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Urban cover mapping using digital, high-spatial resolution aerial imagery

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Abstract. High-spatial resolution digital color-infrared aerial imagery of Syracuse, NY was analyzed to test methods for developing land cover classifications for an urban area. Five cover types were mapped: tree/shrub, grass/herbaceous, bare soil, water and impervious surface. Challenges in high-spatial resolution imagery such as shadow effect and similarity in spectral response between classes were found. Classification confusion among objects with similar spectral responses occurred between water and dark impervious surfaces, concrete and bare-soil, and grass/herbaceous and trees/shrub. Methods of incorporating texture, band ratios, masking of water objects, sieve functions, and majority filters were evaluated for their potential to improve the classification accuracy. After combining these various techniques, overall cover accuracy for the study area was 81.75%. Highest accuracies occurred for water (100%), tree/shrub (86.2%) and impervious surfaces (82.6%); lowest accuracy were for grass/herbaceous (69.3%) and bare soil (40.0%). Methods of improving cover map accuracy are discussed.

Keywords: remote sensing, image processing, NDVI, image texture, map accuracy assessment

Introduction

Understanding the structure of urban cover is very important to urban management for reasons such as runoff control, urban forest planning, air quality improvement, and mitigation of global climate change. Accurate maps of urban tree and other surface cover types can provide critical information to better understand urban ecosystems and help improve environmental quality and human health in urban areas. Urban tree cover analyses in the past were often conducted using medium to small scale aerial photographs. Although these tree cover analyses of individual cities still provide essential data for understanding urban forest structure and quantifying vegetation functions, the spatial scale provided limited detail about tree cover characteristics (Nowak *et al.*, 1996) and the methods are inefficient in terms of resources and personnel. An efficient way to get an urban cover map is to classify digital remote sensing imagery.

Digital image analysis techniques can assist in identifying and mapping various cover maps over large areas. Common sources of imagery for urban cover delineation are Landsat Thematic Mapper (TM) imagery, and the *Systeme Pour l'Observation de la Terre* (SPOT) satellite imagery. Also, for national or continental scale land cover mapping, analysts have used Advanced Very High Resolution Radiometer (AVHRR) imagery. More recently, different sources of imagery such as radar or LIDAR (LIght Detection And Ranging) are being used for urban analysis (Dong *et al.*, 1997; Priestnall *et al.*, 2000; Gamba and Houshmand, 2001). The usage of remote sensing for urban land use analysis has been examined by many researchers (Jensen, 1983; Harris and Ventura, 1995; Ridd, 1995; Jensen and Cowen, 1999; Barr and Barnsley, 2000; Stefanov *et al.*, 2001; Lo and Yang, 2002).

Moderate resolution imagery such as TM or SPOT images have been widely used to understand the characteristics of urban surfaces in various areas (Baraldi and Parmiggiani, 1990; Harris and Ventura, 1995; Gluch, 2002; Zhang *et al.*, 2002; Shaban and Dikshit, 2002). In addition, recently, a national assessment of urban tree cover in the United States was conducted using AVHRR data with a 1.1 km pixel resolution (Dwyer *et al.*, 2000; Nowak *et al.*, 2001). Results from this assessment revealed that urban tree cover in the lower 48 United States averaged 27.1%, with urban tree cover highest in forested regions (34.4%), followed by grassland areas (19.8%), and deserts (9.9%). The national urban tree cover data were combined with field data to estimate national urban tree structural value (Nowak *et al.*, 2002), and national urban forest carbon storage, sequestration, and value (Nowak and Crane, 2002). However, images like AVHRR data, TM or SPOT provide information of very limited use at the scale of an individual neighborhood in the city.

