WATERSHED RESTORATION MANAGEMENT: PHYSICAL, CHEMICAL, AND BIOLOGICAL CONSIDERATIONS
NEW YORK CITY WATER SUPPLY STUDIES
JULY AMERICAN WATER RESOURCES ASSOCIATION 1996

HYDROLOGIC LAND USE CLASSIFICATION WITH THEMATIC AND SPATIAL INPUTS

Christopher A. Scott,[1] Michael F. Walter,[1] Barbara J. Dibeler,[2] Jane R. Frankenberger[3]

ABSTRACT: Land use is an essential input to distributed watershed hydrologic models. Conventional, automated approaches to land use classification rely exclusively on remotely sensed spectral data. This paper assesses the incorporation of raster GIS spatial analysis with Landsat Thematic Mapper (TM) imagery to enhance land use classification accuracy within hydrologically sensitive areas (HSAs). Three separate land use classifications are presented for a 3,148 ha watershed in the Catskill Mountains in New York State imaged on one 7.35 km x 10.11 km TM scene. All classifications used supervised maximum likelihood techniques with equal prior probabilities for the following eight land uses: grass pasture, hay, corn, impervious surfaces, successional forest/pasture, deciduous forest, coniferous forest, and water. For the first classification, training regions totaling 112.2 ha were selected without regard to spatial hydrologic features. For the second, training regions totaled 46.5 ha with 92% of this area located within HSAs as determined by depth to high water table and a topographic index. For the third, the training regions had a total area of 38.1 ha with 7% located within HSAs. Error matrices and kappa coefficients were calculated based on a sample of 84 control pixels determined from 1:40,000 color infrared stereo photography and checked during field visits. The HSA-based procedure provided more accurate land use classification results within HSAs (96% overall accuracy, K^=0.95 for areas within HSAs) than the 'stand alone' procedure (78% overall accuracy, K^=0.74 for areas within HSAs), while the 'outside HSA' procedure provided consistently lower accuracy than the other two classifications.
KEY TERMS: Land use; land use classification; watershed; hydrology.

INTRODUCTION

Modeling non-point source pollution requires data on land features as well as the frequency, magnitude, and spatial distribution of contaminant sources. Inputs to most existing spatially distributed models of hydrologic transport processes include land use, land cover, soil types (with associated hydraulic parameters), topography, and drainage. Because land use continuously changes with time, this input must be updated for model simulations to be valid. As a result, current land use is often the only significant data *not* readily available in digital form as was the case for the Catskill Mountains in New York State, the study area for this paper.

Classification procedures using thematic data aim to identify particular ground surface features from the unique spectral responses they generate. In distributed hydrologic models, however, land use is an input because of its influence on hydrologic processes, in particular evapotranspiration losses at the land-atmosphere boundary, rates of soil surface infiltration, friction for overland flow, and soil loss. A classification resulting in lower errors within hydrologically sensitive areas (HSAs, defined as high water table at or above the soil surface or the quotient of drainage area per unit contour length to the tangent of surface slope > 5000m; refer to the Methods section) may be of greater value for modeling purposes than a separate classification producing greater overall accuracy but resulting in significant errors within HSAs. *The objective of the 'hydrologic land use classification' presented in this paper is increased accuracy within hydrologically sensitive areas.*

---

[1] Cornell University, Department of Agricultural and Biological Engineering, Ithaca, NY 14853.

[2] New York City, Department of Environmental Protection, Shokan, NY 12481.

[3] Purdue University, Department of Agricultural Engineering, W. Lafayette, IN.

The mapping convention established by Anderson, *et al.* (1976) differentiates among broad *land use* classes at level I (forest, agriculture, urban), while level II *land cover* distinguishes deciduous from coniferous forests, and pasture from active agriculture, for example. For hydrologic modeling purposes, level II cover provides appropriate detail, given both the scarcity of consistent, published evaporative loss coefficients for individual species of forest or field crops differentiated at level III, and minor differences in their magnitudes where such coefficients are available. It is evident that classification accuracy should be higher for level I than for level II and so on. In this study, hydrologic land use refers to level II classification within HSAs.

