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Urbanization and the Loss of Resource Lands in the Chesapeake Bay Watershed

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ABSTRACT / We made use of land cover maps, and land use change associated with urbanization, to provide estimates of the loss of natural resource lands (forest, agriculture, and wetland areas) across the 168,000 km^2 Chesapeake Bay watershed. We conducted extensive accuracy assessments of the satellite-derived maps, most of which were produced by us using widely available multitemporal Landsat imagery. The change in urbanization was derived from impervious surface area maps (the built environment) for 1990 and 2000, from which we estimated the loss of resource lands that occurred during this decade. Within the watershed, we observed a 61% increase in developed land (from 5,177 to 8,363 km^2). Most of this new development (64%) occurred on agricultural and grasslands, whereas 33% occurred on forested land. Some smaller municipalities lost as much as 17% of their forest lands and 36% of their agricultural lands to development, although in the outlying counties losses ranged from 0% to 1.4% for forests and 0% to 2.6% for agriculture. Fast-growing urban areas surrounded by forested land experienced the most loss of forest to impervious surfaces. These estimates could be used for the monitoring of the impacts of development across the Chesapeake Bay watershed, and the approach has utility for other regions nationwide. In turn, the results and the approach can help jurisdictions set goals for resource land protection and acquisition that are consistent with regional restoration goals.

From upstate New York to the southeastern corner of Virginia, hundreds of rivers and streams drain five physiographic provinces across the 168,000-km^2 Chesapeake Bay watershed (CBW). Home to a wide variety of fresh and saltwater species, the Chesapeake Bay and its tributaries provide valuable ecologic services and economic benefits (Bockstael and others 1995; Costanza 2003). In presettlement times, much of the CBW was forested, but conversion to agriculture took place throughout the 18th and 19th centuries followed by commercial and residential development (Horton 2003; Benitez and Fisher 2004).

The Chesapeake Bay Program (CBP), a regional partnership that has coordinated the restoration of the Chesapeake Bay since 1983, seeks to restore healthy populations of fish and shellfish by reestablishing submerged aquatic vegetation, protecting wetlands, decreasing sediment and nutrient runoff, and increasing water quality and clarity. Many of these goals involve aspects of land use change such as restoring and conserving riparian forest buffers, wetlands, and areas of contiguous forest and decreasing suburban development rates in forested and agriculture areas (CBP 2000). To assess the feasibility of and progress toward these goals, an accurate assessment of the current development trends shaping the basin is required.

Impervious surface areas (buildings, roads, etc,) can be used to directly measure the location, configuration, and changes in development and provide indicators of ecosystem health and function. Numerous studies have shown that impervious surface areas increase the magnitude and temperature of runoff, magnify the amount of sediments and pollutants in runoff, and fragment natural landscapes. A widely used indicator of stream biotic impoverishment is impervious cover exceeding 10% of watershed area (Schueler 1994), although

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impoverishment may occur at <6% depending on riparian buffer vegetation and landscape configuration (Goetz and others 2003; Snyder and others 2005). Reliable estimates of impervious surface area at local to regional scales thus provide useful information to land managers and policymakers to aid assessments and targeting of stream condition and restoration potential (Roth and others 2004).

Several methods have been used to monitor land use and land cover change within the CBW. The United States Department of Agriculture's National Resource Inventory provides statistical estimates that are useful at broad spatial scales but become less reliable at finer scales. The National Agricultural Statistics Service and the Census of Agriculture provide county-level estimates of land devoted to crops and pasture but do not consider forested lands or subcounty spatial distribution of crops and pasture. The United States Geological Survey (USGS) land use and land cover data set provides regional land cover estimates derived from aerial photographs, but manual interpretation over large areas is time consuming and costly with long repeat intervals and issues of interpreter consistency.

As the limitations of traditional methods to estimate land cover and land use change have become more apparent, use of satellite remote sensing has expanded rapidly. The cost of remotely sensed data has steadily decreased, and new classification techniques coupled with higher-quality imagery have led to ever more reliable land cover maps. The National Oceanographic and Atmospheric Administration's Coastal Change Analysis Program (C-CAP) was developed in the mid-1990s to map coastal land cover using satellite imagery. The USGS Multi-Resolution Landcover Consortium (MRLC) produced a 30-meter resolution land cover map of the Mid-Atlantic region using 1990 Landsat Thematic Mapper (TM) scenes and other ancillary data (Vogelmann and others 1998). The overall spatial accuracy of the land cover classifications was good, although some difficulty distinguishing between certain land cover classes was encountered (Roth and others 1999).

A recent approach to land cover and land use change classification involves the use of decision tree algorithms trained with high-resolution data sets (Hanson and others 1996; Friedl and others 1997; Rogan and others 2002). This method allows for thematic or continuous outputs and has been used to create accurate maps at local to regional scales (Brown de Colstoun and others 2004; Goetz and others 2004a). The National Land Cover Database (NLCD) now uses this approach (Homer and others 2002) rather than unsupervised classification as in the earlier MRLC (Vogelmann and others 1998). We note that for this reason, together with the use of different land cover class definitions, the 1990 MRLC and 2000 NLCD national land cover products are not comparable and cannot be simply differenced to identify land cover change at fine scales.

Satellite mapping focused specifically on urban areas has also progressed rapidly (see review by Tatem and Hay 2004). Most recently this work has focused on mapping the built environment as represented by continuous (0% to 100%) estimates of impervious surface cover using decision tree classifiers (Yang and others 2003a; Goetz and others 2004b). Other recent "subpixel" impervious surface mapping has made use of neural network algorithms (Flanagan and Civco 2001), spectral mixture models (Ji and Jenson 1999; Phinn and others 2002), and a suite of related techniques (see Tatem and Hay 2004).

Our objectives were to estimate the extent and rates of urbanization (suburban and exurban development) and to assess the impact of this land use change on natural resource lands (forest, agriculture, and wetlands) throughout the CBW. Using subpixel impervious surface maps to define developed or built areas, in conjunction with land cover maps (Goetz and others 2004b), we provide reliable estimates of the increase in urbanization from 1990 to 2000 and quantify the loss of resource lands since 1990 associated with this change. Because similar changes are occurring nationwide, even worldwide, this work has wide application and provides techniques and information essential to the land management process for mitigation, prioritization, targeting, and restoration.

Our primary study area for these analyses focused on the counties that are contained within or that intersect the watershed of the Chesapeake Bay (Fig. 1). Although this area is somewhat larger than the land area of the Chesapeake Bay drainage basin, it is important to include the full extent of all counties because this is the political unit at which many land use management decisions will be implemented. However, we report estimates of new development between 1990 and 2000 and the associated loss of natural resource lands for both the full study area and the CBW.

Methods

Overview

To provide a range of estimates of resource land loss since 1990, we used two independently developed land cover maps, the MRLC (Vogelmann and others

Figure 1. The principle study area is the extent of the counties that intersect or that are contained within the CBW boundary, although we also focused on resource land loss estimates within the watershed itself. CBW = Chesapeake Bay Watershed.

1998) and ours, referred to as mid-Atlantic Regional Earth Science Applications Center (MA-RESAC) (Goetz and others 2004b). The most conservative resource land loss estimates were made using the intersection of both maps, i.e., where both agreed on a given land cover type classification. We note that we define natural resource lands strictly by their mapped extent and do not attempt to address the ecologic or economic values of these areas (e.g., CBP 2005a). Before calculating resource land loss estimates, we conducted rigorous accuracy assessments of the various land cover type and impervious surface cover map products.

To estimate the error associated with the data sets, and our analysis, we assessed the accuracy of the 1990 and 2000 impervious surface maps and evaluated different impervious surface area change thresholds to identify the most robust measure of impervious surface change. We also conducted accuracy assessments of our 1990 land cover map as well as the map created by intersecting the two 1990 land cover maps.

