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A Simple Reclassification Method for Correcting Uncertainty in Land Use/Land Cover Data Sets Used with Land Surface Models

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Abstract—With increasing computational resources, environmental models are run at finer grid spacing to resolve the land surface characteristics. The land use/land cover (LULC) data sets input into land surface models are used to assign various default parameters from a look-up tables. The objective of this study is to assess the potential uncertainty in the LULC data and to present a reclassification method for improving the accuracy of LULC data sets. The study focuses on the Southern Great Plains and specifically the Walnut River Watershed in southeastern Kansas, USA. The uncertainty analysis is conducted using two data sets: The National Land Cover Dataset 1992 (NLCD 92) and the Gap Analysis Program (GAP) data set, and a reclassification logic tree. A comparison of these data sets showed that they do not agree for approximately 27% of the watershed. Moreover, an accuracy assessment of these two data sets indicated that neither had an overall accuracy as high as 80%. Using the relationships between land-surface characteristics and LULC, a reclassification of the watershed was conducted using a logical model. This model iteratively reclassified the uncertain pixels according to their surface characteristics. The model utilized normalized difference vegetation index (NDVI) measurements during April and July 2003, elevation, and slope. The reclassification yielded a revised LULC dataset that was substantially improved. The overall accuracy of the revised data set was nearly 93%. The study results suggest: (i) as models adopt finer grid spacings, the uncertainty in the LULC data will become significant; (ii) assimilating NDVI into the land-surface models can reduce the uncertainty due to LULC assignment; (iii) the standard LULC data sets must be used with caution when the focus is on local scale; and (iv) reclassification is a valuable means of improving the accuracy of LULC data sets prior to applying them to local issues or phenomena.

Key words: Land use, land cover, land surface modeling, NDVI, land-surface characteristics, surface heterogeneity.

1. Introduction

An accurate description of land-surface characteristics is important to a wide array of applications. Some examples include managing natural resources (Liu *et al.*, 2005) and local development (Yang and Lo, 2002), understanding the relationship

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between development and economic growth (LAMBIN *et al.*, 2003), and assessing risk for anthropogenic or natural hazards such as landslides (DHAKAL *et al.*, 1999). An accurate land use/land cover (LULC) dataset is also important to both understanding and modeling the exchange of mass and energy between the land surface and the atmosphere (BALLESTER *et al.*, 2003; ISHIZUKA *et al.*, 2005; KOTHAVALA *et al.*, 2005; REITHMAIER *et al.*, 2006), describing the deposition and distribution of atmospheric pollutants (CHOI *et al.*, 2005; NIYOGI *et al.*, 2004, 2006), and characterizing the role of biogeophysical and biogeochemical processes in regional atmospheric processes (WALKO *et al.*, 2000).

Since land-surface characteristics impact environmental processes on micro- (NIYOGI *et al.*, 2006), meso- (HOLT *et al.*, 2006), regional (PIELKE *et al.*, 2002), and global (FEDDEMA *et al.*, 2005) scales, land-surface characteristics exert an important control on the surface-atmosphere exchange and atmospheric processes leading to a broad range of environmental phenomena. For example, LEMONE *et al.* (2002; 2006) have linked land-surface characteristics with the partition of the surface energy balance and the evolution of the atmospheric boundary layer. Similarly, land cover and terrain conditions have been linked to the development of mesoscale circulations (ANTHES, 1984; SEGAL *et al.*, 1988), the initiation of convective storms (PIELKE, 2001; HOLT *et al.*, 2006), and the distribution of atmospheric precipitation (PIELKE *et al.*, 2007).

In order to fully describe or correctly model the role of the land surface in atmospheric or environmental processes, an accurate representation of the characteristics of the LULC is needed. ALAPATY *et al.* (1997) and NIYOGI *et al.* (1999) analyzed the impact of uncertainty in the surface characteristics and concluded that errors in the surface characterization propagate into the modeling of both the surface energy budget and the evolution of the boundary layer. While LULC data sets, which have been developed to represent a generalized regional scale, may provide an adequate representation on that scale, small, yet potentially important, local surface features may not be represented (WARDLOW and EGBERT, 2003; WICKHAM *et al.*, 2005).

In this study, we suggest that such limitations of the LULC data sets should be considered when conducting any study of land-atmosphere processes. Additionally, we propose a simple reclassification method to correct ambiguous LULC classifications. We focus on the Southern Great Plains (SGP) of the United States; specifically, the reclassification test case is the Walnut River Watershed (WRW) located in southeastern Kansas. This watershed was selected because it contains many of the LULC and surface characteristics typical of the SGP as a whole. For example, the WRW contains a mixture of tall- and short-grass prairie, agricultural fields, and developed (urban) areas. In addition, this watershed contains both expanses of gently rolling hills and steeper, more rugged terrain (LEMONE *et al.*, 2000).

This paper presents both a comparison of two LULC data sets, the National Land Cover Dataset 1992 (NLCD 92) and the Gap Analysis Program (GAP) data sets, and a reclassification method to enhance the accuracy of these data sets. The reclassification method utilizes a decision tree logical model based on the relationships between surface characteristics and LULC classification to reclassify those data points with an inaccurate or uncertain classification within the NLCD 92 or GAP data set. For example, the normalized difference vegetation index (NDVI) of an uncertain pixel is used to clarify whether that pixel is correctly categorized as water, developed, or vegetated land cover.

