Digital Classification and Mapping of Urban Tree Cover: City of Minneapolis

FINAL REPORT

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Introduction

Tree cover is an important component of urban environments. In addition to the aesthetic values of trees, numerous studies have shown significant economic and environmental benefits and values of urban trees (Galvin et al.; http://nrs.fs.fed.us/urban/utc/), including:

- Stormwater management: interception of rain, evapotranspiration, reducing runoff and erosion, and increasing the potential for improving water quality.
- Energy conservation: transpiration and shading reduce air temperatures and saves energy; reduces the urban heat island effect.
- Air quality: removes air pollutants, including carbon monoxide, sequesters carbon dioxide, and releases oxygen.
- Economic Value: enhancement of community vitality, stability and property values for residential and business areas.

However, unless we can measure and quantify tree cover, we are not in a good position to manage it. Accurate maps and information on the amount of tree and forest cover are not routinely available and it would be expensive to acquire by field mapping methods. Interpretation of aerial photography is an alternative, but the most appropriate imagery, color infrared photography, is generally not available. Recent available high resolution color ortho imagery is early spring, leaf-off imagery that is not suitable for mapping tree cover in Minneapolis where many trees are deciduous species.

An alternative, and the approach of our project, is to digitally classify high resolution multispectral QuickBird satellite image data that was recently acquired of the Minneapolis area. QuickBird has four spectral bands, blue, green, red and near infrared, at 2.4 meter spatial resolution, with the infrared band being especially useful for mapping vegetation, plus a panchromatic band at 0.6 meter resolution. With "pan-sharpening" of the multispectral bands, a 0.6 meter resolution image can be generated that is higher resolution than the 4-band, 1-meter USDA National Agriculture Imagery Program (NAIP) imagery acquired for Minnesota in the summer of 2008. An additional and significant advantage of the QuickBird data is that the entire City is included in a single image.

The project objective was to generate a digital land cover classification of the City of Minneapolis in GIS-compatible format, with emphasis on mapping the tree cover that can be used by the City to evaluate existing tree cover and potential for additional plantings. Tree cover is defined as the leaves, branches and stems covering the ground when viewed from above.

Approach

Imagery

QuickBird satellite imagery acquired on June 25, 2009 was used for the image classification. The image was clear and cloud-free. Natural color and false color (including the near infrared band) images are shown in Figure 1.

