PRACTICAL PAPER

The Integration of Geographic Data with Remotely Sensed Imagery to Improve Classification in an Urban Area

Paul M. Harris and Stephen J. Ventura

Abstract

Management and planning of urban areas requires current and accurate information about land use. Satellite imagery or aerial photography typically provide this information.The choice of a remotely sensed data source entails tradeoffs between cost, accuracy, specificity, and timeliness; requirements are often dictated by particular applications of the land-use data. This paper investigates the incorporation of ancillary spatial data to improve the accuracy and specificity of a land-use classification from Landsat Thematic Mapper (TM) imagery for nonpoint source pollution modeling in a small urban area — the city of Beaver Dam, Wisconsin.

A post-classification model was developed to identify and correct areas of confusion in the Landsat TM classification. Zoning and housing density data were used to modify the initial classification. Land-use classification accuracy improved and the number of identifiable classes increased. Additionally, confusion between classes that were commonly misclassified (for example, commercial and industrial areas) was reduced.

Introduction

Information about current land use in urban areas is important for the management and planning of these areas. Aerial photography has traditionally been used to collect this information. However, it is costly and difficult to obtain with sufficient frequency. Satellite remote sensing can provide a method for acquiring regular, recent information about urban areas which may be particularly useful for monitoring changes within and on the fringes of urban development. However, given the spatial resolution of satellite imagery currently available, these data alone do not provide the accuracy or specificity required for many urban applications. This paper investigates the incorporation of additional spatial data through a geographic information system (GIS) to improve the accuracy and specificity of a classification derived from satellite data.

Nonpoint source pollution modeling is an example of an urban management application that requires current and accurate land-use information. Models based primarily on land use can be used to locate areas with disproportionately high pollutant loadings, and thus to target pollution control efforts. The Wisconsin Department of Natural Resources (WDNR) was interested in efficient methods of generating urban land-use data for municipalities throughout the state to meet the planning needs of the Wisconsin Nonpoint Source Priority Pollution Program. Agencies throughout the nation may find themselves with similar needs when federal stormwater management requirements for municipalities are implemented (U.S. Environmental Protection Agency, 1990).

A project was designed to evaluate the efficiency and effectiveness of various data sources and interpretation or classification techniques to generate urban land-use data. Satellite imagery and aerial photography were processed with manual and automated techniques and compared on the basis of classification accuracy, class specificity, and cost. This paper reports on one data source and processing procedure that was evaluated (other aspects are reported in Ventura and Harris (1993) and Kim *et al.* (1993)). The combination of classified Landsat TM data with zoning and demographic data was of particular interest because of the low cost and ready availability of all three data sources. Though it was recognized before the study that the spatial resolution of such satellite imagery was probably insufficient for this application, we hypothesized that we could compensate for this deficiency by improving its classification accuracy and specificity with additional spatial data about zoning from local sources and about population density from attributes associated with TIGER line files. This could result in a low-cost method for generating land use that met requirements for nonpoint source pollution planning for many municipalities within a satellite scene.

Background

Attempts at automated classification of land use or land cover in urban areas using satellite imagery have led to mixed results. Haack *et al.* (1987) and Khorram *et al.* (1987) examined Landsat MSS and TM data for urban classification. Although residential classes were detected, and urban and non-urban areas were adequately differentiated, they found that the spatial resolution of TM (30 by 30 metres) was still

P.M. Harris is with Crowe, Schaffalitzky & Associates, Ltd., 58 Kishorn Road, Mount Pleasant, Western Australia 6153, Australia.

S.J. Ventura's address is 1203 Meteorology and Space Science, University of Wisconsin-Madison, Madison, WI 53706.

Photogrammetric Engineering & Remote Sensing,
Vol. 61, No. 8, August 1995, pp. 993–998.

0099-1112/95/6108-993$3.00/0

inadequate for accurate and consistent urban classification. Martin and Howarth (1989), Baraldi and Parmiggiani (1990), and Harrison and Richards (1988) investigated the use of SPOT's multispectral (XS) channels for urban classification. The results were satisfactory for analyzing urban change detection, but the spatial resolution (20 by 20 metres) was still inadequate for a multi-class urban classification. Harrison and Richards (1988) also asserted that the spectral resolution of the SPOT data was inadequate for the accuracy and specificity required for many urban applications.

