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Mapping residential density patterns using multi-temporal Landsat data and a decision-tree classifier

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Abstract. We examined the utility of Landsat Thematic Mapper (TM) imagery for mapping residential land use in Montgomery County, Maryland, USA. The study area was chosen partly because of the availability of a unique parcel-level database of land use attributes and an associated digital map of parcel boundaries. These data were used to develop a series of land use classifications from a combination of leaf-on and leaf-off TM image derivatives and an algorithm based on 'decision tree' theory. Results suggest potential utility of the approach, particularly to state and local governments for land use mapping and planning applications, but greater accuracies are needed for broad practical application. In general, it was possible to discriminate different densities of residential development, and to separate these from commercial/industrial and agricultural areas. Difficulties arose in the discrimination of low-density residential areas due to the range of land cover types within this specific land use, and their associated spatial variability. The greater classification errors associated with these low-density developed areas were not unexpected. We found that these errors could be mitigated somewhat with techniques that consider the mode of training data selection and by incorporation of methods that account for the presence and amount of impervious surfaces (e.g. pavement and rooftops).

1. Introduction

Remote sensing has increasingly been used to map urban development patterns (Masek *et al.* 2000, Stuckens *et al.* 2000, Ward *et al.* 2000, Stefanov *et al.* 2001). Much of this work has utility for the development of spatially explicit models of land use change (Geoghegan *et al.* 1997, Gunter *et al.* 2000, Jantz *et al.*, in press). Effectively mapping residential land use is particularly important for exurban growth models that focus on the individual property owner, as they require fine-scale property parcel information (Bockstael 1996). It has been difficult to achieve this type of mapping with satellite imagery except at very high (1–4 m) spatial resolution (Barnsley and Barr 2000, Kontoes *et al.* 2000, Goetz *et al.*, in press), but

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fine resolution imagery is prohibitively expensive for mapping very large areas ($>1000\,km^2$). This creates a dilemma for meeting the planning needs of many rapidly changing jurisdictions.

The metropolitan area around the District of Colombia (Washington DC) provides an example of the jurisdictional challenges with rapid land use change. A total of 37 784 residential building permits were issued in the DC area in 1999 alone; on average over 29 000 were issued per year over the past 10 years (National Association of Home Builders 2001). This rate of development has had implications for traffic, air pollution, water quality, land value, and infrastructure costs such as utilities and schools (Burchell *et al.* 1998, Leggett and Bockstael 2000). In the USA, the spatial pattern of this conversion has tended to be one of increasingly fragmented, low-density development, popularly called exurban sprawl or simply 'sprawl'. Sprawl is characterized by land conversion at a rate of 2–3 times the rate of population growth and by increases in vehicle miles travelled of 4–5 times the population growth rate (Burchell *et al.* 1998).

In order to effectively map and monitor rates of sprawl, image classification methods must be developed to allow mapping of residential land use with widely available remotely sensed observations, such as those from the Landsat series of Thematic Mappers (TM). Furthermore, monitoring techniques based on analysis of individual landowner decision-making, such as some econometric models, require land use data at a very fine scale. Identifying individual parcels of low-density residential development (built parcels >0.5 acres), which are the fastest growing and most land consumptive forms defining exurban sprawl (Bockstael 1996), would be particularly useful.

Our objectives were to develop a technique for mapping residential density at the parcel level using Landsat TM imagery, and to distinguish these parcels from agriculture and commercial/industrial parcels. The primarily challenge of this effort is determining the spectral characteristics of individual parcels such that spectrally similar land use classes can be separated. Development of the approach would allow precise land use mapping in areas that do not have parcel-level property data available, and would permit expansion of the temporal domain throughout the Landsat TM era when parcel data were not available. These developments would be of particular benefit for agent-based econometric modelling efforts (see Geoghegan *et al.* 1997). Distinctions between land uses with spectrally similar land cover types are notoriously difficult to accomplish with remote sensing, but potential benefits for land use monitoring and planning in an age of extensive exurban sprawl are great (Goetz *et al.*, in press).

2. Study area and methods

2.1. *Study area*

We focused our study on Montgomery County, Maryland, on the northern border of Washington, DC (figure 1). The county contains a diverse mixture of land uses typical of exurban areas, including a 'high-technology' corridor characterized by dense commercial/industrial land use along a major transportation corridor. The county also has a moderately successful rural preservation programme that has preserved a portion of the county in traditional agricultural land uses and in forested parks and reserves (Maryland National Captial Parks and Planning Commission 2000).