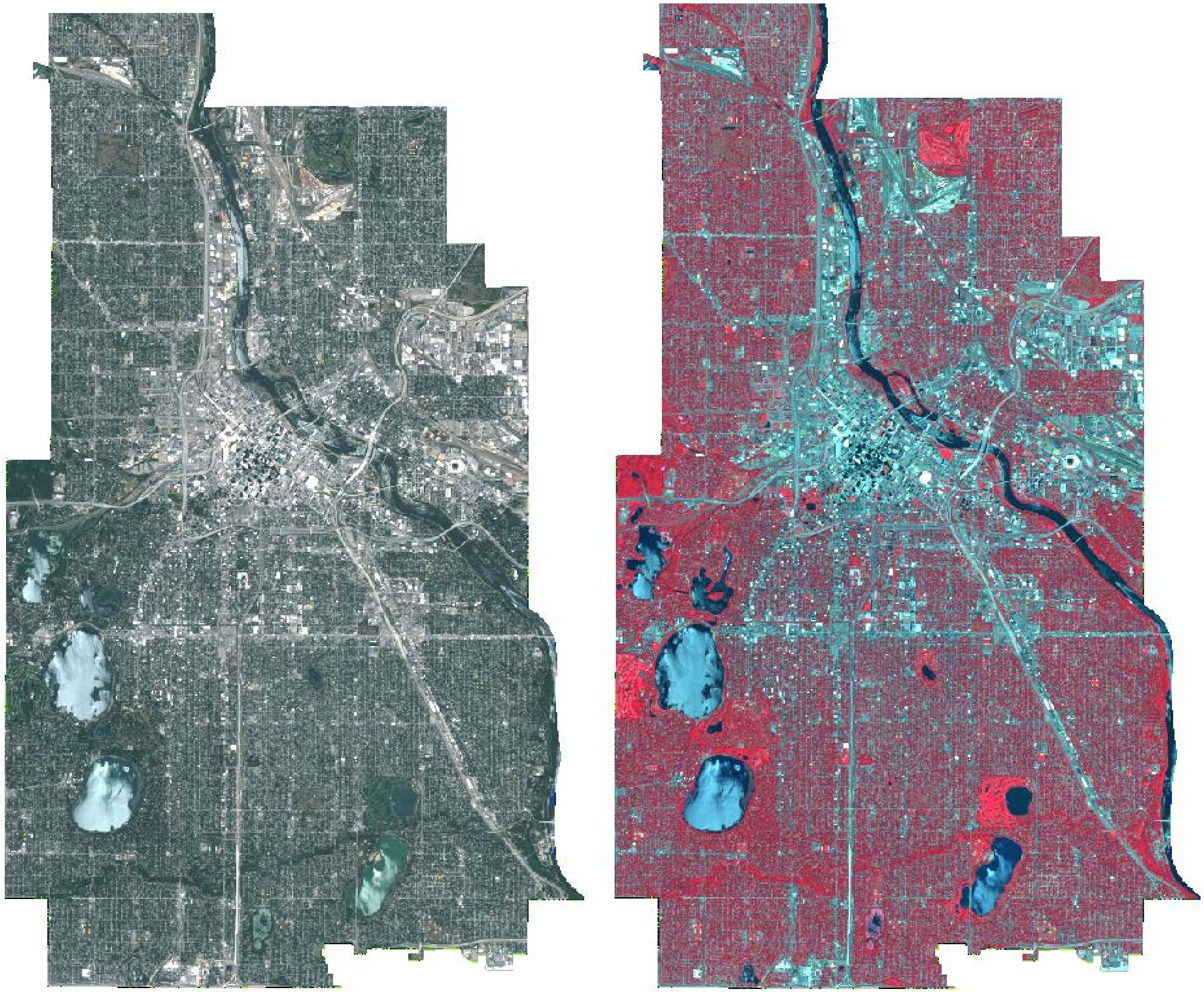

Figure 1. QuickBird imagery of Minneapolis acquired on June 25, 2009; natural color (left) and false color (right).

In addition, LiDAR imagery acquired in June 2007 was available from the U.S. Army Corps of Engineers. LiDAR (Light Detection And Ranging) is a remote sensing technology using pulses from a laser to measure the distance to the surface, and therefore can be used to generate elevation and height information. This imagery consisted of first return information as well as the last return or bare earth; using the two a normalized digital surface model (nDSM) which depicts height above bare earth (for example of buildings and trees). The horizontal accuracy of the data was roughly 0.5 meters and stated to be “better than 1 meter.” Its vertical accuracy compared to 33 control points was 0.087 meters. The LiDAR data included full coverage for the entire City of Minneapolis.

Figure 2. Normalized digital surface model (nDSM) imagery of Minneapolis acquired in June 2007.

As shown in Figure 3 the LiDAR nDSM data corresponds very closely to the buildings and trees, with the height information providing excellent separation of buildings from streets and trees from grass. In the gray-scale image in Figures 2 and 3, black is the bare earth surface elevation, and shades of gray to white are increasingly taller objects.

Figure 3. Enlargements of the LiDAR nDSM (top) and false color QuickBird imagery (bottom). Together these images were used to classify tree canopy and other land cover classes.

Land Cover Classes

The land cover classes are described in Table 1.

Table 1. Land cover classes and descriptions.

Class	Description
Tree Canopy	The layer of leaves, branches and stems of tree that covers the ground when viewed from above.
Grass & Shrubs	Lawns and other grass covered areas and shrubs found in parks, golf courses and playgrounds.
Bare Soil	Areas free of vegetation, primarily in open industrial areas.
Water	Lakes and streams.
Buildings	Houses and commercial, industrial and public structures.
Streets	Streets and highways.
Other Impervious	Includes driveways, sidewalks, parking lots and other impermeable surfaces that are not obscured by tree cover.

In all cases the class is defined as the surface area viewed from above. It should be noted that tree canopies will cover and obscure from view some of the grass, bare soil, streets and parts of some buildings. To take one example, the amount of impervious will by definition typically be less than measured by other methods such as from "leaf-off" high resolution ortho aerial photos in which all impervious surfaces can be seen. Therefore results from the two methods should not be compared. Of the two methods, impervious area measurements from the higher resolution photos should be more accurate.

Classification Procedures

The primary land classifications were produced using object based image analysis (OBIA) techniques available in eCognition Developer version 8.0. Ancillary software utilized included ArcGIS version 9.3.1 and ERDAS Imagine version 2010. Additional customized routines were written in Python version 2.5 scripting language to support processing as required. Shapefile information was provided by the City of Minneapolis to help identify streets, buildings, roads and highways and water features.