The use of remotely sensed data for land use classification is growing rapidly. The alternative to remote sensing for land use determination involves time-consuming and expensive digitizing of land use maps prepared for other end uses, as for instance, crop maps for participation in government price-support programs, for which spatial coverage is invariably less than complete. Early hydrological applications of remotely sensed data were presented by Ragan and Jackson (1980) and Slack and Welch (1980) which used Landsat Multispectral Scanner (MSS) data to classify level I land use for the selection of runoff curve numbers. Landsat Thematic Mapper (TM) imagery is currently enjoying wide appeal as a remotely sensed data source for hydrologic applications (Shih and Jordan, 1992; Trolier and Philipson, 1986), based partly on the increased spatial resolution required by physically-based distributed hydrologic models (≤ 30 m, linked to the resolution of other inputs particularly digital elevation models, or DEMs) and seven channels of spectral data, but also importantly, based on accessibility and cost considerations. For land cover, TM bands TM3 (0.63 - 0.69 μm; red) and TM4 (0.76 - 0.90 μm; near infrared) provide valuable information on vegetation. Soil and vegetation moisture information is provided by TM4, TM5 (1.55 - 1.75 μm; mid-IR), TM6 (10.4 - 12.5 μm; thermal IR) and TM7 (2.08 - 2.35 μm; mid-IR). Given its coarse spatial resolution (120 m), TM6 has limited utility for detailed land cover classification.

The basis for all classification accuracy assessments is the error matrix, with columns representing ground reference (control) data and rows representing classification output. Congalton (1991) presented a useful overview. *Overall accuracy* is the quotient of the number of pixels classified correctly to the total number of pixels in the control sample. However, overall accuracy measures may be misleading, particularly where a particular class is of interest. For this purpose, *producer's accuracy* is defined as the quotient of the number of pixels classified correctly in a given class to the total number actually in that class; this measures errors of omission. *User's accuracy* is the quotient of the number of pixels classified correctly in a given class to the total number classified in that class; it measures errors of commission. Even with this degree of refinement, there is inadequate representation of off-diagonal elements of the error matrix (Rosenfeld and Fitzpatrick-Lins, 1986). To provide a more robust measure of classification accuracy, Congalton (1991) proposed the use of the *kappa coefficient* originally developed by Cohen (1960) for other purposes. Kappa is a discrete multivariate indicator based on diagonal and off-diagonal elements from the error matrix which conveys a measure of the spatial accuracy of the entire classification (analogous to overall accuracy), while simultaneously assessing individual class accuracy (analogous to producer's and user's accuracy). Kappa is generally calculated as K^ for all rows r in the matrix (Congalton, 1991):

$$K\hat{} = \frac{N \sum^{r} x_{ii} - \sum^{r} (x_{Ri} * x_{Ci})}{N^2 - \sum^{r} (x_{Ri} * x_{Ci})}$$

where N = total number of control points,
x_{ii} = number of control points in row *i*, column *i*,
x_{Ri} = marginal total (diagonal) of row *i*,
x_{Ci} = marginal total diagonal) of column *i*.

CLASSIFICATION METHODS AND RELEVANCE TO HYDROLOGIC LAND USE

Several important classification methods are briefly reviewed here in order to assess their suitability for hydrologic land use determination. Care must be exercised not to compare accuracies across land use levels (I, II, etc.). Based on the strong response of chlorophyll in the 0.65 - 0.90 μm range, the simplest vegetation identification procedure involves only two bands, TM3 and TM4, or their equivalents. Several indices have been proposed, including the *normalized difference vegetation index (NDVI)* and its modified form, the *soil-adjusted vegetation index (SAVI),* as presented by Huete (1988). Wittich and Hansing (1995) compared the NDVI with field data for several crops to identify the fraction of vegetative cover on the ground, concluding that the NDVI is highly sensitive to phenological changes. As a result, without prior knowledge of land use, vegetation indices have limited utility for distinguishing different vegetation types.