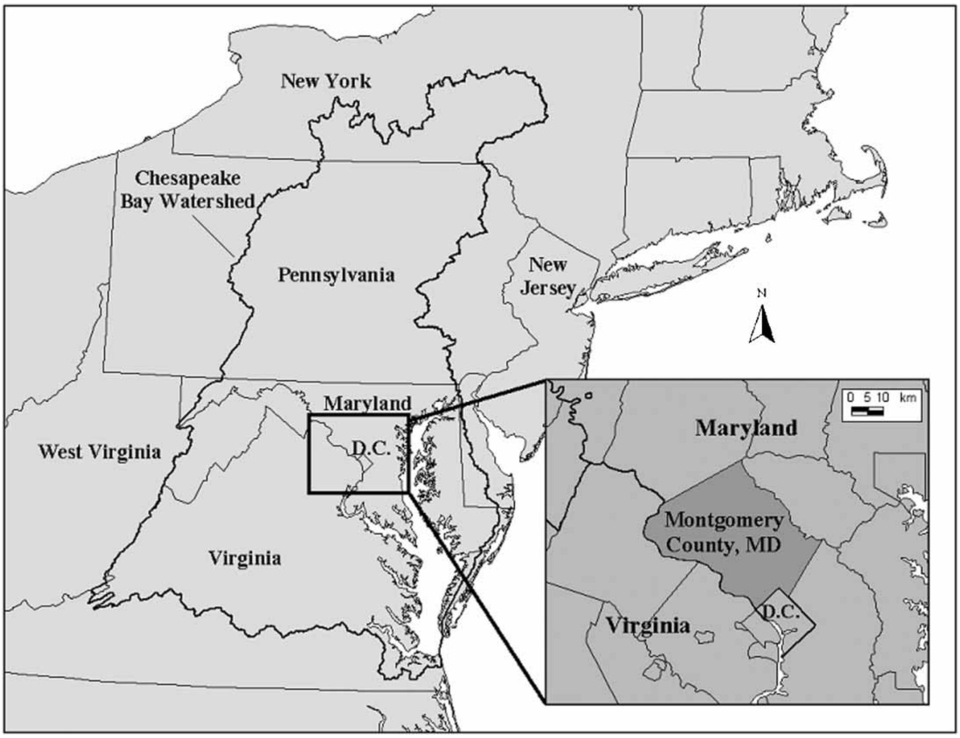

Figure 1. Study area map of Montgomery County, Maryland, USA, within the Chesapeake Bay Watershed and the mid-Atlantic region.

Working in the county permitted us access to numerous land cover/use products available through collaborating partners. A geo-referenced parcel-level tax database exists for Maryland, and Montgomery County Parks and Planning Commission provided a digitized planimetric map of all county parcels. These rich datasets, and the county's willingness to share resources and utilize our results, made it an excellent site in which to develop a land use mapping technique and identify the possibilities of residential land use mapping from Landsat imagery.

Of the nearly 300 000 parcels within the county, 76.6% were coded as residential. These were separated into density classes based on the number of housing units per acre, allowing us to examine the capability of TM imagery to differentiate residential densities while also identifying non-residential land uses that have similar spectral properties as detected by the Landsat 5 TM sensor. These include similarities between high density residential and commercial land uses, and between low density residential and agricultural parcels with built structures.

2.2. *Satellite sensor data*

The input data for the classification was Landsat 5 TM imagery. Cloud-free TM images for path 15 row 33 were collected in leaf-off (27 March 1998) and leaf-on (28 April 1998) conditions. The imagery was orthorectified using manual control point selection and 30 m National Elevation Data (NED) digital topographic maps. It was georeferenced using nearest-neighbour resampling to a Universal Transverse

Mercator (UTM) projection (zone 18, GRS 1980 spheroid, NAD83 datum), and specifying a 30 m output cell size. Additional processing steps were used to obtain parameters for input to the classification algorithm, including converting the raw image pixel values to units of absolute radiance values for each of the visible and near-infrared channels (bands 1–5 and 7).

Normalized Difference Vegetation Index (NDVI) images were derived from the visible and near-infrared band images (differences divided by sums), and an NDVI difference image, comparing NDVI before and after the canopy loses foliage (leaf-on versus leaf-off), was calculated to assist discrimination of residential land uses in highly heterogeneous areas where vegetation varies widely from cell to cell. Brightness, greenness and wetness (i.e. constrained principal component) images were calculated for the two scenes and were used as input to the classification algorithm. The ratio of band 5 to band 1 was included as an indicator of soil moisture, aiding in the discrimination of unvegetated areas (e.g. exposed soil) from impervious surfaces (e.g. concrete, pavement).

The input images were fused to create a single image of the TM scene containing all of the raw image data and the derived layers. The area encompassing Montgomery County was extracted from this composite input image and was used exclusively. Non-parametric predictor variables, such as population data and parcel boundaries, were available but not included in the classification in order to attempt development of a land use mapping technique that would be transferable to areas for which such datasets are unavailable. Similarly, texture images were not included. Texture analyses, such as spatial frequency models and mixture models, are useful for discriminating land uses in highly heterogeneous landscapes by considering the spatial arrangements of neighbouring pixels. We avoided these inputs, however, in order to isolate and test the potential for classifying individual pixels using the decision-tree classifier approach. One of our objectives was to determine if, using a very rich training dataset, we could discriminate subtle differences in spectral signatures at the pixel level. This would avoid the problem of textural metrics being specific for a given TM scene, and it would make classification algorithms more generally transferable to other TM scenes.

2.3. *Land use data for algorithm training*

Training data for the classification algorithm was identified using the 1997 MdProperty View, Maryland's digitized tax database. Developed by the Maryland Department of Planning, MdProperty View links digitized versions of the state's property maps to the State Department of Assessments and Taxation's parcel database, yielding a spatially explicit digital tax database with property-specific data including ownership, acreage, land use zoning, size and value of the property, and any improvements on the property. For every parcel, MdProperty View contains a point centroid (not parcel polygon) which is linked to a database containing over 100 attributes about the parcel. Training pixels for the classification process were selected by querying these attribute fields to identify parcels which represented different land use classes, and then using pixels from within those parcels.

Training data were collected for each of six land use classes: low density residential, medium density residential, high density residential, commercial/industrial, agriculture, and a general class that contained all other land uses.

The 'general' class consisted of known water areas and a sample of centroid points from all land uses other than those listed above, including institutional properties, country clubs, parks and others. While using a parcel's tax code as a surrogate for land use is generally reliable, the tax code for some parcels does not coincide with the actual land use on that parcel, which can introduce errors in training data selection. This problem was mitigated by selecting as training data only parcels with a built structure, with the exception of the agriculture class.

The residential density classes were identified by querying MdProperty View for parcels taxed as residential, containing a built structure and acreage coinciding with the Maryland Department of Planning's definition of residential density. Following this definition, low density residential parcels are greater than or equal to 0.5 acres but less than 5.0 acres. Medium density parcels are greater than or equal to 0.125 acres and less than 0.5 acres. High density residential parcels are less than 0.125 acres (Maryland Department of Planning 1998). Agricultural parcels were identified from MdProperty View's land use field, with no limitations on acreage. Descriptive statistics for the land use classes are shown in table 1.