The following principle steps were followed to implement the project:

- The 2.4-meter resolution multispectral QuickBird imagery was "pan-sharpened" using the 0.6-meter panchromatic band and subtractive resolution in ERDAS Imagine.
- QuickBird Imagery was georeferenced utilizing the available RPC files and a 30-meter DEM layer.
- LiDAR data were georeferenced to match the QuickBird imagery.
- A customized Python script was used to divide the georeferenced imagery into 750 x 1000 meter tiles with 10 percent overlap for further processing. This step created 262 individual tiles.

- The street layer was buffered in ArcGIS by 3 meters to create a polygon shapefile for subsequent use in eCognition.
- The rule set was created using these process steps:
  - eCognition workspace of all 262 tiles was created with a customized load procedure.
  - Imagery was examined to locate a representative tile.
  - Supportive image layers such as Normalized Difference Vegetation Index (NDVI) and Lee's Sigma Edge Extraction were created to aid classification efficacy.
  - Image objects were generated representing buildings, roads and water features from shapefiles and classified as such.
  - Since LiDAR data were available the images were first segmented into tall and short features.
  - Remaining portions of the image were classified utilizing algorithms available in eCognition taking advantage of spectral information as well as other elements of image interpretation such as context, shape, size, site, association, pattern, shadows and texture.
  - Classification was exported from eCognition into a TIF raster file.
- The rule set was fine tuned and tested on additional random tiles distributed throughout Minneapolis.
- The final rule set was used to classify all the tiles using eCognition Server.
- Individual classified tiles were joined into a single mosaic using geometric seam lines in ERDAS Imagine Mosaic Pro.
- The accuracy of the resulting classification was assessed in ERDAS Imagine using 1,413 stratified random points.
- The classification mosaic was then manually examined and edited to eliminate classification errors.
- Error corrections were re-run in eCognition Server to incorporate the corrections.
- The final land cover mosaic was manipulated by ERDAS Imagine and ArcGIS into the output geodatabase utilizing both raster and vector forms of the data.
- A Python script was written to summarize classification information into various shapefiles such as parcels and neighborhoods.

Key to the classification was use of an object-based image analysis approach in which the imagery was first segmented into objects with similar pixels based on the spatial, as well as the spectral-radiometric (color) attributes (Figure 4). Research has shown that it is the best approach for classification of high resolution imagery (Blaschke, 2010; Platt and Rapoza, 2008). Objects include more information than individual pixels, enabling the ability to take advantage of all the elements of image interpretation, particularly spatial information, including shape, size, pattern, texture, and context. Context is especially useful. Humans intuitively integrate "pixels" into objects and use contextual relationships to interpret images and draw intelligent inferences from them. Ancillary data such as GIS layers, for example, of streets and water bodies, can also be incorporated into the decision rules.