For improved land and urban forest planning and management at the neighborhood scale, high-spatial resolution imagery is more valuable and appropriate. The recent advent of relatively low-cost digital high-spatial resolution color-infrared aerial images allows developing urban cover maps with detailed information at the local scale. These maps can be integrated within Geographic Information Systems (GISs) and can provide a wealth of information to managers, planners, and scientists to improve urban vegetation management and understanding of urban ecosystems. Analysis of high-spatial resolution digital images for a small section of Berlin and Duisburg, Germany revealed that these data can be used to produce relatively accurate cover maps (Zhang, 2001). This article reports the results of using high-spatial resolution (0.61 m ground resolution) digital color-infrared aerial imagery to identify five cover classes (tree, grass, bare soil, impervious surface and water) across an entire city (Syracuse, NY) using common digital image analysis techniques and provides initial information about using such high-spatial resolution imagery with established image classification protocols within the context of urban forest assessment and monitoring. This project tested high-spatial resolution in preparation for possible wider application and to

- Assess operational approaches to classification of high-spatial resolution imagery.
- Evaluate additional, but straightforward enhancements (specifically NDVI and texture) to deal with the limited number of spectral bands and other unique challenges of high-spatial resolution imagery.
- Evaluate and compare a few common post-processing methods for their effectiveness in high-spatial resolution imagery for improving the classification results.

This initial experience was needed in preparation for detailed analysis of additional cities.

Methods

Around 0.61 m ground resolution color-infrared (near infrared, red, and green bands) digital aerial images for Syracuse, NY were collected by Emerge® on 13 July 1999. Quackenbush *et al*. (2000) include a description of the sensor system. The images were orthorectified using direct positioning photogrammetric methods (Kinn, 2002) to reduce terrain and tilt displacements and combined into a mosaic of 31 tiles. Six image tiles that encompassed all five cover classes were used to develop and test the classification methods. These methods included the use of normalized difference vegetation index (NDVI), texture analysis, and different post-processing methods. The project evaluated six different classification approaches that used: (a) only the original three bands, (b) three bands, plus NDVI and texture, (c) three bands, NDVI, texture, with post-processing using a sieve function, (d) three bands, NDVI, texture, with post-processing using a majority filter, (e) three bands, NDVI, texture, with post-processing using a sieve function and a majority filter, and (f) three bands, NDVI, texture, with post-processing using a majority filter applied twice. To reduce the confusion between water and dark impervious materials, water areas were manually masked out using the images and topographic maps. The following sections describe the key aspects of implementing the six classification approaches.

Vegetation index

NDVI is a commonly used vegetation index based on the reflectance properties of leaves in red and near-IR wavelengths. Green plant leaves typically have low reflectance in the visible regions of the electromagnetic spectrum due to strong absorption by leaf mesophyll. Meanwhile, in the near infrared region, leaves exhibit high reflectance due to extensive scattering effects in these wavelengths (Tucker and Sellers, 1986; Tucker, 1979; Knipling, 1970). NDVI is based on these properties and generally provides high values for vegetated areas. In addition, NDVI helps compensate for image variations caused by changing illumination conditions, surface slope and aspect (Lillesand and Kiefer, 2000; Quackenbush *et al*., 1999). Therefore, NDVI was used to mitigate the shadow effect of high-spatial resolution imagery and to improve the classification of vegetated areas. NDVI is computed as:

$$\text{NDVI} = \frac{(\text{near IR band} - \text{red band})}{(\text{near IR band} + \text{red band})}$$

NDVI for a given pixel always results in a number that ranges from -1 to $+1$. Generally, non-vegetated areas give values close to zero and vegetated areas give values close to one indicating the high possible density of green leaves. Therefore, NDVI is an efficient index in differentiating vegetation and non-vegetation classes.

Texture analysis

Evaluations of the imagery revealed spectral confusion between vegetation classes, but distinguishable spatial variability in tree cover relative to grass areas. This variability within tree cover provided a visual texture that could be used to help differentiate between classes by considering the spatial relationship of adjacent pixels. Texture is related to the frequency of tonal change on imagery and has high values when areas are heterogeneous and low values when homogeneous. Texture analysis uses the spatial distribution of scene reflectance, and shading and shadows to describe the visual roughness of the surface (Schowengerdt, 1997). Integration of textural information with spectral information has been tested by previous researches (e.g., Berberoglu *et al*., 2000; Stefanov *et al*., 2001; Ryherd and Woodcock, 1996). This study used a semivariogram approach to measure textural variability between tree/shrub and grass/herbaceous cover types. Semivariograms use variance and sampling size to determine the spatial dependence of a pixel relative to neighboring pixels (Curran, 1998). Image texture can be estimated by many measures over various window sizes. In this study, a simple approach was adopted where texture was estimated by computing the variance of a 15 by 15 pixel window. Window size was determined by the semivariogram using Variowin (Pannatier, 1996) and also by considering the size of typical tree crowns and other urban features such as houses.

