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EVALUATION OF THE NATIONAL LAND COVER DATABASE FOR HYDROLOGIC APPLICATIONS IN URBAN AND SUBURBAN BALTIMORE, MARYLAND[1]

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ABSTRACT: We compared the National Land Cover Database (NLCD) 2001 land cover, impervious, and canopy data products to land cover data derived from 0.6-m resolution three-band digital imagery and ancillary data. We conducted this comparison at the 1 km^2, 9 km^2, and gauged watershed scales within the Baltimore Ecosystem Study to determine the usefulness and limitations of the NLCD in heterogeneous urban to exurban environments for the determination of land-cover information for hydrological applications. Although the NLCD canopy and impervious data are significantly correlated with the high-resolution land-cover dataset, both layers exhibit bias at <10 and >70% cover. The ratio of total impervious area and connected impervious area differs along the range of percent imperviousness – at low percent imperviousness, the NLCD is a better predictor of pavement alone, whereas at higher percent imperviousness, buildings and pavement together more resemble NLCD impervious estimates. The land-cover composition and range for each NLCD urban land category (developed open space, low-intensity, medium-intensity, and high-intensity developed) is more variable in areas of low-intensity development. Fine-vegetation land-cover/lawn area is incorporated in a large number of land use categories with no ability to extract this land cover from the NLCD. These findings reveal that the NLCD may yield important biases in urban, suburban, and exurban hydrologic analyses where land cover is characterized by fine-scale spatial heterogeneity.

(KEY TERMS: National Land Cover Database; Baltimore; land use/land cover; urban areas; remote sensing; lawn; impervious surface.)

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INTRODUCTION

Land cover greatly influences runoff production, groundwater levels, channel incision, and stream base flow in urbanized catchments (Wigmosta and Burges, 1997; Naiman and Turner, 2000; Walsh *et al.*, 2005; NRC, 2008). Impervious surface area is known to increase overland flow, streamflow peaks (Leopold, 1968), and create the urban heat island

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effect (Kalnay and Cai, 2003). Percent impervious area is often used as a predictor of hydrologic changes that degrade waterways because it prevents natural soil processes that immobilize pollutants (Schueler, 1994; Arnold and Gibbons, 1996; Brabec *et al.*, 2002), reduces infiltration and evapotranspiration rates (Brun and Band, 2000), alters patterns of soil moisture (Tenenbaum *et al.*, 2006), and increases sediment loads associated with construction that compromise stream processes (Wolman and Schick, 1967).

Many urban policy applications from stormwater modeling to land conservation may rely on land-cover information. An accurate determination of land-cover variables is critical for hydrologic analyses. Hydrologic models are tools that are typically used to link contributing area and polluting sources to their effects on receiving water bodies. However, there is insufficient linkage between regional-lumped and fine-scale distributed approaches; an improved modeling paradigm linking these approaches is needed (NRC, 2008). Progress has been made in determining impacts of heterogeneous land-cover inputs on downstream water quality (Maestre and Pitt, 2006); however, urban hydrologic models developed to examine such impacts [e.g., Source Loading and Management Model (SLAMM)] rely on high-resolution land-cover data due to the heterogeneity of urban stormwater pollutant sources (Pitt and Voorhees, 1989). In addition, large variability in land use categories required by models and provided by land-cover datasets further complicates extensive understanding of land-cover effects on water quality (NRC, 2008).

The National Land Cover Database (NLCD) is widely used for hydrologic study because this dataset is the most detailed land-cover information source made freely available on a national scale. Although extensive quality control and independent evaluations have been conducted (Smith *et al.*, 2003; Homer *et al.*, 2004; Chen *et al.*, 2006), the focus has been the dataset's regional-scale accuracy. The dataset has not been evaluated specifically for urban environments. Urban environments are challenging to summarize with coarse-scale imagery because they are characterized by fine-scale land-cover heterogeneity when compared with less-developed landscapes (Band *et al.*, 2005).

Most urban land within the NLCD is classified by the type of development, rather than raw land cover, which prompted the development of canopy and impervious datasets for the 2001 NLCD (Homer *et al.*, 2004). The NLCD classification incorporates lawn area into developed and agricultural land use classes (e.g., low-density developed and pasture). Although the NLCD 2001 provides impervious and canopy datasets, there is no simple way to determine the percent lawn area in urban regions from this dataset. Incorporation of the effects of urban pervious area in hydrologic models is not common, despite indications that suggest pervious areas can account for a large portion of runoff sources in suburban watersheds (Burges *et al.*, 1998). Soil compaction associated with residential lawns alters hydrologic properties of land cover in increasing bulk density and decreasing infiltration rates (Partsch *et al.*, 1993; Hamilton and Waddington, 1999; Gregory *et al.*, 2006) and subsequently affects suburban watershed hydrology. In addition, lawn area comprising over 40 million acres of the United States (U.S.) (Milesi *et al.*, 2005) is rarely incorporated as a separate land-cover category in hydrologic analyses.

We investigate how well key land-cover elements with the fine spatial scale of heterogeneity in urban environments can be discerned using NLCD products. It is likely that some urban landscapes may be better represented by the NLCD than others according to ranges of percent imperviousness or canopy cover. In addition, NLCD land uses are evaluated to elucidate land-cover composition within each developed category.

This paper evaluates the relative accuracy of NLCD 2001 data in urban areas by comparing the 30-m NLCD 2001 with land-cover data derived from 0.6 m resolution, three-band color-infrared imagery (green: 510-600 nm; red: 600-700 nm, and near-infrared: 800-900 nm). We conducted this comparison at the 1 km^2, 9 km^2, and gauged watershed scales within the Baltimore metropolitan area (Figure 1).

FIGURE 1. Map of Baltimore Ecosystem Study. Map includes the outline of Baltimore City, part of Baltimore County, Gwynns Falls, and Baisman Run main watershed delineations.

The extent to which the 30-m pixel resolution NLCD can be applied in urban environments for the purposes of watershed management, estimates of evapotranspiration, base flow, and urban heat island effects is the focus of this research.