Coverages of the selected training points were overlayed on the composite input image described in the satellite sensor data section above. For all cells underlying a selected parcel centroid, values from the composite image were extracted, so that each training pixel contained information from all of the layers of raw image data and derived layers. Centroid points were thought to provide a representative sample of the land cover found on each type of land use (Martin and Howarth 1989). For high and medium density residential parcels, which are the equivalent size of only one or two pixels, the centroid point was likely to fall, at least partially, on a built structure, capturing the highly mixed land use patterns of high density residential areas and potentially resulting in a unique reflectance pattern. Where the centroid point did not fall on a built structure, the training data included other land cover types found on those parcels (e.g. grass yards).

2.4. *Decision-tree classification*

A decision-tree classification software package, C 5.0 (Quinlan 1993), was used for the land use classifications. Decision trees class data into hierarchical structures through a process of recursive binary partitioning of predictor variables into smaller, more homogeneous groups. A given algorithm searches for the dependent variable that, if used to split the population of cells into two groups, would explain the largest proportion of deviation of the independent variable. The process of

Table 1. Summary of 1997 MdProperty View data, Montgomery County, Maryland. The 'Other' land use class includes institutional properties and parks, among others. The database includes 290 197 total parcels covering 292 777 total acres.

	Land use class				
	Residential	Commercial	Industrial	Agriculture	Other
Parcels (% of total)	76.6	1.2	0.5	0.7	21.0
Total acres (% of total)	36.1	1.6	2.0	31.8	28.5
Mean acres	0.5	1.1	4.1	46.2	1.4
Max. acres	476	139	412	860	2607
With built structure (%)	92.1	74.5	68.5	49.3	44.4

binary partitioning results in traceable splits in the predictor variable data, and these splits provide useful information about the properties of different land cover types (Friedl and Brodley 1997). At each new split in the tree, the same exercise is conducted and the tree is grown until it reaches terminal nodes, or leaves, with each leaf representing a unique set of areas within the image. Every leaf has a land cover type assignment. Trees can be pruned to eliminate or merge terminal nodes that do not contribute to the overall classification accuracy of the decision tree. Decision trees are strictly non-parametric and do not require assumptions regarding the statistical properties of the input data. In addition, they handle nonlinear relations between features and classes, allow for missing values, and are capable of handling both numeric and categorical inputs. Decision trees also have significant intuitive appeal because the classification structure is explicit and therefore easily interpretable. The technique has been shown to provide a robust statistical method by which to predict land cover types at regional and global scales from remotely sensed data (e.g. Hansen *et al*. 1996, Friedl and Brodley 1997).

2.4.1. *Classification scenarios*

We used the decision-tree technique to classify residential land use types at a very fine scale. The classification tree was constrained to a small number of land uses in order to improve class separability and to assess discriminatory power. The classification process was run five times, each time using a different sampling scheme to train the algorithm. We refer to these as cases. The training datasets were varied in terms of size, the proportions of different land use samples within the sets, and the number of land use classes included (table 2). We analyse in detail only the results from the two cases with the highest Kappa statistic.

Training data for Case 1 consisted of 12 890 points drawn randomly from four land use classes: low density residential, medium density residential, high density residential, and the general non-residential class, which included agriculture and commercial/industrial parcels. The relative size of the land use classes represented in the sample were in direct proportion to their occurrence in the state's tax database.

Table 2. Description of the training datasets used for the five different cases of decision-tree algorithm development. Case 1—proportional to size of MdProperty View parcel database; Case 2—equal size training datasets for the residential density classes; Case 3—proportional to size, with full sample of MdProperty View parcels; Case 4—equal size for the residential density classes with additional sampling for other classes; Case 5—same as Case 4 but with samples drawn throughout parcels rather than the centroid. The results of Case 1 are referred to throughout as 'residential density mapping', and the results of Case 4 are referred to as 'land use mapping'.

	Case				
	1	2	3	4	5
Non-residential	3800	4720	18 250	5000	5000
Low density	1270	1260	28 000	5000	5000
Medium density	5760	1260	103 500	5000	5000
High density	2065	1260	22 250	5000	5000
Agricultural	–	–	–	2102	2102
Commercial/Industrial	–	–	–	2863	2863
Total training size	12 890	8500	172 000	24 965	24 965

Agriculture and commercial/industrial classes were not extracted separately for this case to ascertain whether there was a distinct spectral signature associated with residential parcels. The results of this case are analysed below in the section entitled 'Residential density mapping'.

Training data for Case 2 consisted of 8500 points drawn from the same four land use classes used in Case 1. The majority of training points used in this case were drawn from the non-residential class, with the three residential density classes each represented by an equal number of training points. The objective of this case was to emphasize the non-residential class as the default in order to minimize errors of commission in the residential classes. Based on the Kappa statistic the results of this case were not analysed further.

Case 3 consisted of 172 000 training points also drawn from the three residential classes and the non-residential class. The objective of this case was to include all possible centroid points as training data in order to develop the most specific spectral characterization possible for each land use class. The results of this case were not analysed further.

The training dataset for Case 4 included the three residential classes and the non-residential class, as well as separate agricultural and commercial/industrial classes. The training set consisted of 24 566 points, with equal sample sizes from the three residential classes and the non-residential class and smaller samples from the agricultural and commercial/industrial classes (as the latter two classes were limited in number). The objective of this training approach was to reduce the error term experienced in previous cases by separating out specific non-residential classes that might have significant spectral overlap with one or more residential class. The results of this case are analysed below in the section entitled 'Land use mapping'.

The training dataset for Case 5 was similar to that for Case 4, but the training pixels for the low density residential class were collected from throughout low density parcels, rather than from centroid points only. This was done by merging low density residential centroid points from MdProperty View with a digitized polygon property map for Montgomery County. The resulting polygon coverage was used to extract attributes for sample cells falling throughout the low density residential parcels. The objective of this approach was to capture the larger range of reflectance values likely to be found on a low density residential parcel. The training set consisted of 24 566 points, with equal sample sizes from the three residential classes and the non-residential class and smaller samples from the agricultural and commercial/industrial classes. Results of this case were not analysed further but are addressed in the interpretation of results.