Classification of image

A "hybrid" or "guided clustering" method (Bauer *et al.*, 1994) was used to classify the imagery based on the original three bands imagery. The same method was applied to the original three bands of the imagery, NDVI, and texture information. This "hybrid" method combines both unsupervised and supervised classification approaches in an attempt to gain the strengths of each approach. In this method, the analyst outlines sample areas of the main classes that are then divided into subclasses using unsupervised classification. Statistics generated from these subclasses were used to classify the entire image based on the maximum likelihood decision strategy. Reference data for each class were provided by photo interpretation and field visits.

Post-processing — Sieve function and majority filter

After classification of an image on a per-pixel basis, there is often a "salt and pepper" appearance caused by spectral variation among pixels that can cause individual pixels to look different from a neighboring pixel of the same class (Lillesand and Kiefer, 2000). Post-processing methods such as majority filtering and sieve functions can be used to reduce this speckled appearance and improve object integrity and usually classification accuracy. Generally, the improved object integrity and reduction in noise outweigh the instances where the post-processing causes misclassification. This type of post-processing might also cause a shift or removal in certain (usually linear) features. However, major features in this project should not be affected this way because of the very high-spatial resolution.

Sieve functions identify homogeneous clumps up to maximum number of pixels, and then reclassify these small clumps to the surrounding pixels usually with a majority approach.

The sieve function was set to find clumps of three pixels or less which were then reassigned to the class that made up the majority of the neighboring pixels.

Majority filtering passes a moving window over the classified image and determines the majority class within the window. If the center pixel in the window is not the majority class, its final classification is changed to the majority class. In this project, the majority filter approach used a 3 by 3 window and was applied either once or twice to the classified imagery.

Accuracy assessment

Classification accuracy was determined using an error matrix or contingency table. These tables compare known reference data to the corresponding classification results (Story and Congalton, 1986). In this study, accuracy assessment was employed in two stages. The first accuracy assessment was performed to provide information on the accuracy of each of the classification and post-processing methods for comparison purposes. This first accuracy assessment was conducted on the sub-sample of image tiles used to develop and test the individual methods. A stratified random sample of 50 reference sampling points was selected in each of the five cover classes (based on the original three band classification) to estimate accuracy with reasonable precision (Stehman, 1999). When stratified sampling is used in accuracy assessment and the sample size is equal for each mapped land-cover class (equal allocation for each stratum), the analysis must take into account that the strata are not sampled with equal intensity (i.e., rare strata are sampled with higher intensity). If this difference is not accounted for in the analysis, the resulting accuracy estimates for producer's and overall accuracy will be biased (Stehman, 1995). Therefore, for Tables 1 to 3, the error matrices were constructed using the proper weighting of data from each stratum (Stehman, 1995). Ground visits and image interpretation provided the reference information for the 250 sample points.

The second accuracy assessment was performed on the final image classification of the entire city based on a simple random sampling of 400 individual pixels over whole study area. These 400 reference points were verified using field visits and image interpretation.

Results

Overall accuracies increased from the original three-band classification (78.2% accuracy) when NDVI and texture analysis were included (83.2% accuracy) and also increased (84.8% accuracy) when a majority filter was applied twice as a post-processing method (Tables 1, 2 and 3). Applying the post-processing method of the majority filter slightly increased overall accuracy, while the sieve function had no effect on overall accuracy (Table 4). Applying the majority filter once increased accuracy from 83.2 to 84.5%, while applying the filter twice increased the accuracy to 84.8%. Although the statistical improvements were small with the majority filter, visual image inspections revealed that majority filters improved the classification results by removing isolated pixels (figure 1). As the majority filter applied

Table 1. Error matrix for the preliminary classification that used only the original three bands of the image. Error matrix entries are proportion of area times 100

	Reference						
Class name	Tree/ shrub	Grass/ herbaceous	Bare soil	Water	Impervious surface	Row total	User's accuracy (%)
Classified							
Tree/shrub	14.74	0.61	0	0	0	15.35	96.00
Grass/herb	10.68	20.65	2.14	0	2.14	35.60	58.00
Bare soil	0	0.40	1.34	0	4.94	6.68	20.00
Water	0	0	0	0.68	0.01	0.69	98.00
Impervious	0	0.83	0	0	40.84	41.67	98.00
Column total	25.42	22.50	3.47	0.68	47.93	100	
Producer's accuracy (%)	57.98	91.78	38.47	100.00	85.20	57.98	Overall 78.24