DATASETS

The NLCD 2001 is based on medium-resolution imagery, elevation, and ancillary GIS layers. The benchmark dataset was developed from high-resolution imagery, elevation, and ancillary GIS layers. The high-resolution dataset comprised images obtained in 1999 whereas the NLCD 2001 is a composite of multiple images attained from summer 1999 to spring 2001. The 1999 Landsat images were used for all seasons, except spring. Thus, the difference in the imagery used in these datasets is negligible. Although some difference between these datasets may be expected due to land-cover change between 1999 and 2001, an analysis of this change in the Baltimore metropolitan area indicates very little change from 1999 to 2004. The greatest change occurred to percent pavement – an increase of 1.9% in this five-year time period. Decreases of 1.3% fine vegetation and 1.2% bare soil were also measured during this time period. Percent buildings and coarse vegetation increased 0.4 and 0.2% respectively (Zhou *et al.*, 2008). Thus, the maximum attributable error due to the difference in imagery is <1%. The relative accuracies of both datasets are noted in Table 1. Although percent accuracy is not much lower for the NLCD, note that the high-resolution data accuracies are reported for a scale of 2,500 times finer than the 30-m NLCD pixel size. Further detail of the classification processes of the two datasets is reported below.

TABLE 1. Reported Accuracy of High-Resolution (0.6 m) and National Land Cover Database (NLCD) Land Classes (30 m).

Land Class	Dataset	Accuracy (%)
Building	High resolution	83.6[1] user, 94.4[1] producer
Coarse vegetation	High resolution	97.7[1] user, 94.4[1] producer
Fine vegetation	High resolution	94.9[1] user, 89.3[1] producer
Pavement	High resolution	91.9[1] user, 88.3[1] producer
Bare soil	High resolution	90[1] user, 100[1] producer
Overall	High resolution	92.3[1] producer
Percent canopy	NLCD	93[2] producer
Percent imperviousness	NLCD	91[2] producer
Land class categories	NLCD	77[2] producer

[1]Zhou and Troy (2008).
[2]Homer *et al.* (2004).

National Land Cover Database

The second-generation NLCD 2001 was designed by the Multi-Resolution Land Characterization team to provide an updated and improved land-cover classification dataset of the U.S. The NLCD layers used in this analysis are derived from mapping zone 60, including most of Maryland. NLCD 2001 is based on multitemporal Landsat 7 ETM+, Landsat 5 TM imagery, and ancillary data (e.g., digital elevation model data for slope and aspect, population density, buffered roads, NLCD 1992, and NOAA City Lights dataset). The classification scheme is based on Level II thematic detail (Anderson *et al.*, 1976). The Anderson classification scheme was defined at the conference on Land Use Information and Classification in 1971. The system was designed to make Landsat data usable by the majority of user groups and adopted a "resource-oriented," rather than a "people-oriented" approach. Anderson level I categories include data attainable at scales smaller than 1:24,000 (e.g., urban, agriculture, forest, and wetlands). Anderson level II categories are subsets of level I categories (i.e., urban land comprised residential, commercial and mixed urban land uses, using data available at the 1:24,000 to 1:250,000 scale).

In addition to 29 land-cover classes, percent imperviousness and percent canopy products are included in NLCD 2001 (Figure 2). The impervious layer was modeled by comparing several 1-m digital orthophoto quadrangles and Landsat spectral data according to a regression tree algorithm (Yang *et al.*, 2002). The canopy layer was classified according to methods outlined in Huang *et al.* (2001). An assessment of single 30-m-pixel land-cover accuracies is reported in Table 1.

High-Resolution Land-Cover Data

The high-resolution land-cover datasets for the Gwynns Falls and Baisman Run watershed were derived from the digital high-resolution color-infrared aerial imagery collected in 1999 with a pixel size of 0.6 m (Zhou and Troy, 2008) (Figure 2). This dataset, referred to in this text as the "high-resolution dataset," incorporates ancillary data into its classification strategy and infers greater quality to the resulting data beyond its use of finer-scale imagery. The imagery used was of three-band color-infrared, green (510-600 nm), red (600-700 nm), and near-infrared (800-900 nm).

An object-based classification approach was implemented to classify imagery. Ancillary data, such as Light Detection And Ranging (LIDAR) data, parcel boundaries, and building footprint layers were used

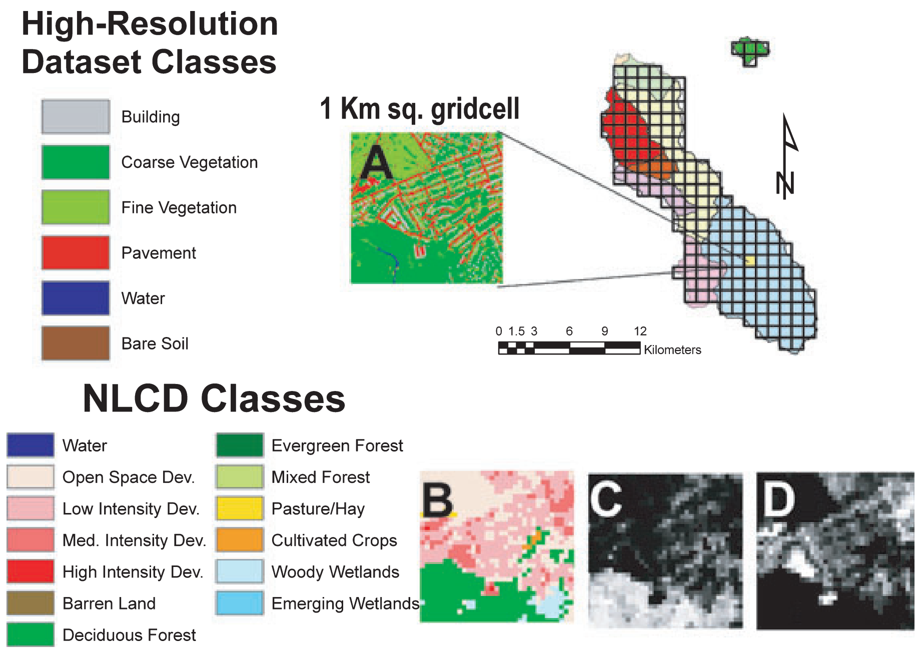

FIGURE 2. One Kilometer Square Extraction of Each of Four Datasets Included in This Analysis. (A) Zhou and Troy's (2008) object-oriented classification of high-resolution dataset; (B) National Land Cover Database (NLCD) land-cover dataset; (C) NLCD percent impervious dataset – white is 100%, black is 0%; (D) NLCD percent canopy dataset – white is 100%, black is 0%.

to aid in the classification. An object-based classification approach allows the definition of classification rules to be developed using multiple datasets (e.g., low-height green space is fine vegetation and high-height green space is coarse vegetation). Conventional image classification, such as that used in the definition of the NLCD, defines land classes using a pixel-based approach. Using DeFiniens Imaging eCognition software (Definiens, 2007), this rule-based classification method was used to first group pixels into objects based on a fractal net evolution algorithm (Baatz and Schäpe, 2000). This approach allows the use of not only spectral response, but also object characteristics such as shape, spatial relations (e.g., connectivity and connectedness), and reflectance statistics for the classification of these objects (Zhou and Troy, 2008).

