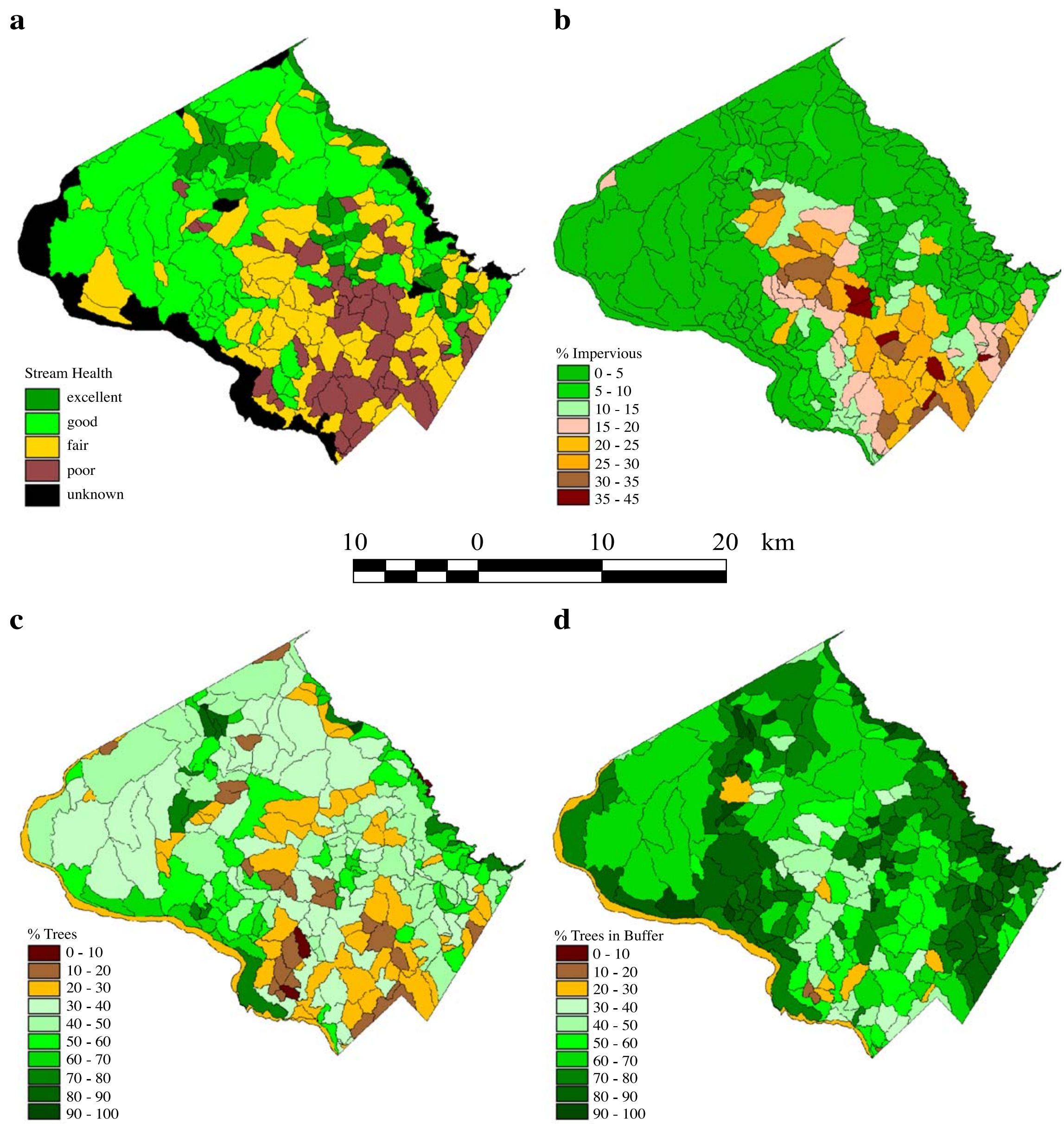

Fig. 6. Maps of small watershed aggregated values for (a) stream health rankings, (b) impervious surface cover (%), (c) tree cover (%), and (d) riparian buffer tree cover (%). (b)–(d) were calculated using the IKONOS-derived maps of these land cover variables.