Land Cover–Type Maps. The MRLC map was derived using data from 45 Landsat TM scenes, acquired between 1987 and 1992, that were georeferenced, orthocorrected, and projected to a Lambert Azimuthal coordinate system. An unsupervised classification algorithm was used to identify classes according to a modified C-CAP classification scheme (Dobson and others 1995) incorporating ancillary data sources used to refine the classification. In particular, spatial data from the National Wetlands Inventory (NWI) and other sources were incorporated into the final map for the wetlands classes (Vogelmann and others 1998). For consistency with the MA-RESAC 1990 land cover map, we reprojected the MRLC map to UTM/NAD83 coordinates and clipped it to the same geographic extent.

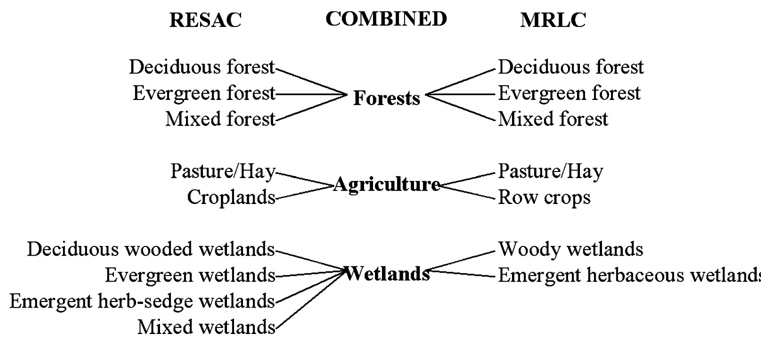

Figure 2. Generalization of the resource land cover classes in the two data sets.

The MA-RESAC 1990 land cover map was developed with many of the same TM scenes used by the MRLC but augmented where possible with additional scenes, acquired subsequently, that had decreased cloud cover. Scene dates ranged from 1988 through 2002 including both leaf-on and leaf-off imagery to aid cover type discrimination. Georegistration of all images was done using the orthorectified GeoCover image database as a reference, which accounted for topographic distortions as well as horizontal displacement. All subject scenes were verified to have <0.5-pixel spatial misregistration (representing an area <15 m on the ground) as measured using root mean square error between the reference and subject scenes. A range of image preprocessing steps were conducted to ensure the scenes were consistent radiometrically across the region and through time (Goetz and others 2004b).

Rather than using an unsupervised classification approach, the MA-RESAC map was produced with a decision tree algorithm using a modified Anderson Level II classification. The natural land cover classes were derived solely from spectral characteristics of the imagery (Goetz and others 2004a). We also created a land cover map using areas of agreement between the 1990 MA-RESAC map and the 1990 MRLC map. For ease of comparison, to decrease errors, and to increase utility, we collapsed the more specific categories of resource land into three general categories: forests, agriculture, and wetlands (Fig. 2).

Finally, we used a current (2000) land cover map that included agricultural areas (Goetz and others 2004a) to mask commission errors in the impervious cover maps, discussed later, that were associated with fallow or bare soil areas. The satellite imagery used for the 2000 land cover and subpixel impervious surface maps included 60 spring, summer, and fall Landsat 7 ETM + scenes acquired between 1999 and 2001, which were extensively preprocessed for image consistency (Goetz and others 2004b). The level-1 images were orthocorrected using the National Elevation Database digital elevation model while simultaneously georeferencing them to the Earthsat GeoCover database.

Impervious Surface Maps. To create the 2000 impervious surface map, the same 60 Landsat-7 ETM + scenes were used with a vector planimetric database of Montgomery County, MD, consisting of hand-delineated polygons of impervious surfaces (roofs, streets, sidewalks, etc.) as interpreted from aerial photographs. By rasterizing or ‘‘gridding’’ the vector planimetric data, a 3-meter resolution impervious surface coverage was derived. The number of 3-meter cells within each overlying 30-meter cell was then enumerated to produce a 30-meter image of continuous subpixel impervious surface values ranging from 0% to 100%. This provided the training data used to develop the decision tree algorithms to map subpixel impervious surface values using the satellite imagery. In other words, the impervious surface values of each 30-meter area in the county could be associated with spectral characteristics of the corresponding Landsat pixel.

A set of predictor variables were derived from the Landsat TM/ETM+ bands, which included the normalized difference vegetation index (NDVI) and the first three principal components of the six band image data (Crist and Cicone 1984). Two additional multiseason variables—maximum NDVI and maximum greenness—were also included. The decision tree was then crossvalidated to select the smallest set of variables that adequately explained variations in the data (Goetz and others 2004a).

To minimize commission errors (false positives), any impervious surface values <10% were assigned a value of zero in the final map (Fig. 3). In an effort to further decrease commission errors, we developed a mask consisting of areas that were classified as agriculture in both the 1990 MRLC and 2000 MA-RESAC land cover maps and used this to screen consistently bare agricultural areas, which can have surface reflectance properties similar to those of impervious surfaces. We conducted extensive efforts to discriminate

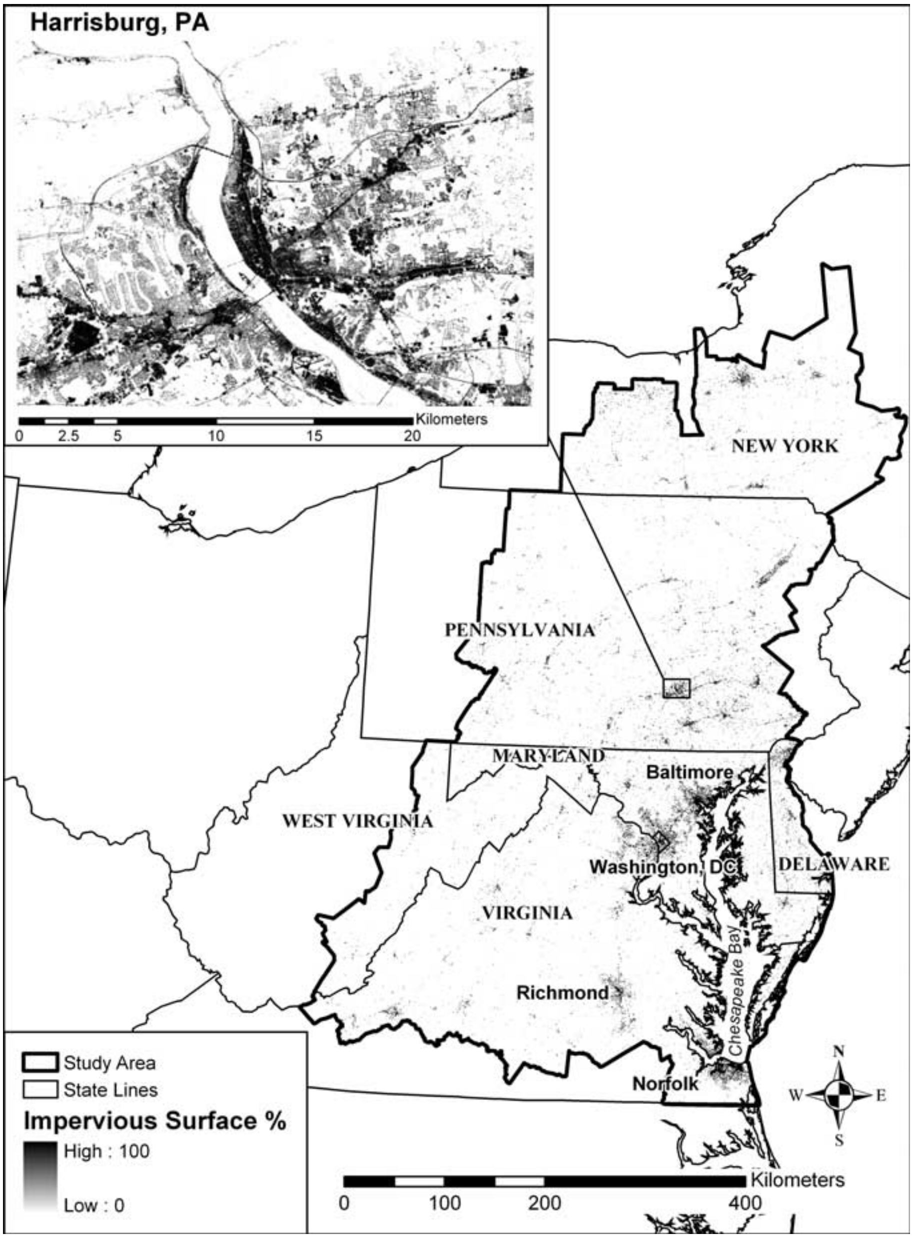

Figure 3. Subpixel impervious surface data for the study area for 2000.

these areas from one another using both automated and manual (visual-screening) techniques as well as the agricultural cover–type masking, which had classification accuracies of 90% to 95% (Goetz and others 2004a).