Five land-cover classes were included in the land-cover dataset according to the HERCULES land-cover classification system: fine vegetation (grass and herbs), coarse vegetation (trees and shrubs), building, pavement, and bare soil (Cadenasso *et al.*, 2007). The HERCULES approach to classification captures land-cover heterogeneity in urban areas in a more consistent way defining land cover explicitly so that relative density of vegetation or development types can be redefined at the time of use. Further details about the classification methods and results of the high-resolution dataset are documented in Zhou and Troy (2008).

METHODS

This analysis was conducted within the Baltimore Ecosystem Study (BES) Gwynns Falls and Baisman Run watersheds (Figure 1). These watersheds represent a gradient of suburban to urban land cover in addition to agricultural, exurban, and forested park land. Thus, the land cover being analyzed in the BES represents a range of urban density.

The benchmark high-resolution dataset has an overall accuracy of 92.3% at the 0.6-m scale (Zhou and Troy, 2008). Given that most metropolitan areas do not have access to such an accurate and detailed land-cover dataset, the purpose of the study is to use this high-resolution dataset as reference data to assess the usefulness of coarse-resolution NLCD to urban applications given the fine-scale heterogeneity that characterizes urban watersheds. However, this evaluation will not elucidate NLCD misclassifications that coincide with errors in the high-resolution dataset. For example, given that the high-resolution dataset was developed with leaf-on imagery, canopy may obscure roads and sidewalks, which may infer minor underestimation of percent pavement. Systematic bias within this dataset was reduced in building classification by incorporating building footprint data, and in fine-vegetation and coarse-vegetation classes by use of LIDAR ancillary data.

A 1-km^2 and 9-km^2 square grid system was created, and the percent land-cover composition was compiled per grid cell for each spatial scale to examine dataset accuracy and the effects of scale (Figure 3). Given the coarse resolution of the NLCD, it is likely to be more accurate at the 9-km^2 than 1-km^2 scale if errors are random and average out at the coarser scale. These grids allow the examination of NLCD applicability when single pixel differences (between the NLCD and fine-resolution dataset) are averaged over a larger area of interest.

The segment boundaries of each gauged BES watershed were used as a third scale of analysis (Figure 3). Watershed-scale analysis in this study compares watershed "segments," that is, the contributing area of each watershed minus the contributing area of the nested gauged headwaters catchments (as shaded in Figure 3). The segment approach is used so that calculation of land cover does not occur in overlapping areas and creates independent data. The use of the watershed scale in this study illustrates the percent land-cover differences at a scale relevant in tying land cover to BES stream gauge data. The catchment segments range from 0.3 to 26 km^2 in area. Regression and residual analysis was conducted to determine biases of the NLCD canopy and impervious layers in characterizing the urban environment.

National Land Cover Database developed land use categories (Table 2) were extracted for the study area. These developed land categories make up the majority of urbanized areas in the NLCD land-cover product. The extracted NLCD categories were combined with the high-resolution dataset's land-cover classes (i.e., fine vegetation, pavement, etc.) to determine the composition of *land cover* that comprise each of the NLCD-developed classes (i.e., open, high-intensity, etc.) within the Gwynns Falls watershed.

In addition, the fine-vegetation class was extracted from the high-resolution land-cover dataset for the Gwynn's Falls watershed. This layer was used to determine which NLCD classes include fine vegetation or lawn area – which is a major urban land-cover class of interest that is absent in current NLCD products.

TABLE 2. Table Describing National Land Cover Database (NLCD) Developed Land Categories.

NLCD-Developed Category Number	Name	Description (Homer *et al.*, 2004)
21	Developed open space	Some constructed materials, but mostly lawn grasses with <20% imperviousness
22	Low-intensity developed	Areas with 20-49% imperviousness
23	Medium-intensity developed	Areas with 50 to 79% imperviousness
24	High-intensity developed	Areas with >80% imperviousness

RESULTS

NLCD Canopy Layer

A regression analysis between NLCD canopy layer and the high-resolution coarse vegetation land class (trees and woody shrubs) was conducted, resulting in an r^2 = 0.94 at the 1-km^2 scale (Figure 4). The slope of the regression equation associated with this correlation is unity. The intercept, however, is 10.66, which indicates that the NLCD canopy product generally under-reports urban canopy cover by 11% as determined by the high-resolution dataset. The heteroscedastic scatter of the residual analysis (Figure 4)

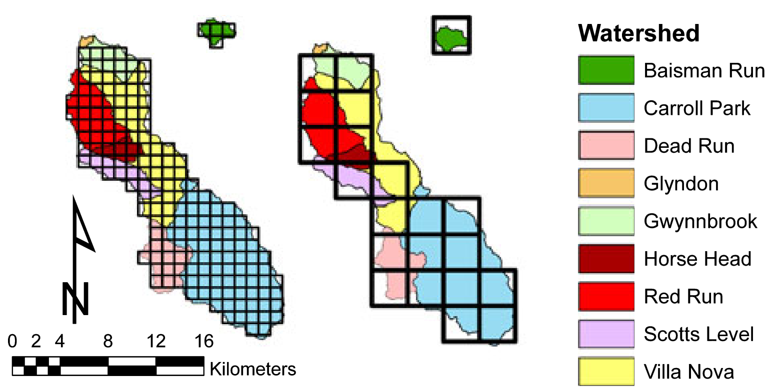

FIGURE 3. Illustration of the Three Spatial Scales Used in This Analysis. (Left) One-km^2 grid and (Right) 9-km^2 grid overlaying the gauged watersheds (third scale) of the Baltimore Ecosystem Study.