2.5. *Accuracy assessment*

Three methods were used to assess classification accuracy. Cross-validation statistics were derived from the output of the decision-tree software, and additional sampling of the MdProperty View was conducted for an independent accuracy assessment. Visual assessment at very fine scales, comparing the classified TM output and the MdProperty View data, was done to highlight issues associated with classification accuracy.

For the cross-validation assessment, 25% of the training cells for each case were withheld from the training process to be used in post-classification cross-validation. The Kappa statistic was calculated as a measure of actual agreement and chance agreement between training data and classified data (Kalkhan *et al.* 1998).

Although there are limitations with the use of Kappa statistics to measure levels of agreement, generally the closer the statistic is to 1.0, the higher the accuracy and the further the classification is from chance agreement (see Monserud and Leemans 1992 and DeFries and Chan 2000 for more thorough assessments). Accuracy assessments and associated errors of commission and omission were calculated using the technique outlined in Congalton and Green (1999).

For the independent sampling assessment, land use data from the MdProperty View point coverage was merged with Montgomery County's digitized parcel coverage to produce a polygon coverage containing the MdProperty View land use data, from which independent sample pixels could be tested. This step allowed for random selection of test pixels falling throughout any parcel, rather than only from the centroid point. The error rate in merging the point data file with the polygon data file, determined by the number of polygons not containing a single centroid point, was 4%. From the merged polygon coverage, separate coverages were extracted for each land use class (low density residential, medium density residential, etc.) containing all parcels falling within that class according to the MdProperty View data. For each of these individual land use coverages, the classified image output was assessed to determine the accuracy of pixel classification. Again, Kappa statistics and errors of commission and omission were calculated.

3. Results

3.1. *Residential density mapping*

Visual assessment of the residential density map, which contains the results from the classification using Case 1 training data, showed success in distinguishing between different densities of residential development. Figure 2 shows that medium density residential areas were identified relatively well, as were clusters of high density residential properties. Low density residential communities were discriminated but with more disjunct patterns and 'speckle' within areas of medium and high density residential. There were also indications of medium and high density residential

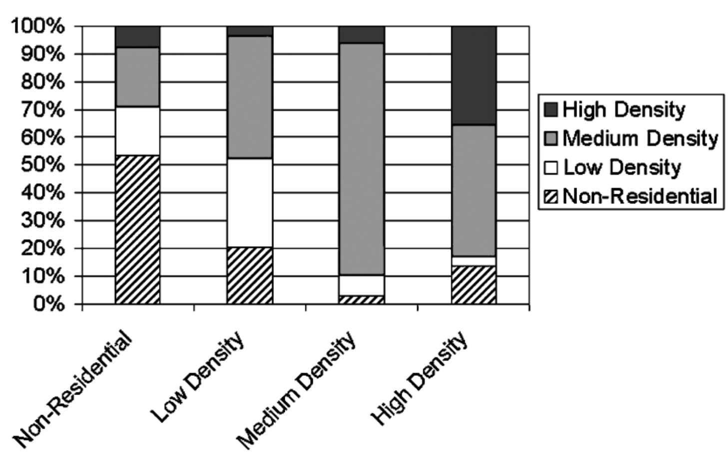

Figure 2. Distribution of classified samples in each MdProperty View land use class for the residential density mapping Case 1.

speckle within low density residential areas due to the presence of impervious surface areas such as driveways and paved areas, which increase likelihood of classification as medium or high density.

The cross-validation analysis of Case 1 yielded an overall accuracy of 71.6%, with a Kappa of 0.56. Table 3 shows that the medium density residential class and the general non-residential class were classified with over 80% accuracy. The low density residential class had an accuracy of just 25%, with much of the error attributed to confusion with the medium density residential class. The high density residential class was classified accurately for 40% of cells, with the error again attributed to confusion with the medium density class. Thus the amount of low and high density residential area were underestimated and medium density areas were overestimated.

Using independent sampling to assess Case 1, the overall accuracy was 53.8% and the Kappa statistic was 0.25. Comparison of the decision-tree classification with MdProperty View land use classes (table 4) shows that the highest accuracy was in the non-residential and medium density classes. The other classes had relatively high error rates (figure 3). In the low density polygon coverage, the error was attributed to confusion with both the medium density residential class and the non-residential class. In the high density polygon coverage, a high proportion of cells again were classified as medium density residential. The medium density residential class included the highest percentage of correctly classified cells, with 84% of all pixels within the medium density polygon coverage correctly classified. Producer's accuracies for the residential classes were less than User's accuracies, thus errors of omission were greater than those of commission (i.e. inclusion or false positives).

Table 3. Results of cross-validation accuracy assessment for Case 1, residential density mapping. The Kappa statistic was 0.56 and overall accuracy 71.6%. Omission errors can be estimated as 100% less Producer's accuracy, and commission (inclusion) errors as 100% less User's accuracy.

	Classified as			
	Non-residential	Low density	Medium density	High density
Non-residential	**784**	28	92	49
Low density	41	**81**	185	13
Medium density	37	75	**1254**	106
High density	60	17	211	**189**
Producer's accuracy (%)				
Non-residential	**82.3**	2.9	9.7	5.1
Low density	12.8	**25.3**	57.8	4.1
Medium density	2.5	5.1	**85.2**	7.2
High density	12.6	3.6	44.2	**39.6**
User's accuracy (%)				
Non-residential	**85.0**	13.9	5.3	13.7
Low density	4.4	**40.3**	10.6	3.6
Medium density	4.0	37.3	**72.0**	29.7
High density	6.5	8.5	12.1	**52.9**

Table 4. Results of independent accuracy assessment comparing the decision-tree classification versus MdProperty View land use classes for Case 1, residential density mapping. The Kappa statistic was 0.25 and overall accuracy 53.8%. See table 3 legend regarding errors of omission and commission.