TM and SPOT panchromatic (PAN) data have been combined by various methods (Welch and Ehlers, 1987) to produce hybrid image data having the spectral resolution of TM and the spatial resolution of SPOT PAN (10 by 10 metres). Alwashe *et al.* (1988) and Baudot *et al.* (1988) found that an intensity-hue-saturation (IHS) transformation improved the delineation of residential, commercial, and industrial areas, but sub-classifications within these categories were not possible. Other techniques employing textural and structural information (Gong and Howarth, 1990), delineation of linear features (Lalitha, 1989), thermal bands (Leak and Venugopal, 1990), and the use of expert systems (Shamsi *et al.*, 1991; Wharton, 1987; Møller-Jensen,1990) have produced some improvement in the accuracy of urban classifications, but they are still below the limits and specificity required for most urban planning applications. Cushnie (1987) and other authors have noted that increased spatial resolution may increase urban land-use classification problems because of the high degree of spectral heterogeneity in urban environments.

A number of methods have been developed in an attempt to improve image classification using additional spatial data, such as thematic maps and terrain characteristics. These methods can be generalized into three approaches:

- Pre-classification stratification,
- Classifier modification, and
- Post-classification sorting.

Improvements in classification accuracy have been observed for all three methods; however, there are constraints associated with each technique. A detailed discussion of the advantages and disadvantages of each approach was developed by Hutchinson (1982).

Stratification involves the division of a scene into smaller areas based on some criterion. This enables land covers that are spectrally similar to be classified independently. For example, stratification of a scene into urban and rural areas enables spectrally similar grass land covers to be classed as lawn and pasture in urban and rural areas, respectively. This technique provides the convenience of working with smaller data sets and reduces variation within land-cover types. It is easily implemented, effective, and inexpensive in terms of computer time. However, it does not allow for gradual changes between classes or for anomalous land uses such as rural lawns, and hence care should be taken when determining stratification criteria.

There are two approaches to using ancillary data during classification. The first incorporates the information as a separate channel to be used during the classification process. Spooner (1991) used this technique for assessing urban change by combining, as an additional band, the land use derived from a scanned 7.5-minute topographic quadrangle map with a SPOT panchromatic image. Although easily implemented, this approach increases computer time considerably.

The second approach to classifier modification involves changing the *a priori* probabilities of classes based on either estimated areal composition or on a known relationship between the classes and the ancillary data. This technique, although theoretically sophisticated, requires considerable additional sampling and is scene dependent. Unlike typical data from a satellite image, ancillary data incorporated in a classifier by either approach do not have normal spectral distributions. This may violate distribution conditions required for maximum-likelihood classifiers, leading to misleading results.

Post-classification sorting allows individual pixels to be refined based on decision rules derived from the ancillary data. It is quick, simple, easily implemented, and efficient because it needs only to alter "problem" classes. It allows several categories of ancillary data to be included at once and it is a technique that is particularly suited to raster images and raster *GIS*. However, it is deterministic and best suited to data where the boundaries among land-use types are well defined. A number of studies have used post-classification sorting to gain improved results. A matrix overlay analysis was used by Treitz *et al.* (1992) to combine zoning data with SPOT imagery of the urban fringe of Toronto, Canada. Golden and Lackey (1992) used topographic data and a post-classification model to identify and correct misclassifications of forest tree species in western Oregon and Washington. Janssen *et al.* (1990) found that the inclusion of topographic data improved land-cover classification accuracy by between 12 and 20 percent for areas within the Netherlands.

Artificial intelligence (AI) techniques have also been investigated in an effort to automate the integration of geographic and descriptive information with spectral data. Bolstad and Lillesand (1992) used a rule-based classifier to incorporate soil texture and topographic data with Landsat Thematic Mapper (TM) data in northern Wisconsin with improvements of up to 15 percent in classification accuracy.