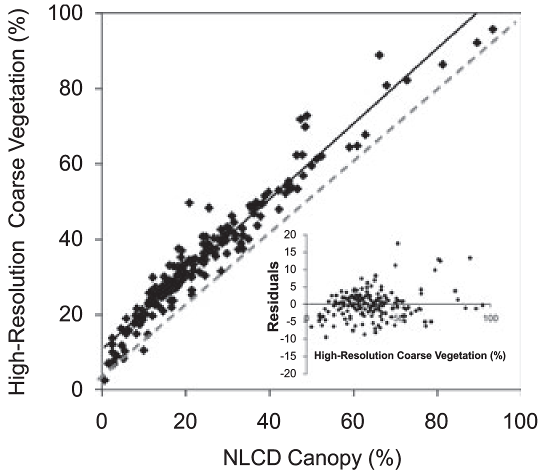

FIGURE 4. Correlation Between the Coarse Vegetation Class and the National Land Cover Database (NLCD) Canopy Data for 1-km^2 Grid; r^2 = 0.94, n = 174, p-Value = 0. The regression equation is: $y = x + 10.66$. The 1-to-1 line of the plot area is depicted as a dotted gray line. Regression residuals are included in inset.

reflects the bias of the NLCD classification with respect to the high-resolution dataset. The analysis suggests that the NLCD largely underpredicts canopy cover of <10% of a 1-km^2 area of interest (Figure 4). When the correlation between the NLCD canopy layer and the high-resolution dataset's coarse vegetation class was assessed according to a 9-km^2 square grid size, the resulting linear equation was $y = 1.07x + 8.96$ with an r^2 = 0.98, n = 21 (Figure 5). The residual analysis of the larger area of interest results in reduced error (±5%) and more homoscedastic scatter. The canopy layer evaluated on a watershed scale according to individual segments (i.e., excluding upstream segments) of gauged BES watersheds correlated well with the high-resolution dataset, r^2 = 0.99, with an intercept over 10 (Figure 6). The residual analysis of the watershed-scale comparison results in reduced error (±3%) and greater homoscedasticity.

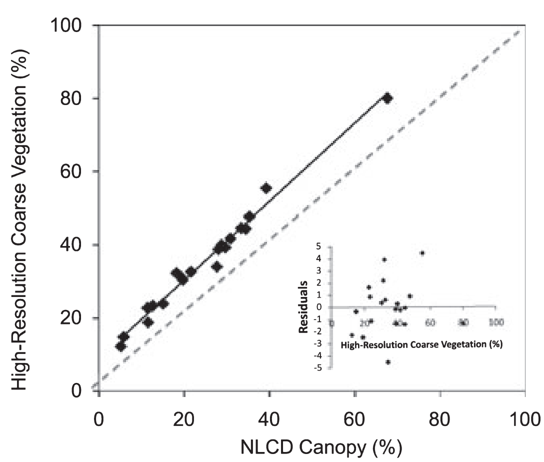

FIGURE 5. Correlation Between the Coarse Vegetation Class and the National Land Cover Database (NLCD) Canopy Data for 9-km^2 Grid; r^2 = 0.98, n = 21, p-Value = 0. The regression equation is: $y = 1.07x + 8.96$. The 1-to-1 line of the plot area is depicted as a dotted gray line. Regression residuals are included in inset.

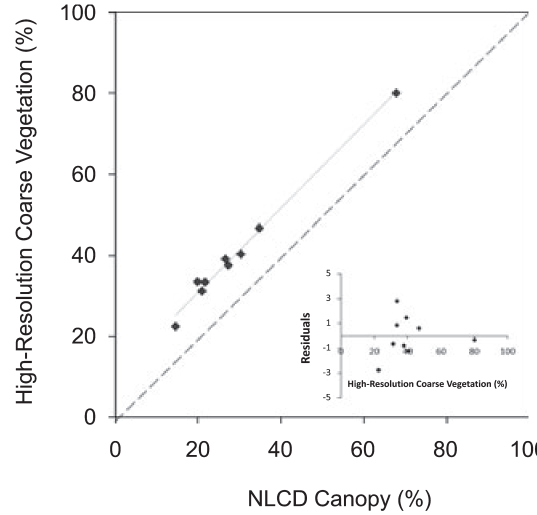

FIGURE 6. Correlation Between the Coarse Vegetation Class and the National Land Cover Database (NLCD) Canopy Data for Baltimore Ecosystem Study Subwatershed Scale. The regression equation is: $y = x + 10.23$, r^2 = 0.99, n = 9, p-value = 0. The 1-to-1 line of the plot area is depicted as a dotted gray line. Regression residuals are included in inset.

NLCD Impervious Layer

The NLCD impervious data layer is significantly correlated to the high-resolution land-cover data for pavement and imperviousness (buildings + pavement; Figure 7). Inclusion of buildings improves correlation from an r^2 of 0.86 to an r^2 of 0.94 at the 1-km^2 scale and increases the slope toward unity (from 0.6 for pavement alone) with a larger y-intercept term (8-10, respectively). The residual error of the impervious layer is narrower (largely within ±5% scatter of residuals) than the canopy layer's 10-40% impervious land-cover range as predicted by the high-resolution dataset. The canopy layer's residual error spread ±10% in both directions at that same 10-40% interval (Figure 4). However, the range of the residual error of the total imperviousness analysis widens ±15% for areas >40% imperviousness. The dramatic increase in the residual error at 40% imperviousness is also seen in the residual plot between the high-resolution dataset's percent pavement and the NLCD imperviousness (Figure 7). If separate regressions are run for areas within the range of 0-10% imperviousness, the regression coefficients increase, but the intercept values drop significantly: $1.611x + 3.72$, r^2 = 0.77 for

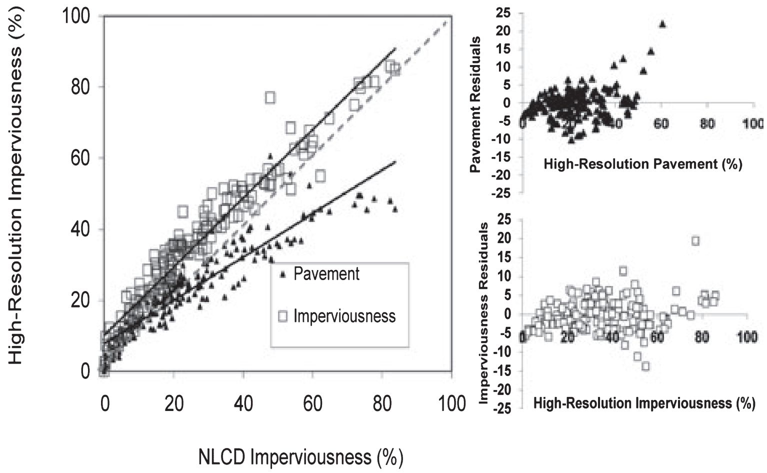

FIGURE 7. Correlation Between National Land Cover Database (NLCD) Percent Imperviousness and High-Resolution Dataset at the 1-km^2 Scale. Two lines compare percent pavement class (triangles) and total percent imperviousness (i.e., percent pavement + percent building, as squares) for each 1-km grid cell. Pavement: $y = 0.61x + 7.87$, $r^2 = 0.86$, $n = 174$, p-value = 0. Impervious: $y = 0.96x + 10.17$, $r^2 = 0.94$. The 1-to-1 line of the plot area is depicted as a dotted gray line. Residuals of each regression are included to right.

imperviousness; $1.2x + 2.4$, $r^2 = 0.80$. However, correlation coefficients are much lower for the 0-10% than for the entire range of imperviousness.