Table 2. Error matrix for the preliminary classification that used the original three bands, NDVI, and texture. Error matrix entries are proportion of area times 100

	Reference						
Class name	Tree/ shrub	Grass/ herbaceous	Bare soil	Water	Impervious surface	Row total	User's accuracy (%)
Classified							
Tree/shrub	21.35	2.04	0.71	0	0	24.10	88.59
Grass/herb	3.77	17.49	1.42	0	4.88	27.56	63.46
Bare soil	0	0	0.80	0	0.13	0.94	85.71
Water	0	0	0	0.68	0.01	0.69	98.00
Impervious	0.31	2.97	0.53	0	42.90	46.72	91.84
Column total	25.42	22.50	3.47	0.68	47.92	100	
Producer's accuracy (%)	83.96	77.74	23.08	100.00	89.51		Overall 83.22

twice produced the best results, it was selected for the post-processing of the final image classification for the entire city.

Final classification

The final classification of the entire city produced an estimate of overall accuracy of 81.75% (Table 5). The producer's and user's accuracies for a grass/herbaceous and bare soil class were problematic as discussed below. The final estimates of land cover percentage for the

Table 3. Error matrix for applying the majority filter twice to the image evaluated in Table 2. Error matrix entries are proportion of area times 100

	Reference						
Class name	Tree/ shrub	Grass/ herbaceous	Bare soil	Water	Impervious surface	Row total	User's accuracy (%)
Classified							
Tree/shrub	21.65	1.73	0.71	0	0	24.10	89.86
Grass/herb	3.46	18.63	0.71	0	4.88	27.69	67.30
Bare soil	0	0	0.80	0	0	0.80	100.00
Water	0	0	0	0.68	0.01	0.69	98.00
Impervious	0.31	2.14	1.25	0	43.04	46.73	92.10
Column total	25.42	22.50	3.47	0.68	47.93	100	
Producer's accuracy (%)	85.17	82.81	23.08	100.00	89.79		Overall 84.80

Table 4. Overall accuracy comparison of different classification and post processing methods

Method	Overall accuracy (%)[a]
Original three bands only (Table 1)	78.24
Three bands + NDVI + Texture (Table 2)	83.22
Sieve function[b]	83.22
Majority filter[b]	84.49
Sieve function + majority function[b]	84.49
Majority function twice (Table 3)[b]	84.80

[a]Although some accuracies are identical, classification results were different.
[b]Method applied in addition to use of three bands, NDVI and Texture.

City of Syracuse were: 26.6% tree/shrub cover, 21.6% grass/herbaceous cover, 1.3% bare soil, 48.1% impervious surface and 2.3% water cover (figure 2).

Discussion

In spite of numerous challenges inherent in high-spatial resolution imagery (compared with moderate or low-resolution imagery), the methods successfully produced a general cover classification for the City of Syracuse that is spatially detailed. The overall accuracy exceeded 80% for the five classes of tree/shrub, grass/herbaceous, water, impervious, and bare soil. Urban foresters consider the results to be very useful over areas as small as blocks, census tracks, neighborhoods, and the entire city. However, there is room for improvement in terms of the accuracy of site-specific individual pixels.

A number of specific difficulties arose as shown by relatively low individual accuracies for a few classes. The classification using the original three bands of high-spatial resolution

Table 5. Error matrix (pixel count) for the final classification of the entire city. Matrix entries are proportion of area times 100

	Reference							
Class name	Tree/ shrub	Grass/ herbaceous	Bare soil	Water	Impervious surface	Row total	User's accuracy (%)	Standard error (%)
Classified								
Tree/shrub	**25**	3.75	0	0	0.25	29	86.21	3.22
Grass/herb	3.5	**13**	0.75	0	1.5	18.75	69.33	5.36
Bare soil	0	0	**0.5**	0	0.75	1.25	40.00	24.49
Water	0	0	0	**6.5**	0	6.5	100.00	0
Impervious	2.25	4.5	1	0	**36.75**	44.5	82.58	2.85
Column total	30.75	21.25	2.25	6.5	39.25	100		
Producer's accuracy (%)	81.30	61.18	22.22	100.00	93.63		Overall **81.75**	
Standard error (%)	3.53	5.32	14.70	0	1.96			Overall 1.93