Predicated on the assumption of independent response in different spectral bands, the *unsupervised classification* disaggregates land cover by assigning pixel membership on the basis of computed class mean and variance. The result is non-nominative, allowing the user considerable latitude to decide (presumably on the basis of ground data) which regions correspond to which land uses. Because unsupervised classification requires ground data for positive class identification, it often proves less desirable (more time-consuming) than using these ground data as training regions. As with vegetation indices, unsupervised classification resulting in spatial aggregation appears to be most relevant to the selection of homogeneous training regions. This approach has been reported by Skidmore (1989).

Supervised classification generically refers to the use of known control (training) points or regions to compute class parameters (mean, variance, and eigenvalues) prior to thematic data analysis. The result is nominative class identification, a distinct advantage over unsupervised classification. Again, the method assumes independence of spectral bands. Numerous specific methods of supervised classification are reviewed by Hardin (1994), who compared parametric (per-pixel) methods with nearest-neighbor (spatial) methods, concluding that with unrestricted training regions spatial methods were superior, but that parametric methods provided as good or better accuracy with restricted training regions.

The *maximum likelihood* method has been found to provide robust results and high overall accuracy. Assuming that the data are normally distributed, the probability that a pixel is a member of a given class is calculated as (Conese and Maselli, 1992):

$$P = (2\pi)^{-1/2n} |c|^{-1/2} e^{-(1/2)[(\mathbf{X}-\mathbf{M})'\mathbf{C}{-1}(\mathbf{X}-\mathbf{M})]}$$

where n = number of bands
C = class variance-covariance matrix
M = class mean
X = pixel

Assigning prior probabilities (based on either prior knowledge of the area being classified, or on other data enhancement techniques) may improve maximum likelihood classification accuracy. *Principal component analysis* is a data enhancement technique which may be used to assign prior probabilities. Beaubien (1994) applied principal component analysis to TM3, 4, and 5 and Taylor color space enhancement (brightness, red-green and blue-yellow) to classify boreal forest types in Quebec. Skidmore (1989) reported that principal components identified that TM5, 4, and 7 accounted for 86% of total variance for one region of eucalypt forest in southeastern Australia. Additionally, *fuzzy set theory,* reviewed by Wang (1990), and *neural networks*, used by Bischof, *et al.* (1992), and Yoshida and Omatu (1994) appear to improve classification accuracy only marginally at best.

The potential for integrated processing of spectral and spatial data represents a distinct advantage over the more straightforward 'stand alone' classification methods described. Classification accuracy, both overall and feature-specific, may be enhanced through the integration of GIS spatial analysis. In *rule-based classification*, the GIS is encoded with norms for the probable occurrence of land features based on additional (non-thematic) data sources; these are processed to evaluate classification output. Rule structure and conditional exception are important factors. The conceptual model for a GIS-based classification procedure was presented by Bolstad and Lillesand (1991), who reported increases of 7 to 21% in overall level II classification accuracy based on GIS integration. Sader, *et al.* (1995) reported on GIS rule-based classification of forest wetlands based on topographic position and slope; however, the resulting accuracy improvements were not as significant as expected (8% compared to unsupervised classification), the approach perhaps being limited by DEM accuracy and the omission of pertinent soils data. Skidmore (1989) included slope, aspect and topographic position with thematic data and prior probabilities derived from supervised nonparametric classification of the first two principal components. The resulting overall accuracy (level III land cover) was 26% greater than for maximum likelihood.

Given the opening discussion on the selection of hydrologic parameters (evaporative loss coefficients, hydraulic surface roughness, and subsurface flow parameters) from land cover, the objective of hydrologic land use determination is accurate classification within HSAs. As a result, spatial data which locate HSAs were used in this study for both training region identification and accuracy assessment, but were not used within the classification procedure itself. The study compares stand alone thematic classification and this enhanced method for accuracy of hydrologic land use classification within and outside HSAs.