	Classified as			
	Non-residential	Low density	Medium density	High density
Non-residential	**470 812**	153 127	190.944	65 230
Low density	31 442	**48 823**	67 670	5451
Medium density	3789	10 087	**110 610**	7942
High density	1862	468	6449	**4824**
Producer's accuracy (%)				
Non-residential	**53.5**	17.4	21.7	7.4
Low density	20.5	**31.8**	44.1	3.6
Medium density	2.9	7.6	**83.5**	6.0
High density	13.7	3.4	47.4	**35.5**
User's accuracy (%)				
Non-residential	**92.7**	72.1	50.8	78.2
Low density	6.2	**23.0**	18.0	6.5
Medium density	0.7	4.7	**29.4**	9.5
High density	0.4	0.2	1.7	**5.8**

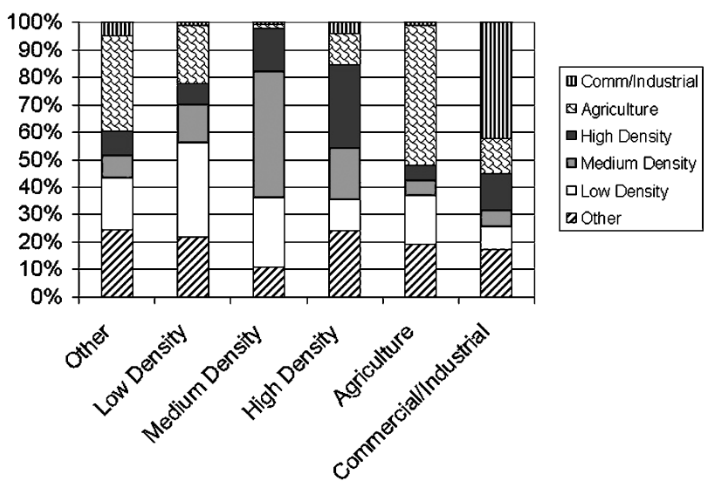

Figure 3. Distribution of classified samples in each MdProperty View land use class for the land use mapping Case 4.

3.2. *Land use mapping*

Visual assessment of the land use map, which contains the results from the classification using Case 4 training data, revealed a high degree of speckle and misclassification of land use types. Agricultural parcels and high density residential areas were identified (figure 2), but errors of commission were high for both classes (tables 5 and 6). Medium and low density residential communities were intermingled, and the commercial/industrial class showed little accuracy in this classification.

Cross-validation assessment showed a moderate Kappa statistic of 0.47.

Table 5. Results of cross-validation accuracy assessment for Case 4, land use mapping. The Kappa statistic was 0.47 and overall accuracy 56.8%. See table 3 legend regarding errors of omission and commission.

	Classified as					
	Low density	Medium density	High density	Agriculture	Commercial/ Industrial	Other
Low density	**296**	57	36	4	41	26
Medium density	51	**318**	92	0	3	46
High density	41	102	**255**	3	1	85
Agriculture	4	11	24	**231**	1	41
Commercial/Industrial	106	8	5	1	**66**	4
Other	52	68	113	51	3	**254**
Producer's accuracy (%)						
Low density	**64.3**	12.4	7.8	0.9	8.9	5.7
Medium density	10.0	**62.4**	18.0	0.0	0.6	9.0
High density	8.4	20.9	**52.4**	0.6	0.2	17.5
Agriculture	1.3	3.5	7.7	**74.0**	0.3	13.1
Commercial/Industrial	55.8	4.2	2.6	0.5	**34.7**	2.1
Other	9.6	12.6	20.9	9.4	0.6	**47.0**
User's accuracy (%)						
Low density	**53.8**	10.1	6.9	1.4	35.7	5.7
Medium density	9.3	**56.4**	17.5	0.0	2.6	10.1
High density	7.5	18.1	**48.6**	1.0	0.9	18.6
Agriculture	0.7	2.0	4.6	**79.7**	0.9	9.0
Commercial/Industrial	19.3	1.4	1.0	0.3	**57.4**	0.9
Other	9.5	12.1	21.5	17.6	2.6	**55.7**

Agricultural class had the highest Producer's accuracy, with 231 out of 312 or 74% of samples correctly classified (table 5). Classification of low density residential and high density residential were improved over the 'residential density mapping' results, while accuracy of the medium density and the non-residential classes dropped. The commercial/industrial class was just 34.7% accurate, with the majority of error unexpectedly occurring in the low density residential class.

Assessment of the land use mapping results using the independent MdProperty View polygon parcel coverage showed a substantial amount of error. Only the agriculture class contained over 50% correctly classified cells (table 6). The medium density residential and commercial/industrial classes were just over 40% correctly classified. All land use polygon coverages showed speckle and an inability to accurately separate residential density land use to the full extent of parcel boundaries (figure 4).

4. Discussion

Of the five classifications that were conducted using different sampling methods, only two of the five samples were examined in detail, based on overall accuracy and the Kappa statistic of agreement. We assessed the most accurate and generally applicable approach for residential density mapping (Case 1) and for broader land use mapping (Case 4). The residential density mapping case showed high visual correspondence with the MdProperty View land use data (figure 4). Residential communities, including individual parcels of different densities, were identified from

Table 6. Results of independent accuracy assessment comparing the decision-tree classification versus MdProperty View land use classes for Case 4, land use mapping. The Kappa statistic was 0.15 and overall accuracy 34.5%. See table 3 legend regarding errors of omission and commission.

