A Quantitative Assessment of a Combined Spectral and GIS Rule-Based Land-Cover Classification in the Neuse River Basin of North Carolina

Ross S. Lunetta, Jayantha Ediriwickrema, John Iiames, David M. Johnson, John G. Lyon, Alexa McKerrow, and Andrew Pilant

Abstract

The 14,582 km² Neuse River Basin in North Carolina was characterized based on a user-defined land-cover (LC) classification system developed specifically to support spatially explicit, non-point source nitrogen allocation modeling studies. Data processing incorporated both spectral and GIS rule-based analytical techniques using multiple date SPOT 4 (XS), Landsat 7 (ETM^{+}), and ancillary data sources. Unique LC classification elements included the identification of urban classes based on impervious surfaces and specific row crop type identifications. Individual pixels were aggregated to produce variable minimum mapping units or landscape "patches" corresponding to both riparian buffer zones (0.1 ha), and general watershed areas (0.4 ha). An accuracy assessment was performed using reference data derived from in situ *field measurements and imagery (camera) data. Multiple data interpretations were used to develop a reference database with known data variability to support a quantitative accuracy assessment of LC classification results. Confusion matrices were constructed to incorporate the variability of the reference data directly in the accuracy assessment process. Accuracies were reported for hierarchal classification levels with overall Level 1 classification accuracy of 82 percent (*$n = 825$*) for general watershed areas, and 73 percent (*$n = 391$*) for riparian buffer zone locations. A Kappa Test Z statistic of 3.3 indicated a significant difference between the two results. Classes that performed poorly were largely associated with the confusion of herbaceous classes with both urban and agricultural areas.*

Introduction

Land-cover (LC) type, extent, and condition in both the spatial and temporal domains, represent important landscape characterization elements. These data can be used to support environmental monitoring and assessment efforts, and to study dynamic ecosystem processes. LC characterization variables are required for the study of numerous ecosystems processes, including habitat suitability, wetland functions, identification of non-point nutrient sources, hydrologic transport, and erosion and sedimentation processes. Of particular importance, is the application of LC data for the generation of landscape-based assessment metrics to evaluate relative ecosystem condition over a wide range of analysis scales (i.e., watershed to national) to assess impacts attributable to human land-use activities (Wickham and Norton, 1994; Jones *et al.*, 1997; Riitters *et al.*, 1997).

Currently, high priority non-point-source (NPS) issues are focused on nutrient and sediment transport from the landscape to receiving streams. These NPS loadings are used to support the development of total maximum daily loads (TMDL) determinations of streams and rivers (USEPA, 1999). These dynamic, ecosystem NPS processes function at multiple analytical scales and require relatively high-resolution geospatial data to support watershed-scale modeling efforts. Landscape parameters required to support these spatially explicit modeling approaches, include the identification and delineation of individual LC elements or "patches." Landscape "patches" typically represent the primary modeling unit of a spatially explicit landscape model. They are defined in this study as contiguous and relatively homogeneous LC types that can be repetitively mapped using remote sensor data.

The characterization of riparian buffer zones is required to evaluate their functional capacity and ecosystem value. Typically, riparian buffer zones are defined as areas directly adjacent to the top-of-the-stream bank and extending outward in a perpendicular direction for a distance of approximately 20 to 30 m. Riparian buffer zones play important functional roles in nutrient cycling and erosion/sedimentation deposition processes (Verchot *et al.*, 1998). Characteristics associated with high quality riparian buffer zones include the presence of well established natural vegetative cover to provide (1) stream bank stabilization; (2) shading; and (3) a physical and biological barrier to the migration of sediment, nutrients, and microbes from the surrounding landscape to receiving watercourses. Vegetated riparian buffers also function as nutrient processors through the absorption and assimilation of nitrogen and phosphorous compounds into soils and vegetative structures (Peterjohn and Correll, 1984). Associated microbial communities fix and process nutrients associated with both surface water flow and shallow groundwater seepage (Verchot *et al.*, 1997).

R.S. Lunetta, J. Iiames, and A. Pilant are with the U.S. Environmental Protection Agency, National Exposure Research Laboratory (E243-05), Research Triangle Park, NC 27711 (lunetta.ross@epa.gov).

J. Ediriwickrema, D. Johnson, and A. McKerrow are with Lockheed Martin Services, Inc., Research Triangle Park, NC 27709.

J.G. Lyon is with the U.S. Environmental Protection Agency, National Exposure Research Laboratory, 944 E. Harmon, Las Vegas, NV 89119.

Photogrammetric Engineering & Remote Sensing
Vol. 69, No. 3, March 2003, pp. 299–310.

0099-1112/03/6903–299$3.00/0

The objective of this study was to develop a multiple resolution LC database for the Neuse River Basin (NRB) in North Carolina that was used to support NPS nitrogen mass-balance modeling and hydrologic surface water transport to receiving water courses across the Basin. To obtain the optimal classification outcome, data subsets were analyzed using both supervised and unsupervised spectral analysis, and a geographic information system (GIS) rule-based analytical data processing approach. A quantitative assessment of LC class accuracies was performed using *in situ* field measurement and digital (camera) imagery to provide a reference data source with known variability for hierarchical classification of Levels 1, 2, and 3 corresponding to a user-defined classification system as modified from Anderson *et al.* (1972).

Study Area

The NRB is contained entirely within the boundaries of the state of North Carolina (Figure 1). By definition, basin boundaries correspond with the U.S. Geological Survey (USGS), six-digit hydrologic unit code (HUC), code number 030202. The upper, northwestern third of the basin is located in the Piedmont physiographic region and the remainder in the mid-Atlantic coastal plain. The Piedmont portion of the Basin is characterized by highly erodible clay soils, rolling topography with broad ridges and stream valleys, and low gradient streams composed of a series of sluggish pools separated by riffles and occasional small rapids. In contrast, the coastal plain is characterized by flat terrain, "blackwater streams," low-lying wetlands, and productive estuarine areas. Elevations within the NRB range from 276 meters in the western part of the basin to sea level at the confluence of the Neuse River to Pamlico Sound that represents the southern extent of the Albemarle-Pamlico Sound estuary system which is bordered by a series of barrier islands known as the North Carolina's Outer Bank (NCDEM, 1993).

Methods

Imagery data used in support of the NRB analysis included two SPOT 4 (XS) data acquisitions (20 scenes) and three complete sets of Landsat 7 Enhanced Thematic Mapper Plus (ETM^+) level-1G data (12 scenes), collected between fall 1998 and summer 1999. The 1998 XS imagery was first rectified to 1993 Digital Ortho-photo Quarter Quads (DOQQs), then re-sampled to 15- by 15-m pixels using a cubic convolution algorithm. This mosaic was used as the basis for all subsequent image-to-image rectifications of XS and ETM^+ data. Data processing was performed separately on a total of eight subsets that were subsequently assembled to provide a final seamless NRB LC product. Subset boundaries were established based on the XS and ETM^+ scenes corresponding to imagery acquisition dates. The serial processing of individual image segments circumvented the variability associated with the different imagery acquisition dates, thus negating the requirement for radiometric normalization of data across multiple scene segments. Data obscured by dense clouds or flood inundation conditions due to Hurricane Floyd were excluded from processing.