DESCRIPTION OF THE STUDY AREA

The study area comprises a 3,148 ha mixed land use watershed in the Catskill Mountains of New York State (Figure 1). Related hydrologic research on surface runoff, lateral flow, and ground water recharge focuses on one 170-ha farm within the watershed. Regional drainage is impounded by one of several reservoirs with a combined watershed area of over 5,000 km^2 supplying New York City with approximately 6 x 10^9 liters of water per day. Surface- and ground water hydrology and contaminant transport processes are of critical importance in maintaining water quality in the watershed--this is the largest unfiltered water supply in the United States. Non-point pollution sources include mixed land use agriculture, rural septic systems, fuel storages, and dumps. The principal contaminants of interest are pathogens (*Cryptosporidium* and *Giardia*), nutrients (particularly phosphorus), pesticides, and fuel. In order to effectively mitigate surface water quality impacts, the ongoing watershed management program has identified the need to investigate and model the distribution of contaminant sources with the spatial and temporal distribution of surface runoff generating areas.

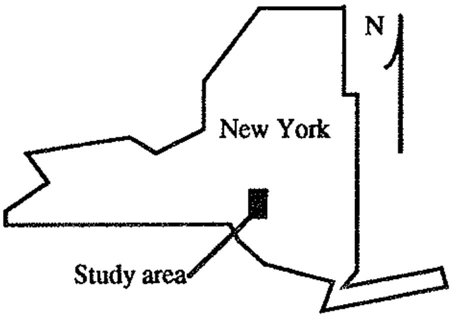

Figure 1. Study Area

METHODS AND DATA SOURCES

Hydrologically sensitive areas (HSAs) are defined as areas generating surface runoff capable of transporting contaminants to a perennial water course. HSAs are spatially and temporally variable following the hydrologic processes described by Dunne and Black (1970), and Hewlett and Nutter (1970). For the purposes of this study, watershed areas have been defined as HSAs by membership in either or both of the following spatial categories:

- high water table seasonally at or above the soil surface,
- topographic index $a/\tan\beta > 5000$ [m].

where a = cumulative area which drains through a unit length of contour line,
β = ground surface slope.

Depth to water table data are recorded in the soil survey (Universal Transverse Mercator UTM-registered Soils 5 database). The topographic index is a relative measure of the topographic likelihood of soil saturation calculated as the quotient of cumulative drainage (a) per meter of contour to the tangent of ground surface slope (β). The threshold of 5000 m was selected based on mapping of saturated areas on the farm. The $a/\tan\beta$ index was developed for TOPMODEL, a distributed hydrologic model, and has been described by Beven and Kirkby (1979) and reviewed by Beven (1986). Its incorporation into a raster GIS has been described by Chairat and Delleur (1993). The topographic index for this study was calculated using GRASS v. 4.1 at 30 m resolution from a UTM-registered digital elevation model (DEM) scanned from 1:24,000 scale, 20-ft contour interval USGS quad maps. The combined dataset of high water table and $a/\tan\beta > 5000$ m puts 737 ha (23.4%) of the watershed area within HSAs.

The spectral data source was a 7.35 km x 10.11 km sub-scene of Landsat TM pass 14, row 31, imaged on 09 May 1993. Image analysis of the six non-thermal bands was performed using ERMapper v. 4.0 on a Sun/Sparc 10 workstation platform at the Department of Geological Sciences at Cornell University. A UTM coordinate comparison of stream lines and ponds from the DEM, soils, and TM datasets for the study area indicated spatial error ≤ 50 m. The following eight level II land cover classes were identified:

- grass pasture (AP)
- hay (AH)
- corn (AC)
- impervious surfaces (IM)
- successional forest/pasture (FS)
- deciduous forest (FD)
- coniferous forest (FC)
- water (WA)

Training region selection proceeded in a parallel manner for the three classifications performed (refer to Table 1). For all classes except IM and FC, training data were taken from the 170 ha farm; for IM and FC, additional field data from within the watershed were incorporated. For the stand alone classification, 24 polygons were selected without regard to HSAs; of the total area of 112.2 ha, 19.2% occurred within HSAs (slightly less than the 23.4% for the entire watershed). Subsequently, 28 polygons totaling 46.5 ha which occur primarily (91.9% of their area) *within* HSAs, were selected with some overlap from the stand alone training regions. Finally, a separate set of 28 polygons totaling 38.1 ha which occur primarily (93.4% of their area) *outside* of HSAs, were selected, again with some overlap from the stand alone training regions. While water was included in the training regions for the non HSA-based procedure, by definition, it is entirely within an HSA. Each set of training regions was used to run maximum likelihood classifications on identical 6-band TM datasets with equal prior probabilities for all eight classes (12.5% for each class).