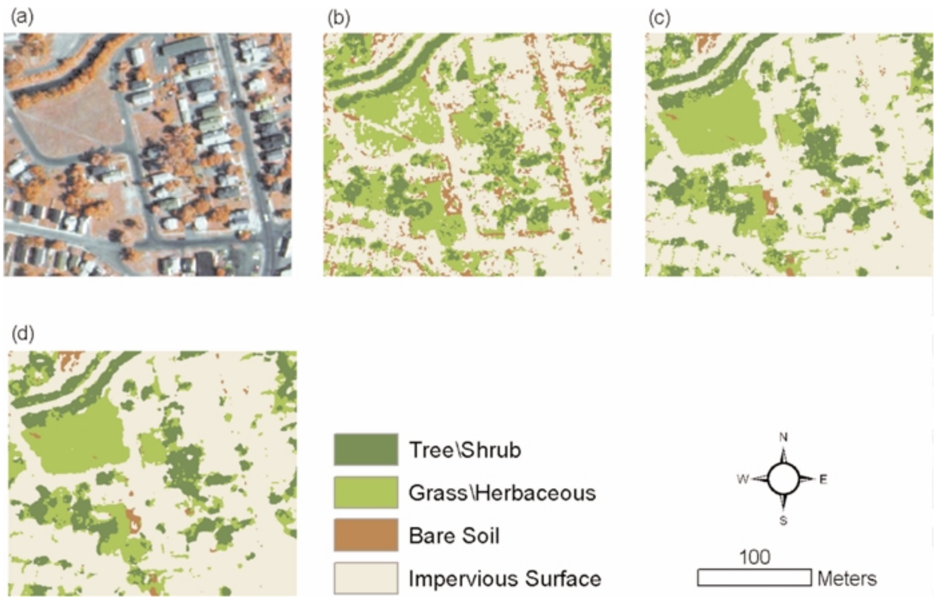

Figure 1. Visual comparison of classification results for an example area. (a) Original three-band image, (b) classification three-band image, (c) classification of combined image (three bands with NDVI and texture), and (d) majority filter applied twice to the combined image.