The following section describes the WRW and the LULC data sets used in this analysis. Section 3 discusses the methods used in the preliminary analyses and the reclassification process. Section 4 presents the results of the analyses and section 5 presents the conclusions. A follow-up study will evaluate the influence of surface features on boundary layer evolution and mesoscale processes.

2. Site Description and Data Sets

2.1. Walnut River Watershed

The Walnut River Watershed is located in southeastern Kansas between the city of Wichita to the west and the Flint Hills to the east. The watershed encompasses an area of approximately 5000 km^2 with a maximum extent of approximately 100 km from north to south and approximately 60 km from east to west (SONG and WESELY, 2003). The watershed is characterized by east-west gradients in precipitation, geology, and vegetation cover (LEMONE *et al.*, 2000). The western side of the WRW, which consists of gently rolling hills rising out of the watershed, is dominated by agricultural use including winter wheat, sorghum, and soybeans with some urban encroachment. The eastern side of the WRW is characterized by steeper slopes along the edge of the Flint Hills. In addition, this portion of the WRW is characterized primarily by grassland environments with a mixture of both tall– and short–grass prairie species (LEMONE *et al.*, 2000), some of which is used for pasture (Fig. 1).

2.2. National Land Cover Data Set 1992

The National Land Cover Data set 1992 dataset is a consistent, generalized, 30 m resolution LULC dataset for the contiguous United States (VOGELMANN *et al.,* 2001). Using Landsat thematic mapper imagery captured primarily during the period from 1990 to 1993, NLCD 92 was developed using a two-step classification process. In the first step, an unsupervised classification was applied to the Landsat imagery and each cluster was assigned one or more land-use categories according to the Anderson Level II scheme (ANDERSON *et al.*, 1976) shown in Table 1. In the second step, the confounded clusters, i.e., clusters that may be assigned to multiple land use classes, were refined using logical models based on ancillary data such as terrain, population density, and soil characteristics (VOGELMANN *et al.*, 2001). A recent analysis of the NLCD 92 dataset for the state of Kansas indicated an overall accuracy of 80.5%, with grasslands being the most accurately classified LULC type and wetlands being the least accurately classified LULC type (WARDLOW and EGBERT, 2003).

2.3. Kansas Gap Analysis Program Data Set

The Gap Analysis Program dataset for the state of Kansas was developed to provide a more accurate description of vegetation characteristics, biodiversity, and habitat conservation (SCOTT *et al.*, 1993). As such, it consists of the 41 vegetation and 2 non-vegetation LULC types shown in Table 1 (EGBERT *et al.*, 2001). The classification scheme is based on the National Vegetation Classification System (WARDLOW and EGBERT, 2003). The dataset was developed using multi-temporal Landsat thematic mapper imagery collected from 1991 to 1994. After masking open water and urbanized areas, the images were classified using an unsupervised method; each cluster was then assigned to one of three broad categories: natural vegetation, cropland, and mixed. Using supervised classification techniques, these broad categories were further classified into the appropriate final category. A smoothing algorithm was then applied to remove speckle (EGBERT *et al.*, 2001). Overall, the GAP dataset was found to have an

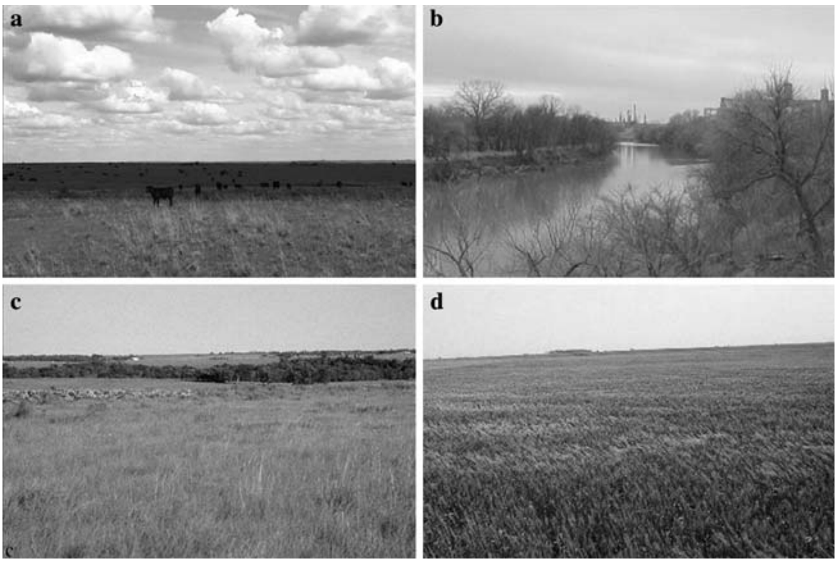

Figure 1
These images taken in or near the Walnut River Watershed show the broad range of land cover types found within the watershed and include pasture: (**a**), riparian areas (**b**), grasslands (**c**), and croplands, in this case winter wheat (**d**). Image **a** is from the CASE-99 field campaign (http://www.eol.ucar.edu/rtf/projects/cases99/isff.html), image **b** is available at http://www.srh.noaa.gov/abrfc/rivers/photo_gallery/arkk1/arkk1.jpg, and image **c** and **d** are from the IHOP field campaign (http://www.rap.ucar.edu/projects/land/IHOP/).