The Beaver Dam, Wisconsin Study

This research integrates zoning data and housing densities with a TM classification using post-classification sorting for the city of Beaver Dam, Wisconsin. Post-classification sorting was selected because of its ease of implementation, its ability to alter only those classes that were "confused," and its suitability for use with raster data.

In recognition of problems caused by nonpoint source pollution to the state's streams and lakes, the Wisconsin Legislature authorized the Wisconsin Department of Natural Resources (WDNR) to create a Nonpoint Source Priority Watershed Program. This program aims to have detailed nonpoint source management plans for up to 330 priority watersheds initiated by the year 2000. The city of Beaver Dam, in Dodge County, Wisconsin, is typical of many of the smaller communities in Wisconsin which will be required to develop a nonpoint source pollution management program. It has an area of approximately 20 square kilometres and a population of about 15,000. The current land uses consist of a central business district surrounded by residential areas. Industrial land is located adjacent to the central business area and on the outskirts of the city, where newer commercial complexes are also found. The city is surrounded by farmland on three sides and a lake on the fourth.

WDNR uses an empirical model known as SLAMM (Source Loading and Management Model) (Pitt, 1989) to estimate the type and concentrations of nonpoint source contaminants found in urban stormwater. This model calculates runoff characteristics and pollutant loadings for individual rain

Table 1. Urban Land-Use Categories Identified from Different Data Sources.

Land Use	TM only	TM and Zoning	TM, Zoning and Housing Densities
Residential:	X		
High density (more than 6 dwellings/acre)		X	
Medium density (between 2 and 6 dwellings/acre)		X	X
Low density (less than 2 dwellings/acre)			X
Multi-family		X	X
Commercial:	X		
Shopping centers		X	X
Strip commercial		X	X
Downtown		X	X
Industrial:	X		
Medium (manufacturing)		X	X
Light (non-manufacturing)		X	X
Institutional:			
Hospitals		X	X
Education		X	X
Open Spaces:	X		
Parks		X	X
Cemeteries		X	X
Undeveloped		X	X
Freeways:	X	X	X

events, using the Soil Conservation Service runoff curve number approach and pollutant loading coefficients empirically derived from past urban stormwater studies. In determining the runoff characteristics of a study area, SLAMM requires information about land cover, including porous and impervious areas, grass swales, building density, presence of alleys, and road materials. These land-cover classes are inferred from land-use data within the model. Special cases such as nonpoint source management practices are also specifically noted. SLAMM also uses land-use data directly, associating pollutant loadings with land uses according to coefficients developed through monitoring in other communities. The classes used in SLAMM to categorize urban land use are summarized in Table 1. They are a modified version of the USGS (Anderson *et al.*, 1976) Level III urban land-use categories.

Several types of digital data were generated for the broader study of data sources and processing techniques. For the study reported herein, four were pertinent — a Landsat TM scene, U.S. Bureau of Census geographically referenced housing data, local zoning data, and "ground-truth" land-use data for accuracy assessment. Housing, zoning, and "ground-truth" data were compiled within the framework of an automated city street map.

Zoning data were automated by assigning zoning to city street blocks from a 1:4,800-scale zoning map provided by the City of Beaver Dam. This proved to be a simple and quick method to automate zoning for rule development. The map showed zoning to parcel level specificity, though most street blocks had homogeneous zoning. Blocks were sub-divided as necessary to show sub-block zones of significance from a SLAMM modeling standpoint. A non-ambiguous many-to-many relation existed between SLAMM land-use classes and zoning categories. The zoning map was considered to be up-to-date by city officials, but it was not an accurate indicator of current land use. Areas that were zoned but not yet developed and areas of non-conforming uses were not shown on the maps.

Housing densities were obtained in the form of U.S. Bureau of Census Topologically Integrated Geographic Encoding and Referencing (TIGER) line files and associated attribute data (number of residences per block). These were conflated to a more spatially accurate city street block coverage by point in polygon overlay processing. Housing densities were calculated for each block and separated into three classes — low, medium, and high — corresponding to the SLAMM definitions.