amounts of impervious surface area, tree cover, and riparian tree buffers. Variance ratios (F statistics) were 42.1, 16.3, and 15.0, respectively, all significant at $p<0.001$ ($N=245$). Streams with excellent ratings had significantly lower impervious cover and higher tree cover, both within the watershed and riparian buffers, than streams rated good, fair, or poor. This trend continued progressively through each rating category, with increasing average impervious area and decreasing tree cover as stream health decreased. All pairwise comparisons confirmed statistically significant differences ($p<0.001$) between stream rating categories. There were no substantial differences between those streams with preliminary assessments and those with completed assessments, except in the case of those rated excellent ($n=32$) versus preliminary excellent ($n=6$), but this was likely a result of the small sample size of the latter.

The goodness of fit test of Hosmer and Lemeshow (1989) failed to reject the null hypothesis of no difference between the observed and model-predicted values of stream health; thus, the multivariate model was an adequate predictor of stream health rating. There is no variance-explained statistic in logistic regression when the dependent variable is categorical, but reduction in residual deviance from the null model was highly significant ($\chi^2=33.1$, $p<0.001$). There was, however, multicollinearity among variables in the regression. Across watersheds, the extent of tree cover both within and outside of the 100-ft buffer was positively correlated with each other ($r=0.71$), so the properties of the 100-ft buffer were not independent of the surrounding land cover. Impervious area and total tree cover were inversely correlated ($r=-0.55$), as were impervious area and tree buffers ($r=-0.43$), but these relationships were reduced in agricultural areas, which had both low tree and impervious cover. As implied by the ANOVA, the individual independent variables in the logistic regression were each statistically significant, and stepwise inclusion tests revealed that impervious cover was the primary predictive variable, followed by tree cover within the buffers, and then total tree cover. Residual deviance was significantly reduced when riparian buffers were added to a model based on impervious surfaces alone, but subsequent addition of total watershed tree cover did not further contribute to model significance. The results suggest that guidelines for excellent stream health rating would be no more than 6% impervious with at least 65% forested buffers, and no more than 10% impervious with at least 60% buffered for a rating of good. These values would clearly be affected by the landscape configuration of buffers in relation to impervious areas, and by mitigation measures like sediment retention ponds.

Table 8
Small watershed sample size and average statistics by stream health rating category

Stream health rating	n	Area (km^2)	Impervious (%)	Tree cover (%)	Buffered (%)
Excellent	38	272	3.6	50.6	76.8
Good	81	658	4.9	44.6	71.3
Fair	76	451	13.9	37.0	63.2
Poor	50	356	19.5	29.6	56.3

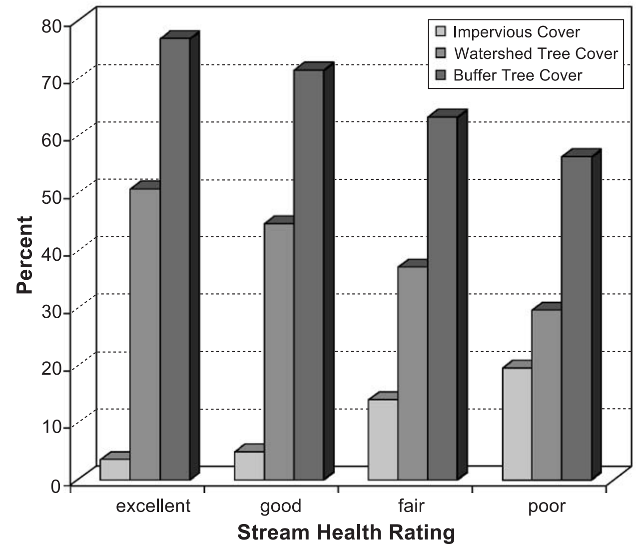

Fig. 7. Stream health rankings in relation to (a) impervious surface cover, (b) watershed tree cover, and (c) riparian buffer tree cover, each derived from the IKONOS image data.