Table 1

The NLCD 92 and GAP classifications associated with each of the simplified classes

NLCD 92	GAP	Simplified	NLCD 92	GAP	Simplified
Open Water	Water	Water	Shrub.	Sandsage Shrub.	Grassland
Perennial Snow/Ice			Grassland	Saltbrush Shrub.	
			Pasture/Hay	Willow Shrub.	
				Buttonbush Shrub.	
				Salt Cedar/Tamarisk Shrub.	
				Tallgrass Prairie	
				Sand Prairie	
				Sandstone Prairie	
				Western Wheatgrass	
				Prairie	
				Mixed Prairie	
				Alkali Sacaton	
				Prairie Shortgrass Prairie	
				Non-native Grassland	
				CRP	
				Weedy Upland	
Low Intensity Residential	Urban	Urban			
High Intensity Residential					
Commercial/Industrial					
Urban/Recreational Grasses					
Bare Rock/Sand/Clay	Mixed	Barren			
Quarries/Strip Mines/Gravel Pits	Prairie-Disturbed				
Transitional	Land				

Table 1

(Contd.)

NLCD 92	GAP	Simplified	NLCD 92	GAP	Simplified
Deciduous For	Maple-Basswood For.	Wooded	Row Crops	Cropland	Cropland
Evergreen For	Oak-Hickory For.		Small Grains		
Mixed For	Post Oak-Blackjack Oak For.		Fallow		
	Pecan Floodplain For.		Orchards/Vineyards		
	Ash-Elm-Hackberry Floodplain				
	For. Cottonwood Floodplain For.				
	Mixed Oak Floodplain For.				
	Bur Oak Floodplain Wood.				
	Mixed Oak Ravine Wood.				
	Post Oak-Blackjack Oak Wood.				
	Cottonwood Floodplain Wood.				
	Evergreen For.-Disturbed Land				
	Deciduous For.-Mined Land				
	Maple Floodplain For.				
	Deciduous Wood.				
			Woody Wetlands	Grass Playa Lake	Wetland
			Herbaceous Wetland	Salt Marsh/Prairie	
				Spikerush Playa Lake	
				Playa Lake	
				Low or Wet Prairie	
				Freshwater Marsh	
				Bulrush Marsh	
				Cattail Marsh	
				Wetland	
				Weedy Marsh	

accuracy of slightly more than 87% and agree with the NLCD 92 dataset for approximately 68% of the land area of Kansas. As with the NLCD 92 data set, grasslands are the most accurately classified LULC type and wetlands are the least accurately classified LULC type (WARDLOW and EGBERT, 2003).

2.4. Additional Data Sets

Aerial photographs taken as a part of National Agricultural Imagery Program (NAIP) were used as ground truth during the validation stage of the analysis. These photographs, which have a 2 m resolution, were collected during 2003. Two Landsat images collected on clear sky days during April and July 2002 were also used to calculate both NDVI and its distribution. Finally, the 1″ (approximately 30 m) National Elevation Data set (NED) digital elevation model (DEM) was used to determine the terrain characteristics including elevation, slope, and aspect employed in the analysis.

3. Reclassification Method

3.1. Simplification of the Data Sets and Preliminary Analyses

The NLCD 92 and GAP data sets are not directly comparable since they do not utilize the same classification scheme. Thus, the first step of the analysis was to map each of the categories in the NLCD 92 and GAP data sets to a single, simplified classification scheme (Table 1). This simplified scheme consists of seven categories representing each of the broad categories of the Anderson land cover scheme used with the NLDC 92 data set. The categories used to develop the simplified data sets for the study area were: Water, Urban, Barren, Wooded, Grassland, Cropland, and Wetland (Table 2).

The resulting LULC data sets, which are shown in Figure 2a and 2b, were then assessed for accuracy through a pixel-by-pixel comparison. The accuracy assessment used 500 randomly selected points distributed throughout the catchment; the locations of each of these random points were the same for all accuracy assessments. The ground truth for the accuracy assessment was interpreted from the 2003 NAIP imagery. The accuracy assessments for both the NLCD 92 and GAP data sets are summarized in Table 3. The Producer's Accuracy, which provides an estimate of how well the data were classified during the development of the data set, is defined as the ratio of the number of pixels within a given category that is correctly classified to the total number of pixels in that category based on ground truth. The User's Accuracy is the ratio of the number of pixels within a given category that is correctly classified to the total number of pixels classed into that category. Overall Accuracy is defined as the total number of pixels that is correctly classified to the total number of pixels in the dataset (LILLESAND *et al.*, 2004).