A Landsat TM image acquired 7 May 1990 was used for the image classification. This was a good time for urban land-use classification in southern Wisconsin. Deciduous trees were not fully leafed out yet, so rooftops and residential streets were still visible, yet lawns and other grassy areas were fully vivified and green.

A panchromatic aerial photograph, obtained during April 1990 at a scale of 1:4,800, was photo-interpreted to provide ground truth and to assist with the accuracy assessment. Extensive "windshield survey" ground-truthing (40 percent of the study area, including all non-residential areas) was conducted to verify this photo-interpretation. This photo-interpretation and ground-truthing were used to create a ground-truth coverage registered to the city street block coverage. The ground-truth coverage included all 15 classes shown in Table 1. Residential housing density was interpreted, not precisely measured, on a per block basis.

Methods

The TM image was classified using a supervised technique, based on signatures from 65 training sites and maximum-likelihood decision rules. The classification delineated five broad classes: open space, residential, commercial, industrial, and freeway. The overall classification accuracy was 77 percent (see Table 2). Institutional classes (churches, schools, and hospitals) were not used because they were found to be

Table 2. Contingency Table Resulting from Supervised Classification of TM Imagery

Ground Truth	Total	Classified Land Use 1	2	3	4	5	Accuracy (%)	Commission error (%)	Omission error (%)
1. Open Space	251	189	28	12	18	4	75.3	22.3	24.7
2. Residential	428	34	363	12	18	1	84.8	9.3	15.2
3. Commerical	37	3	5	16	13	0	43.2	100.0	56.8
4. Industrial	79	19	7	13	40	0	50.6	62.0	49.4
5. Freeway	5	0	0	0	0	5	100.0	100.0	0.0
Total	800	245	403	53	89	10	76.6		

Total is total number of pixels randomly selected from ground truth coverage. The overall classification accuracy: 76.6%, with $\hat{\kappa}$ = 0.623.

TABLE 3. SUMMARY OF CLASSIFICATION ACCURACIES FOR DIFFERENT DATA SOURCES. NUMBERS IN BOLD REPRESENT ACCURACY FOR AGGREGATED CLASSES, OTHER NUMBER REPRESENT ACCURACY FOR ALL CLASSES.

	TM Classification	TM and Zoning	TM, Zoning, and Housing
Residential:	**84.8**	**90.2**	**93.2**
High density			62.7
Medium density		89.9	72.8
Low density			66.7
Multi-family		40.9	45.5
Commercial:	**43.2**	**83.1**	**83.1**
Shopping centers		68.4	68.4
Strip commercial		56.3	56.3
Downtown		90.9	90.9
Industrial:	**50.6**	**70.5**	**70.5**
Medium		70.9	70.9
Light		30.4	30.4
Institutional:		**88.9**	**88.9**
Hospitals		100.0	100.0
Education		87.5	87.5
Open Spaces:	**75.3**	**82.2**	**82.2**
Parks		67.4	67.4
Cemeteries		100.0	100.0
Undeveloped		87.1	87.1
Freeways:	**100.0**	**78.6**	**78.6**
TOTAL- aggregate classes	**76.6**	**85.3**	**86.8**
TOTAL- all classes		81.6	73.8

inseparable from the other classes due to the spectral similarity of buildings and the large content of open space associated with them.

For the accuracy assessment, 800 pixels (representing about three percent of the total number of pixels) were randomly selected from the ground-truth coverage for comparison purposes and contingency tables. $\hat{\kappa}$ statistics, as defined by Congalton *et al.* (1983) were calculated. The $\hat{\kappa}$ statistic gives an indication of accuracy after random agreement is removed from consideration. It is particularly well suited to applications of remote sensing classification because the entire contingency matrix is used in the analysis. Rosenfield and Fitzpatrick-Lins (1986) showed that it is an appropriate measure of agreement between remotely derived information and ground information. It also enables comparison between different classification techniques.

Post-classification sorting of the land-use classes was performed using the GIS modeling capabilities of ERDAS software, known as GISMO. Models were written using GISMO that allowed the classification derived from the remote sensing data to be modified using the spatial information. Each model consisted of a series of conditional statements that combined the data sets in a way that was considered to improve the accuracy or specificity of the land-use results. GISMO also allows the results of each modification to be displayed directly to the screen, where they can be assessed and revised.