TABLE 1. Training Regions by Classification Procedure

	STAND ALONE			HSA-BASED			NON HSA-BASED		
Class	No. of training polygons	Total polygon area (ha)	Area within HSAs (%)	No. of training polygons	Total polygon area (ha)	Area within HSAs (%)	No. of training polygons	Total polygon area (ha)	Area within HSAs (%)
AP	3	15.12	51.2	4	5.94	90.9	4	4.14	2.2
AH	3	5.13	19.3	4	2.79	90.3	4	3.51	0.0
AC	3	2.61	37.9	3	2.07	95.7	3	1.44	6.3
IM	2	1.71	31.6	3	0.99	81.8	3	0.63	14.3
FS	3	4.59	47.1	3	3.78	100.0	3	2.16	4.2
FD	5	72.18	2.5	6	23.94	90.6	6	22.05	0.0
FC	3	9.18	60.8	3	5.31	91.5	3	2.34	15.4
WA	2	1.71	100.0	2	1.71	100.0	2	1.80	100.0
Total	24	112.23	19.2	28	46.53	91.9	28	38.07	6.6

CLASSIFICATION ACCURACY ASSESSMENT

Accuracy was assessed for each of the three classification procedures (stand alone, HSA-based, and non HSA-based) using 84 control pixels with a minimum of 10 pixels per class distributed throughout the TM scene. Control pixel classes were interpreted from 1:40,000 color infrared aerial photography flown on 23 June 1993 (six weeks after the TM pass). Additional land use data were collected during extensive field visits from 1992-95. As with the training region selection, initial accuracy assessments were made with control pixels located both within and outside HSAs (refer to the error matrix in Table 2). Subsequently, for each of three classification procedures, assessments were made of hydrologic land use accuracy, i.e., based on the subsample of 49 control pixels located within HSAs (Table 3). Finally, classification accuracies were assessed for the remaining 35 control pixels located outside HSAs (Table 4). For Tables 2 - 4, the following legend applies (with class abbreviations as listed above):

- OA = overall accuracy
- K^ = kappa coefficient
- PA = producer's accuracy
- UA = user's accuracy

TABLE 2. General Land Use Classification Accuracy (Combined Within and Outside HSAs)

STAND ALONE (Within and Outside HSAs)							**OA = 0.810**		**K^ = 0.782**	
Class	AP	AH	AC	IM	FS	FD	FC	WA	Total	UA
AP	8	2	0	0	0	0	0	0	10	0.800
AH	3	6	0	0	0	0	0	0	9	0.667
AC	0	0	6	1	0	0	0	0	7	0.857
IM	0	0	4	9	1	0	0	2	16	0.563
FS	0	2	0	0	10	0	0	0	12	0.833
FD	0	0	0	0	0	11	0	1	12	0.917
FC	0	0	0	0	0	0	11	0	11	1.000
WA	0	0	0	0	0	0	0	7	7	1.000
Total	11	10	10	10	11	11	11	10	84	
PA	0.727	0.600	0.600	0.900	0.909	1.000	1.000	0.700		

HSA-BASED (Within and Outside HSAs)							**OA = 0.917**		**K^ = 0.905**	
Class	AP	AH	AC	IM	FS	FD	FC	WA	Total	UA
AP	7	0	0	0	1	0	0	0	8	0.875
AH	3	10	0	0	0	0	0	0	13	0.769
AC	0	0	10	0	0	0	0	0	10	1.000
IM	0	0	0	9	0	0	0	0	9	1.000
FS	1	0	0	0	10	0	0	0	11	0.909
FD	0	0	0	1	0	10	0	0	11	0.909
FC	0	0	0	0	0	1	11	0	12	0.917
WA	0	0	0	0	0	0	0	10	10	1.000
Total	11	10	10	10	11	11	11	10	84	
PA	0.636	1.000	1.000	0.900	0.909	0.909	1.000	1.000		