Table 2

The description of the seven classification categories utilized to simplify both the NLCD 92 and GAP data sets

Classification	Description
Water	Open water such as lakes and rivers; perennial snow and ice are also included
Urban	Developed areas including residential, such as single-family homes, commercial, and industrial areas; recreational grasslands, such as parks and golf courses, are also included
Barren	Areas perennially devoid of vegetation, such as strip mines, gravel pits, and quarries, and areas sparsely vegetated due to disturbance.
Wooded	Wooded areas including deciduous, evergreen, and mixed forest
Grassland	Grassland, shrubland, and herbaceous vegetation; pasture and hayfields are also included
Cropland	Row crops, small grains, such as wheat, and fallow fields
Wetland	Herbaceous and woody vegetation in areas that have periodically saturated soils or are covered in water

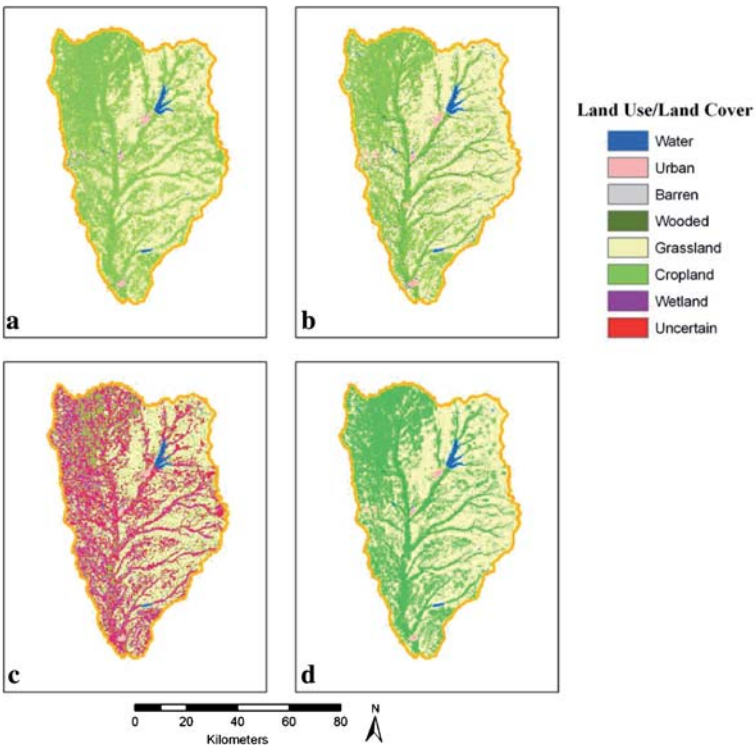

Figure 2
The simplified NLCD 92 (**a**) and GAP (**b**) data sets are shown for the Walnut River Watershed. The areas of uncertainty between these data sets (**c**) are shown. The revised LULC dataset (**d**) is also shown.

Table 3

The summarized accuracy assessment for each of the land use/land cover data sets

Classification	Water	Urban	Barren	Wooded	Grassland	Cropland	Wetland
				NLDC 92			
Producer's	69.8	73.5	100.0	15.4	89.9	68.7	33.3
User's	88.6	73.5	50.0	71.4	64.0	72.0	12.5
Overall	**68.7**						
				GAP			
Producer's	77.8	82.4	0.0	64.6	92.4	73.7	66.7
User's	94.6	93.3	0.0	72.4	73.0	90.1	15.4
Overall	**79.2**						
				Reclassified			
Producer's	84.4	82.4	0.0	90.8	97.5	94.4	66.7
User's	100.0	96.6	0.0	89.0	89.0	93.0	100.0
Overall	**92.9**						

3.2. Relationships between Surface Characteristics and Land Use/Land Cover

Histograms of the NDVI distribution for the simplified GAP dataset were generated for each of the LULC classifications. The NDVI values for each of the LULC classifications, as well as the complete data set, were sorted into 20 bins. The number of pixels within each bin was then normalized by the total number of pixels and plotted. Normalization enables a comparative analysis of the NDVI distributions for the various LULC classifications, while using the complete simplified GAP dataset facilitated the analysis for misclassification errors while clarifying the change in NDVI with time.

Using only those pixels for which both NLCD 92 and GAP data sets agree, the relationships of the land surface characteristics, including elevation, slope, and aspect, with the percent coverage of each LULC classification were developed. To accomplish this task, the WRW was first divided into slices based on a given land surface characteristic (Table 4). For example, the study region was sliced into seven elevation levels ranging from the lowest elevation with the WRW (330 m) to the highest (510 m) in nominally 20 m increments. Next, the percent coverage of each LULC classification was calculated for each slice. Finally, by plotting the percent coverage of each LULC classification as a function of the surface characteristics, relationships were developed that could be used during the reclassification process.

3.3. Reclassification Model

A five-step reclassification method (Fig. 3; Table 5) was developed to reclassify uncertain pixels. This method used a logical model that focused on four surface

Table 4

The criteria of slicing or subdividing the Walnut River Watershed when calculating the relationships between these surface characteristics and land use/land cover classification

Data Type	Nominal Data Range	Number of Slices	Slice Interval	Comments
Elevation	330 to 510 m	9	20 m	—
Slope	0° to 30°	7	0.0° to 0.5° 0.5° to 1.0° 1.0° to 1.5° 1.5° to 2.5° 2.5° to 3.5° 3.5° to 6.0° 6.0 to 30°	the slice intervals were selected based on a standard deviation partition of the data
Aspect	Flat and 0 to 360°	9	45°	each slice is centered on a defined direction; for example, the North slice include aspects from 337.5° to 22.5° with due north being 0°; flat has an aspect of −1.