5. Discussion

5.1. Mapping applications

Land cover classification in the study region using IKONOS imagery with traditional supervised and unsupervised approaches produced substantially different maps and, for example, tree cover estimates. There were several factors that impacted the classifications, including the timing of data acquisition (thus phenological stage), associated viewing and atmospheric conditions, the quality of training data (in the case of supervised classification), and insufficient discrimination resulting from limited IKONOS spectral bands. Some of the more pronounced classification errors were between wet agricultural fields, dense forests, and shadows. For example, spring small grains (wheat, barley, and rye) and hay (alfalfa and grasses) had emerged in agricultural fields, which produced a similar spectral response as deciduous trees in partial leaf flush. In other areas, the visibility of the forest floor through the tree canopy produced spectral responses similar to residential areas. Shadows were also an especially important consideration with the use of this high spatial resolution imagery, particularly shadowing within the forest canopy from adjacent trees. Some of these issues can be reduced through the use of multi-temporal imagery, but this would be logistically difficult to accomplish in many areas, and cost-prohibitive for most applications using IKONOS.

In order to reduce the impact of some of these issues, the decision tree classification approach we adopted made use of a large number of reference (training) data for the study area. The resulting classification reinforced the considerations noted above regarding the use of IKONOS imagery for vegetation mapping. Two classification issues were especially problematic, each dependent on the timing of scene acquisition. In the early spring images (Panels 4 and 7) (see Table 1 and Fig. 1), the primary source of classification error was confusion between mature deciduous forests and bare ground areas such as untilled agricultural or partially vegetated abandoned areas. In these scenes, mature forests had just begun to leaf out, and undergrowth, bare ground, and litter beneath the trees were spectrally similar to agricultural fields with crop residue still in place from no-till farming practices. In the spring and early summer images (Panels 1–3 and 5), the primary confusion occurred between active agricultural fields and deciduous trees. Despite these issues, we were able to achieve accurate maps of tree and impervious cover.

Although the above points are not unique to IKONOS imagery, they are accentuated by the high spatial resolution relative to other imaging sensors such as Landsat TM. In the case of the early season deciduous forest, the 4-m IKONOS resolution included data in the intercanopy space, whereas with TM, the pixels include a mixture of canopy and higher biomass woody stems, generally producing higher NDVI values. In the case of the leaf-on scenes, the high vegetation index values of actively growing agricultural fields appeared spectrally similar to that of the dense deciduous tree canopy. This was partly due to greater spatial variability in IKONOS scene elements. For example, a single tree may be contained within one TM pixel, whereas the same tree may be represented by 5 or 10 IKONOS pixels, resulting in greater variation with foliage density and canopy shape (see also Blonski, 2001; Goward, Davis, Fleming, Miller, & Townshend, this issue). Inclusion of the ARVI image helped reduce this effect, but cannot completely resolve this unique aspect of high spatial resolution imagery. Clearly, this "issue" could be considered an advantage for some applications (e.g., assessments of defoliation or tree health). There have also been suggestions that high-resolution imagery could provide information capable of discriminating different habitat types and complex forest associations (e.g., oak/hickory versus beech/maple), or permit mapping of invasive species such as *Kudzu*. Based on our results with IKONOS, we believe that these applications would be difficult to accomplish within reasonable confidence limits.

The capability of IKONOS to point in a desired direction adds to the flexibility in acquisition strategies, and also has implications for the spectral properties of image components. The relationship between sun, surface, and sensor for our image acquisitions (Table 1) shows that Panels 0 and 1 were acquired on the same orbit, but the sensor azimuth angles differed. As a result, many of the water bodies in Panel 0 show the effect of sun glint, whereas those in Panel 1 do not. Similar, albeit less dramatic, conditions occur in areas that are mostly vegetation or impervious cover types. This type of information can be useful for analyses of bidirection reflectance properties, but complicates image classification for many applications, particularly where many IKONOS tiles or overlapping image panels are required to completely map a study area.

The work reported here also permitted algorithm development for application to other IKONOS imagery in the region, and significantly allowed for the development of subpixel mapping techniques using Landsat imagery, which we will report on in future publications (e.g., Smith et al., fourthcoming).