Changing the scale of analysis to the 9-km^2 grid slightly improves correlation between these datasets from an r^2 of 0.86-0.88 (for pavement) and 0.94-0.95 (for total imperviousness) (Figure 8). Regression analysis of percent impervious datasets at the watershed scale found a correlation of $r^2 = 0.94$, but the slope coefficient of its regression equation steepens ($y = 1.15x + 7.38$); pavement alone is $y = 0.77x + 5.38$, $r^2 = 0.89$, $n = 9$, and p-value = 0 (Figure 9).

NLCD-Developed Classes

We conducted an analysis to determine which land-cover classes comprise the Gwynns Falls subcatchments (Table 3) and the land-cover composition of the NLCD developed land-use classes of the entire Gwynns Falls. NLCD-developed classes (Table 2) range substantially in land-cover composition. Both building and pavement classes increase proportionally from open to high-intensity developed NLCD classes (Figure 10). Both coarse-vegetation and fine-vegetation classes decreased from open to high-intensity development.

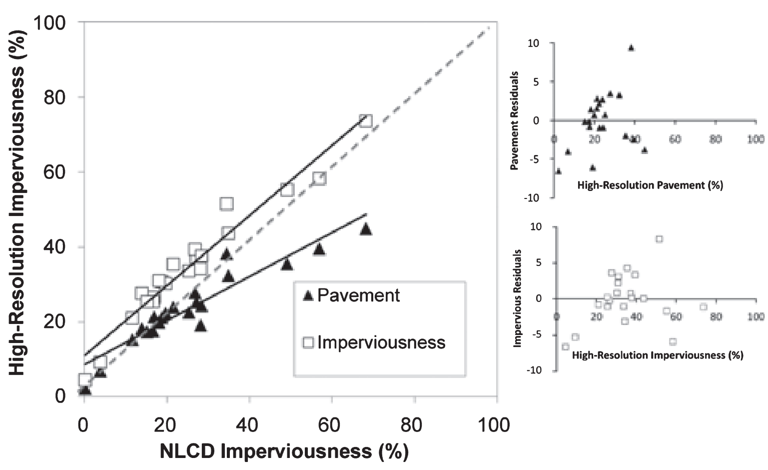

FIGURE 8. Correlation Between National Land Cover Database (NLCD) Percent Imperviousness and High-Resolution Dataset at the 9-km^2 Scale. Two lines compare percent pavement class (triangles) and total percent imperviousness (i.e., percent pavement + percent building, as squares) for each 3×3 km grid cell. The relationship at the 9-km^2 scale for pavement: $y = 0.59x + 8.56$, $r^2 = 0.88$, p-value = 0, and impervious is: $y = 0.94x + 10.91$, $r^2 = 0.95$, p-value = 0. The 1-to-1 line of the plot area is depicted as a dotted gray line. Residuals of each regression are included to right.

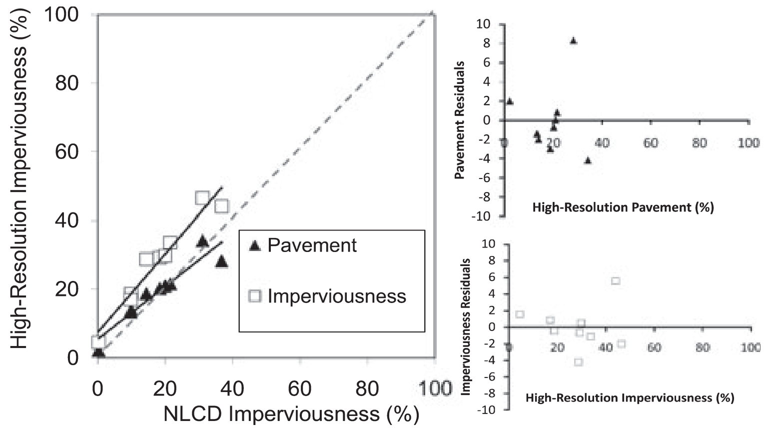

FIGURE 9. Relationship Between National Land Cover Database (NLCD) Percent Imperviousness Layer and Percent Pavement + Building Classes in Zhou and Troy's (2008) High-Resolution Dataset at the Watershed Scale. The regression equations are: total imperviousness: $y = 1.15x + 7.38$, $r^2 = 0.94$, $n = 9$, and p-value = 0; pavement alone: $y = 0.77x + 5.38$, $r^2 = 0.89$, $n = 9$, and p-value = 0. The 1-to-1 line of the plot area is depicted as a dotted gray line. Residuals of each regression are included to right.

TABLE 3. Percent Land Cover for Each of the Baltimore Ecosystem Gauged Watersheds as Reported by Zhou and Troy's (2008) Object-Oriented Classification of High-Resolution Imagery.

Watershed	Building	Coarse Vegetation	Fine Vegetation	Pavement	Water	Bare Ground
Horse Head	5	40	37	14	1	3
Baisman Run	2	80	15	2	0	0
Glyndon	9	39	30	20	0	1
Villa Nova	9	38	32	21	0	1
Gwynnbrook	10	33	35	19	0	3
Red Run	4	47	30	13	0	6
Scotts Level	12	34	32	22	0	1
Carroll Park	16	31	23	29	0	1
Dead Run	12	23	29	34	0	1
Entire Gwynns Falls	12	34	30	24	0	2

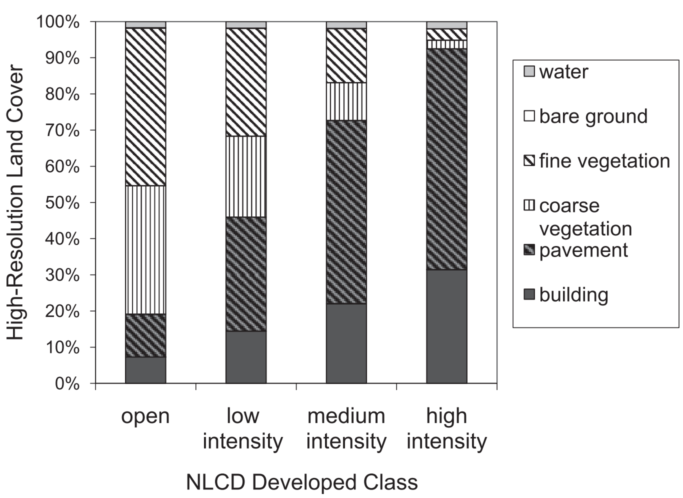

FIGURE 10. Land-Cover Composition of National Land Cover Database (NLCD) Developed Classes: Open, Low Intensity, Medium Intensity, and High Intensity Based on High-Resolution Dataset (Zhou and Troy, 2008).