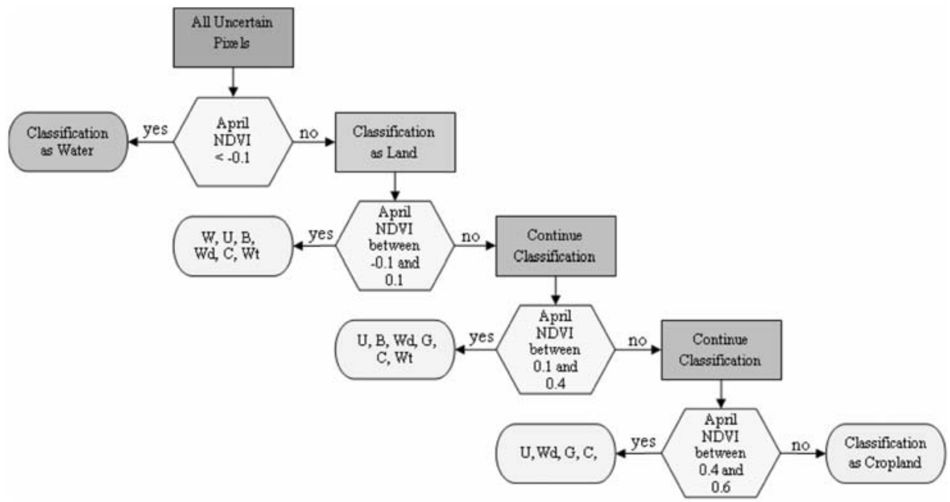

Figure 3
A flowchart showing the classification decisions made during the first step of the reclassification process is shown. Beginning with all of the uncertain pixels in the Walnut River Watershed, the NDVI during April is used as the basis for this initial step of the reclassification process. The symbol key is as follows: W – Water, U – Urban, B – Barren, Wd – Wooded, G –Grassland, C – Cropland, and Wt – Wetland.

characteristics: NDVI during April, NDVI during July, elevation, and slope. These four factors were selected because each showed a strong relationship of the LULC categories; for example, a low or negative NDVI is associated with the Water and Urban classes while a high positive NDVI is often associated with the Wooded. (The

Table 5

The conditional statements used in this research for reclassifying the uncertain data based on each of the four surface characteristics are shown. The symbol key is as follows: W – Water, U – Urban, B – Barren, Wd – Wooded, G – Grassland, C – Cropland, and Wt – Wetland

	April NDVI	July NDVI	Elevation	Slope
All Uncertain Pixels	NDVI < −0.1 Water			
	−0.1 < NDVI < 0.1 W, U, B, Wd, C, Wt	NDVI < −0.1 Water		
		−0.1 < NDVI < 0.0 U, B	Elevation < 420 m Urban	
			420 m < Elevation Barren	
		0.0 < NDVI < 0.2 U, B, C	Elevation < 420 m U, C	Can Not Be Differentiated
			420 m < Elevation B, C	Slope < 18° Cropland 18° > Slope Barren
		0.2 < NDVI < 0.4 U, C, Wt	Elevation < 380 m U, C, Wt	Slope < 3° U, C 3° < Slope Wetland
			380 m < Elevation < 420m U, C	Can Not Be Differentiated
			420 m < Elevation Cropland	
		0.4 < NDVI < 0.7 Wd, C, Wt	Elevation < 380 m Wd, C, Wt	Slope < 5° Cropland 5° < Slope Wd, Wt
			380 m < Elevation < 440 m Wd, C	Slope < 5° Cropland 5° < Slope Wooded
			440 m < Elevation Cropland	
		0.7 < NDVI Wooded		
	0.1 < NDVI < 0.4 U, B, Wd, G, C, Wt	NDVI < 0.0 Urban		
		0.0 < NDVI < 0.3 U, B, C	Elevation < 420 m U, C	Can Not Be Differentiated

Table 5

(*Contd.*)

April NDVI	July NDVI	Elevation	Slope
		420 m < Elevation B, C	Slope < 18° Cropland
			18 > Slope Barren
	0.3 < NDVI < 0.5 U, Wd, G, C, Wt	Elevation < 380 m U, Wd, C, Wt	Slope < 3° U, Wd, C
			3° < Slope Wetland
		380 m < Elevation < 420 m G, C	Slope < 1° Cropland
			1° > Slope Grassland
		420 m < Elevation Grassland	
	0.5 < NDVI < 0.7 Wd, G, Wt	Elevation < 380 m Wd, Wt	Slope < 3° Wooded
			3° < Slope Wetland
		380 m < Elevation Grassland	
	0.7 < NDVI Wd, G	Elevation < 380 m Wetland	
		380 m < Elevation Grassland	
0.4 < NDVI < 0.6 U, Wd, G, C	NDVI < 0.0 Urban		
	0.0 < NDVI < 0.3 U, C		
	0.3 < NDVI < 0.5 U, G, C	Elevation < 420 m U, C	Can Not Be Differentiated
		420 m < Elevation Grassland	
	0.5 < NDVI < 0.7 Wd, G, C	Elevation < 420 m Wd, C	Slope < 5° Cropland
			5° < Slope Wooded
		420 m < Elevation Grassland	
	0.7 < NDVI Wd, G	Elevation < 420 m Wooded	
		420 m < Elevation Grassland	
0.6 < NDVI Cropland			