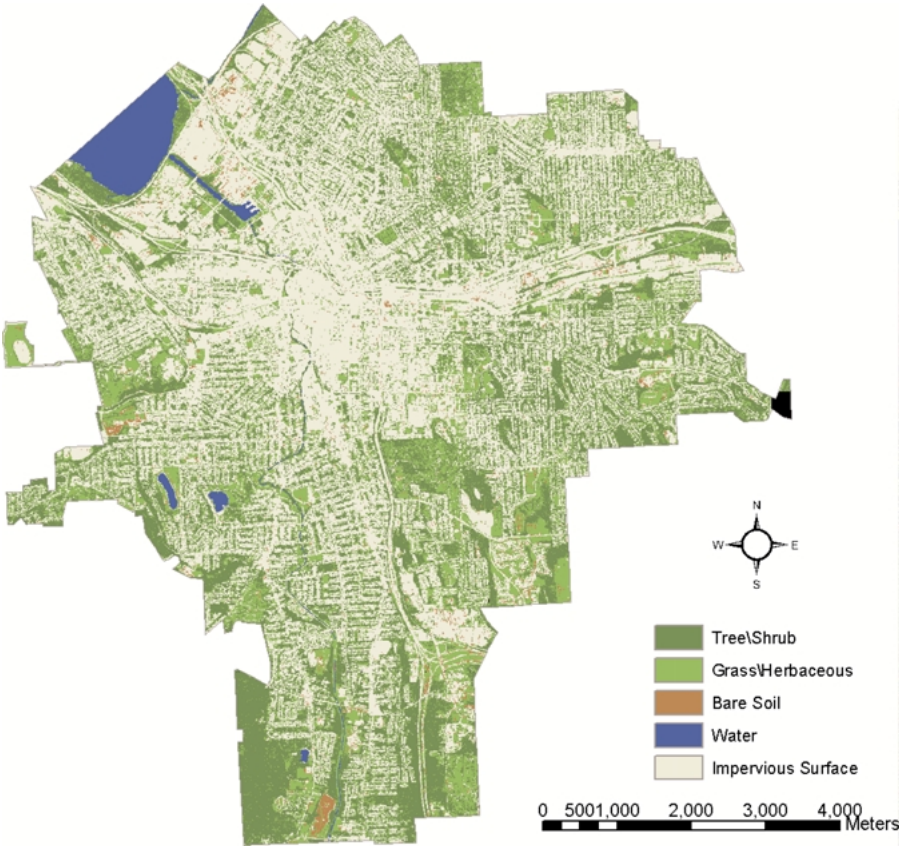

Figure 2. The final classified image of Syracuse.

imagery revealed difficulty in identifying the five classes because some features have similar spectral responses with other classes. Specifically, confusion occurred between bare soil and certain impervious surfaces, grass/herbaceous and tree/shrub, and water and dark impervious surfaces. These spectral similarities are especially evident when using only three broad spectral bands. Increased spectral resolution would very likely clarify some of the class confusion, but current technology limits the spectral capabilities when operating with high-spatial resolution. There is a trade off between the need for spatial detail and increased specificity of cover classes. Also, shadow effects cause trouble for classification of spectral data, and shadows are distinct and endemic when using high-spatial resolution imagery (Quackenbush *et al*., 2000). In high-spatial resolution imagery, as compared with lower resolution images (e.g., Landsat Thematic Mapper 30 m pixels), shadow effects become much more evident as individual pixels can be encompassed by shade, while larger pixels integrate the shade with the pixel data.

A few techniques were found to assist the classification of high-spatial resolution images that have variations from shading and limited spectral content. Because shaded pixels will have shadow in each band, band ratios can be used to produce image values that are less sensitive to shading and more consistently related to cover type (Quackenbush *et al.*, 1999). Using the NDVI helped compensate for shadow effects and improve the final classification result. Interestingly, the shadow effects can also help to separate different types within the same general class. For example, shadow and other variables help to give trees a more heterogeneous appearance than grass. Texture measures are designed to capture some of this variability and use it within the classification routines. For the Syracuse images, adding texture information especially improved classification between grass/herbaceous and tree/shrub, and between bare soil and impervious surfaces.

The grass/herbaceous class confused substantially with the tree/shrub category. Grass cover with shadow tends to be classified as tree class and tree canopy which has low texture tends to be classified as grass. The inclusion of a texture measure reduced this confusion, but the spectral similarity of the two vegetation classes still remains a concern. Other channels of information (spectral or geometric) or supplementary processing (e.g., expert classifiers) would further reduce the confusion between grass and trees. Finding local surface heights (or height differences) might also help separate herbaceous cover from shrubs and trees.

The bare soil class also had low classification accuracy. However, the standard error of bare soil was relatively large due to sampling limitations. Bare soil occurs relatively infrequently in the Syracuse area, but in a couple of locations where there was extensive exposed soil, the classification result was reasonable. The misclassification of soil occurred mostly with grass or impervious surfaces. It is likely that the confusion between grass and bare soil is because bare soil often exists within or near the grass cover type (e.g., thin grass cover or pathways). Thus, the edge pixels located between grass and bare soil may cause low accuracy of bare soil. Also, the reference pixels for grass and bare soil contained varying levels of vegetation density leading to indistinct assignment to the discrete classes. The confusion of bare soil with impervious surfaces is likely because urban bare soil usually has a spectral response that is similar to concrete.

There were also classification problems with water. Even though the error matrices show high accuracies for water, these accuracies are based on a masking process that was applied to the imagery to stratify water and assure a good classification. This type of stratification process is useful and acceptable when there is good ancillary information about the location of water in the study area. However, this type of fusion impedes the use of imagery for updating water information. The classification problem with water occurred because the spectral nature of water was similar to the spectral nature of dark impervious surfaces. In particular, dark rooftops were often classified as water. Apparently, asphalt-based surfaces have spectral reflectance patterns similar to water (in the bands measured). In addition, there may be lack of ability in the sensor to distinguish detailed levels of low radiance.