To create the 1990 impervious surface map, the circa 1990 Landsat 5 TM imagery was used instead of the circa 2000 Landsat 7 ETM+, and a decision tree algorithm was developed to detect the extent of impervious surface land cover. For training data, we identified a subset of the Montgomery County, MD, planimetric data set where no change had occurred between 1990 and 2000. To identify areas of no change, we used a vector grid consisting of 689 2.2-km^2 rectangular cells. Using the 1990 and 2000 Landsat imagery as reference, we noted whether or not change had occurred in each cell and whether or not the planimetric data were complete. We identified 193 training blocks containing complete planimetric coverage with a high certainty of no change. Where a pixel was identified as having been developed in 1990, information regarding the proportional value of impervious surface within each 30-m cell was derived from the 2000 data set. Although this method fails to

Table 1. Summary of data sets used to validate the MA-RESAC circa 1990 land cover map and the 1990 and 2000 impervious surface area maps

Target map	Total area (km^2) of validation data	Extent within CBW (km^2)	Source type	Date range
1990 MA-RESAC land cover	6.2[a]	168,000	NHAP	1987–1997 (Roth and others 2000)
1990 ISA	19.2	6,030	DOQQ	1990–1992
2000 ISA	70.8	54,264	DOQQ	Late 1980s to 1990s (Yang and others 2003b)

[a]Seven Hundred and Sixty Nine points, each representing approximately 0.008 km^2.
CBW = Chesapeake Bay watershed.
DOQQ = Digital orthophoto quarter quadrangles.
ISA = Impervious Surface Area.
MA-RESAC = Mid-Atlantic Regional Earth Science Applications Center.
NHAP = National High Altitude Photography Program.

detect intensification of development, limitations of the Landsat 5 sensor and the historic images available prevented direct estimation of fractional impervious surfaces for 1990 at the same level of accuracy achieved for the 2000 data set.

To create an impervious surface change map, we identified areas that underwent change between 1990 and 2000. Previously undeveloped cells, where we observed an increase in impervious surface area ≥20% between 1990 and 2000, were found to produce a robust estimate of change, thus we used 20% Impervious Surface Area (ISA) change as a minimum threshold defining recently developed areas. Filtering out single isolated pixels of change—which in some cases may have resulted from the commission errors, edge effects, or spectral mixing that occurs in Landsat pixels—created a second, more conservative change map.

Validation Data Sets. To assess the accuracy of the MA-RESAC 1990 land cover–type map, the same aerial photo reference data set that was used to assess the 1990 MRLC land cover map was used. This also allowed for direct comparison of the two land cover maps. The validation data set consisted of 202 1:40,000 aerial photos from the National High Altitude Photography Program (NHAP) distributed across the entire watershed (Roth and others 1999). The photos were randomly selected, and a stratified random selection process was used to select 1,166 points within the photos. Of these, a total of 783 points fell within the extent of the CBW. Fourteen points were unusable because they either fell on a boundary of two photo-interpreted polygons or had no data associated with them; thus, the final sample size was 769.

The 1990 and 2000 impervious surface maps were validated using two sets of high-resolution digital orthophoto quarter quadrangles (DOQQs). The 1990 impervious surface reference data consisted of 64 0.3-km^2 DOQQs with a cumulative area of 19.2 km^2 distributed across 6,030 km^2 of the Piedmont physiographic province near Washington, DC. The extent of impervious surfaces in the DOQQs were visually identified and manually digitized, and the type of impervious cover (*e.g.*, roof, street, sidewalk, parking lot, etc.) was also noted. The resulting vector file was then converted to a 3-meter raster. To make a direct comparison between these high-resolution maps of impervious surfaces and the estimates of subpixel impervious surface area derived from Landsat imagery, the 3-meter cells were summed within overlying 30-meter cells to create a 30-meter continuous image of impervious surface percentage estimates.

The 2000 impervious surface map validation data consisted of 12 5.9-km^2 interpreted DOQQs with a cumulative area of 70.8 km^2 spread across 54,264 km^2 of the central and northern portions of the watershed provided by the NLCD (Yang and others 2003b). Although the 1990 reference data set provided additional information regarding the type of impervious surfaces, the 2000 data set represents only the extent of impervious surface features, See Table 1 for a summary of the data sets used to validate each map.

Validation

Land-Cover Maps. Assessments of the MRLC cover-type map were made using several methods reported elsewhere (Vogelmann and others 1998; Roth and others 1999) and summarized here. Land cover classifications were assessed with point-to-point comparisons between the NHAP data set and the MRLC map. In addition, the selected pixels in the MRLC map were compared with any pixel in a 3 × 3–pixel block, centered on the MRLC pixel, in the NHAP data set. Following the MRLC validation effort (Roth and others

Table 2. Land cover classes used in the comparison of the MA-RESAC land cover map and the NHAP data set[a]

Eleven-class classification scheme	Eight-class classification scheme
Water	Water
Developed	Developed
Barren	Barren
Extractive	Extractive
{Deciduous forests, Evergreen forests, Mixed forests}	Forests
{Pasture/hay, Croplands}	Agriculture
"Grass"	"Grass"
Wetlands	Wetlands

[a]Brackets indicate classes in the 11-class scheme that were combined to create the 8-class scheme.
MA-RESAC = Mid-Atlantic Regional Earth Science Applications Center.
NHAP = National High Altitude Photography Program.

1999), we considered a pixel classification correct if any one of the 9 pixels in the overlying NHAP data set were matched. If not, the mismatch (error type) was attributed to the majority class in the 9-pixel window. This one-to-many comparison was done with the 11 original land cover classes and also with similar cover class types grouped together. A point-to-point comparison is the most accurate, but it can amplify spatial mismatch. The one-to-many point comparison decreases spatial mismatch and was therefore used as the primary estimate of accuracy, but it can increase the possibility of chance agreements. Comparisons of spatial agreement as well as class area estimates were made with C-CAP and LUDA data. Area estimates for agricultural classes were compared with 1992 Census of Agriculture data (Roth and others 1999).

To compare land cover classes between the 1990 MA-RESAC land cover map and the NHAP data, it was necessary to collapse the multiple developed classes and the multiple wetland classes into two classes—developed and wetlands—respectively. In the NHAP data set, we also merged the bare rock and transitional classes into one class to correspond with the MA-RESAC barren class. This decreased the number of classes to 11 for both data sets (Table 2). For each NHAP data point, we identified the center pixel of a 3 × 3–pixel window centered on the data point with the corresponding pixel of the MA-RESAC map. Following the method used by the MRLC (Roth and others 1999), we compared the selected MA-RESAC pixel with any pixel in the 3 × 3–pixel window in the NHAP data set.

Finally, we combined the similar land cover classes (Table 2), resulting in 8 classes, and again performed a one-to-many analysis. This allowed us to quantify the effect that confusion between similar land cover classes had on agreement between the data sets. We performed the same one-to-many analysis on the land cover agreement map.