NON HSA-BASED (Within and Outside HSAs)							**OA = 0.738**		**K^ = 0.700**	
Class	AP	AH	AC	IM	FS	FD	FC	WA	Total	UA
AP	6	3	0	0	2	0	0	0	11	0.545
AH	3	6	0	0	0	0	0	0	9	0.667
AC	0	0	10	1	1	0	0	0	12	0.833
IM	0	0	0	1	0	0	0	0	1	1.000
FS	2	1	0	1	8	0	1	0	13	0.615
FD	0	0	0	7	0	11	0	0	18	0.611
FC	0	0	0	0	0	0	10	0	10	1.000
WA	0	0	0	0	0	0	0	10	10	1.000
Total	11	10	10	10	11	11	11	10	84	
PA	0.545	0.600	1.000	0.100	0.727	1.000	0.909	1.000		

Grass pasture, hay, and successional forest/pasture resulted in the lowest producer's and user's accuracies for all three classification procedures based on their similar phenological (and consequently spectral) characteristics in May in the Catskills. On the other hand, water, coniferous forest, and corn (plowed land) with distinct spectral signatures produced the highest accuracies. The relatively small area of training polygons for impervious surfaces lowered the accuracy of this class. Although the impervious surfaces training polygon area for the stand alone procedure included 19 pixels (1.71 ha), these likely included some non-impervious areas (especially lawns) interspersed in the residential hamlet where one of the polygons was delineated. Shadow effects in sloping terrain lowered the user's accuracy of deciduous forest, giving it low digital number values like coniferous forest.

TABLE 3. Hydrologic Land Use Classification Accuracy (Within HSAs Only)

STAND ALONE (Within HSAs Only)							**OA = 0.776**		**K^ = 0.743**	
Class	AP	AH	AC	IM	FS	FD	FC	WA	Total	UA
AP	4	0	0	0	0	0	0	0	4	1.000
AH	2	3	0	0	0	0	0	0	5	0.600
AC	0	0	3	1	0	0	0	0	4	0.750
IM	0	0	2	4	1	0	0	2	9	0.444
FS	0	2	0	0	5	0	0	0	7	0.714
FD	0	0	0	0	0	6	0	1	7	0.857
FC	0	0	0	0	0	0	6	0	6	1.000
WA	0	0	0	0	0	0	0	7	7	1.000
Total	6	5	5	5	6	6	6	10	49	
PA	0.667	0.600	0.600	0.800	0.833	1.000	1.000	0.700		

HSA-BASED (Within HSAs Only)							**OA = 0.959**		**K^ = 0.953**	
Class	AP	AH	AC	IM	FS	FD	FC	WA	Total	UA
AP	4	0	0	0	0	0	0	0	4	1.000
AH	2	5	0	0	0	0	0	0	7	0.714
AC	0	0	5	0	0	0	0	0	5	1.000
IM	0	0	0	5	0	0	0	0	5	1.000
FS	0	0	0	0	6	0	0	0	6	1.000
FD	0	0	0	0	0	6	0	0	6	1.000
FC	0	0	0	0	0	0	6	0	6	1.000
WA	0	0	0	0	0	0	0	10	10	1.000
Total	6	5	5	5	6	6	6	10	49	
PA	0.667	1.000	1.000	1.000	1.000	1.000	1.000	1.000		

NON HSA-BASED (Within HSAs Only)							**OA = 0.735**		**K^ = 0.693**	
Class	AP	AH	AC	IM	FS	FD	FC	WA	Total	UA
AP	3	2	0	0	0	0	0	0	5	0.600
AH	2	2	0	0	0	0	0	0	4	0.500
AC	0	0	5	1	1	0	0	0	7	0.714
IM	0	0	0	0	0	0	0	0	0	NA
FS	1	1	0	0	5	0	1	0	8	0.625
FD	0	0	0	4	0	6	0	0	10	0.600
FC	0	0	0	0	0	0	5	0	5	1.000
WA	0	0	0	0	0	0	0	10	10	1.000
Total	6	5	5	5	6	6	6	10	49	
PA	0.500	0.400	1.000	0.000	0.833	1.000	0.833	1.000		

The classification procedure based on training region definition within HSAs provided significantly higher overall accuracy (95.9%) and K^ (0.953) for hydrologic land use than did the stand alone classification procedure based on random training region definition (OA = 77.6%; K^ = 0.743). Of the three classifications presented, the procedure based on training region definition outside of HSAs provided consistently lower accuracies than the other two procedures. Because of greater sample diversity (28 training polygons vs. 24), the HSA-based method also provided better accuracy (OA = 91.7%; K^ = 0.905) for the combined areas (within and outside HSAs) than did the stand alone procedure (OA = 81.0%; K^ = 0.782). The importance of including a diverse sample of training regions cannot be overstated.