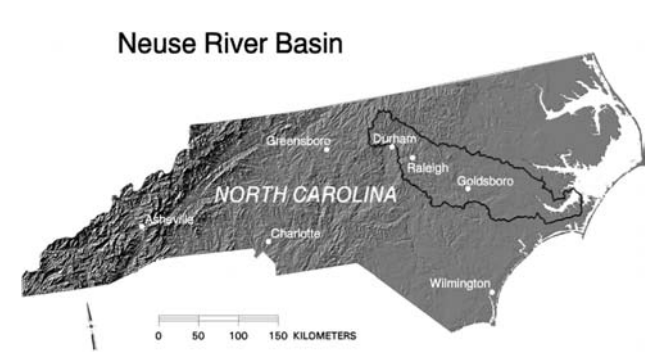

Figure 1. Neuse River Basin location map.

Initial Classification

The NRB LC classification system included three hierarchical classification levels (see Table 2). Classifications were performed using a hybrid approach that combined supervised, unsupervised, and rule-based classification techniques. First, a supervised classification was performed that identified those pixels corresponding to unique image end-members (pure spectral classes). Next, pixels representing more than one LC class (mixed pixels) were each grouped and classified using an unsupervised classification. The unsupervised classification was applied sequentially to hierarchical image segments. Areas that could not be assigned to a unique LC class were isolated, spectrally grouped, and reprocessed. Ancillary GIS data were used to refine the urban, agriculture, and water classes.

Classifications were performed using multiple dates of imagery in a composite analysis (CA) approach for each of the eight processing areas. Because subsets had unique combinations of input images, data stacks ranged from 14 to 22 bands. To standardize the approach, principal component (PC) transformation images were created for each area. The first eight bands were then used to support the classification process. In each case, the first eight PC bands accounted for more than 99 percent of the total data variance.

An automated training area identification process was used to account for both within-scene spectral variance and inherent within-class variability. Only the fall XS 1998 imagery was used in this automated process because it was determined that "change areas" were being selected on a disproportionate basis using the multiple-date imagery. Additionally, the XS data had low spectral variability in homogeneous areas relative to the ETM^+ data, and thus provided a more favorable environment for training set selection. First, an ISODATA clustering was performed on the 1998 XS image subsets that provided 32 clusters. Clumps of pixels greater than 5.8 ha were then selected within each cluster class as prospective areas for signature extraction. Both the number and size of clusters influenced the degree of cover-class generalization in the training area identification process. For example, increasing either the number of clusters or the minimum size requirement, reduced the number of prospective training sites. The protocol was optimized using a number of image subsets, different number of clusters, and minimum size thresholds.

ARC/INFO polygon coverages were then developed to support pixel-based signature extractions. Because polygon boundary pixels had a high probability of being mixed, they were excluded by buffering inside the polygons. All polygons were buffered to distances of 15, 30, 45, and 60 m. Subsequent to buffering, polygons were selected to represent each cluster class starting with the 60-m buffer group and progressing to lower buffer distances until an adequate number of polygons were identified for each unique cluster class. Finally, the selected polygon coverages corresponding to each unique spectral cluster were used to identify potential training areas for unique LC classes.

The polygon coverage was then converted to ERDAS/IMAGINE areas of interest (AOIs), or training sites, to develop representative signature files corresponding to the eight-band PC images. A signature contingency classification (SCC) was performed to evaluate training set purity. The SCC table compared signature class statistics versus pixel signatures. Pure training sites exhibited no confusion (off-diagonal values) and were selected to develop the final signature files in PC space. The AOI corresponding to each training area was displayed on the fall 1998 XS false-color composite (FCC) and interpreted with the aid of reference data within the context of the classification scheme (Table 1). Reference data included a series of 1998-1999 National Aerial Photography Program (NAPP) color-infrared photographs (1:40,000-scale), as well as basin-wide 1993 DOQQs. Although this process provided high quality LC training sites, it was deficient in the generation (discrimination) of land-use training areas. Accordingly, AOIs for land-use types (i.e. maintained lawns) were identified manually.

To implement the supervised classification, a maximum-likelihood classifier (MLC) was first applied using equal prior probabilities (PP). The outcome class frequencies were then used to calculate the PP for a second MLC. Several studies have determined that equal PP can be used in the MLC, but that actual PP provided for a more robust classification (Maher, 1985; Lee and Landgrebe, 1991). Individual class verifications of the second supervised classification (MLC with estimated PP) in the form of manual reviews were performed to provide quality assurance for the assigned LC labels and to identify confused training signature classes that represented more than one cover type.

An unsupervised classification was then used to improve class assignments for pixels associated with confused training signature classes. For example, the classes from the supervised classifications that were confused among multiple cover types were processed independently to provide greater classification detail. First, confused classes were grouped based on their general cover class. Confused class groups were then repetitively clustered and labeled until all pixels were assigned to the most representative cover class with minimal confusion.

Sub-Level Classifications

Agriculture and Herbaceous

Crop statistics (1999) for the counties within the NRB were acquired from the North Carolina Department of Agriculture and Consumer Services (NCDA&CS). The probabilities of occurrence were computed for each crop type on a county level basis. Major row crops included cotton, corn, soybean, and tobacco. All row crops other than the crops listed above were categorized as "other row crops" because they represented less than five percent of the total row crop acreage. Field-based ground truth data were collected during the 1999 agricultural growing season and the post-harvest period during early 2000. Field data were used to derive the phenologies for each major crop type. Aerial photographs and DOQQs were also used as reference data to determine differences between row crops, pasture/hay, and transitional vegetation.

Of the five dates of satellite imagery available for our analysis, only two dates were deemed useful for sub-level classification of agricultural land. The fall 1998 SPOT (XS) data were excluded because they represented crop types from the previous growing season, which were likely to have been different due to crop rotations. Also excluded were the early spring 1999 SPOT (XS) imagery which was collected too early in the growing season and the July 1999 ETM^+ imagery which was cloudy over much of the region. However, the September 1999 imagery was relatively good and the October 1999 ETM^+ imagery was high in quality throughout the NRB. Even with the limited amount of available temporal data, images that only corresponded to the harvest period were useful in the classification of agricultural pixels.