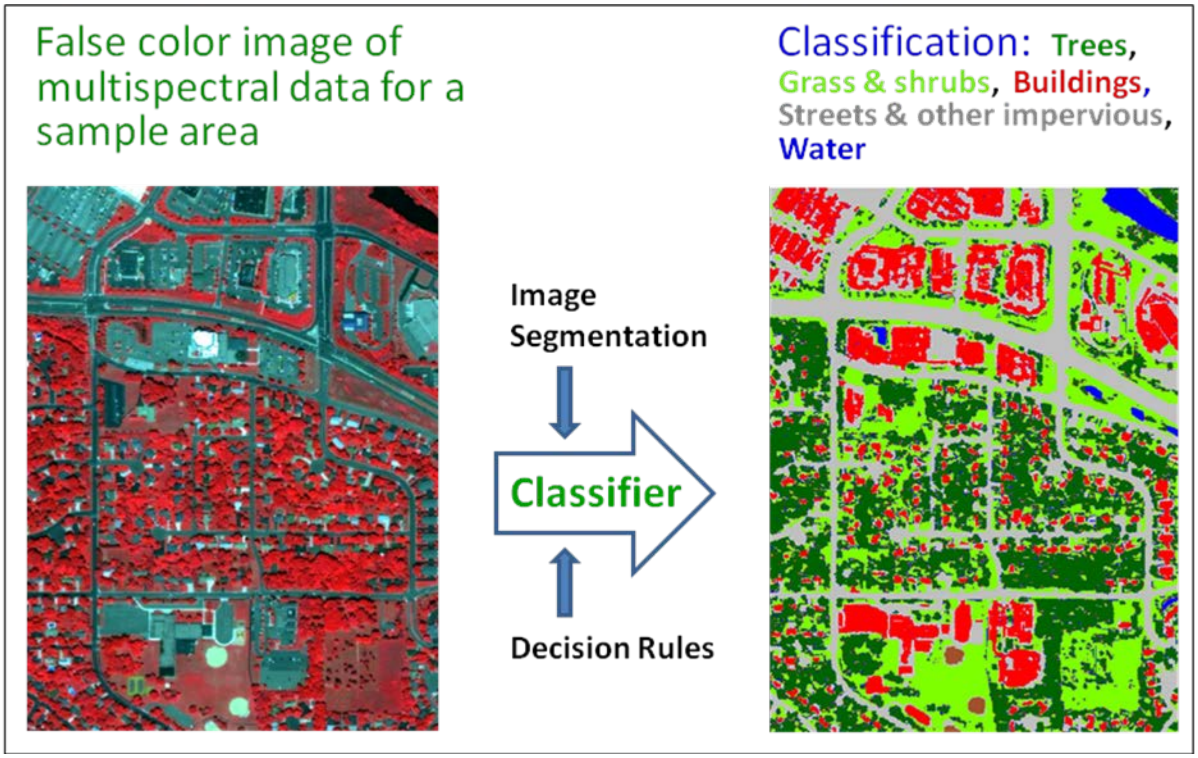

Figure 4. Major steps in the object based image analysis approach to image classification.

The object based image analysis process in eCognition can broadly be split into two components, segmentation and classification. Segmentation primarily uses spectral information about individual pixels in the imagery to combine them into larger image objects or segments. As an example, individual pixels which comprise the roof of a building with similar brightness, normalized difference vegetation index (NDVI) and color values are combined to form an image object that represents the building. Other scaling information can be specified to regulate the size range of the desired objects. Once these image objects are created, they can be classified using a multitude of decision rules which utilize not only their spectral characteristics but also spatial information such as shape, size, proximity to other object types, texture, and context. The overall process is dependent on the quality of the initial segmentation into image objects.

Accuracy Assessment

Accuracy assessment was performed after the tiles were edited for misclassifications by generating stratified random points across the image and comparing the classified results to reference imagery of color ortho photos provided by the City and imagery from ArcGIS online. Stratified random point selection assures each class will be weighted proportionately to the total number of points in that class across the image. There were 1,413 points in the sample (Figure 5).