	Classified as					
	Low density	Medium density	High density	Agriculture	Commercial/ Industrial	Other
Low density	**71 624**	29 365	15 364	44 220	2165	71 624
Medium density	33 837	**61 198**	20 495	2205	650	14 285
High density	3010	5069	**8154**	3003	1112	6495
Agriculture	75 147	23 567	21 864	**212 412**	4430	79 727
Commercial/Industrial	3693	2720	5953	5819	**18 904**	7773
Other	166 710	73 148	74 865	306 925	41 727	**216 738**
Producer's accuracy (%)						
Low density	**34.4**	14.1	7.4	21.2	1.0	21.8
Medium density	25.5	**46.1**	15.4	1.7	0.	10.8
High density	11.2	18.9	**30.4**	11.2	4.1	24.2
Agriculture	18.0	5.6	5.2	**50.9**	1.1	19.1
Commercial/Industrial	8.2	6.1	13.3	13.0	**42.1**	17.3
Other	18.9	8.3	8.5	34.9	4.7	**24.6**
User's accuracy (%)						
Low density	**20.2**	15.1	10.5	7.7	3.1	12.2
Medium density	9.6	**31.4**	14.0	0.4	0.9	3.9
High density	0.9	2.6	**5.6**	0.5	1.6	1.8
Agriculture	21.2	12.1	14.9	**37.0**	6.4	21.5
Commercial/Industrial	1.0	1.4	4.1	1.0	**27.4**	2.1
Other	47.1	37.5	51.0	53.4	60.5	**58.5**

the Landsat imagery. The larger scale map in figure 5, while only a sample of the area, reveals some of the issues associated with land use mapping at the pixel level. The scattered medium and high density residential cells among what should be low density residential parcels corresponded almost entirely to roads and other impervious surfaces. Medium density parcels were occasionally identified as low density when the structure was built at the fringe of the property and there was a substantial portion of the remainder of the parcel in vegetation. Despite speckling in the residential land use map, our results suggest that the approach is useful for mapping residential development and discriminating residential parcels from adjacent land uses. To a lesser extent, the approach was useful for discriminating different densities of residential development from one another.

The map of land use (from Case 4) had greater errors in some land use types but showed statistical improvement over Case 1 in residential density discrimination because agricultural and commercial/industrial classes were specifically identified in the training data. The addition of these classes helped separate non-residential parcels that had land cover similar to that found in these residential classes. Improvement in the high and low density classes came at the expense of somewhat lower accuracy in the medium density residential class.

The results of Cases 2, 3 and 5 were not assessed extensively because of their lower overall accuracies of 0.48, 0.38 and 0.44, respectively. Case 2 featured a large sample of non-residential training points, which improved the selection of the

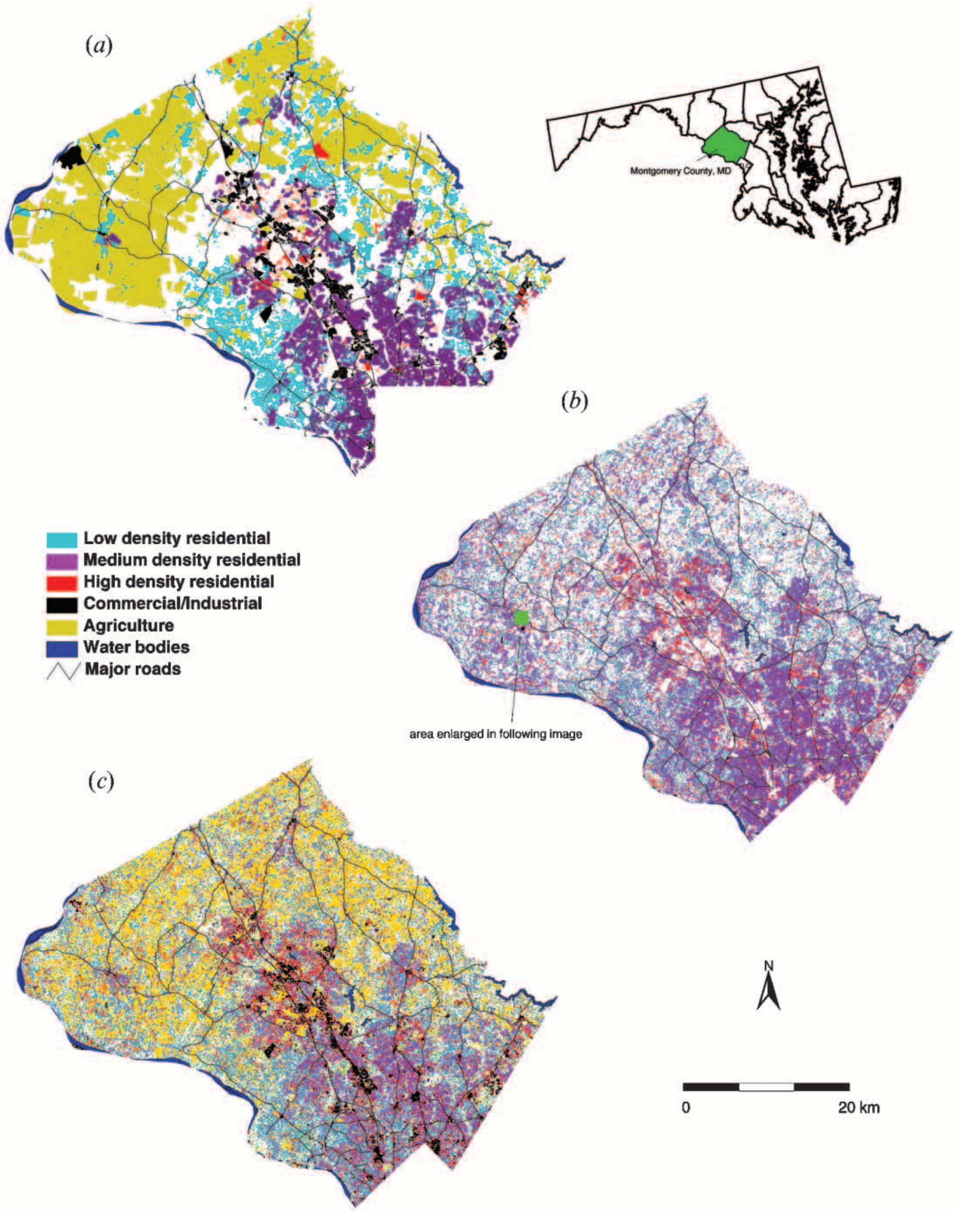

Figure 4. Land use and residential density patterns across Montgomery County, Maryland. (*a*) Residential density by parcel, coded from the MdProperty View parcel database that was used for training; (*b*) residential density mapping (Case 1) derived from Landsat TM; (*c*) land use mapping (Case 4) from Landsat TM.