Impervious-Surface Maps. To measure spatial agreement between our 1990 impervious surface map and the 1990 DOQQs, we reclassified both data sets as binary impervious/not impervious by characterizing pixels >10% impervious as developed (*i.e.*, part of the built environment). We then overlaid the data sets and quantified the areas of agreement and disagreement. In addition, we compared the MA-RESAC continuous (subpixel) impervious surface estimates with similar estimates calculated from the DOQQs. We made comparisons using 2,586 samples (approximately 13% of the data set) where both had non-zero values.

Because the 2000 DOQQ data set was considerably larger than the 1990 data set, we randomly selected 10,127 non-zero samples (approximately 12% of the data set) to perform a correlation analysis between continuous impervious surface estimates in the satellite maps relative to observed impervious estimates derived from the DOQQs. Again, to measure spatial extent agreement, we also performed an overlay analysis between the binary on/off DOQQ impervious extent and the binary satellite-derived impervious surface map. Thus, we conducted accuracy assessments of both the amount (%) and the spatial extent of impervious cover as mapped with the satellite imagery.

Changes in the Built Environment: 1999 to 2000. The amount and location of change in the built environment was estimated by simply differencing the 1990 and 2000 impervious surface area maps. Areal estimates of developed land in 1990 and 2000 were calculated by summing the area of all pixels with an impervious surface percentage value of at least 10%. Areal estimates of change were also calculated on a per-pixel basis. We derived a second, more conservative change map where single pixels were removed.

We also tested the effects of increasing the threshold of impervious surface changes. Thresholds are based on differences in subpixel impervious surface values between 1990 and 2000. A 20% threshold represents pixels with ≥20% increase in impervious surface between 1990 and 2000. We evaluated thresholds ranging from 20% to 50% in 10% increments for the initial change map and the derivative map of change with single pixels removed.

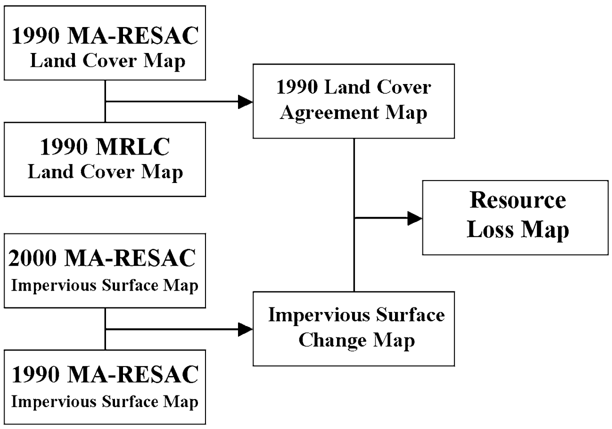

Figure 4. A series of map overlays was used to create four different estimates of resource land loss. This flow chart illustrates the map overlays that were used to create the estimate of resource land loss based on the initial impervious surface change map and the land cover agreement map.

Calculation of Resource Lands Loss

Using map overlays, we calculated four different estimates of resource land loss. First, we overlaid the initial impervious surface change map on the three maps of 1990 land cover (*i.e.*, MA-RESAC, MRLC, and the land cover agreement map). For the most conservative estimate of resource land loss, we used the filtered impervious surface change map to estimate change on the land cover agreement map. A graphical representation of our analysis is depicted in Figure 4. This technique allowed us to identify the land cover classification of pixels that experienced change between 1990 and 2000 and provided a range of estimates. It also gave us area estimates and geographic distribution of natural resource lands converted to impervious surfaces.

Results

Data Sets

Land-Cover Maps. The 1990 MA-RESAC land cover map was visually similar to the MRLC map, and class area estimates were comparable. The MA-RESAC map estimated that 56% of the CBW was forest, 29% agriculture, and 4% was wetland. This compared with MRLC estimates of 60% forest, 26% agriculture, and 3% wetland.

The results of the overlay of the two land cover maps show high levels of agreement between forests and agriculture classes in terms of both classification and area estimates (Table 3). Agreement for the wetland class was lower and indicates important differences in the two maps for this class. Areas classified as wetlands by MRLC agreed with the MA-RESAC map 78% of the time, whereas the MA-RESAC wetlands classification agreed with the MRLC map only 56% of the time. In addition, the MA-RESAC map estimates for wetland area was almost 30% higher than the MRLC estimate.

Across classes, the MRLC map generally agreed more frequently with the MA-RESAC than the reverse. Classes where the MA-RESAC classification agreed with the MRLC map at a rate <50% included extractive (46%), barren (8%) and ‘‘grass’’ (46%). Because the total mapped area for these classes was low, these differences contributed little to overall map disagreement. Overall agreement was 89% with a kappa value of 0.81.

Combining the land cover maps resulted in a decrease in the area of land available for analysis because areas of disagreement were essentially eliminated. Areas of disagreement totaled 29,194 km^2, which was 11% of the total analysis area. We noted that the effect of these differences was a decrease in of the area of resource lands that could be considered in the analysis. For example, where new development occurred over areas of disagreement, 76% was classified as forests, agriculture, or wetlands by the 1990 MA-RESAC. For the MRLC map, 49% was classified as a resource land cover class, and 29% was classified as low-density residential. Although the use of two land cover maps increased our confidence in the accuracy of the 1990 land cover classification, it resulted in conservative estimates of resource lands lost to development.

Impervious-Surface Maps. In 1990, pixels that were at least 10% impervious surface cover comprised an area of 6,705 km^2 of the study area. By 2000, developed pixels of at least 10% impervious cover had increased 61% to 10,806 km^2. Within the watershed, developed pixels increased 62% from 5,111 km^2 in 1990 to 8,363 km^2 in 2000. If the subpixel values are used to estimate the actual impervious surface area (*e.g.*, CBP 2005b), a 41% increase in impervious surface area within the watershed is observed from 2,473 km^2 in 1990 to 3,480 km^2 in 2000. The change map for the study area consisted of impervious surface pixels representing previously undeveloped areas that had experienced an increase ≥ 20% in impervious surface area between 1990 and 2000 (Fig. 5). A 3,083-km^2 portion of the study area experienced an increase in impervious surface area of at least 20%. Pixels that showed an increase of 20% to 50% accounted for 65% of new development. When single pixels of impervious surface change were removed from consideration, the total amount of new development decreased by > 598 km^2 to 2,485 km^2.

Table 3. Confusion matrix showing hectares of agreement and disagreement and percent agreement by class between the MRLC and MA-RESAC land cover maps[a]

	MRLC								
	Water	Development	Extractive	Forests	Agriculture	Wetlands	Barren	''Grass''	%Agree
MA-RESAC									
Water	1537631	7756	2998	43297	13176	38369	1701	280	93
Development	12600	503753	9154	192787	243321	4271	17301	15875	50
Extractive	116	425	45165	983	262	36	219	15	96
Forests	30382	233393	22397	13858086	139982	104650	79013	12475	96
Agriculture	11689	96171	14124	1002029	6348420	19859	40509	6842	84
Wetlands	55070	15449	2919	326094	72562	600125	7614	576	56
Barren	1060	2301	739	258	144	697	12480	16	71
''Grass''	349	10921	559	682	1942	207	813	30872	67
% Agree	93	58	46	90	93	78	8	46	
Class Area (km^2)									
MA-RESAC	16452	9991	472	144804	75396	10804	177	463	
MRLC	16489	8702	981	154242	68198	7682	1597	670	
% Difference	0.2	13	52	6	10	29	89	31	

[a]Total class area in square kilometers estimated by each data set is also indicated.
MA-RESAC = Mid-Atlantic Regional Earth Science Applications Center.
MRLC = Multi-Resolution Landcover Consortium.