TABLE 4. Other Land Use Classification Accuracy (Outside HSAs Only)

STAND ALONE (Outside HSAs Only)						**OA = 0.886**		**K^ = 0.867**	
Class	AP	AH	AC	IM	FS	FD	FC	Total	UA
AP	4	1	0	0	0	0	0	5	0.800
AH	1	4	0	0	0	0	0	5	0.800
AC	0	0	3	0	0	0	0	3	1.000
IM	0	0	2	5	0	0	0	7	0.714
FS	0	0	0	0	5	0	0	5	1.000
FD	0	0	0	0	0	5	0	5	1.000
FC	0	0	0	0	0	0	5	5	1.000
Total	5	5	5	5	5	5	5	35	
PA	0.800	0.800	0.600	1.000	1.000	1.000	1.000		
HSA-BASED (Outside HSAs Only)						**OA = 0.857**		**K^ = 0.833**	
Class	AP	AH	AC	IM	FS	FD	FC	Total	UA
AP	3	0	0	0	1	0	0	4	0.750
AH	1	5	0	0	0	0	0	6	0.833
AC	0	0	5	0	0	0	0	5	1.000
IM	0	0	0	4	0	0	0	4	1.000
FS	1	0	0	0	4	0	0	5	0.800
FD	0	0	0	1	0	4	0	5	0.800
FC	0	0	0	0	0	1	5	6	0.833
Total	5	5	5	5	5	5	5	35	
PA	0.600	1.000	1.000	0.800	0.800	0.800	1.000		
NON HSA-BASED (Outside HSAs Only)						**OA = 0.743**		**K^ = 0.700**	
Class	AP	AH	AC	IM	FS	FD	FC	Total	UA
AP	3	1	0	0	2	0	0	6	0.500
AH	1	4	0	0	0	0	0	5	0.800
AC	0	0	5	0	0	0	0	5	1.000
IM	0	0	0	1	0	0	0	1	1.000
FS	1	0	0	1	3	0	0	5	0.600
FD	0	0	0	3	0	5	0	8	0.625
FC	0	0	0	0	0	0	5	5	1.000
Total	5	5	5	5	5	5	5	35	
PA	0.600	0.800	1.000	0.200	0.600	1.000	1.000		

CONCLUSIONS

This paper has demonstrated the need for procedures to improve automated land use classification for watershed hydrologic modeling. Based on a review of existing methods, an enhanced procedure was proposed using GIS spatial analysis for the selection of training regions, followed by supervised maximum likelihood classification using spectral data. Results in the form of error matrices with percentage overall accuracy figures and kappa coefficients calculated separately for all watershed areas,

areas within HSAs, and non-HSAs demonstrate that the enhanced procedure can significantly improve accuracy, particularly within HSAs. The topographic effects of sloping terrain on thematic data quality exert an important influence on watershed land use classification. Separating training regions into shadowed and non-shadowed regions for the same class, i.e., accommodating non-normal distributions, would likely improve accuracy. It is crucial to improving hydrologic land use classification that watershed HSAs tend to spatially overlap with topographic depressions that have reduced spectral reflectances. This situation necessitates a larger sample of carefully selected training region polygons to increase classification accuracy, as demonstrated by the higher accuracies of the HSA-based procedure over the stand alone, despite the fact that the latter had a larger area of training polygons. The improved results of the enhanced approach used in this study are based on this principle.

REFERENCES

Anderson, J.R., E.E. Hardy, J.T. Roach, and R.E. Witmer. 1976. A land use and land cover classification system for use with remote sensor data. USGS Professional Paper 964. 28p.