The distribution of the land-cover composition within the developed classes was examined in more detail (Figure 11). The interquartile range of the percent imperviousness, fine vegetation and coarse vegetation is narrow for the high-intensity development class. However, the interquartile range in predicting land cover from these NLCD classes widens as development intensity declines. Although the interquartile range spans <5% for high-intensity development, the interquartile range of the canopy cover in the open development land class spans over 15%.

NLCD Grass-Related Classes

The NLCD includes fine-vegetation land cover within four land-use classes: developed open space, pasture, grassland, and cultivated crops. No NLCD "grasslands" are classified in the Gwynns Falls

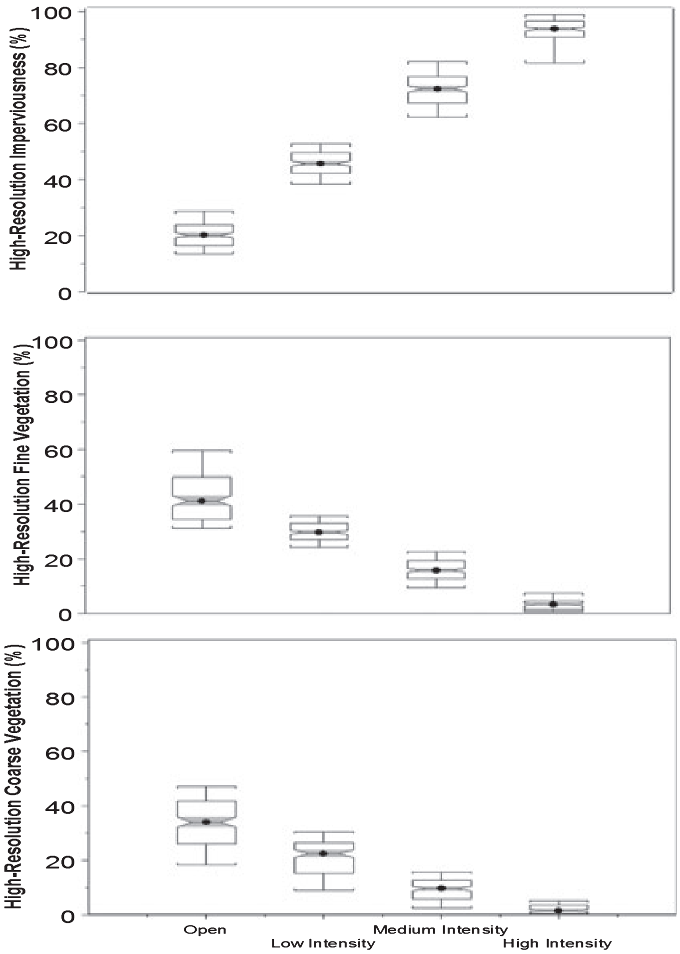

FIGURE 11. Comparison of National Land Cover Database (NLCD) Developed Land Classes to High-Resolution Dataset (Zhou and Troy, 2008) According to 1-km^2 Grid Cells. Box plots of NLCD development classes: open, low-intensity, medium-intensity, and high-intensity for impervious, fine vegetation, and tree cover composition within each. The circle depicts the median, the shaded notch represents the 95% confidence interval, the box indicates the interquartile range, and the 10 and 90% quartile ranges are illustrated with the "whisker" bars.

watershed. The fine-vegetation class was extracted from the high-resolution land-cover dataset to determine which NLCD classes incorporate fine-vegetation land cover into their land use categories (Figure 12). The majority of fine vegetation or grass is found in the developed open space and low-density residential NLCD classes. The remainder exists primarily in the pasture and crop categories. The range/distribution of the percent fine vegetation of these grass-related classes was examined (Figure 13). This figure displays the median, interquartile range, and confidence interval of percent fine vegetation coinciding with NLCD land-cover categories within 1-km^2 grid cells. The interquartile range is over 20% for open and low-intensity development.

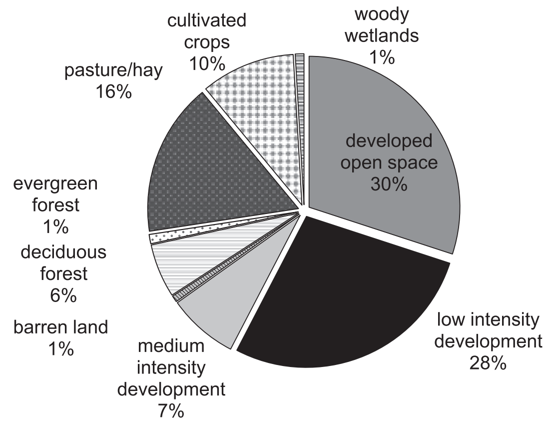

FIGURE 12. Apportionment of Fine Vegetation in National Land Cover Database (NLCD) Mixed Land-Cover Categories. The fine vegetation land-cover class of Gwynn's Falls was extracted from the high-resolution dataset (Zhou and Troy, 2008) to determine which land use categories are primarily comprised of lawn.