5.2. Stream health application

Riparian buffers have been recognized as important landscape features that provide unique habitat for many wildlife species (Iverson, Szafoni, Baum, & Cook, 2001), as well as filtering capabilities for removing nutrient pollutants from agricultural runoff before they reach waterways (Cooper, Gilliam, Daniels, & Robarge, 1987; Correll, 1997; Lowrance et al., 1997). Traditional approaches to mapping and monitoring riparian zone vegetation have relied on photographic interpretation (e.g., Lonard, Judd, & Desai, 2000), but this is not practical over large areas. For example, the Chesapeake Bay Program has been tasked with establishing 2000 miles of forested riparian buffers by the year 2010, but does not have a practical methodology to accurately assess current buffer statistics, let alone monitor new plantings. Landsat data are simply not of sufficient spatial resolution to adequately map riparian buffer vegetation within the widely accepted 100-ft (~ 30 m) buffer width used as a common reference for buffer effectiveness.

Our analyses of impervious surfaces and tree cover within the small watersheds and riparian buffer zones of Montgomery County provide an example of the capabilities conveyed by consistent mapping over large areas using IKONOS imagery. A key advantage to the IKONOS-derived maps was the fine spatial resolution that allowed very-local-scale analysis of riparian buffers, and statistically meaningful sample populations within the small watersheds. The results confirm that there are clear linkages between the land cover within a watershed and the stream water quality. Specifically, the amount of impervious surface area within a watershed and tree cover within riparian buffer zones provided robust indicators of stream health rating. This suggests that the buffers were functioning to reduce pollutants and sediments from built areas before they entered the waterways. Conversely, buffers alone were insufficient for protecting waterways in highly impervious areas or where forest cover outside buffer zones was low, including agricultural areas that presumably affected stream health through chemical run-off. Additional analyses beyond the scope of this paper are being completed to explore these relationships further, and to assess the effectiveness of mitigation approaches in controlled and uncontrolled paired watersheds.

The high-resolution land cover maps that can be derived from IKONOS imagery and the associated landscape variables that can be calculated from them (e.g., buffer configuration) thus provide an important contribution to these types of resource management applications. In the case of Montgomery County, these statistics are actively used to determine whether resources are focused on watershed preservation (streams of excellent health), protection (good or excellent health), or restoration (fair or poor health).

6. Conclusions

Utilizing high spatial resolution imagery can be beneficial to many different resource management applications. Imagery like IKONOS can aid in the development of a wide range of mapping and spatial modeling applications, but a number of issues must be considered with these relatively new and unique data sets. The issues include (i) programmatic considerations of the timing of acquisitions to capture features of interest (e.g., leaf-off for impervious versus leaf-on for tree cover), as well as timely data acquisition (ours took 18 months to acquire); (ii) technical considerations, such as compensation for the effects of object shadowing resulting from improved resolution of individual scene elements, and limited spectral resolution and range; and (iii) economic factors, such as cost per square kilometer relative to DOQs, and feasibility of consistent repeat acquisitions. For example, we noted an inability of IKONOS to adequately spectrally discriminate some land cover types due to high spatial variability within scene elements resulting from variable illumination and viewing conditions. Spectral variability within scene objects also contributed to reduced class type discrimination between more generalized land cover types (e.g., confusion between deciduous forest and some agricultural crops).

New sets of interpretation strategies need to be developed to maximize the information obtained from IKONOS, while minimizing the problematic issues specific to high spatial resolution imagery. Our exploration of several such approaches relevant to resource mapping applications suggests the great practical utility of IKONOS imagery, particularly for impervious surface, tree cover, and riparian buffers, all of which are related to stream health. Our results provided very specific guidelines for predicting stream health ratings, which allows for targeted and adaptive protection and restoration management decision making. Other applications for which the maps are currently being utilized include resource lands monitoring and acquisition planning, analyses of habitat connectedness and bird habitat suitability, and hydrodynamic modeling for mitigation of stream bank erosion. IKONOS imagery can augment traditional mapping approaches and, in many cases, may provide a cost-effective alternative.

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