Beaubien, J. 1994. Landsat TM satellite images of forests: from enhancement to classification. *Canadian J. Remote Sens.* 20(1): 17-26.

Beven, K. 1986. Runoff production and flood frequency in catchments of order n: an alternative approach. In: Scale Problems in Hydrology. V.K. Gupta, I. Rodríguez-Iturbe, and E.F. Wood, (eds.) D. Reidel. Dordrecht.

Beven, K.J., and M.J. Kirkby. 1979. A physically based, variable contributing area model of basin hydrology. *Hydrol. Sci. Bull.* 24(1): 43-69.

Bischof, H. W. Schneider, and A.J. Pinz. 1992. Multispectral classification of Landsat-images using neural networks. *IEEE Trans. Geosci. Remote Sens.* 30(3): 482-490.

Bolstad, P. and T.M. Lillesand. 1991. Automated GIS integration in landcover classification. ACSM-ASPRS Ann. Conven. Tech. Papers. 3: 23-32.

Chairat, S. and J.W. Delleur. 1993. Integrating a physically based hydrological model with GRASS. *HydroGIS 93: Application of Geographic Information Systems in Hydrology and Water Resources* (Proceedings of the Vienna Conference, April 1993). IAHS Publ. no. 211.

Cohen, J. 1960. A coefficient of agreement of nominal scales. *Educ. Psych. Measur.* 2(1): 37-46.

Conese, C. and F. Maselli. 1992. Use of error matrices to improve area estimates with maximum likelihood classification procedures. *Remote Sens. Environ.* 40: 113-124.

Congalton, R.G. 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sens. Environ.* 37: 35-46.

Dunne, T., and R.D. Black. 1970. An experimental investigation of runoff production in permeable soils. *Water Resour. Res.* 6: 478-499.

Hardin, P.J. 1994. Parametric and nearest-neighbor methods for hybrid classification: a comparison of pixel assignment accuracy. *Photogram. Engineering Remote Sens.* 60(12): 1439-1448.

Hewlett, J.D. and W.L. Nutter. 1970. The varying source area of streamflow from upland basins. In Symposium on Interdisciplinary Aspects of Watershed Management. Montana State Univ.

Huete, A.R. 1988. A soil-adjusted vegetation index (SAVI). *Remote Sens. Environ.* 25: 295-309.

Ragan, R.M., and T.J. Jackson. 1980. Runoff synthesis using Landsat and SCS model. *ASCE J. Hydraul. Div.* 106(HY5): 667-678.

Rosenfeld, G.H., and K. Fitzpatrick-Lins. 1986. A coefficient of agreement as a measure of thematic classification accuracy. *Photogram. Engineering Remote Sens.* 52(2): 223-227.

Sader, S.A., D. Ahl, and W.S. Liou. 1995. Accuracy of Landsat-TM and GIS rule-based methods for forest wetland classification in Maine. *Remote Sens. Environ.* 53: 133-144.

Shih, S.F. and J.D. Jordan. 1992. Landsat mid-infrared data and GIS in regional surface soil-moisture assessment. *Water Resour. Bull.* 28(4): 713-719.

Skidmore, A.K. 1989. An expert system classifies Eucalypt forest types using Thematic Mapper data and a digital terrain model. *Photogram. Engr. Remote Sens.* 55(10): 1449-1464.

Slack, R.B., and R. Welch. 1980. Soil Conservation Service runoff curve number estimates from Landsat data. *Water Resour. Bull.* 16(5): 887-893.

Trolier, L.J. and W.R. Philipson. 1986. Visual analysis of Landsat Thematic Mapper Images for hydrologic land use and cover. *Photogram. Engr. Remote Sens.* 52(9): 1531-1538.

Wang, F. 1990. Fuzzy supervised classification of remote sensing images. *IEEE Trans. Geosci. Remote Sens.* 28(2): 194-201.

Wittich, K.P. and O. Hansing. 1995. Area-averaged vegetative cover fraction estimated from satellite data. *Int. J. Biometeorol.* 38: 209-215.

Yoshida, T., and S. Omatu. 1994. Neural network approach to land cover mapping. *IEEE Trans. Geosci. Remote Sens.* 32(5): 1103-1109.