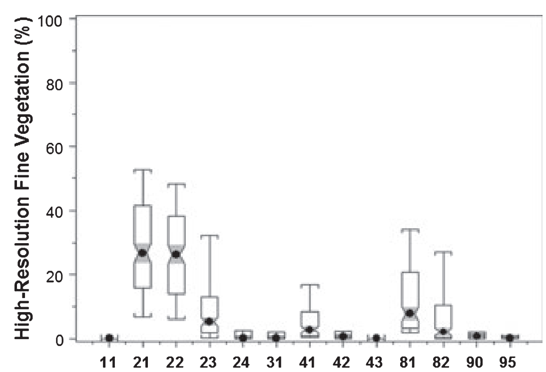

FIGURE 13. Distribution of National Land Cover Database (NLCD) Grass-Related Categories Displaying Percent of 1-km Grid Cells Occupied by Fine Vegetation as Defined by High-Resolution Dataset (Zhou and Troy, 2008). NLCD classes on the x-axis are defined as 11: open water; 21: developed, open; 22: developed, low density; 23: developed, medium density; 24: developed, high density; 31: barren; 41: deciduous forest; 42: evergreen forest; 43: mixed forest; 81: pasture/hay; 82: cultivated crops; 90: woody wetlands; 95: emergent herbaceous wetlands. The circle depicts the median, the shaded notch represents the 95% confidence interval, the box indicates the interquartile range, and the 10 and 90% quartile ranges are illustrated with the "whisker" bars.

DISCUSSION

Canopy

The correlation between the NLCD canopy layer and the high-resolution dataset is the weakest for 1-km^2 areas with <10% canopy cover. However, the y-intercept of all of these regression models is near 10, indicating that the NLCD consistently under-reports canopy cover by nearly 10% in urbanized areas. The regression intercept term and residuals indicate that NLCD subpixel canopy-cover algorithms poorly discern small or patchy tree cover. Because the assumption of heteroscedasticity is violated, the regression equation cannot be universally applied to NLCD data. Thus, adding 11% to all percent forest calculations will not consistently account for the bias of the canopy dataset. The NLCD predictions of canopy cover are highly variable at canopy covers between 10 and 70%. Canopy cover over 70% is frequently overpredicted by the NLCD. Although the regression equation indicates a slope of 1 and a high r^2 value, this effect occurs largely due to the balance of biases at the low and high percent canopy levels with a large degree of scatter at the mid-range percent canopy cover.

Increasing the area of interest to 9 km^2 from 1 km^2 improved the fit, indicating that the regional studies of canopy cover with the NLCD canopy layer have high correlation with a very fine-resolution dataset. As expected, land-cover analysis of areas exceeding 9 km^2 is more accurate and more heteroscedastic. However, percentages are averaged over a larger area of interest and, subsequently, the major ranges from bias <10% to >70% are not included. Thus, augmenting percentages by the intercept, 9%, may adjust for the urban bias or simply obviate the bias by averaging out the extremes.

Imperviousness

The high correlation between the NLCD impervious layer and the high-resolution dataset is surprising given that many buildings are smaller than the 30-m detection limit of the NLCD. The effect of combining 1 m digital orthophoto quadrangles and Landsat spectral data, and dense row-house development with minimal intervening yard space may account for the accuracy of the product in urban environments. The differences in slopes of these regression lines, 0.59 (pavement alone) and 0.96 (total imperviousness), also indicates that the determination of percent pavement/directly connected or effective imperviousness is roughly 60% of the NLCD reported impervious layer value at the 1-km^2 scale of analysis. Directly connected or effective impervious area refers to the fraction of impervious surfaces that conveys directly to the stream through gutters and stormwater infrastructure. However, biases along the range of imperviousness should be factored in if considering this estimation of effective imperviousness.

The error of the NLCD increases at 40%, which is surprising given that one might expect medium-resolution data to better define areas of lower heterogeneity (Figure 7). Areas with large percent imperviousness, >70%, for example, are most frequently overpredicted by the NLCD relative to the high-resolution dataset – vegetated areas surrounded by large percent impervious surface (e.g., road medians or parking lot rain gardens) are not discerned by the NLCD, and the entire area is attributed as impervious. Thus, fine-scale low-impact development practices are not apparent in the NLCD.

Areas <10% impervious are largely underestimated by the NLCD. The marginal difference between the NLCD makes a large difference for areas of <10% imperviousness because this percentage marks a critical threshold with respect to the relationship between land-cover and hydrologic response. When the high-resolution dataset suggests that an area is 10% impervious, the NLCD typically reports that it is <10%. When the NLCD reports that the percent imperviousness is 10%, the high-resolution imagery suggests that the imperviousness is approaching 20%. Although the difference is marginal, areas with <10% imperviousness maintain stream function and, thus, are important areas to target for land conservation or other mitigation practices.

Improved accuracy of the 9-km^2 scale results from decreasing areas that fall within the ranges from bias <10% to >70%. Regression analysis at the watershed scale found a correlation of $r^2 = 0.94$, but the steeper slope coefficient of its regression ($y = 1.15x + 7.38$) indicates a bias of imperviousness by the NLCD relative to the high-resolution dataset (Figure 9). Thus, use of the NLCD in urban areas for developing modeling parameters for areas exceeding 9 km^2 may be valid.

This analysis indicates that the overall accuracy of the NLCD impervious layer is beyond that reported for mapping zone 60 of 91% (Homer *et al.*, 2004). The residual analyses indicate that at percent imperviousness <20%, the NLCD residuals for pavement alone are less than pavement plus buildings. Thus, for areas of low-density development (<20% impervious), the NLCD impervious layer is more representative of pavement alone – directly connected or effective impervious area – than total imperviousness. However, the residuals suggest that in areas of higher-density development (>70% impervious), the NLCD is a better indicator of total imperviousness including buildings. In medium-density areas (40 to 70% impervious), the NLCD exhibits the least amount of similarity with the high-resolution data, indicating that studies of areas of medium density should supplement NLCD sources to gain more accurate estimates of total imperviousness.

Use of the NLCD canopy and impervious products for hydrologic purposes in urban areas may be possible when the land cover is 10-40% at 9 km^2 because error increases dramatically at 40%. Comparatively, the error for areas <10% impervious or canopy cover is greater. This difference is of particular importance with regards to the important threshold of stream degradation defined at 10% imperviousness. Separate regression models for the <10% range of imperviousness has a weaker correlation than the full range. This result emphasizes the irregularity of the NLCD in defining fine-scale imperviousness.

Land Cover

Land-cover composition of developed land classes falls within the expected range of impervious cover as described in Homer *et al.* (2004; Table 2). However, no detailed information for vegetation composition within NLCD land-cover categories has been reported previously. The land-cover breakdowns illustrated in Figure 11 indicate more consistent land-cover composition within the NLCD highly developed land class than in the less-developed land classes. The reduced consistency of land-cover composition in less dense land classes may be due to the trend to develop either former forest or farm to low-density neighborhoods attributing greater percent coarse or fine vegetation, respectively. Fortunately, the NLCD canopy layer provides a useful tool to help discern total tree cover. However, the interquartile range for fine vegetation or grass in the NLCD open development class spans over 20%, emphasizing the high variability of land-cover composition of the NLCD land-cover categories. The ranges of land-cover composition of NLCD-developed and grass-related classes denote critical limitations in the use of the NLCD alone for urban hydrologic applications. This evaluation did not elucidate errors in the high-resolution dataset coinciding with those of the NLCD. However, the error of the high-resolution dataset averaged at the 1-km^2 scale (~2.8 million pixels) is likely less than the error for 30 m data for the same area of interest (~1,111 pixels).