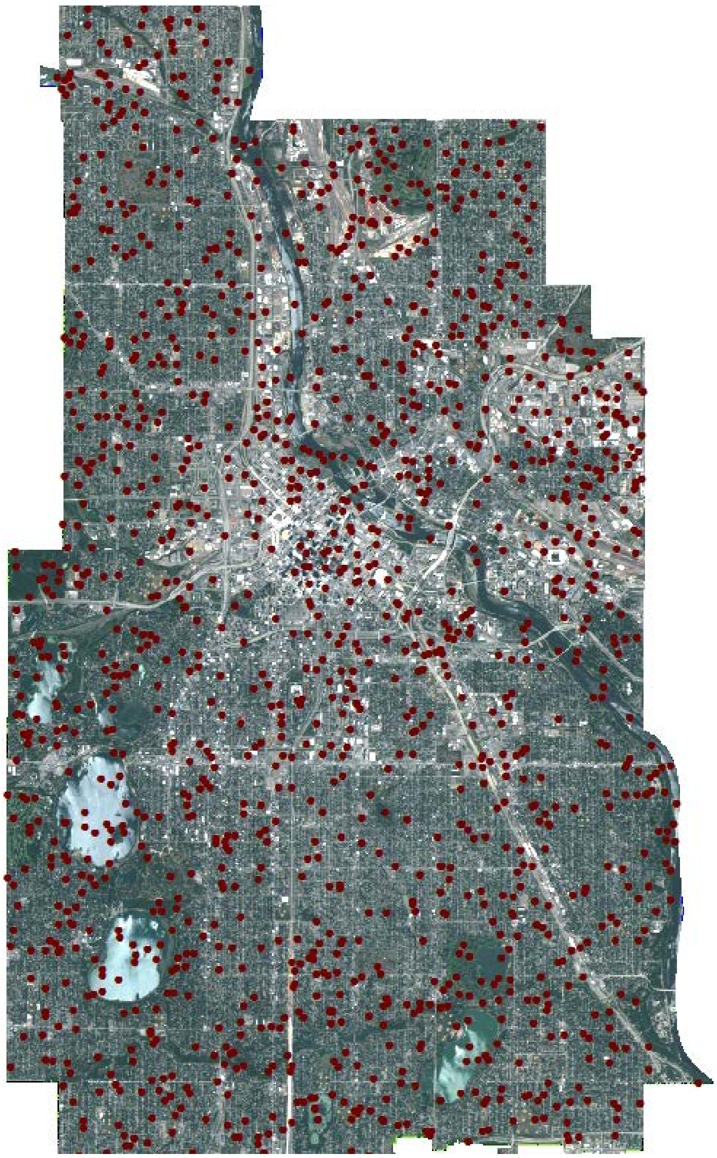

Figure 5. Locations of 1,413 sample points used for the final accuracy assessment.

The assessment points are displayed large enough to be visible on the map, but in reality these points are geometric points that ERDAS Imagine randomly designates in the image. Figure 6 is a close-up showing one of the assessment points randomly selected by the software. As is quite typical in an urban setting, it can be quite difficult to determine just what land cover is at a given point. In this example the shadowed areas exacerbate the task of determining if this point was tree canopy, grass or building roof.

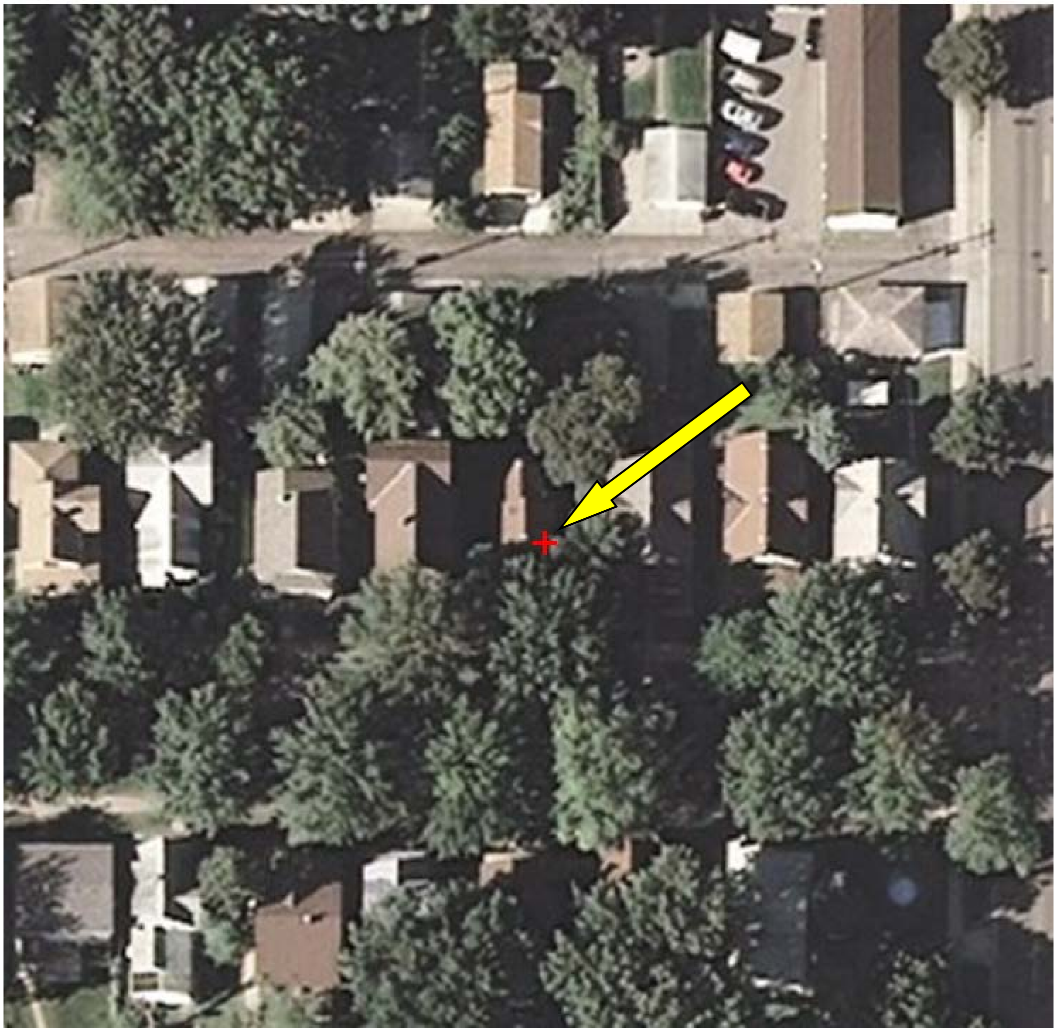

Figure 6. Example of a randomly selected sample point for accuracy determination.