Where confusion between two classes exists, rules were used to separate classes with significant overlap. For example, zoning reduced the confusion between spectrally similar industrial and commercial classes with the rule "*if the zoning is commercial and the classification industrial, then recode as commercial.*" Post-classification sorting was also employed to increase specificity. For example, population counts were used to break a residential class into low, medium, and high densities using a rule such as "*if classification is residential and housing density is greater than six residences per acre, then recode as high density residential.*" For some classes, confusion was eliminated and specificity increased. For example, an "open space" class could be part of industrial parks, institutional grounds, or one of the SLAMM model open space classes. A rule such as "*if the zoning is park and the classification open space, then recode as park*" was used to identify such open spaces. Because the zoning coverage had recognizable deficiencies, such as undeveloped areas zoned as residential (for future growth), it was not used to override TM classes such as open space.

Two sets of rules were written: one that revised the supervised TM classification using zoning only, another that used zoning and housing densities to modify the classification. Housing density was used only to subdivide areas that were considered residential based on the classification and zoning into residential density classes. Results obtained from these post-classification sorting models were compared to the results derived from the image classification and to ground truth in terms of the number of classes discriminated, the degree of confusion between classes, and the overall classification accuracy.

The sensitivity of the SLAMM model results to each classification was assessed by comparing the results of the model output (the loading of priority pollutants) to results generated by the model using the ground-truthed reference data. Deviations from the reference data results were calculated. WDNR staff considered that deviations less than 20 percent were "acceptable" in that they were unlikely to warrant changes in pollution control strategies. Therefore, for a land-use classification to be acceptable for nonpoint source pollution modeling, the model output for each pollutant should be within 20 percent of the value calculated from the reference. The SLAMM model was used to estimate the loadings of four heavy metals (lead, zinc, copper, and cadmium) and two other pollutants, phosphorus and suspended sediments. It was run for a full year over the Beaver Dam watershed as a whole and for 11 basins of the storm sewer system using the local average rainfall of 813 millimetres per year.

Results and Discussion

The inclusion of zoning information with the TM classification increased the number of urban land-use classes from five to 13. The overall classification accuracy for the 13 classes was 81.6 percent (see Table 3). If the classes are aggregated to the broader information classes used in the TM classification (in order to compare classification accuracies), the classification accuracy increases to 85 percent (from 77 percent). The $\hat{\kappa}$ values verify, with 95 percent confidence, that this is a statistically significant improvement. The classification for each land-use category also improves and an institutional class is now identifiable. Confusion between commercial and industrial land use is also substantially reduced. Table 4 is the contingency matrix for the classification results using the broad categories.

Misclassifications remain within residential classes and between parks and residential land use. It was anticipated that the inclusion of data on housing densities would reduce this confusion. However, just the opposite effect was observed. Although the inclusion of this information increased the number of identifiable classes, misclassifications among residential classes increased (see Table 3). Inspection of the aerial photography in areas of misclassification indicates that it was probably the delineation of residential density classes in the ground survey that was in error. As previously noted, residential classes differentiated by housing density were the

TABLE 4. CONTINGENCY TABLE RESULTING FROM MODIFICATION OF SUPERVISED TM CLASSIFICATION WITH ZONING INFORMATION. THESE ARE THE SPECIFIC CLASSES OF THE TM/ZONING CLASSIFICATION AGGREGATED TO THE BROADER CLASSES OF THE INITIAL TM CLASS. AN ADDITIONAL CLASS HAS BEEN ADDED (INSTITUTIONAL), BECAUSE THERE WAS NO CORRESPONDING CLASS IN THE INITIAL CLASSIFICATION.