CONCLUSIONS

This study aims to evaluate the usefulness of the NLCD to estimate hydrologically significant land-cover parameters in an urban environment and finds three primary limitations to the use of the NLCD for urban hydrologic applications. (1) The canopy and impervious layers exhibit bias at <10% and >70%, (2) The ratio of total impervious area and connected impervious area differs along the range of percent imperviousness, (3) The variability of vegetation of NLCD categories limits the usefulness of the NLCD for determining the composition of pervious urban land cover.

Urban hydrology depends on many factors – slope, sewer infrastructure, soil type and compaction, and other management practices, which cannot be derived from urban land-cover datasets. The emphasis of this paper was the derivation of land-cover parameters for hydrologic use in urban settings. Land cover is a major factor controlling catchment response in urban systems and is an important parameter in most hydrologic models. Land-cover parameters are frequently derived from the NLCD for the purpose of hydrologic modeling. However, given the biases of the NLCD at low and high percent canopy or imperviousness, ground-truthing with high-resolution imagery or orthophotos is necessary to acquire accurate estimates of land-cover parameters.

The NLCD canopy layer is biased by 10-11% at the 1-km^2, 9-km^2, and watershed scales. However, the agreement is best for larger areas of interest due to the averaging of error. The systematic error of the NLCD percent canopy dataset in areas <10 and >70% is important due to urban tree canopy goals that are associated with stormwater runoff controls (see Raciti *et al.*, 2006). A critical aspect of these urban canopy policies and their implementation is the ability to measure land cover, including both canopy and impervious surface cover, at a high spatial resolution and accuracy to facilitate assessments, long-term monitoring, and watershed management. The NLCD would most likely report that small tree patches, comprising <10% area, are closer to 0% canopy cover. This omission could translate into a reduced estimate of hydrologic sinks, increased prediction of floods and pollutant transport, and misguide urban canopy policies. For areas of high canopy cover, the NLCD more often overestimates percent forest cover, which may inaccurately indicate that urban canopy goals are met. The overall accuracy of the canopy dataset is balanced by averaging the biases at each end of the land-cover spectrum. Use of higher-resolution imagery is suggested when possible given this bias and the range of residual error.

Similarly, the NLCD impervious layer does not detect the fine-scale impervious features that make up <10% of the area of interest. Channel degradation associated with urban catchments is commonly cited to occur when the threshold of imperviousness exceeds 10% effective impervious area (Schueler, 1994; Booth and Jackson, 1997). Thus, the 0-20% range of total imperviousness is a particularly important threshold for determining changes in the resulting hydrograph. Although the lack of correlation could potentially be attributed to errors within high-resolution dataset, it is unlikely given the degree of ancillary data used in the classification of the high-resolution dataset. The shift in residuals at the 10% point makes the use of the NLCD for hydrologic applications particularly difficult. Percent imperviousness at and beyond the 10% critical threshold cannot be consistently corrected using the included regression equations because of the biases of the associated residuals.

A rough estimate of connected imperviousness is indicated to be an overall 60% of the NLCD total imperviousness. However, this percentage differs for areas of low and high percent imperviousness (i.e., in areas of high-density development, the NLCD more accurately reports total imperviousness, and in areas of low-density development, the NLCD reflects connected imperviousness [pavement] alone). Inability to accurately estimate this variable is critical given that effective impervious area (the product of total imperviousness and connected imperviousness) is a strong predictor of stream ecological condition (Hatt *et al.*, 2004; Walsh *et al.*, 2005). However, estimating effective imperviousness from the NLCD is a moving target given the inclusion of buildings in high percent impervious areas and exclusion of such structures at low density.

The NLCD land categories limit users' ability to discern land-cover composition in developed areas. Although this paper attempts to provide information on the land-cover composition comprising the developed land categories, the information is more variable for less-densely developed areas frequently categorized as low-density development, open development or row crops by the NLCD. Thus, the NLCD is less applicable in lawn-dominated suburbs – the most pervasive and rapidly growing development in the U.S. (Brown *et al.*, 2005). In addition, suburban development yields the highest urban nutrient pollutant loads (Law *et al.*, 2004; Shields *et al.*, 2008) and is a key target for nonpoint source pollution reduction.

The differences identified among the developed classes of NLCD 2001 suggest misclassification errors based on an Anderson level II classification system (Anderson *et al.*, 1976) and the subjectivity of incorporating land use into the land-cover datasets. The HERCULES approach offers potential improvement to capturing land-cover heterogeneity in urban areas in a more consistent way (Cadenasso *et al.*, 2007). Using this system, land cover is defined explicitly as building, pavement, coarse vegetation, fine vegetation, or bare land. Based on the HERCULES system, the relative density of vegetation or development types can be redefined at the time of use. The NLCD 2001 use of development density classes imposes land use information into the land-cover database. Although the added value may be useful to some users, the imposed definitions cannot be removed to determine the underlying land cover types more explicitly.

Hydrologic models rely on accurate land-cover inputs, including impervious surface, lawn, and canopy data to predict water quality and quantity impacts of policy changes and climate variability. Water quality impacts may include the changes in pollutant sources and deposition related to vegetation data and pollutant transport via impervious surface and the connectivity of subsurface flow. Water quantity impacts related to flash flooding and groundwater recharge are greatly influenced by percent imperviousness or soil compaction. Thus, assessment of land-cover variables is an important part of land conservation policy and targeting of low impact development strategies. The findings of this study hold implications for other disciplines (e.g., the estimation of urban nutrient fluxes and micro-climate effects).

The bias of the impervious and canopy layers of the NLCD inhibits the development of comprehensive watershed models based on an inability to link regional and fine-scale data. The large variability in land use categories in this dataset further complicates its use for the determination of land-cover parameters for hydrologic modeling applications. The NLCD is a great resource for many regional scale applications and initial analyses; however, it is limited given the fine-scale heterogeneity of urban land cover, lack of discernment of lawn area, and the biases of both the canopy and impervious subpixel classification layers.

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