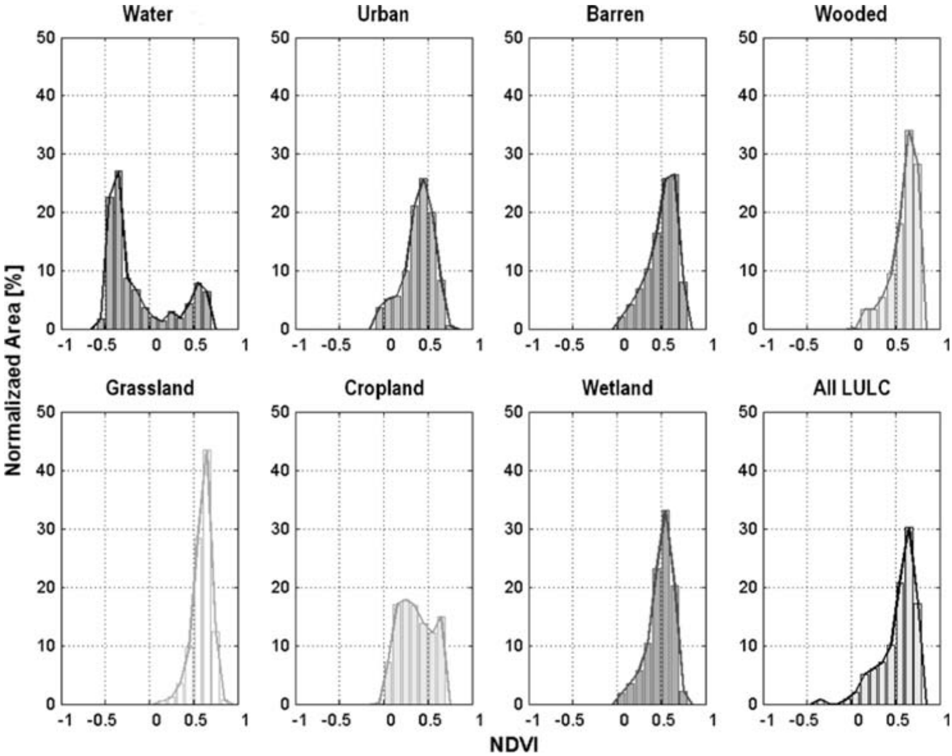

Figure 4
Histograms showing the distribution of NDVI for each land use/land cover classification provide evidence for both misclassification error and a potential method for improving the overall accuracy of a land use/land cover dataset for the Walnut River Watershed.

relationship between of the LULC categories and the various surface characteristics used in the logical model are discussed further below.) The logic model is a decision tree functioning analogously to a dichotomous key and focusing on each surface characteristic in turn to reclassify the uncertain pixels (FRIEDL and BRODLEY, 1997; DEFRIES and CHAN, 2000).

While the specific conditional statements are provided in Table 5, the five-step reclassification process can be summarized as follows. In the first step of the reclassification process, the data are first partitioned as either a water or land-based LULC type based on the NDVI during April 2002 (Fig. 3). Those pixels with an uncertain classification that had an NDVI during April less than –0.1 were reclassified as Water. Since nearly 90% of the pixels that have a known classification and an NDVI during April greater than 0.6 are classified as Cropland, those pixels with an NDVI value greater than 0.6 were reclassified as Cropland. The pixels that were not classified as Water or Cropland were then divided into three subsets

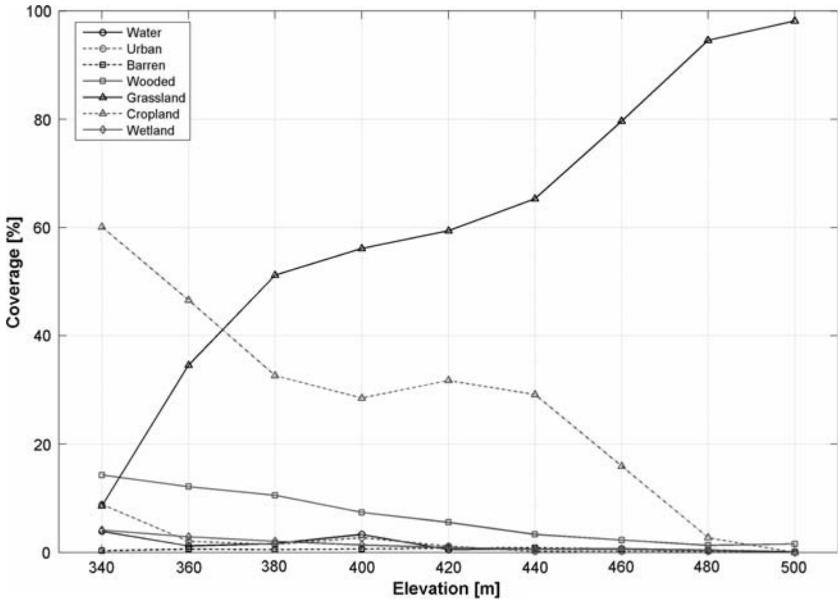

Figure 5
The change in the percent coverage with elevation for each of the land use/land cover types demonstrates the dominance of Grassland and Cropland throughout the Walnut River Watershed.

depending on their NDVI during April. Each of these subsets represents a unique grouping of potential LULC classifications. Those subsets are further refined in subsequent steps.