Ground Truth	Total	Classified Land Use 1	2	3	4	5	6	Accuracy (%)	Commission error (%)	Omission error (%)
1. Open Space	186	153	16	0	9	8	6	82.2	24.2	17.8
2. Residential	389	19	351	1	16	2	0	90.2	7.7	9.8
3. Commercial	65	4	3	54	4	0	0	83.1	4.6	16.9
4. Industrial	78	11	11	1	55	0	0	70.5	37.2	29.5
5. Institutional	54	6	0	0	0	48	0	88.9	18.5	11.1
6. Freeway	28	5	0	1	0	0	22	78.6	0.0	21.4
Total	800	198	381	57	84	58	22	85.3		

Total is total number of pixels randomly selected from ground truth coverage (in a different sampling than those of Table 2). The overall classification accuracy: 85.3%, with $\hat{\kappa} = 0.788$.

only categories in the reference data that had some between-class confusion. Most of the confusion between the classification from TM, zoning and housing density, and the ground truth was in areas that had housing densities near the cutoff points of density categories. Only intensive door-to-door surveys would resolve these discrepancies.

In this watershed, increased class specificity did not result in significant differences in model results from a water quality practice perspective. Table 5 shows the difference in loadings from the reference data compared to loadings from the classification, classifications and post-sorting, and zoning data alone. Under all scenarios except zoning, the pollutant loadings do not approach the 20 percent deviation from the reference data that could warrant consideration of different management practices. The classifications generally underestimate pollutant loadings relative to the ground truth because open areas of industrial parks and institutional grounds are classified as open space. The use of zoning data alone results in significant overestimates of pollutant loadings; it is the only way of generating land-use data that would not be acceptable for SLAMM modeling. For the other methods and combinations, increased class specificity and categorical accuracy does not necessarily improve model results when examined in aggregate for the entire watershed or for individual storm sewer drainage basins. This implies that broad land-use classes may be sufficient for estimating urban pollutant runoff with lump-sum models. Time and effort for small improvements in classification accuracy may not be justified for SLAMM modeling purposes, though typically such data will also be used in other aspects of non-point pollution control. For example, accurate and specific land-use information is desirable for targeting control practices.

Conclusions and Recommendations

The addition of ancillary geographic data improved the accuracy and specificity of an urban land-use classification that was derived from multispectral remotely sensed imagery. A post-classification sorting procedure was developed to merge these data in a raster GIS. Post-classification sorting was used because it enabled only the "problem" areas of the classification to be updated, it allowed for the inclusion of more than one spatial data layer at a time, and it was easy and quick to perform. The routines developed are also portable to other study areas with only minor alterations.

The integration of the zoning data with the supervised classification of Landsat TM imagery improved the accuracy and specificity of the classification. The accuracy was increased significantly by eight percent (from 77 percent to 85 percent) when the broader categories of the initial classification are considered. The number of identifiable classes also increased. For the 13 classes generated from TM plus zoning, accuracy increased five percent; accuracy decreased three percent for the 15 classes generated from TM plus zoning and housing density. The confusion between classes that were cross-classified in our image classification (e.g., commercial and industrial areas) was generally reduced considerably.

The hypothesis that housing density data would improve the classification accuracy of residential classes was neither supported nor rejected because of uncertainty in the "ground truth" data. There was greater confusion among residential classes when post-sorting included housing density data, but this is at least partially attributable to errors in the reference data.

The general process of developing rules based on various possible combinations of land-use classes and zoning and housing density should be transferable to other applications. The precise rules will depend on the kind of ancillary data available, including its quality, specificity, and currency. Some information about potential misclassification of the satellite imagery, such as omission and commission data from cross-tabulation tables, will be useful to develop rules that resolve discrepancies without introducing additional errors from the zoning or density data.

Model sensitivity analysis indicated that any of the data sources and methods, except zoning alone, would provide sufficiently accurate and specific land-use information for the SLAMM model in this community. However, geographic data such as land use is typically used for other purposes beyond that for which it is generated. In this case, these data will be used for non-point source pollution control planning, for example, to target nonpoint source best management practices (Kim *et al.*, 1993).