non-residential class, but at the expense of accuracy in the residential classes. Case 3 consisted of the largest sampling set available but, importantly, did not improve results. Case 5 included a low density residential training set that was drawn from entire low density residential parcels, but this also did not improve classification results. The high variability of accuracy between classifications produced through

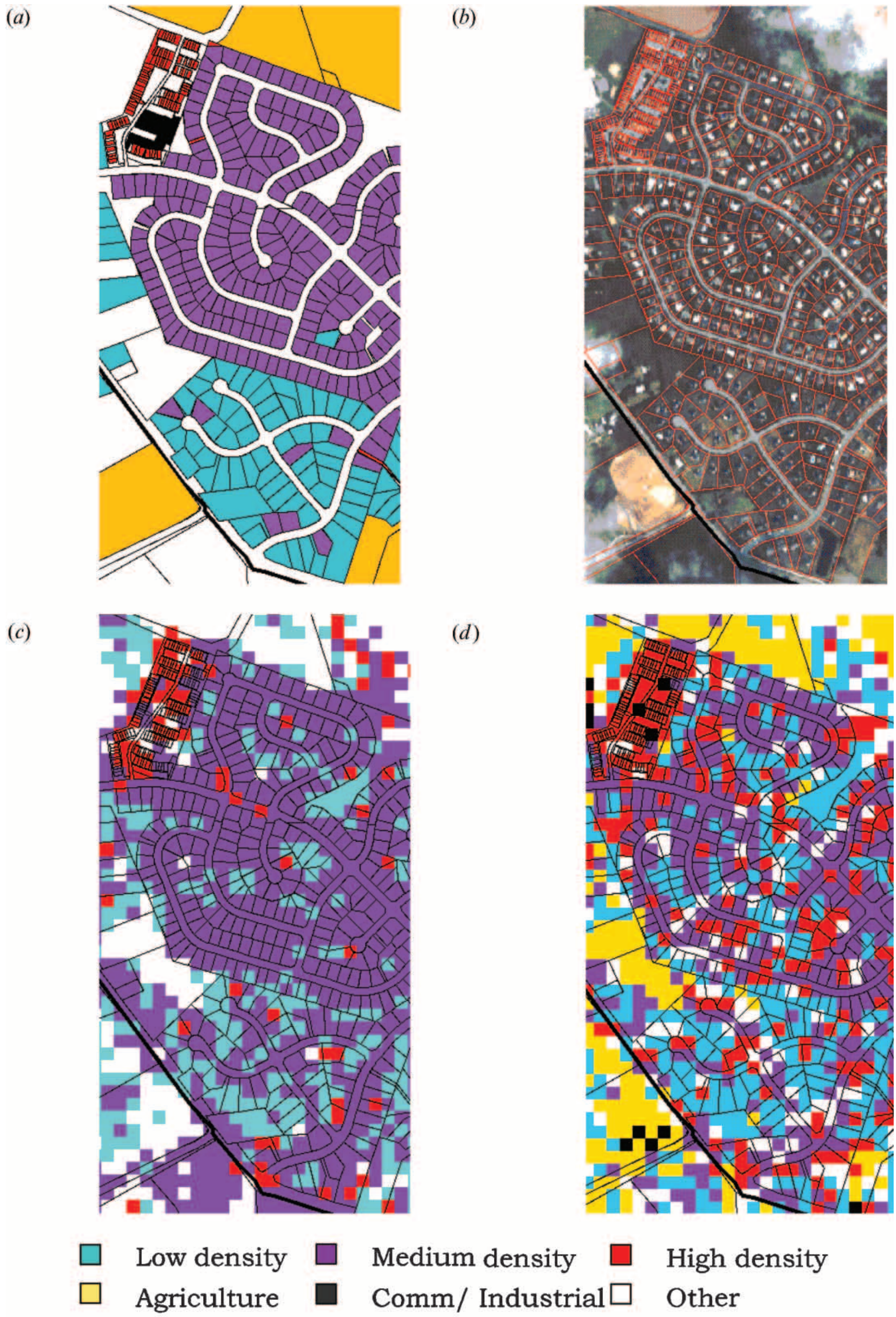

Figure 5. Residential density patterns in Gaithersburg, Montgomery County, Maryland. (*a*) Residential density by parcel, coded from the MdProperty View parcel database that was used for training; (*b*) Ikonos imagery overlaid with Montgomery County property base map; (*c*) residential density mapping (Case 1) derived from Landsat TM; (*d*) land use mapping (Case 4) from Landsat TM.

different training sampling methods emphasizes the importance of the mode of sampling for training set selection. Decision-tree algorithms are known to require large sample sizes (Friedl and Brodley 1997, Friedl *et al.* 2000), but our results suggest that there are additional issues, which we address further in the following sections.

4.1. *Training datasets*

Even when extensive training data are available, as in this study, the size and composition of the training data influence results. The low accuracy for Case 3 suggests that, in terms of sampling size, bigger is not necessarily better. We hypothesized that a very large sampling size would capture more of the subtle variation between land cover on different land use classes. Results suggest, however, that with the large training set there was reduced likelihood of spectral discrimination between land uses. A smaller training set of the most representative parcels in each class apparently allows the decision tree to capture more of the differences in land cover between land use classes. Thus the spatial distribution of sampling sites is at least as, if not more, important than the size of the sample.