Normalized difference vegetation index (NDVI) images were developed for the agricultural classes corresponding to the two harvest periods. Next, ISODATA-based clustering was performed on the combined NDVI images. The training data were overlaid on the clusters in the two-dimensional feature space and the clusters were labeled accordingly. The clusters not associated with available training data were labeled based on the expected greenness response corresponding to predicted agricultural phenological time lines (Table 1). Generally,

Table 1. Summary of NDVI for Late Growing Season Imagery Dates. Corn Was Harvested before September and thus Low Greenness at Either Time. Soybeans Were the Last Crops to Be Planted and Harvested and Typically Remained Green Throughout the Fall. Hay/Pasture Had Biomass Year-Round; thus, Minimal Change Was Observed between Dates. The Pattern for Tobacco and Cotton Tended to Fall between Corn and Soybean

Crop Type	NDVI (September–October)	NDVI (October–November)
Corn	Low	Low
Tobacco	Low-medium	Low
Cotton	Medium	Low
Soybean	High	Low-medium
Hay/Pasture	Medium-high	Medium-high

corn was harvested before September and resulted in no biomass peak occurrence between the September and November index period. Soybeans were harvested late in the season and thus typically remained green throughout the fall with some senescence occurring between October and November. Hay and pasture had relatively stable levels of biomass in the fall and changed little between imagery data collections. Tobacco and cotton tended to fall between the corn and soybean extremes.

Due to the variability of planting and harvesting practices, a small percentage of training data did not follow the typical phenological patterns. Therefore, after NDVI labeling, cluster labels were reassessed on a county-by-county basis and reassigned from improbable classes to spectrally similar but more probable classes. For example, any pixel in Beaufort County that was found spectrally to be tobacco was changed to corn because there was only a three percent probability of finding a tobacco in the region, but a 39 percent probability for corn.

Wetland and Water

Water and wetland classes were based on the 1:24,000-scale 1991-1992 National Wetland Inventory data (NWI) for North Carolina, corresponding to the U.S. Department of Interior, Fish and Wildlife classification system (Cowardin *et al.*, 1979). Locations classified spectrally as water that did not occur in the NWI were labeled as ponds. In the editing process some pond edges (soil) were determined to be incorrectly classed as urban from the spectral data alone. To correct for these outliers, a 3-by 3-pixel neighborhood majority algorithm was applied to urban pixels. Urban pixels falling below this threshold were recoded to pond. NWI wetland scrub/shrub and forest were labeled as woody wetland, and emergent and aquatic beds were labeled as herbaceous wetland.

Urban (Impervious)

The 1:24,000-scale DLG roads coverage was used to differentially buffer the primary, secondary, and tertiary road types. Primary roads were buffered at 15 m, while secondary and tertiary roads were buffered at 10 m. The buffered roads were merged with the urban pixels from the spectral classification. A 4- by 4-pixel neighborhood count (0.4 ha) was applied to determine the number of urban pixels surrounding the pixel of interest. Based on this neighborhood analysis, an impervious surface image was created, with urban pixels being assigned to high (12 to 16 urban neighbors), medium (7 to 11 urban neighbors), or low density (2 to 6 urban neighbors). Pixels were then re-coded based on a combination of the spectrally determined LC class and the impervious level. For example, a pixel classed as deciduous and located in a medium density impervious neighborhood was re-coded to medium density urban-woody vegetation.

Spectrally Inseparable Areas

Some cover types were spectrally inseparable and required manual editing. On-screen digitizing was used to delineate

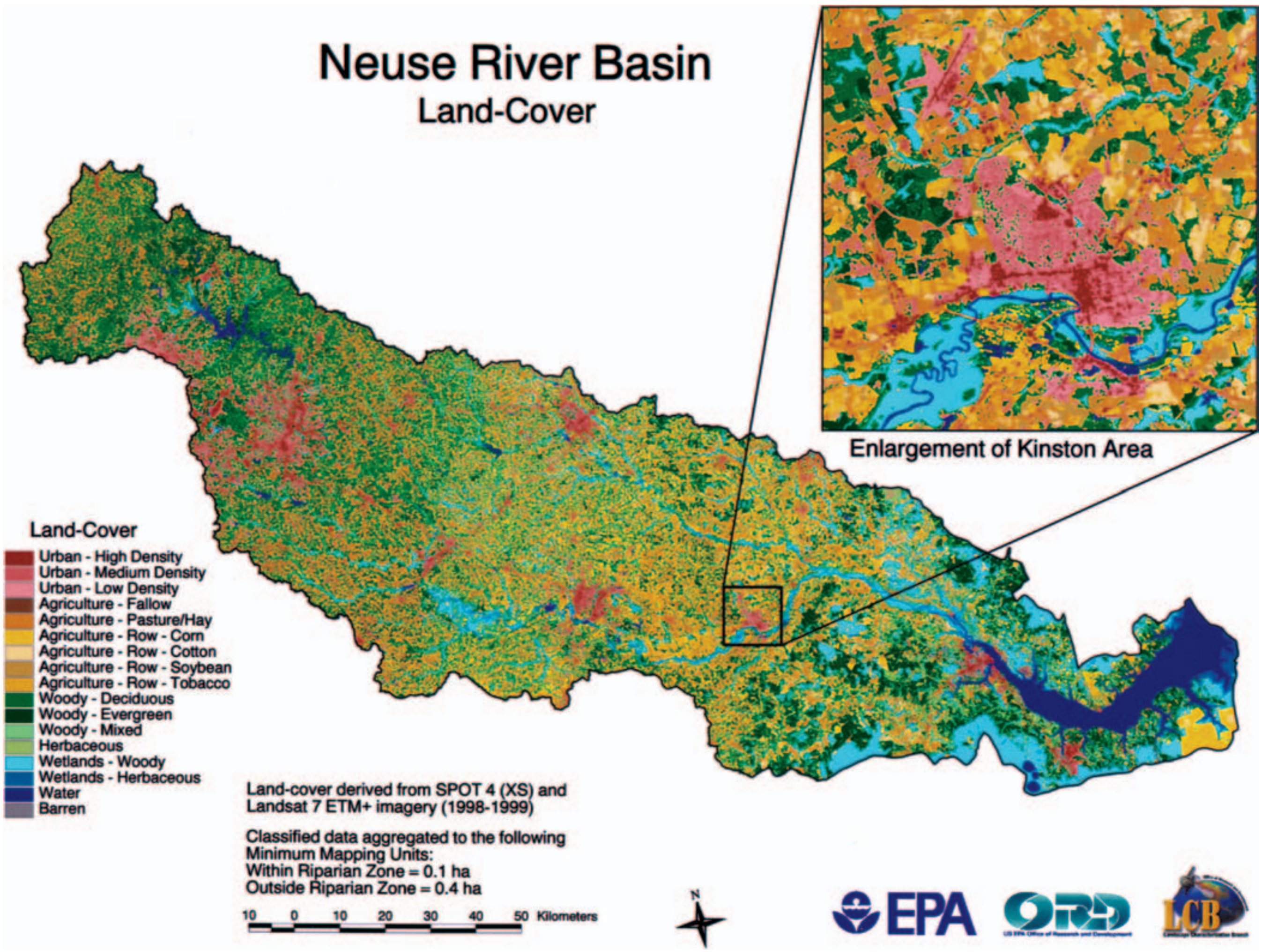

Plate 1. Neuse River Basin land-cover classification results. Note the finer resolution mapping units in the riparian buffer zones (0.1 ha) and coarser resolution watershed mapping units (0.4 ha).