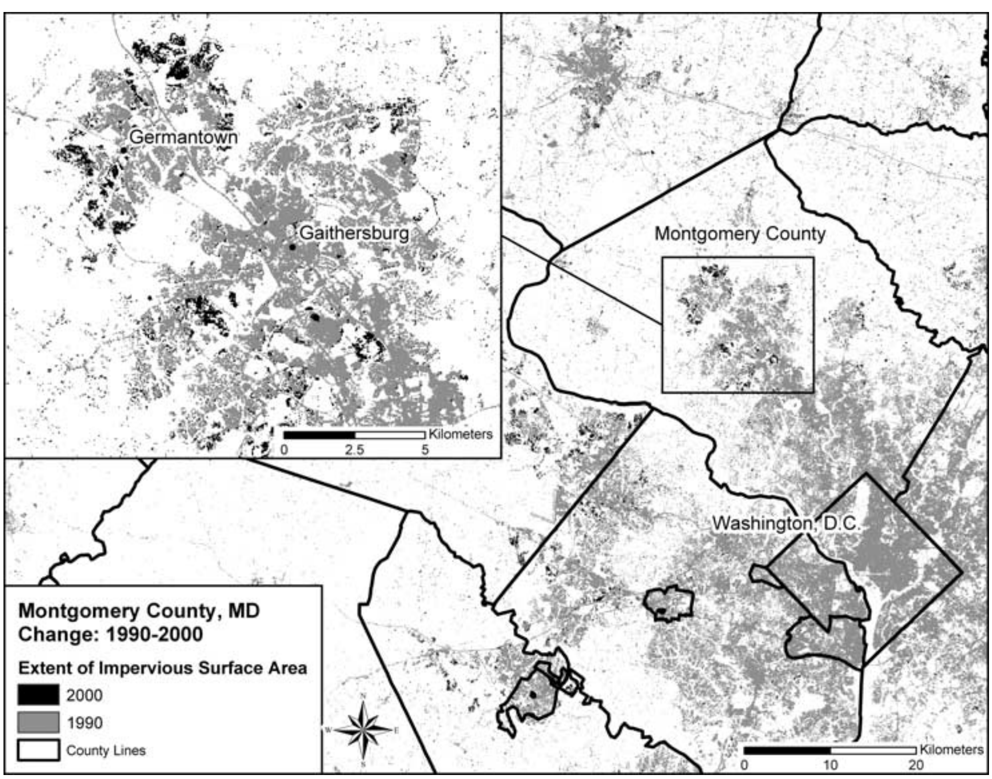

Figure 5. New impervious surfaces that appeared between 1990 and 2000 in Montgomery County, a suburban county adjacent to Washington, DC.

Table 4. Summaries of commission and omission errors, compared with the NHAP data points, for the three land cover maps for the target land cover classifications

Land cover class	Omission (%)	Commission (%)
MRLC		
Forests	37	17
Agriculture	26	24
Wetlands	7	34
MA-RESAC		
Forests	32	28
Agriculture	19	33
Wetlands	12	36
LCA		
Forests	26	16
Agriculture	17	19
Wetlands	4	30

NHAP = National High Altitude Photography Program.
LCA = Land Cover Agreement map.

Table 5. Spatial agreement between 1990 and 2000 impervious surface maps and classified DOQQs

Data of IS map	Hectares	%
1990		
Omission	319	18.4
Commission	45	2.6
Agreement	1367	78.9
2000		
Omission	875	12.1
Commission	377	5.2
Agreement	6028	82.7

DOQQ = Digital orthophoto quarter quadrangles.
IS = Impervious surface.

Table 6. Results of correlation analysis of 1990 and 2000 mapped impervious surface values against impervious surface values derived from classified DOQQs

Date of IS map
1990
$R = 0.61$
$P \leq 0.05$
Slope = 0.61
N = 2,586
2000
$R = 0.68$
$P \leq 0.05$
Slope = 0.66
N = 10,127

DOQQ = Digital orthophoto quarter quadrangles.
IS = Impervious surface.

Validation

Land-Cover Maps. For their one-to-many comparison with the NHAP data, the MRLC researchers reported overall agreement of 74% and a kappa coefficient of 0.66 across the 11 land cover classes (N = 769) (Table 2). The major source of confusion was between specific agricultural classes. When row crops and pasture were combined into one class, overall agreement increased to 84%, and the Kappa value increased to 0.78. Another noted area of confusion was within forest classes (Vogelmann and others 1998).

For the 1990 MA-RESAC land cover map one-to-many analysis using 11 land cover classes, the kappa value was 0.54, and overall agreement was 59%. Like the MRLC map, the major sources of confusion for natural resource classes were similar natural resource classes. For example, mixed forest classes were primarily confused with either deciduous or evergreen classes. Pasture and cropland classes were confused primarily with each other. Predictably, agreement increased when we combined similar forest and agricultural classes to create a classification scheme of just 8 classes overall (Table 2). Kappa increased to 0.67, and overall agreement increased to 73%.

Of the three land cover maps, the land cover agreement map had the lowest rates of commission and omission errors compared with the NHAP data. The sample size decreased to 590 points because 179 points fell within areas of disagreement between the MRLC and MA-RESAC land cover maps. Summaries of commission and omission errors for the three land cover maps for the target land cover classifications are shown in Table 4. Kappa for the agreement map was 0.77.

Impervious-Surface Map Validation. Overall spatial agreement between the 1990 MA-RESAC impervious surface map and the DOQQs was 79%. Spatial agreement for the 2000 impervious surface map with the relevant DOQQs was higher: at 83% (Table 5). Comparisons between mapped and DOQQ estimates of subpixel (continuous) impervious surface values produced a correlation of 0.61 for 1990 and 0.68 for 2000 (Table 6). Large omission errors in the 1990 MA-RESAC impervious surface map–where the aerial photo measured 70% to 100% imperviousness and the MA-RESAC map measured 0%—made up 12% of total omission errors. Sixty-nine percent of those 12% occurred in areas defined as transitional (recently cleared or disturbed areas) in the DOQQs, suggesting they may have been developed after the satellite imagery was acquired.

Table 7. The area in km^2 of new impervious surfaces detected between 1990 and 2000 using different percentage impervious surface change thresholds for the initial change map and the map with single-pixels removed ("single-pixel filter")

Change threshold (%)	Initial change map	Single-pixel filter
20	3,083	2,485
30	2,056	1,770
40	1,489	1,320
50	1,085	979

Temporal inconsistencies also existed between the 2000 DOQQs and the 2000 MA-RESAC map. Unfortunately, the impervious surface type in the circa 2000 DOQQs was not specified, so it was not possible to determine the specific type of omission errors that may have occurred because of temporal differences.

As we increased the change threshold from 20% to 50%, the amount of new development detected decreased significantly (Table 7). As the threshold increased from 20% to 30%, the amount of new development decreased by 33% for the initial impervious surface change map and 29% for the filtered change map. Increasing the threshold from 20% to 50% resulted in a 65% decrease for the initial change map and a 61% decrease for the filtered change map. The effect of filtering out single, isolated pixels of change was also apparent. Using a 20% threshold of change, the initial map showed 3,083 km^2 of new development, whereas the filtered change map showed 2,485 km^2, nearly 20% less than the initial estimate. Differences between the two maps were smaller at higher impervious surface change thresholds, indicating that many of the single pixels had low impervious surface change values.

Observed Resource Land Loss

Forest, Agriculture, and Wetland Loss: 1990 to 2000. Most of the new impervious surface areas were in the form of low-density development at the edges of urban areas (*e.g.*, Fig. 6). Resource lands losses in square kilometers are presented in Table 8 for each case, and Figure 7 shows the proportion of class area lost for full study area (A) and for the watershed only (B).

The MA-RESAC land cover map generally provided slightly higher estimates of resource land loss than the MRLC land cover map. The most conservative estimates of resource land loss were those calculated using the development map with single pixels removed and the land cover agreement map. Agricultural lands experienced roughly twice as much loss as forests despite occupying about half of the area. Wetlands experienced the least overall loss and showed the largest differences in estimates between the different land cover maps.