Using the NDVI during July as a basis, the classification of the three subsets of pixels that could not be classified uniquely in the previous step was further refined in the second step of the reclassification process. This resulted in each of the subsets from step one being further subdivided into four smaller, more refined subsets. For example, the subset of uncertain pixels with an NDVI during April between −0.1 and 0.1 was refined into four subsets, based on the NDVI for July 2002, including a subset containing NDVI values between −0.1 and 0.0, a subset containing NDVI values between 0.0 and 0.2, a subset containing NDVI values between 0.2 and 0.4, and a subset containing NDVI values between 0.4 and 0.7. Approximately 10% of the uncertain pixels were reclassified during this step.

In the third step of the reclassification process, each of the twelve subsets generated during the previous step was further refined, based on elevation. Using elevation as the criterion, the subsets developed previously were further refined and subdivided into a total of 14 subsets. Additionally, it was possible to reduce the size of eight of the twelve subsets developed in the previous two steps by uniquely reclassifying at least a portion of the pixels contained within those subsets.

The fourth step of the reclassification process utilized slope as the partition criterion. This step allowed for more than 99.9% of the uncertain pixels to be classified into a unique LULC classification. The 307 pixels that could not be classified based on the decision tree were reclassified based on the classification of the majority of their nearest neighbors defined here as a 5×5 grid centered on the pixel to be classified.

To illustrate the reclassification process, consider an uncertain pixel within the riparian zone with NDVI $= 0.2$ during April, NDVI $= 0.6$ during July, elevation $=$ 375 m, and slope $= 2°$. In the first step of the reclassification process, this pixel would be partitioned into the subset for NDVI during April with a range from 0.1 to 0.4. This subset included all of the land-based LULC classifications. In the second step, the pixel would be partitioned into the subset for NDVI during July ranging from 0.5 to 0.7, thereby reducing the potential LULC classifications by half. In the third step of the reclassification process, which used elevation as the decision criterion, the pixel would be partitioned into the subset for elevations less than 380 m. This subset included both the Wooded and Wetland LULC types. In the final step, which used slope as the decision criterion, this pixel would be reclassified as Wooded.

Once the reclassification process was completed, an accuracy assessment was conducted using the same method as used with the simplified NLCD 92 and GAP data sets. This analysis showed an overall accuracy of nearly 93% (Table 3). This is an improvement in the overall accuracy of 24.2% and 13.7% compared to the NLCD 92 and GAP data sets, respectively.

4. Results

4.1. Simplification of the Data Sets and Preliminary Analyses

While the classification represented by the two simplified data sets (Figs. 2a and 2b) appears reasonable, the accuracy assessments of these data sets (Table 3) indicate that they contained errors. The accuracy assessments indicated that the NLCD 92 overall accuracy was approximately 68.7%. For NLCD 92, the classification with the highest Producer's Accuracy was associated with the Barren and Grassland categories while the highest User's Accuracy was associated with the Water classification. The classification of Wetland was particularly weak for the NLCD 92 data set.

Similarly, the accuracy assessment for the GAP dataset indicated an overall accuracy of 79.2% for the WRW. The classification categories with the highest accuracy were Grassland and Water for Producer's and User's Accuracy, respectively. Like the NLCD 92 data set, the GAP dataset was least accurate for the Wetland category. Moreover, a more accurate representation of all of the classification categories is reflected in an improved overall accuracy of more than

10% as compared to the NLCD 92 data set. However, while the GAP dataset is more accurate than the NLCD 92 data set, it still contains significant errors.

The comparison of the simplified NLCD 92 and GAP data sets conducted through an overlay process demonstrated where the two data sets agreed and where the LULC classification was uncertain (Fig. 2c). This analysis indicated that the two LULC data sets agree in the classification of approximately 73% of the area of the WRW. Further analysis of the 27% of the WRW with an uncertain classification, i.e., the two data sets did not agree, suggests that the differences are located primarily in one of the following three geographic regions:

1. Along the transitions from large areas of contiguous LULC, specifically the Water and Urban classifications, with another LULC classification. This is, at least in part, reflective of the changing boundaries of these LULC types with time.
2. Within riparian zones where clusters of trees, as well as grassland and cropland environments, were often misclassified. This may be the result of mixed pixels containing multiple LULC types, the application of smoothing algorithms during the development of these two data sets, or signature confusion such that the classification algorithms used were unable to differentiate the correct LULC type.
3. In areas containing a mixture of LULC. In areas of mixed agricultural and grassland environments there are often differences between the NLCD 92 and GAP classification. This is most likely due to either mixed pixels or signature confusion.

4.2. Relationships between Surface Characteristics and Land Use/Land Cover

Analysis of the NDVI histograms – Figure 4 shows the NDVI during April - indicates both a degree of misclassification error and a cause for that error. These plots also suggest that NDVI may be used as a part of the reclassification process aimed at eliminating that error to produce a more accurate representation of the WRW. Specifically, the analysis demonstrated that both the absolute value of the NDVI during April and July and its change over that period were linked with their LULC classification. As such, NDVI could be used to reclassify uncertain pixels, and assimilating NDVI within land-surface models can assist in minimizing errors.

Examples of potential misclassification can be seen in the Water histogram. The histogram for April and July both show a bimodal distribution with approximately 30% of the pixels classified as Water in the GAP dataset contained within the second peak and having an NDVI greater than 0. The position and shape of the second peak is consistent with the NDVI distribution of Wetland. Finally, the majority of the pixels contained within the second peak are located near rivers, lakes, or small ponds within the WRW. Together, these results suggest those pixels may have been misclassified. These results also suggest that reclassifying pixels categorized as Water but having a positive NDVI would result in a more accurate data set.