AOIs for land-use types including golf courses, quarries, and maintained lawns in the large urban centers. For example, pasture/hay pixels were re-coded to maintained lawns for golf courses or within urban areas, and urban pixels were re-coded to bare soil in areas identified as quarries.

Final Data Processing

Using the cutline feature within ERDAS/IMAGINE, the eight subset classifications were edge-matched to create a basin-wide mosaic. Three separate minimum mapping units (MMU) filters were then applied to produce two separate LC coverages, each with multiple MMUs. The finer resolution coverage included a five-pixel (0.1-ha) MMU for the riparian buffer zones (within 30 m of streams, canals, and rivers) and a 16-pixel (0.4-ha) MMU for the non-riparian areas of the watershed (Plate 1). The coarser resolution product included the same five-pixel MMU within the riparian zone and a 256-pixel (5.8-ha) MMU outside the riparian zone.

Accuracy Assessment

An accuracy assessment was performed for classification Levels 1, 2, and 3. The classification results were compared to reference data (1998-1999) and reported in the form of error or confusion matrices (Story and Congalton, 1986). To support the LC accuracy assessment, a "Virtual Field Reference Database" (VFRDB) was developed for the NRB (Lunetta *et al.*, 2001). The VFRDB provided an independent source of *in situ* measurement and imagery (camera) data that was interpreted to provide reference data that correspond directly to the NRB classification systems. Two interpreters independently assigned class labels corresponding to the NRB hierarchical classification system for 1,360 sampling sites within the study area. Interpretations were recorded as either a single (confident) call or as multiple calls, which included the most confident (primary) and less confident (secondary) class designations.

The accuracy assessment procedure first incorporated an analysis of interpreter calls to evaluate reference data variability. Second, an accuracy assessment was performed comparing both interpreter calls to the LC classification results. This was accomplished using both single and multiple class possibilities. Multiple class calls represented 11 percent, 23 percent, and 25 percent of sampling points used for classification Levels 1, 2, and 3, respectively. A single class call occurred when both interpreters had only primary calls that were an identical match. Multiple class calls occurred when the interpreters primary calls were different or when secondary calls were encountered. The maximum allowable number of calls was two and were represented as 0.5 for each class. If the number of calls exceeded this threshold, secondary calls were dropped from the accuracy assessment analysis. Thus, fractional numbers appear in the error matrices presented in this paper.

Sampling Frame Design

The sampling frame design for the NRB-VFRDB was based on three separate elements in an attempt to provide an adequate distribution of sampling points across the entire watershed. They incorporated a systematic unaligned random (SUR) samples based on the USGS Quarter Quadrangles (732 points), stratified random samples (SRS) based on the Multi-Resolution Land Characteristics (MRLC) LCLU data (374 points), and riparian multiple stratified random (RMSR) sampling of first- and second-order riparian buffer zones (450 points). Riparian buffer zone stratifications included a systematic distribution of points by 11-digit HUC, followed by multiple stratification based on stream order and major LC type. The systematic unaligned sampling element effectively provided an even distribution of points across the entire study area, but resulted in an under-sampling of rare classes. The stratified random design was performed to provide for sample intensification of the less abundant classes throughout the watershed. Lastly, the systematic multiple random riparian design provided a representative sampling of riparian buffer zone areas along the first- and second-order stream reaches. Sampling sites were circular plots with a radius of 36.5 meters to provide a 0.4-ha plot. Of the total 1,360 sampling sites, 545 sites were sampled in 1998 and 815 during the 1999 field sampling seasons, coinciding with satellite remote sensor data collections. It should be noted that probability inclusions were not accounted for with either the SRS or RMSR sampling design elements.

Results

The results of the LC classification are depicted in both tabular (Table 2) and graphic (Plate 1) formats. Plate 1 serves to illustrate the multiple resolution characteristics of the landscape "patches" that were mapped by the LC classification analysis. Within the general watershed locations, "patches" were mapped at a minimum resolution of 0.4 ha, while riparian buffer zones were mapped at a 0.1-ha MMU. Riparian buffer zones were located within a distance of two pixels (30 m) perpendicular from the watercourse pixel(s). The resolution difference was apparent along the stream reaches in the enlargement of the Kinston area where numerous fine resolution riparian features were captured (Plate 1).

The distribution of LC types within the NRB were 13.5 percent urban, 29.3 percent agricultural land, 38.4 percent woody vegetation, 0.1 percent herbaceous vegetation, 4.3 percent water, 14.3 percent wetlands, and 0.2 percent barren land (Table 2). Urban classes were further subdivided into high (71 to 100 percent), medium (36 to 70 percent), and low (10 to 35 percent) density classes based on the percent impervious surfaces. By definition, any urban class with $\leq$49 percent impervious surfaces was dominated by another LC type and was assigned an additional (Level 3) classification identification. For example, low density urban (10 to 35 percent impervious) represented 69.7 percent of all urban classifications. Of these, 43.4 percent were dominated by woody and 30.0 percent by herbaceous vegetation. Of the agricultural lands, approximately 61 percent were in row crop production, 39 percent in pasture/hay, and less than 1.0 percent were fallow. Row crops were dominated by soybeans (41.8 percent), cotton (24.9 percent), corn (23.2 percent), and tobacco (10.1 percent). Woody vegetation was further classified as deciduous (52.0 percent), evergreen (34.0 percent), and mixed (14.0 percent). Herbaceous vegetation (non-urban) was extremely rare, representing only 0.1 percent of the study area and was dominated by maintained grassland (79.5 percent). Water classes were dominated by streams/rivers/canals (75.0 percent), reservoirs (11.5 percent), lakes (6.3 percent), and ponds (6.5 percent). Wetlands were predominately woody (95.3 percent). The small fraction of barren lands (0.2 percent) were composed of non-vegetated (69.8 percent) and transitional pioneer vegetation (30.2 percent).