Many misclassified pixels occurred along the edge between vegetated and non-vegetated areas. This misclassification reveals that high-spatial resolution imagery still has problems with mixed pixels. This problem is an inherent limitation of raster-based data. Urban areas contain one of the most complex cover types and therefore will exhibit higher proportion of mixed pixels. When the edge/mixing problems result in isolated or small groups of pixels with a distinct class, post processing can be used to decrease the misclassification. Post processing also reduces isolated geometric or radiometric problems that cause a pixel to be different even though the cover class is the same as the surrounding pixels. Currently, there is little objective information on the advantage of post-processing, especially for high-spatial resolution imagery and there is no clear guidance for selecting a post processing method. Therefore, several different post classification methods were compared by visual inspection and statistical accuracy assessment. In the Syracuse images, both visual results and error matrices show that post processing by applying the majority filter twice generated slightly better results over both a single application and over a sieve function. However, users should be cautious because this type of post processing can cause small shifts in the locations of edges and some correctly classified pixels will be changed. These consequences will have effects on very detailed pixel-level classification results. Users should be also cautious about determining the window size of filtering, which must depend on the resolution of the input imagery and the characteristics of study area. Study areas with more homogeneous cover types have better results from filtering.

Older methods of estimating urban cover types using sampling of aerial photographs provide estimates with known standard errors, but are also relatively time-consuming to produce, subject to interpreter error, and do not provide the spatial resolution or geographic positioning of the cover types that digital image processing can provide. Other digital data sets (e.g., Landsat) can be used to produce cover maps for urban areas, but cannot provide the spatial resolution of the high-spatial resolution (sub-meter) digital images. A perfectly accurate digital cover map may never be attainable given current technologies, but future high-spatial resolution imagery with more spectral content or the incorporation of other image or spatial measurements may help increase overall cover accuracy. Localized height information from LIDAR or photogrammetric processing could also enhance classification accuracy. The local height information might help separate tree/shrub from ground-level vegetation (grass/herbaceous) and dark rooftops from water.

Although there are inherent inaccuracies of developing digital cover maps for urban areas, the results from this initial project are promising and offer an opportunity to enhance research in urban ecology and improve management in urban areas. Overall accuracies of greater than 80% are sufficient to aid in understanding the geography of urban elements and to aid in integrating digital cover maps within urban GIS management layers. Although some individual pixels may be misclassified, statistical aggregation of cover over wider areas (e.g., census tracts) will yield improved accuracy of cover type estimates as classification errors of commission tend to balance errors of omission. Thus, the individual location of cover types may be in error, but assessments of larger areas (e.g., blocks or neighborhoods) should yield more accurate results.

Digital urban cover maps can be used to better estimate spatially specific urban vegetation functions (e.g., effects of trees on building energy use, air pollution removal, and hydrologic effects). In addition, high-spatial resolution cover maps can help determine the best locations with available space to plant trees and most important tree cover locations to preserve (e.g., trees in locations that offer the most environmental and human health benefits). Integration of urban cover types into GIS offers the opportunity to develop spatially specific urban models and management tools. This article reports classification results designed to explore potential utility to urban forestry activities and represents only one study area. More areas with various land use type and imagery of various resolutions should be tested in the future.

As the development of urban cover maps from high-spatial resolution digital data is relatively new, future research is needed to produce detailed maps more effectively and efficiently.

Conclusion

High-spatial resolution, digital, color infrared (3 band) aerial imagery was evaluated for producing detailed urban cover information in Syracuse, NY. A multi-layered analysis approach using the original three bands, NDVI, texture analysis, and post-processing with a majority filter twice provided the best results in classifying five general urban cover types. For specific detailed reference locations, the overall accuracy was greater than 80%. Other data or approaches, such as integrating more spectral bands or incorporating differential height information from LIDAR or photogrammetric processing, may help improve the classification accuracy. Although there was some error in predicting individual pixels, statistical aggregation of cover estimates over wider areas will improve accuracy as classification errors of commission tend to balance errors of omission. High-spatial resolution digital imagery can provide accurate land cover information for urban areas using computer classification routines. The advantages of this type of data include spatially-specific cover data that can be useful for describing the cover types and locations within different areas of a city. This type of information can aid in urban ecosystem research and management to improve human health and environmental quality in cities.

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