Hot Spots of Resource Lands Loss. Because the satellite data products capture fine-scale information across the landscape, we were able to aggregate the statistics on land transitions to specific political and management units (*e.g.*, counties, watersheds, etc.). The different patterns of forest and agricultural land consumption across the CBW are depicted for counties in Figure 8 for the estimates derived from the initial change map and the land cover agreement map. Because of our uncertainties associated with wetland loss, discussed later, we do not present maps of wetland loss. We found that some smaller municipalities, particularly those adjacent to growing urban centers such as Norfolk and Richmond in Virginia, lost as much as 17% of their forest lands and 36% of their agricultural lands to development (Figs 8A and B). High losses are also observed in the counties near Washington, DC, Baltimore, MD, and Philadelphia, PA. Outlying counties further from rapidly urbanizing centers experienced losses from 0% to 1.5% for forests and 0% to 2.5% for agriculture. The spatial pattern of these ''hot spots'' of change was different depending on the resource land considered, with the greatest losses of forest land concentrated in southern Virginia, but also concentrated around the Washington, DC, metropolitan region. Agricultural land losses were largely focused on these same areas but also included a cluster of counties in south-central Pennsylvania and across Delaware.

When considered as a proportion of the loss that occurred over the entire study area, *i.e.*, focusing on the contribution that each county in the region made to total resource land loss, we found a different spatial configuration of the hot spots of regional importance (Figs. 8C and D). Some of the counties surrounding Richmond, VA, were responsible for 2.0% to 3.8% of the total forest loss in the watershed. Similar levels of deforestation were observed in northern Virginia, central Maryland, and a chain of counties extending along the Wilkes-Barre–Scranton area of Pennsylvania. The effects of development pressure from Washington, DC, and Philadelphia, PA, were even more apparent in the map of agriculture loss, where some counties in eastern Maryland, Delaware and southern Pennsylvania each accounted for 2.5% to 6.3% of the total regional loss.

Discussion

Data Sets

The MRLC and MA-RESAC maps are qualitatively similar products in terms of the forest and agriculture

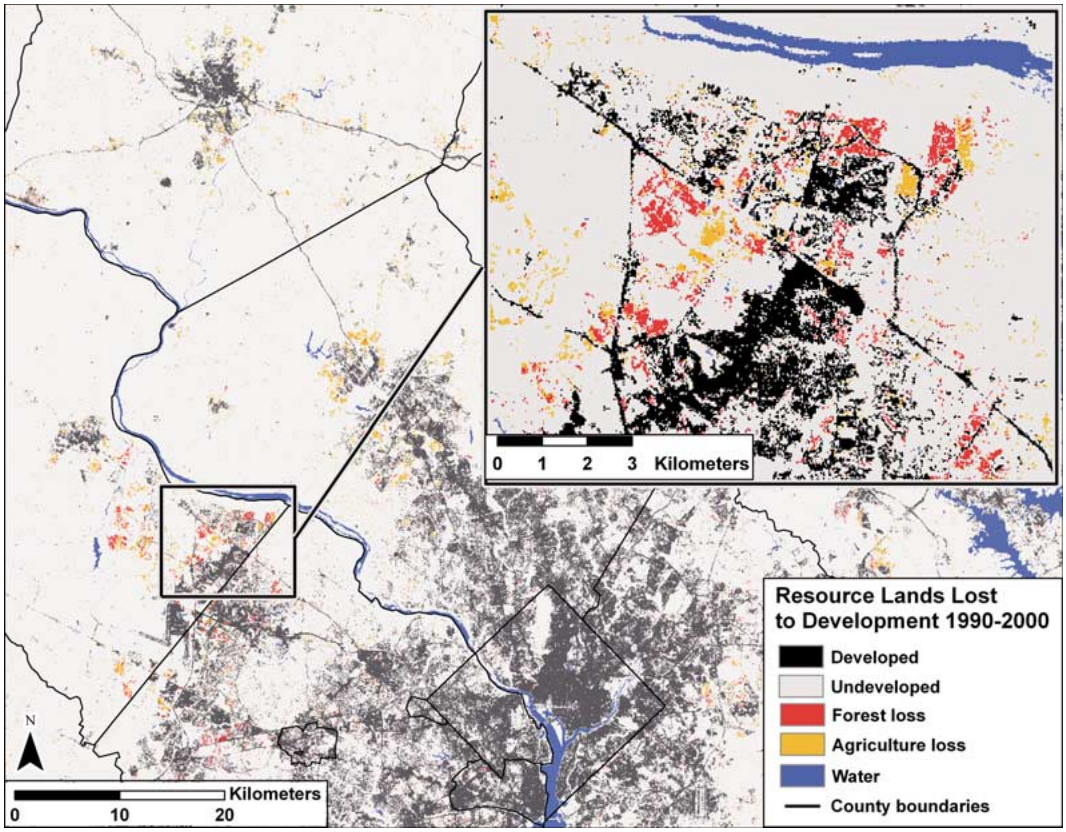

Figure 6. Loss of forests and agriculture that occurred between 1990 and 2000 in northern Virginia.

Table 8. Estimates of resource lands lost to development between 1990 and 2000 using different land cover maps: MA-RESAC, MRLC, and an agreement map where both the MA-RESAC and MRLC classifications agree[a]

Extent	MA-RESAC	MRLC	Agreement map	Single-pixel filter
Full extent				
Forests	826	758	504	388
Agriculture	1,543	1,450	1,266	1,016
Wetlands	60	4	2	2
Watershed only				
Forests	573	530	334	259
Agriculture	1,130	1,025	903	717
Wetlands	44	3	2	1

[a]In the last case (''single-pixel filter''), single pixels were removed from the impervious surface change map, and resource land loss was estimated using the agreement map. Estimates for the full extent of the study area and for the watershed area only are reported in km^2. Note that 1 km^2 = 2477 acres.

MA-RESAC = Mid-Atlantic Regional Earth Science Applications Center.

MRLC = Multi-Resolution Landcover Consortium.

classes. Thus, we have high confidence in estimates of the extent of these land cover categories in the land cover agreement map. We do note differences in the wetland class, however. The MRLC map incorporated wetland data from ancillary sources, primarily the United States Fish and Wildlife Services NWI. As they note, this data set was (and still is) at various stages of completion at the time MRLC was released, and the data sources used for generating NWI data ranged from 1971 to 1992. Furthermore, it is known that the NWI data set is conservative in delineating wetlands and does not capture many smaller and isolated wetland areas (Vogelmann and others 1998).

In this analysis, we found that where the MRLC map identifies wetlands, there is relatively good agreement with the MA-RESAC map (Table 3). The extent of

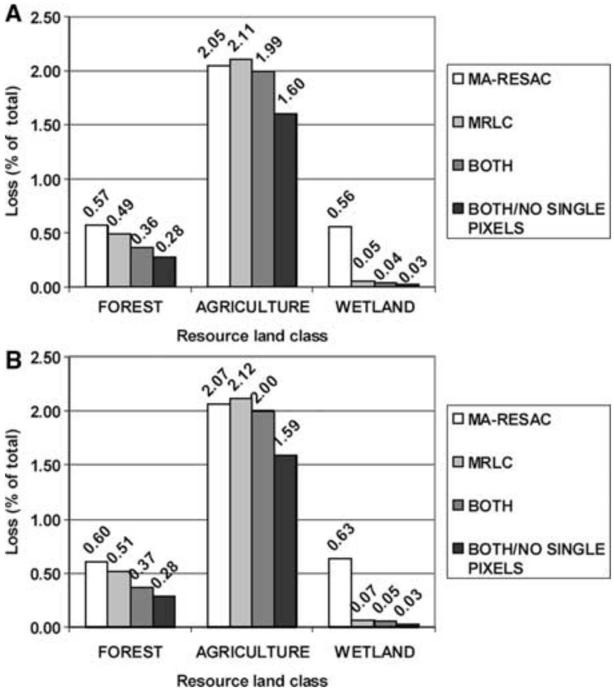

Figure 7. Resource land loss normalized by the class area for each land cover map. (**A**) shows estimates for full study extent, (**B**) shows estimates for the CBW only. CBW = Chesapeake Bay watershed.

wetlands identified in the MA-RESAC map, however, is almost 30% higher than the MRLC map, and in these areas of disagreement we cannot adequately judge the accuracy of the classification without additional field visits.