Reference Data Variability

The results of the reference data variability analyses are illustrated in Tables 3, 4, and 5. It should be noted that only the primary interpreter calls were used in this analysis. Thus, multiple secondary calls were omitted from the analysis (Table 3). Level 1.0 overall agreement between interpreters ranged from a high of 98.8 percent for wetlands to a low of 40.5 percent for barren. Herbaceous also performed poorly with an agreement of 58.8 percent. The overall Level 1.0 agreement was 89.2 percent (n = 1,360) with a Kappa statistic (KHAT) of 0.85. The major areas of disagreement among interpreters was between the agricultural and herbaceous classes (n = 31), woody and herbaceous (n = 18), urban and woody (n = 12), and urban and agriculture (n = 10).

Level 2.0 agreements are illustrated in Table 4 (a–f). The best performing interpreter agreements were obtained for the water (n = 35) and wetland (n = 84) classes (100 percent, respectively). However, Level 2.0 sample numbers for these classes were insufficient for a rigorous statistical analysis. Urban classes had a 78.5 percent (n = 144) agreement and KHAT of 0.56, with disagreements almost equally distributed between high and medium and medium and low density urban classes. Agricultural class agreement was 95.7 percent (n = 446) with a KHAT of 0.83, with the majority of disagreement between fallow field (n = 15) and both row crops and pasture. Overall woody vegetation class agreement was 89.5 percent (n = 446) with a KHAT of 0.83, and disagreements were nearly equally distributed among all classes (n = 47). Interpreter agreement for the two herbaceous classes was 83.7 percent (n = 49) with a KHAT of 0.65. Data for the barren classes was not presented here due to the insufficient sampling size (n = 9).

Data for two Level 3.0 classes were processed and are presented in Tables 5a and 5b. Overall interpreter agreement for low-density urban classes was 81.9 percent (n = 83) with a KHAT of 0.67. Nearly all low-density urban disagreement was between the woody and herbaceous classes (n = 13). Agricultural row crop class agreement was 94.7 percent (n = 339) with a KHAT of 0.92. The single greatest interpreter disagreement was between the cotton and corn classes (n = 7).

Accuracy Assessment

An accuracy assessment of the LC classification map was performed for all Level 1.0 classes, three Level 2.0 classes, and one Level 3.0 class. Assessments were not performed for the remainder of the Level 2.0 and 3.0 classes due to insufficient sampling size to support a rigorous statistical analysis. The assessment was performed using both primary and secondary calls in the protocol described in the methods section. Thus, non-integer numbers were incorporated into confusion matrices. Assessments were performed independently for both the SUR and RMSR sampling designs. The MRLC-based SRS provided insufficient data corresponding to the intended rare classes (i.e., natural grassland and barren) to provide usable data. The separate assessments for individual samples was required to support a valid statistical analysis and also provided insights relative to the performance of the disparate LC MMUs. Level 2.0 and 3.0 accuracies were reported to provide an assessment of errors introduced at each classification level. Total classification accuracy at any level or accumulated errors can be calculated using hierarchical multiplication. This method of reporting accuracies provided a more robust approach than the reporting of a single total accuracy value.

The overall Level 1.0 accuracies were 82 percent (n = 825) for the SUR sample (Table 6a) and 73 percent (n = 391) for the

TABLE 2. NEUSE RIVER BASIN LAND-COVER CLASSIFICATION SYSTEM AND FINAL CLASSIFICATION RESULTS BY PERCENT [ ] FOR EACH CLASS TYPE CORRESPONDING TO CLASSIFICATION LEVELS 1, 2, AND 3

Level 1	Level 2	Level 3
1.0 URBAN [13.5%]	1.1 High Density [14.0%] (71–100% Impervious)	
	1.2 Medium Density [16.3%] (36–70% Impervious)	1.2.2 Agricultural Land [94.9%] 1.2.3 Woody Vegetation [2.7%] 1.2.4 Herbaceous Vegetation [1.0%] 1.2.5 Water [1.4%] 1.2.6 Wetlands [0.0%] 1.2.7 Barren Land [0.0%]
	1.3 Low Density [69.7%] (10–35% Impervious)	1.3.2 Agricultural Land [9.0%] 1.3.3 Woody Vegetation [43.4%] 1.3.4 Herbaceous Vegetation [30.0%] 1.3.5 Water [15.7%] 1.3.6 Wetlands [1.1%] 1.3.7 Barren Land [0.8%]
2.0 AGRICULTURAL LAND [29.3%]	2.1 Row Crops [60.8%]	2.1.1 Cotton [24.9%] 2.1.2 Corn [23.2%] 2.1.3 Soybeans [41.8%] 2.1.4 Tobacco [10.1%]
	2.2 Pasture/Hay [38.6%] 2.3 Fallow Land [0.6%]	
3.0 WOODY VEGETATION [38.4%]	3.1 Deciduous [52.0%] 3.2 Evergreen [34.0%] 3.3 Mixed [14.0%]	
4.0 HERBACEOUS VEGETATION [0.1%]	4.1 Natural Grasslands [20.5%] 4.2 Maintained Grasslands [79.5%]	
5.0 WATER [4.3%]	5.1 Streams/Rivers/Canals [75.0%] 5.2 Lakes [6.3%] 5.3 Reservoirs [11.5%] 5.4 Estuaries [0.7%] 5.5 Ponds [6.5%]	
6.0 WETLANDS [14.3%]	6.1 Herbaceous [4.7%] 6.2 Woody [95.3%]	
7.0 BARREN LAND [0.2%]	7.1 Non-vegetated [69.8%] 7.2 Transitional (Pioneer) [30.2%]	

[Level 1] = Percent overall [Level 2] = Percent within class [Level 3] = Percent within subclass

TABLE 3. LEVEL 1.0 CONFUSION MATRICES FOR INTERPRETER A VERSUS B. OVERALL AGREEMENT WAS CALCULATED BASED ON A WEIGHTED AVERAGE OF COLUMN AND ROW PERCENTAGES

		Interpreter B									
		Urban	Ag	Woody	Herb	Water	Wetland	Barren	Row Total	% Agreement	
Interpreter A	Urban	**144**	3	0	5	1	0	1	154	94	
	Agriculture	10	**446**	7	9	0	0	8	480	93	
	Woody Veg	12	5	**446**	9	1	0	2	475	94	
	Herbaceous	5	31	18	**49**	1	1	1	106	46	
	Water	0	0	1	1	**35**	0	0	37	95	
	Wetland	1	0	0	0	0	**84**	0	85	99	
	Barren	3	1	8	2	0	0	**9**	23	39	
	Column Total	175	486	480	75	38	85	21	n = 1360		
	% Agreement	78	92	93	77	79	99	43			
	Overall Agreement	85	92	93	59	87	99	41		Total Agreement 673/825 = 82%	$\hat{K}$ = 0.85