The use of ancillary spatial information to improve a supervised classification has been demonstrated. For a single

TABLE 5. DIFFERENCE IN POLLUTANT LOADINGS FROM VALUE ESTIMATED USING GROUND TRUTH DATA SET FOR DIFFERENT CLASSIFICATIONS TECHNIQUES

Pollutant	Classification TM	TM and Zoning	TM, Zoning, and Housing	Zoning
Lead	−4.9	−11.5	− 9.0	47.2
Copper	−7.6	−14.1	−12.3	30.6
Zinc	−6.6	−12.5	−11.1	40.1
Cadmium	−3.4	−8.2	−12.8	29.7
Phosphorus	−2.8	−5.6	−11.0	28.7
Suspended Sediment	−3.5	−7.9	−12.1	32.6

coverage of a single municipality, available aerial photography is a better source of land-use data, both in terms of cost and specificity (Ventura and Harris, 1993). However, if a land use in an extensive region is needed, or continuous updates are needed, satellite information should be considered. The additional effort to improve the accuracy and specificity of satellite classification may be cost-effective for large areas or in subsequent uses.

Acknowledgments

This study was funded in part by the Wisconsin Department of Natural Resources as part of their Priority Watersheds Nonpoint Source Pollution Program. During the course of this study, considerable advice and support was provided by WDNR officer, Jeff Prey. We would like to thank our colleague, Kye Kim, for his help with technical aspects of this project. We also acknowledge the guidance provided by Professors Tom Lillesand and Frank Scarpace of the University of Wisconsin-Madison, Environmental Remote Sensing Center, and Pete Thum of the University of Wisconsin-Madison Land Information and Computer Graphics Facility.

References

Alwashe, M. A., S. Jutz, and J. Zilger, 1988. Integration of SPOT and Landsat Thematic Mapper Data for Land-use and Urban Mapping of At'taif, Saudi Arabia, *Digest - Int. Geoscience & Remote Sensing Symp. (IGARSS '88)*, Edinburgh, U.K., p. 629.

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, U.S. Gov. Printing Office, Washington, D.C.

Baraldi, A., and F. Parmiggiani, 1990. Urban Area Classification by Multispectral SPOT Images, *IEEE Trans. on Geoscience and Remote Sensing*, 28(4):674-680.

Baudot, Y., I. Nadasdi, and J. Donnay, 1988. Towards an Urban Land-Use Classification Using Textural and Morphological Criteria, *Digest - Int. Geoscience & Remote Sensing Symp, (IGARSS '88)*, Edinburgh, U.K., pp. 211-212.

Bolstad, P., and T. M. Lillesand, 1992. Rule-Based Classification Models: Flexible Integration of Satellite Imagery and Thematic Spatial Data, *Photogrammetric Engineering & Remote Sensing*, 58(7):965–971.

Congalton, R. G., R. G. Oderwald, and R. A. Mead, 1983. Assessing Landsat Classification Accuracy Using Discrete Multivariate Analysis Techniques, *Photogrammetric Engineering & Remote Sensing*, 49(12):1671-1678.

Cushnie, J.L., 1987. The Interactive Effect of Spatial Resolution and Degree of Internal Variability within Landcover Types on Classification Accuracies, *International Journal of Remote Sensing*, 8(1):15-29.

Golden, M., and L. Lackey, 1992. Using Ancillary Data in Post-Classification Modeling to Increase the Accuracy of Conifer Species Classification from Landsat Thematic Mapper Data, *GIS'92 Symposium*, Vancouver, British Columbia, Canada.

Gong, P., and P.J. Howarth, 1990. Use of Structural Information for Improving Land-Cover Classification Accuracies at the Rural-Urban Fringe, *Photogrammetric Engineering & Remote Sensing*, 56(1):67-73.

Haack, B., N. Bryant, and S. Adams, 1987. Assessment of Landsat MSS and TM Data for Urban and Near-Urban Landcover Digital Classification, *Remote Sensing of Environment*, 21(2):201-213.

Harrison, A.R., and T.R. Richards, 1988. Multispectral Classification of Urban Land Use Using SPOT HRV Data, *Digest - International Geoscience and Remote Sensing Symposium*, Edinburgh, U.K., pp. 205-206.