When the percent coverage of a given LULC classification was plotted as a function of a land-surface characteristic, several strong relationships were found between elevation and LULC coverage. This is particularly interesting given the ongoing discussion regarding whether mesoscale circulations in the SGP are a function of vegetation cover (WEAVER and AVISSAR, 2001) or topography (DORAN and ZHONG, 2001). Using 20 m elevation slices spanning the WRW, the percent coverage of each LULC classification was determined. Plotting the percent coverage for each LULC classification (Fig. 5) revealed several important relationships. In addition to demonstrating the dominance of the Grassland and Cropland classifications throughout the WRW, it showed clearly that Cropland was the most prevalent LULC classification at lower elevations while Grassland was most common at the higher elevations. Indeed, at the highest elevations above 480 m, the percent coverage of Grassland approaches 100%. Additionally, there is a nearly linear, inverse relationship between the percent coverage of the Wooded classification and elevation. Finally, it was found that Water, Wetland, and especially Urban were confined mainly to the lowest elevations.

A similar analysis relating LULC classification with slope also yielded strong relationships. For example, Cropland is confined primarily to the flattest portions of the WRW. For slopes less than 0.5°, Cropland is the dominant LULC classification with a percent coverage of nearly 47%; the percent coverage drops to less than 10% when the slope exceeds 4.5° and less than 3% when the slope exceeds 6°. Additionally, the steepest slopes were dominated by either Grassland at the higher elevation or Wooded areas in riparian zones. The steepest slopes in the WRW are found along the shorelines and channel cuts of lakes, streams, and rivers. Finally, while Urban LULC was most common when the slope was less than 2°, Water, Barren, and Wetland classifications were somewhat more prevalent at slopes greater than 4.5°; however, it must be noted that in all cases these LULC classifications constitute a small percentage of the total land cover.

The relationship of LULC classification with aspect was more ambiguous. No specific LULC classification or subset of classifications could be uniquely associated with any given aspect. The LULC classifications were evenly distributed among all aspects. As such, aspect would not provide a useful relationship for the reclassification of uncertain LULC classifications within the Walnut River Watershed.

4.3. *Reclassification Model*

The results of the reclassification (Fig. 2d) indicate a substantially improved classification of the LULC within the WRW. The accuracy assessment, which was conducted using the same methods as used with the simplified NLCD 92 and GAP data sets, yielded an overall accuracy of 92.9% for the revised data set. This is more than 13% greater than the GAP dataset and nearly 25% greater than the overall accuracy of the NLCD 92 dataset (Table 3).

In particular, the revised data sets showed strong improvements in the classification of all LULC categories as compared to the NLCD 92 data set. The revised dataset also showed strong improvements in the classification of the Wooded, Grassland, and Cropland environments as compared to the GAP data set. For example, the Producer's Accuracy for the Wooded LULC classification increased from 64.6% to 90.8% while the User's Accuracy increased from 72.4% to 89.0%. Similarly, the User's Accuracy increased from 73.0% and 90.1% to 89.0% and 93.0% for the Grassland and Cropland classifications, respectively.

5. Conclusions

The comparison of the NLCD 92 and GAP data sets demonstrates significant differences; these two dataset agree for only 73% of the Walnut River Watershed. Moreover, accuracy assessments of these data sets indicate an overall accuracy of less than 80% in both cases. The results strongly suggest that these data sets should be used with caution when they are applied to local areas. We offer a reclassification approach using a logical model that could greatly improve the accuracy of these LULC data sets when the focus is on a local scale.

The reclassification process is based on several strong relationships between land-surface characteristics and LULC classification that are evident from this research. In particular, NDVI, elevation, and slope demonstrated useful relationships. For example, based on this research, Cropland is confined to flat or gently sloping areas while Grassland is more prevalent in areas of steeper slopes and higher elevation. Similarly, developed land use, i.e., the Urban classification, is greatest at the lowest elevations within the WRW where the slope is minimal. In contrast to these land surface characteristics, aspect appeared to have no influence on LULC classification.

The relationships of LULC classification and surface characteristics evident from this research not only indicate a strong linkage between LULC and the land surface, but they also suggest the reclassification method tested in this research. That method, a logical model that acts like a dichotomous key, uses surface characteristics to reclassify uncertain LULC classifications to produce a more accurate representation of the WRW. Indeed, the reclassification method resulted in improvements in the overall accuracy of the LULC dataset by as much as 24.2% when compared with the NLCD 92 data set.

While the results of this research are unique for the WRW, the strong relationship between LULC type and surface features is broadly applicable. As a result, by developing relationships of the type used here for other local areas, the reclassification method applied here also could be applied to those areas.

As modelers adopt finer grid spacing for land surface models, the impacts of the surface specifications become increasingly more important. As a result, an accurate LULC dataset also becomes increasingly more important. This is because uncertainty in LULC could introduce errors into model simulations that could propagate into the results. The magnitude of the influence of the uncertainty in LULC data sets on land surface model output is the focus of ongoing research and will be presented in a follow up paper. Study results suggest that assimilating NDVI into the land surface models can reduce the uncertainty due to LULC assignment.

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