RMSR sample (Table 6b). The Z statistic calculated for the seven-class matrix was 3.3 and represented a statistically significant difference (1.98, $p = 0.95$). Urban results were 70 and 72 percent, respectively, with the majority of errors attributed to the commission of herbaceous classes and the omission of areas incorrectly classified as agriculture. Agricultural areas were 85 ($n = 259$) and 79 ($n = 88$) percent correct with classification errors primarily attributed to the commission of herbaceous and barren areas. Woody vegetation classes were 80 ($n = 275$) and 78 ($n = 126$) percent correct with classification errors attributed to the omission of forested wetland classes and, to a lesser extent, the commission of herbaceous areas. Water was correctly mapped at 99 percent ($n = 33.5$). Wetland accuracy was 47 ($n = 38$) and 44 ($n = 19$) percent with the majority of errors dis-

Table 4. Level 2.0 Confusion Matrices for Interpreter A versus B. Overall Agreement was Calculated Based on a Weighted Average of Column and Row Percentages

	(a) Land-Cover Classes (Urban)	Interpreter B HD	MD	LD	Row Total	% Agreement	
Interpreter A	High Density Urban (HD)	**5**	1	0		83	
	Medium Density Urban (MD)	13	**21**	5	6	54	
	Low Density Urban (LD)	1	11	**87**	39	88	
	Column Total	19	33	92	99		
	% Agreement	13	64	95	n = 144	Total Agreement	
	% Overall Agreement	30	58	91		113/144 = 79%	$\hat{K}$ = 0.56

	(b) Land-Cover Classes (Agriculture)	Interpreter B RC	P/H	F	Row Total	% Agreement	
Interpreter A	Row Crops (RC)	**363**	2	1	366	99	
	Pasture/Hay (P/H)	2	**50**	6	58	86	
	Fallow Field (F)	3	5	**14**	22	64	
	Column Total	368	57	21	n = 446		
	% Agreement	99	88	67		Total Agreement	
	% Overall Agreement	99	87	65		427/446 = 96%	$\hat{K}$ = 0.86

	(c) Land-Cover Classes (Woody Vegetation)	Interpreter B D	E	M	Row Total	% Agreement	
Interpreter A	Deciduous (D)	**215**	7	2	224	96	
	Evergreen (E)	13	**107**	11	131	82	
	Mixed (M)	5	9	**77**	91	85	
	Column Total	233	123	90	n = 446		
	% Agreement	92	87	86		Total Agreement	
	% Overall Agreement	94	84	85		399/446 = 90%	$\hat{K}$ = 0.83

	(d) Land-Cover Classes (Herbaceous Vegetation)	Interpreter B NG	MG	Row Total	% Agreement	
Interpreter A	Natural Grasslands (NG)	**13**	8	21	62	
	Maintained Grasslands (MG)	0	**28**	**28**	100	
	Column Total	13	36	n = 49		
	% Agreement	100	78		Total Agreement	
	% Overall Agreement	76	88		41/49 = 84%	$\hat{K}$ = 0.65

	(e) Land-Cover Classes (Water)	Interpreter B R	L	RES	EST	P	Row Total	% Agreement	
Interpreter A	Rivers (R)	**23**	0	0	0	0	23	100	
	Lakes (L)	0	**2**	0	0	0	2	100	
	Reservoirs (RES)	0	0	**0**	0	0	0	100	
	Estuaries (EST)	0	0	0	**4**	0	4	100	
	Ponds (P)	0	0	0	0	**6**	6	100	
	Column Total	23	2	0	4	6	n = 35		
	% Agreement	100	100	100	100	100		Total Agreement	
	% Overall Agreement	100	100	100	100	100		35/35 = 100%	$\hat{K}$ = 1.0

	(f) Land-Cover Classes (Wetlands)	Interpreter B HW	WW	Row Total	% Agreement	
Interpreter A	Herbaceous (HW)	**4**	0	4	100	
	Woody (WW)	0	**80**	80	100	
	Column Total	4	80	n = 84		
	% Agreement	100	100		Total Agreement	
	Overall Agreement	100	100		84/84 = 100%	$\hat{K}$ = 1.0

Table 5. Level 3.0 Confusion Matrices for Interpreter A versus B. Overall Agreement Was Calculated Based on a Weighted Average of Column and Row Percentages

	(a) Land Cover Classes (Urban)	Interpreter B: Ag	Woody	Herb	Row Total	% Agreement	
Interpreter A	Agriculture (Ag)	**6**	0	1	7	86	
	Woody	0	**22**	7	29	76	
	Herbaceous (Herb)	1	6	**40**	47	85	
	Column Total	7	28	48	$n = 83$		
	% Agreement	86	79	83			
	% Overall Agreement	86	77	84		Total Agreement 68/83 = 82%	$\hat{K} = 0.67$

	(b) Land-Cover Classes (Row Crops)	Interpreter B: Cotton	Corn	Soy	Tobacco	Row Total	% Agreement
Interpreter A	Cotton	**69**	7	3	0	79	87
	Corn	1	**59**	0	0	60	98
	Soybeans	2	1	**142**	3	148	96
	Tobacco	0	0	1	**51**	52	98
	Column Total	72	67	146	54	$n = 83$	
	% Agreement	96	88	97	94		
	% Overall Agreement	91	93	97	96	Total Agreement 321/339 = 95%	$\hat{K} = 0.92$

Table 6a. Level 1.0 Confusion Matrix Incorporating Multiple Reference Data Interpretations (Stratified Unaligned Random)

	Ground Visited Reference Data: Urban	Ag	Woody	Herb	Water	Wetland	Barren	Row Total	% Correct	% Commission
Urban	**67**	6.5	2.5	17.5	0	0	2.5	96	70	30
Agriculture	13.5	**259**	11	14.5	0	1	7.5	306	85	15
Woody Veg	3	0	**275**	15	0.5	13	0.5	307	90	10
Herbaceous	0	1	0	**0**	0	0	0	1	0	100
Water	0	0	0.5	0	**33.5**	0	0	34	99	1
Wetland	0	0	40.5	0	1	**38**	1	80.5	47	53
Barren	0	0	0	0	0	0	**0.5**	0.5	100	0
Column Total	83.5	266	329.5	47	35	52	12	$n = 825$		
% Correct	80	97	83	0	96	27	99			
% Omission	20	3	17	100	4	73	1		Overall Accuracy 673/825 = 82%	

Table 6b. Level 1.0 Confusion Matrix Incorporating Multiple Reference Data Interpretations (Riparian Multiple Stratified Random)

	Ground Visited Reference Data: Urban	Ag	Woody	Herb	Water	Wetland	Barren	Row Total	% Correct	% Commission
Urban	**49.5**	2.5	2	9	0.5	1	4.5	69	72	28
Agriculture	9	**88**	5	5	0	2	2	111	79	21
Woody Veg	9.5	5.5	**126**	10.5	0	10	1	162.5	78	22
Herbaceous	0	0.5	0.5	**0**	0	0	0	1	0	100
Water	0	0	1	0	**2**	0	0	3	67	33
Wetland	2	1.5	15.5	5	0	**19**	0	43	44	66
Barren	0	0	0	1	0	0	**0.5**	1.5	33	77
Column Total	70	98	150	30.5	2.5	32	8	$n = 391$		
% Correct	71	90	84	0	80	59	6			
% Omission	29	10	16	100	20	41	94		Overall Accuracy 285/391 = 73%	

Z statistic (6a versus 6b) = 3.3. Difference test was significant (1.98, p = 0.95).

tributed between woody vegetation commission and omission. The herbaceous and barren sampling sizes were insufficient for statistical analysis.