The number of classes included in the classification training set also influenced the classification accuracy of individual land use types. The results of Case 4 show that the three residential density classes were separated better when the agricultural and commercial/industrial classes were included. Identifying these additional classes, rather than lumping them in the general class, allowed them to be separated from residential parcels that had similar land cover, reducing error in the classification of residential densities. Increasing the number of training classes can improve classification, although this introduces difficulties associated with identifying other land use classes that can be spectrally defined accurately.

A third consideration associated with training set selection was the influence of drawing training values from entire parcels (Case 5), which did not improve the accuracy of the classification over training data selected from the parcel centroids alone. Accuracy for the low density residential class from Case 5 was consistent with other samples, but the overall accuracy decreased relative to Case 4, which was drawn only from centroids. This confirms that the mix of land covers found within low density residential parcels is not distinguishable spectrally from similar land covers found on other parcels such as parks, institutions, or agricultural parcels.

While the size of the overall training sample did not improve results, the relative size of each land use class in the training sample can influence results. The class with the largest training sample tended to be over-selected because of the increased variability of the class's spectral range usually associated with a larger relative sample. The high accuracy rate for the medium density residential class in Case 1 appears to be associated with the larger sample size for that class relative to other residential areas (low and high density). More samples do not, however, necessarily improve classification accuracy because they can result, in the case of residential density discrimination, in greater commission errors.

4.2. *Parcels versus pixels and land cover versus land use*

A problem with mapping parcel level land use from TM is that larger parcels exhibit higher variability in land cover. Just over two 30 m cells fit within a 0.5 acre parcel, the mean residential parcel size in Montgomery County. A high density residential parcel is equivalent to the size of less than one 30 m pixel. The largest low density residential parcel, 5.0 acres, is equivalent in area to 18 pixels and can contain highly heterogeneous land cover.

Another challenge is the failure of cell boundaries to match parcel boundaries. Resolution limitations cause pixels to extend beyond or overlap parcel boundaries. This can introduce error both in training data selection and in classified output.

The primary challenge in mapping residential density from Landsat, however, is that remote sensing imagery provides information on land cover, which does not translate directly into land use information (Cihlar and Jansen 2001). Land cover can be a surrogate for land use where the land cover is homogeneous and clearly representative of a particular land use, such as a quarry, an agricultural field, or a parking lot. Where residential development is of a high density and is highly contiguous, it can be captured from TM imagery. It is more difficult to map land uses for which the land cover is highly heterogeneous. While sensors can detect radiances associated with the presence of built structures, it remains difficult to map residential parcels of mixed land cover, particularly low-density residential areas. Unfortunately these parcels are of greatest interest to land use change modellers because these denote areas where land use is typically most rapidly transforming (Bockstael 1996, Burchell *et al.* 2000), i.e. where exurban sprawl is occurring.

Mapping land use at the parcel level involves identifying all land covers on a parcel, both built structures and other land covers, and grouping them together in the same land use class. In order to correctly identify low density residential parcels, for example, a classification technique must discriminate between residential structures and other impervious surfaces, and between non-built cells on low density residential parcels, such as yards, from non-built cells that occur on other parcels, such as parks. Using the decision-tree technique with the MdProperty View data, we made progress in mapping residential land use of higher densities but we were unable to develop a general algorithm or 'decision rules' that could be applied to other locations with sufficient confidence in mapping unit accuracy. Mapping parcel level land use from Landsat imagery remains a difficult problem that requires extensive and accurate training information, which must be sampled and applied judiciously.

In separate analyses we have developed algorithms to map impervious surface areas (Smith *et al.*, in press). While the presence of impervious surfaces indicates human alteration of the landscape frequently associated with urbanization and residential development, we found that including impervious surface coverages as input in the classification process did not substantially improve our ability to map different densities of residential land use. The amount of impervious surface area increased with the density of development, but there was significant overlap in the amount of impervious area among adjacent density classes. For example, low density residential areas had impervious area ranging from 5 to 30%, medium density from 10 to 40%, and high density from 20 to 80%. The differences between the means of these classes were statistically significant ($p < 0.001$), partly because of the very large sample sizes, but the amount of impervious land cover was not a good predictor of residential land use because of the wide range of land cover within these land use categories.

5. Conclusions

There is a great deal of interest in mapping residential density patterns because of the rapid transformation of exurban lands through what has commonly come to be known as 'suburban sprawl', which is best captured through monitoring the development of low-density residential areas. We have tested a method of residential land use classification using a decision-tree classifier and found that there are inherent limitations to mapping residential density in a complex area of heterogeneous land use such as suburban Maryland. Classification accuracies were insufficient to provide an algorithm or decision rules of general practical utility that can be transferred to other TM scenes. The results did show some potential for separating different densities of residential development where the development occurs in clusters, and this may be a tool that can have practical applicability for monitoring sprawl. We explored a number of case scenarios accounting for the effects of sample size and, in the case of low density residential areas, sampling variability expressed through selection of entire parcels rather than representative parcel centroids. Results suggest increased sample size and greater spatial representation do not necessarily improve accuracy, particularly if sampling does not represent the distinctive between-class variability of land use types.

A number of considerations on the practical utility of training datasets and inherent limitations in the distinction between land cover and land use can be made. Disaggregation and 'speckling' of land use classes shown in figures 1 and 2 resulted primarily from the presence of impervious surfaces (e.g. concrete, pavement, rooftops) in residential areas, and the resulting confusion of these with more intensive land uses (high density residential and commercial/industrial areas). Conversely, low density residential areas often consisted of a mixture of land cover types that occurred in various densities and types sufficiently to introduce mapping errors with other vegetation classes (e.g. trees and grass). Future work will focus on the potential for fusion of impervious surface maps with vegetation cover type classifications derived from TM imagery, and the development of generalized decision rules that can be applied to TM spectral reflectance values in other study areas and over even larger areas.

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