The impervious surface maps for 1990 and 2000 provide a unique opportunity to identify areas that have undergone development during this decade. In addition to providing assessments of resource land loss such as those presented here, this data set offers the prospect to explore many aspects of land cover change processes over a large area with relevance to a range of land management issues and mutlistate efforts focused on restoration of the Chesapeake Bay (Goetz and others 2004b).

An analysis of this area in comparable detail would not be possible with any other currently existing data sets. The NLCD released 2000 subpixel impervious and land cover–type maps of an area encompassing approximately one third of the CBW (NLCD mapping zone 60) using a similar approach to that described here. In addition to having incomplete coverage of the watershed, there is no corresponding NLCD/MRLC ISA map for an earlier time period on which changes in the built environment could be assessed. Moreover, even if it were possible to compare land cover–type classes from the 1992 MRLC and 2001 NLCD maps, this would result in an urban presence absence-type map that would provide substantially less detailed estimates of the magnitude of change in the built environment or its associated impact on resource lands.

Because we used consistent methods to develop the 1990 and 2000 impervious surface maps, and have conducted the extensive accuracy assessment described here, we have known confidence in the changes and errors associated with different mapping techniques. The accuracy assessments derived from comparisons with high-resolution aerial photos also provide the likely source, magnitudes, and directions (omission vs. commission) of the estimated mapping errors.

Validation

This represents the first assessment of the MA-RESAC land cover map for 1990. In this analysis, we used the same data set that was used to assess the MRLC map, providing a direct comparison between these two data sets, which were produced using different classification techniques. When compared with the NHAP reference data set, both classifications achieved acceptable accuracy levels for the forest and agriculture classes. Considering only those areas where both maps agreed maximized agreement with the NHAP data set. As previously noted, however, the sample size of the NHAP validation data set is small given the size of the study area, and temporal inconsistencies between the air photos and the Landsat imagery likely contributed to decreased levels of quantitative similarity (Vogelmann and others 1998). That the MRLC and MA-RESAC data sets displayed high agreement for the forest and agriculture classes lends credibility to both data sets despite these uncertainties. As discussed above, issues with the wetland classifications in both data sets remain.

We note that agreement between ''developed''-type classes in the land cover maps was not high, but these type classes were not used in our analysis because urban areas were much more accurately captured in the impervious surface maps that we used to represent urban change. The impervious maps also allowed for better representation of developed land gradients. Moreover, the primary impact the relatively poor agreement in the urban types had on our analysis is that it removed from consideration resource lands (particularly forest areas) that fell in more developed areas; thus, it has the effect of making our estimates of resource land losses that much more conservative.

Throughout the analysis we used different techniques to quantify and decrease errors in the impervious surface maps. Removing pixels classified as

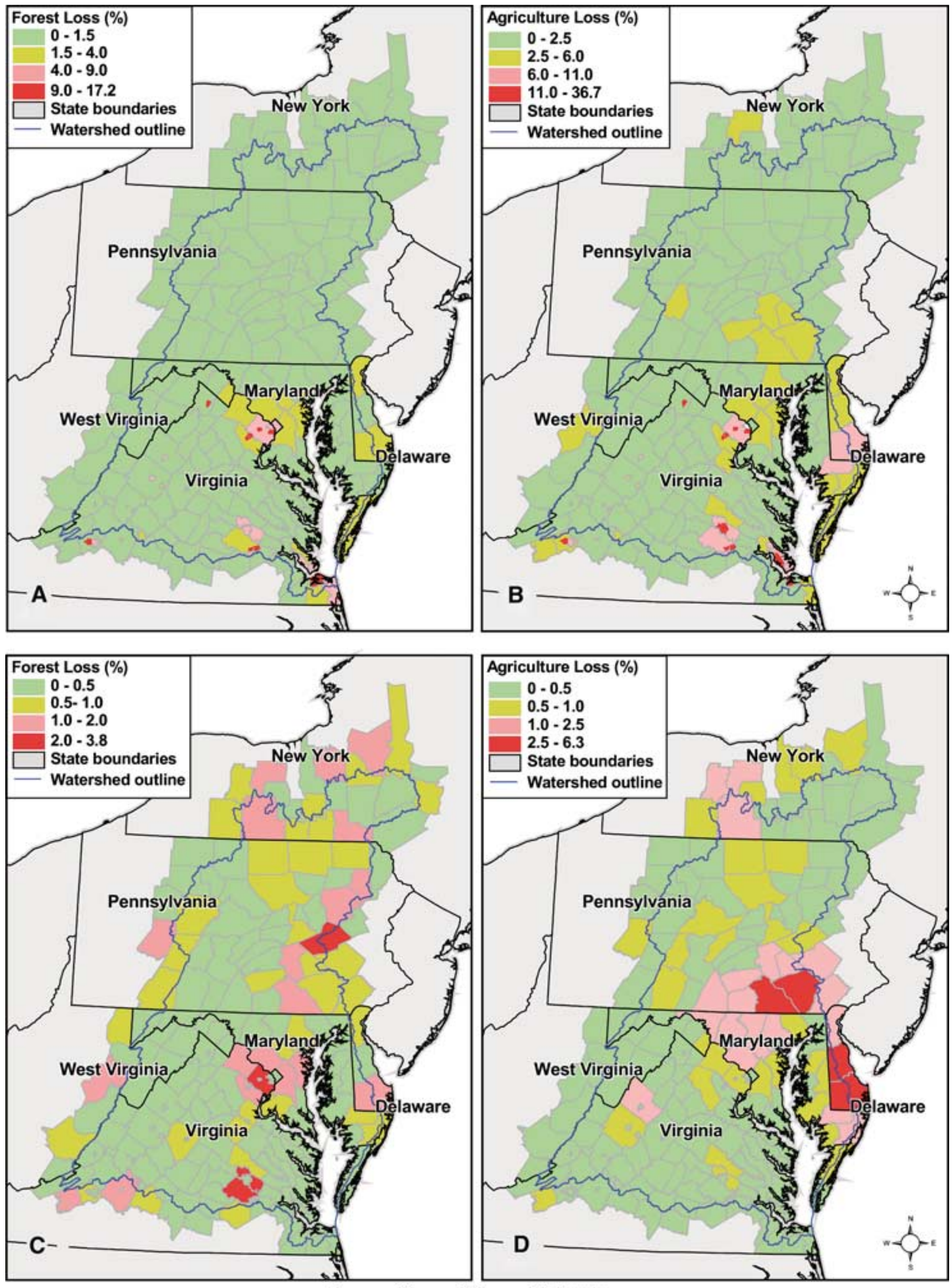

Figure 8. The upper two maps shows the percentage of forest (**A**) or agriculture (**B**) lost between 1990 and 2000 in each county. The lower two maps shows the percentage contribution of each county to the total loss of forest (**C**) or agriculture (**D**) in the study area.

impervious where both the 1990 MRLC map and the 2000 MA-RESAC map classified them as agriculture minimized commission errors caused by bare agricultural fields. Issues arise from using this method when impervious surface areas are considered agriculture in both land cover maps, but results from the validation of the 1990 MRLC map indicate this occurs across a very small area. Of the 244 points classified as urban by the NHAP data set, 13 were classified as agriculture in the 1990 MRLC map (omission). Of the

232 points classified as urban in the 1990 MRLC map, 15 were classified as agriculture in the NHAP data set (commission). Of the 140 points classified as urban in the NHAP data set, 7 were classified as agriculture in the 1990 MA-RESAC map (omission), and of the 132 points classified as urban in the 1990 MA-RESAC map, just 1 was classified as agriculture in the NHAP data set (commission). Accuracy of the 2000 MA-RESAC land cover map, again used in this study simply to decrease errors associated with bare agricultural fields in the impervious change map, was even better for a number of reasons including more extensive and recent training data sets, improved quality and fidelity of Landsat ETM+ imagery relative to older Landsat TM, and multidate seasonal imagery rather than two-date leaf-on and leaf-off conditions (Goetz and others 2004a, 2004b).