Level 2.0 urban, agricultural, and woody vegetation classification results are presented in Table 7 (a–c) and Table 8 (a–c) corresponding to the SUR and RMSR sampling design elements, respectively. Analyses are not reported for herbaceous, water, wetland, and barren classes because of insufficient sampling sizes. Differentiation between high, medium, and low urban classes were 87 percent, $n = 67$ (Table 7a) and 88 percent, $n = 49.5$ (Table 8a). Agricultural areas were differentiated as row crops, pasture/hay, and fallow field, with an overall accuracy of 78 percent, $n = 258$ (Table 7b) and 80 percent, $n = 88$ (Table 8b). The majority of confusion was attributable to the omission of row crops and fallow fields that were incorrectly classified as pasture/hay. The results for differentiating between deciduous, evergreen, and mixed forest types, was an accuracy of 72 percent, $n = 275$ (Table 7c) and 67 percent, $n = 126$ (Table 8c).

The assessment of Level 3.0 classification results included only row crop classes (Table 9). Agricultural row crops were assessed only for the 1999 growing season because of the availability of multi-temporal ETM+ data to support NDVI analysis. The overall accuracy was 64 percent ($n = 158.5$). Individual crop types accuracies were cotton 67 percent ($n = 25.5$), corn 53 percent ($n = 18.5$), soybeans 73 percent ($n = 45$), and tobacco 52 percent ($n = 12$). Errors of commission and omission fairly balanced and evenly distributed across all crop types.

Discussion

LC Classification

The study goals were to create an LC classification for the NRB containing adequate categorical detail and sufficient spatial resolution to support spatially explicit non-point source nitrogen modeling efforts. A multi-resolution LC classification was developed to provide a high spatial resolution product developed on a cost-effective basis using currently available remote sensor technologies and ancillary data to support non-point source modeling studies. The higher resolution riparian buffer "patches" were obtained using an MMU of five adjacent pixels (0.1 ha), while areas located outside riparian buffer zones were identified based on a 16-pixel (0.4-ha) MMU. The multi-resolution product represented a trade-off between the maximum obtainable mapping resolution versus accuracy and repeatability. A significantly ($p = 0.05$) lower accuracy was obtained for the riparian buffer zones versus the non-riparian buffer zone areas (73 and 82 percent, respectively). Additionally, the reduced MMU of riparian buffer zones would theoretically have a lower

TABLE 7a. LEVEL 2.0 URBAN CONFUSION MATRICES INCORPORATING MULTIPLE REFERENCE DATA INTERPRETATIONS (STRATIFIED UNALIGNED RANDOM)

	Ground Visited Reference Data					
	Hd	Md	Ld	Row Total	% Correct	% Commission
High Dens Urban (Hd)	**6**	1	1.5	8.5	71	29
Med Dens Urban (Md)	1	**13**	1	15	87	13
Low Dens Urban (Ld)	0.5	3.5	**39.5**	43.5	78	22
Column Total	7.5	17.5	42	$n = 67$		
% Correct	80	74	94			
% Omission	20	26	6	Overall Accuracy 58.5/67 = 87%		

TABLE 7b. LEVEL 2.0 AGRICULTURAL CONFUSION MATRICES INCORPORATING MULTIPLE REFERENCE DATA INTERPRETATIONS (STRATIFIED UNALIGNED RANDOM)

	Ground Visited Reference Data					
	Rc	P/H	F	Row Total	% Correct	% Commission
Row Crops (Rc)	**173.5**	6	4	183.5	95	5
Pasture/Hay (P/H)	33.5	**28.5**	11.5	73.5	39	61
Fallow Field (F)	1	0	**0**	1	0	100
Column Total	208	34.5	15.5	$n = 258$		
% Correct	83	83	0			
% Omission	17	17	100	Overall Accuracy 202/258 = 78%		

TABLE 7c. LEVEL 2.0 WOODY VEGETATION CONFUSION MATRICES INCORPORATING MULTIPLE RREFERENCE DATA INTERPRETATIONS (STRATIFIED UNALIGNED RANDOM)

	Ground Visited Reference Data					
	D	E	M	Row Total	% Correct	% Commission
Deciduous (D)	**107.5**	11.5	24.5	143.5	75	25
Evergreen (E)	13	**74**	17.5	104.5	71	29
Mixed (M)	7.5	3.5	**16**	27	59	41
Column Total	128	89	58	$n = 275$		
% Correct	84	83	18			
% Omission	16	17	72	Overall Accuracy 197.5/275 = 72%		

TABLE 8a. LEVEL 2.0 URBAN CONFUSION MATRICES INCORPORATING MULTIPLE REFERENCE DATA INTERPRETATIONS (RIPARIAN MULTIPLE STRATIFIED RANDOM)

	Ground Visited Reference Data					
	Hd	Md	Ld	Row Total	% Correct	% Commission
High Dens Urban (Hd)	**1**	0	1	2	50	50
Med Dens Urban (Md)	0	**6.5**	0.5	7	93	7
Low Dens Urban (Ld)	0	4.5	**36**	40.5	89	11
Column Total	1	11	37.5	n = 49.5		
% Correct	100	59	96			
% Omission	0	41	4	Overall Accuracy 43.5/49.5 = 88%		

TABLE 8b. LEVEL 2.0 AGRICULTURAL CONFUSION MATRICES INCORPORATING MULTIPLE REFERENCE DATA INTERPRETATIONS (RIPARIAN MULTIPLE STRATIFIED RANDOM)

	Ground Visited Reference Data					
	Rc	P/H	F	Row Total	% Correct	% Commission
Row Crops (Rc)	**55**	1	2.5	58.5	94	6
Pasture/Hay (P/H)	9.5	**15**	5	29.5	51	49
Fallow Field (F)	0	0	**0**	0	0	100
Column Total	64.5	16	7.5	n = 88		
% Correct	85	94	0			
% Omission	15	6	100	Overall Accuracy 70/88 = 80%		