Janssen, Lucas L. F., Marijke N. Jaarsma, and Erik T. M. van der Linden, 1990. Integrating Topographic Data with Remote Sensing for Land-Cover Classification, *Photogrammetric Engineering & Remote Sensing*, 56(11):1503-1506.

Kim, K., S. J. Ventura, P.M Harris, P.G. Thum, and J. Prey, 1993. Urban Nonpoint Source Pollution Assessment Using A Geographical Information System. *Journal of Environmental Management*, in press.

Hutchinson, C.F., 1982. Techniques for Combining Landsat and Ancillary Data for Digital Classification Improvement, *Photogrammetric Engineering & Remote Sensing*, 48(1):123-130.

Khorram, S., J. A. Brockhaus, and H. M. Cheshire, 1987. Comparison of Landsat MSS and TM Data for Urban Land-Use Classification, *IEEE Trans. on Geoscience and Remote Sensing*, GE-25(2):238-243.

Lalitha, L., 1989. Technique for Road Detection from High Resolution Satellite Images, *Digest - Int. Geoscience & Remote Sensing Symp.*, Vancouver, Canada, pp. 2246-2249.

Leak, S. M., and G. Venugopal, 1990. Thematic Mapper Thermal Infrared Data in Discriminating Selected Urban Features, *Int. J. Remote Sensing*, 11(5):841-857.

Martin, L.R.G., and P. J. Howarth, 1989. Change Detection Accuracy Assessment Using SPOT Multispectral Imagery of the Rural-Urban Fringe, *Remote Sensing of Environment*, 30(1):55-66.

Møller-Jensen, L., 1990. Knowledge-Based Classification of an Urban Area Using Texture and Context Information in Landsat TM Imagery, *Photogrammetric Engineering & Remote Sensing*, 56(6): 899-904.

Pitt, R., 1989. *SLAMM 5. Source Loading and Management Model: An Urban Nonpoint Source Quality Model*, Univ. of Alabama, Birmingham.

Rosenfield, G. H., and K. Fitzpatrick-Lins, 1986. A Coefficient of Agreement as a Measure of Thematic Classification Accuracy, *Photogrammetric Engineering & Remote Sensing*, 52(2):223-227.

Shamsi, U. M., J. M. Maslanik, and S.E. McGimsey, 1991. Remote Sensing and GIS Assess Storm Sewer Master Plan, *GIS World*, September, pp. 82-86.

Spooner, J.D., 1991. Automated Urban Change Detection Using Scanned Cartographic and Satellite Image Data, *Technical Papers, 1991 ACSM-ASPRS Fall Convention*, Atlanta Georgia, pp. B118-B126.

Treitz, P.M., 1992. Application of Satellite and GIS Technologies for Land-Cover and Land-Use Mapping at the Rural-Urban Fringe: A Case Study, *Photogrammetric Engineering & Remote Sensing*, 58(4):439-448.

U.S. Environmental Protection Agency, 1990. *EPA Administered Permit Program; The National Pollutant Discharge Elimination Program*, Washington, D.C.

Ventura, S.J., and P.M. Harris, 1993. A Comparison of Classification Techniques and Data Sources for Urban Land Use Mapping, *GeoCarto International*, 9(3):5-14.

Welch, R., and M. Ehlers, 1987. Merging Multiresolution SPOT HRV and Landsat TM Data, *Photogrammetric Engineering & Remote Sensing*, 53(3):301-303.

Wharton, S. W., 1987. Spectral-Knowledge-Based Approach for Urban Land-Cover Discrimination, *IEEE Trans. Geoscience & Remote Sensing*, GE-25:3, pp. 272-282.

(Received 6 January 1993; revised and accepted 7 July 1993)

Paul Harris

Paul Harris conducted this study as part of his MS degree in the Environmental Monitoring Program, Institute for Environmental Studies, University of Wisconsin-Madison. He has returned to his native Australia where he is now developing GIS capabilities for Crowe, Schaffalitzky & Associates, Ltd.

Stephen J. Ventura

Stephen J. Ventura is an Assistant Professor of Environmental Studies and Soil Science at the University of Wisconsin-Madison. Research interests include GIS technology transfer and the use of GIS with environmental and resource management models.