As in the assessments of the MRLC and MA-RESAC land cover maps, our errors in the impervious surface maps could be fewer than what we calculated because of temporal differences in the validation data sets. Changes in land cover that occurred after the satellite scenes were taken likely contributed to our assessment of omission errors. For the 1990 impervious surface map, for example, the majority of the largest omission errors occurred in areas defined as transitional in the aerial photos.

We decreased errors in the impervious surface change map by using a 20% threshold for change. Although the 20% threshold was not the most conservative estimate we could provide, it captured the most change without resulting in unacceptable trade-offs between omission and commission errors. Although the use of the filtered change map provided the most conservative estimate of resource land loss, omission errors increased. Specifically, low-intensity, dispersed development was predominantly detected as single pixels in remotely sensed data sets. By excluding single pixels, we increased omission errors in low-intensity developed classes, but we decreased commission errors in sites that were commonly detected as single pixels. This trade-off of errors is an important consideration and is discussed further in the next section.

Potential sources of error in the impervious surface maps included our use of training data from only one county in Maryland and radiometric variation between different Landsat scenes to which the decision tree algorithm was applied. Montgomery County contains a variety of development types, from high-intensity urban to low-intensity exurban sprawl, and our accuracy analysis results across much larger areas indicated that these are representative of the greater study region. An area of greater concern, and one we took great efforts to address, was radiometric variation between scenes and across acquisition dates. Extensive preprocessing of the 100 + Landsat scenes we used for this analysis was conducted to address this as was removal of clouds, cloud shadows, topographic distortion and illumination variations, and geometric orthorectification for locational precision necessary for change detection work (Goetz and others 2004a,b).

As a result of this attention to consistency across the image data sets, as well as the quality of the training data and the classification methodology used to create the land cover and impervious surface maps, they were in good agreement with the validation data sets. We further minimized any remaining sources of error by calculating conservative estimates of loss based only on areas where both of the 1990 and cover type maps agreed.

Observed Resource Land Loss

By overlaying maps of newly developed impervious surface areas on land cover maps at the beginning of the observational period, we were able to produce estimates and maps of resource lands impacted by land development associated with the urbanization process. These maps are already being used from the local to the entire watershed scale to address land management issues.

Most of the resource land loss throughout the watershed occurred on agricultural lands (64%). Home buyers are increasingly willing to live further away from places of employment in exchange for more open space, lower housing costs, and more land on which to build. Predictably, counties with a significant amount of agricultural lands near fast-growing urban areas experienced the highest rates of agricultural land conversion. Although overall loss of agricultural lands across the entire CBW was approximately 2%, when viewed at finer scales the amount of loss was quite variable, with some counties experiencing losses >30%.

Fast-growing urban areas surrounded primarily by forested lands experienced the most loss of forest to impervious surfaces. Other sources of forest loss were second-home building in relatively undeveloped areas and in-fill in urban areas. We expect actual forest loss to be higher than what we measured because of conversion of forest to other land uses besides development, such as crops and pasture, as well as timber harvesting, which we did not measure. We also noted that during this 10-year period, the amount of change associated with transitions from abandoned agriculture to woodland or forests was not likely to be very large, and agricultural lands are being converted to residential development much faster than they are reverting to forest. A final point on this topic involves the use of categoric and cover maps of forest cover that may include patches of trees found in residential areas. Our forest type classes, however, were relatively homogenous across the landscape, suggesting that most isolated patches of ''forest'' were mostly included in other cover-type classes, such as low-intensity developed. These areas would not be included in estimates of resource lands loss. In future work, we hope to incorporate use of continuous subpixel tree cover maps, which are currently nearing completion and undergoing accuracy assessment to be reported in a follow-on article.

Much of the wetland change was detected as single pixels or groupings of two or three pixels. Because of our concerns regarding the wetland classifications in the MRLC and MA-RESAC maps, discussed previously, we emphasized the most conservative estimate of wetland loss using the combined 1990 land cover map considering areas of agreement only. This is undoubtedly an underestimate. Although wetland areas are notoriously difficult to map using optical remote sensing, particularly forested wetlands, we believe the range of wetland loss estimates provides land managers an opportunity to decide whether the shortcomings of these estimates outweigh the interest in having at least a range of values otherwise only available through the NWI mapping activity, which has a range of other limitations including timeliness and omission of smaller and more isolated wetlands. We are currently conducting wetland-mapping work using radar remote sensing of wetlands in the region, but the maps are not yet ready for use, and their discussion is beyond the scope of this article.

In general, we provided a range of likely resource land losses that can be interpreted for a comparable range of land-management applications. For example, the filtering of single pixels will decrease the amount (and location) of development in areas that we know have a relatively high likelihood of having changed to a low-intensity residential land use characteristic of exurban sprawl. We included results of both the filtered and unfiltered results so the user of the data sets can weigh the considerations for specific management or planning objectives. Our intent was to provide the best possible estimate of change and loss of resource lands and also to bound the upper and lower limits.

Conclusion

Land use changes and associated losses of resource lands have not previously been calculated at this level of spatial detail for the CBW or, as far as we are aware, across any comparably sized area. Assessments of residential and commercial development impacts on resource lands were made possible by the use of subpixel classification algorithms that used Landsat image data, from which we used a 20% change in impervious cover threshold to define areas as having been developed. This level of spatial resolution could not otherwise have been achieved without much larger mapping errors than those we have documented. Accuracy was also improved by extensive processing of the imagery to ensure a high degree of geometric fidelity and radiometric consistency between scenes (Goetz and others 2004a, 2005b). Moreover, our estimates of resource land losses include a range of possible values because they were assessed for areas where two different and independently developed maps (MRLC and MA-RESAC) were produced. The more conservative estimates were derived from the use of both land cover maps and considered only those areas where they agreed that any given area was accurately classified as a resource land (whether forest, agricultural, wetland).

In our most conservative estimate, we calculate that at least 388 km^2 of forest lands, 1,016 km^2 of agricultural lands, and 2 km^2 of wetlands, have been lost to commercial and residential development within the CBW since 1990. As much as 826 km^2 of forests, 1,543 km^2 of agricultural lands, and 60 km^2 of wetlands have been converted, although we emphasize the more moderate results derived from the land cover agreement map indicating losses of 504 km^2 for forests, 1,266 km^2 for agricultural lands, and 2 km^2 for wetlands. However, we would expect functional losses, particularly for forests and wetlands, to be much higher because of increased edge effects and fragmentation (*e.g.*, Brown and others 2000; Riiters and others 2002).

If these rates of conversion continue, we suggest it will be difficult for the CBP to meet its targeted objectives of constraining the loss of forest and agricultural lands by 30% by the year 2012 (CBP 2000). Indeed, rates of loss at the municipal scale could be significantly higher. The results we present here can be used to improve the targeting and monitoring process and aid adaptive management practices aimed at modifying behaviors, particularly in those specific locations where our maps show that the greatest changes have occurred.

The same or similar approaches can be used in other areas, particularly with the increased availability of land cover map products from various sources. Nevertheless, it is important that rigorous accuracy assessments be conducted, and that a range of resource land loss is presented, including the most conservative estimates that the data are capable of providing. We have attempted to do both of these in the analyses presented here, which have increasing relevance in a rapidly urbanizing world.

Our current work is focused on addressing vulnerability of resource lands to urbanization by using a combination of spatial predictive models including those based on resource allocation of population growth projections and associated housing demands, microeconomic theory associated with land value and related probabilities of conversion, and cellular automata models that employ a range of rule-based growth parameters (proximity, attraction, etc.). We will report on those results in a follow-up publication.

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