TABLE 8c. LEVEL 2.0 WOODY VEGETATION CONFUSION MATRICES INCORPORATING MULTIPLE REFERENCE DATA INTERPRETATIONS (RIPARIAN MULTIPLE STRATIFIED RANDOM)

	Ground Visited Reference Data					
	D	E	M	Row Total	% Correct	% Commission
Deciduous (D)	**60**	8	5.5	73.5	82	18
Evergreen (E)	6	**15**	9.5	30.5	49	51
Mixed (M)	7.5	5.5	**9**	22	41	59
Column Total	73.5	28.5	24	n = 126		
% Correct	82	53	38			
% Omission	18	47	62	Overall Accuracy 84/126 = 67%		

TABLE 9. LEVEL 3 AGRICULTURAL ROW CROPS (1999) CONFUSION MATRICES INCORPORATING MULTIPLE REFERENCE DATA INTERPRETATIONS (STRATIFIED UNALIGNED RANDOM)

	Ground Visited Reference Data						
	Ct	Cn	Soy	Tob	Row Total	% Correct	% Commission
Cotton (Ct)	**25.5**	5.5	4	4	38.5	67	33
Corn (Cn)	4.5	**18.5**	8.5	3.5	35	53	47
Soybeans (Soy)	4	10.5	**45**	2.5	62	73	27
Tobacco (Tob)	1	2.5	7.5	**12**	23	52	48
Column Total	34.5	37	65	22	n = 158.5		
% Correct	74	50	69	55			
% Omission	26	50	31	45	Overall Accuracy 101/158.5 = 64%		

degree of repeatability. Based on these results, the benefit derived from the delineation of finer scale riparian buffer zone landscape elements that were considered important to adequately model biological process associated with nutrients, can be further evaluated. The coarser resolution "patch" size, with a higher degree of accuracy and repeatability, was considered optimal for the modeling of non-riparian areas.

Unique aspects of the classification performed here included the classification of urban areas based on impervious surfaces, and the identification of specific row crop types for calendar year 1999. Urban classifications were accomplished using 15-m multi-temporal spectral data to first identify impervious pixels, followed by a GIS rule-based neighborhood proximity analysis (road networks) resulting in impervious class designations. Impervious class designations provided important hydrologic modeling input data for the partitioning of ground and surface water flow contributions, and to support the development of rate functions for the transport of source nitrogen to receiving streams. Additionally, impervious designations will support the future development of landscape-based metrics for aquatic indicators.

Row crop types corresponding to the four major NRB crops were developed using a rudimentary phenology-based analysis to separate the known crop types. These delineations were directly incorporated into nitrogen mass balance calculations, which included both the quantification of differential nitrogen fertilizer applications, nitrogen fixation and denitrification processes, at the landscape "patch" scale of analysis.

Although the overall classification accuracy was relatively high at 82 percent, there were deficiencies that were attributed to distinctions associated with land-use activities, as opposed to LC types. A recurring problem was that associated with distinguishing between herbaceous type classes; i.e., differentiation between numerous maintained herbaceous cover types and natural herbaceous vegetation. Specifically, confusion between low/medium density urban manicured lawns and pasture, and to a lesser extent woody vegetation, was a recurring problem throughout the study. The poor performance of the NWI wetlands classification was thought to be an anomaly associated with our accuracy assessment procedures. Reference data interpretations were based on quantitative flora inventory (hydrophytic vegetation) and qualitative surface moisture conditions (wetland hydrology). Hydrophytic soil determinations were not made at sampling locations due to the lack of sufficient resources. Thus, we defer to NWI accuracies reported by other researchers (Tiner, 1997; Kudray and Gal, 2000). Also, barren classes were frequently confused with herbaceous areas due to the rapid regrowth of transitional pioneer vegetation types.

Accuracy Assessment

Multiple elements were incorporated into the NRB accuracy assessment to support a quantitative evaluation of the NRB classification results. They included (1) the development of a VFRB to support reference data development, (2) an analysis of reference data variability using multiple database interpretations, (3) the incorporation of reference data variability into the development of accuracy assessment confusion matrices, and (4) the reporting of errors for individual classes and classification levels to detail specific error sources. In this study, inherent reference data variability was directly incorporated into the development of confusion matrices through the incorporation of multiple (two) calls, for a subset of the sampling sites. Because multiple calls were limited to only two correct possibilities (some sites had three or four calls), this approach was thought to provide a conservative compensation for reference data variability, and thus a conservative assessment value.

Numerous benefits were realized through the application of the VFRB. First, it was used to generate reference data developed to correspond specifically to the user-defined LC classification systems for non-point source nitrogen modeling. Also, measurement and imagery data were interpreted by multiple (two) individuals to provide an evaluation of reference data variability. Lastly, reference data variability was directly incorporated into the accuracy assessment to provide a more accurate assessment of LC classification results. In principal, this approach for assessing LC classification accuracy is equally applicable using other source data for reference data development, including aerial photography (Yang *et al.*, 2001).

Conclusions

The combined spectral and GIS rule-based analysis, performed sequentially on eight subsets representing the entire NRB, provided a quality LC product to support spatially explicit patch-based nitrogen mass balance analysis and hydrologic modeling efforts. Our analytical approach for characterizing impervious surfaces should be applicable elsewhere in patchy landscapes with high biomass (or greenness) sufficient to provide a high degree of contrast compared to impervious surfaces. Similarly, methods used to differentiate crop types should be applicable in agricultural areas with moderate crop diversity and available detailed crop statistics. The application of multiple interpretations for individual field reference data sites facilitated the incorporation of reference data variability directly into the confusion matrices, which formed the basis of the LC accuracy assessment. This approach represents a relatively simple approach for performing a quantitative accuracy assessment. The poor performance of herbaceous cover classes was attributed to the inclusion of land-use attributes into the LC classification system. The incorporation of automated pattern recognition algorithms could be used to minimize further confusion associated with herbaceous, urban, and agricultural areas.

Acknowledgments

The U.S. Environmental Protection Agency funded and conducted the research described in this paper. It has been subject to the Agency's programmatic review and has been approved for publication. Mention of any trade names or commercial products does not constitute endorsement or recommendation for use.

The authors would like to acknowledge Mr. Malcolm Wilkins for his technical support to field crews over the duration of this study. Thanks are also extended to the fine efforts of the Environmental Careers Organization interns who served as field crew members in support of this study. They included Betsy Albright, Daniel Burgos, Ashton Horne, Kristin Kulow, Robin Morris, Craig Morton, Mike Obryon, Naomi Patterson, Gabriela Ramirez, and Joseph Scwartz.

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(Received 21 August 2001; accepted 12 April 2002; revised 02 August 2002)