Situations like these occurred quite commonly throughout the process. In an attempt to assure an effective process, mismatches were reviewed to confirm the interpretation of the reference image.

Results

The final classification raster image is depicted in Figures 7 and 8. The results in Table 2 show that 31.5 percent of the area of the City is tree canopy.

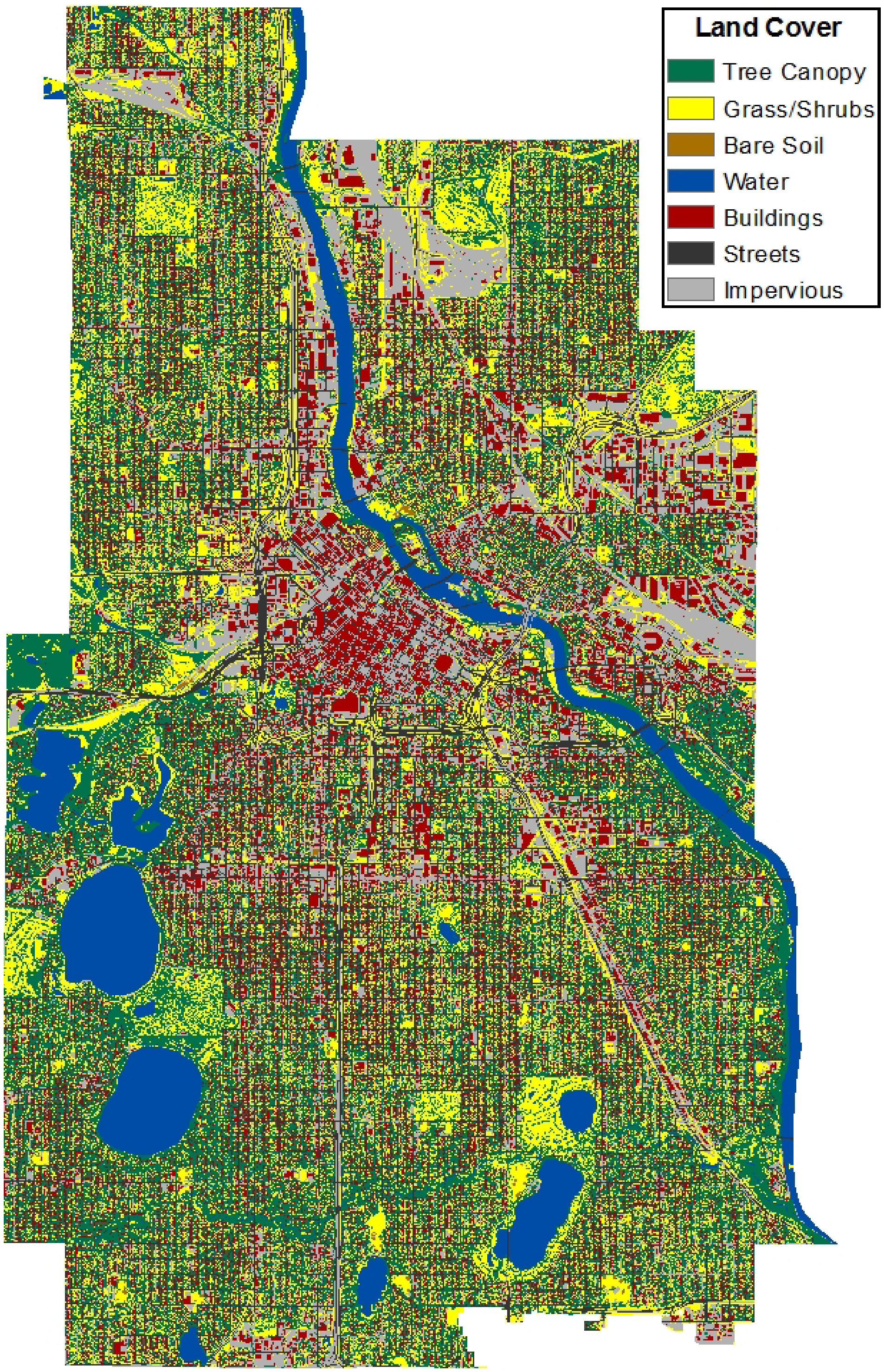

Figure 7. Land cover classification of Minneapolis.

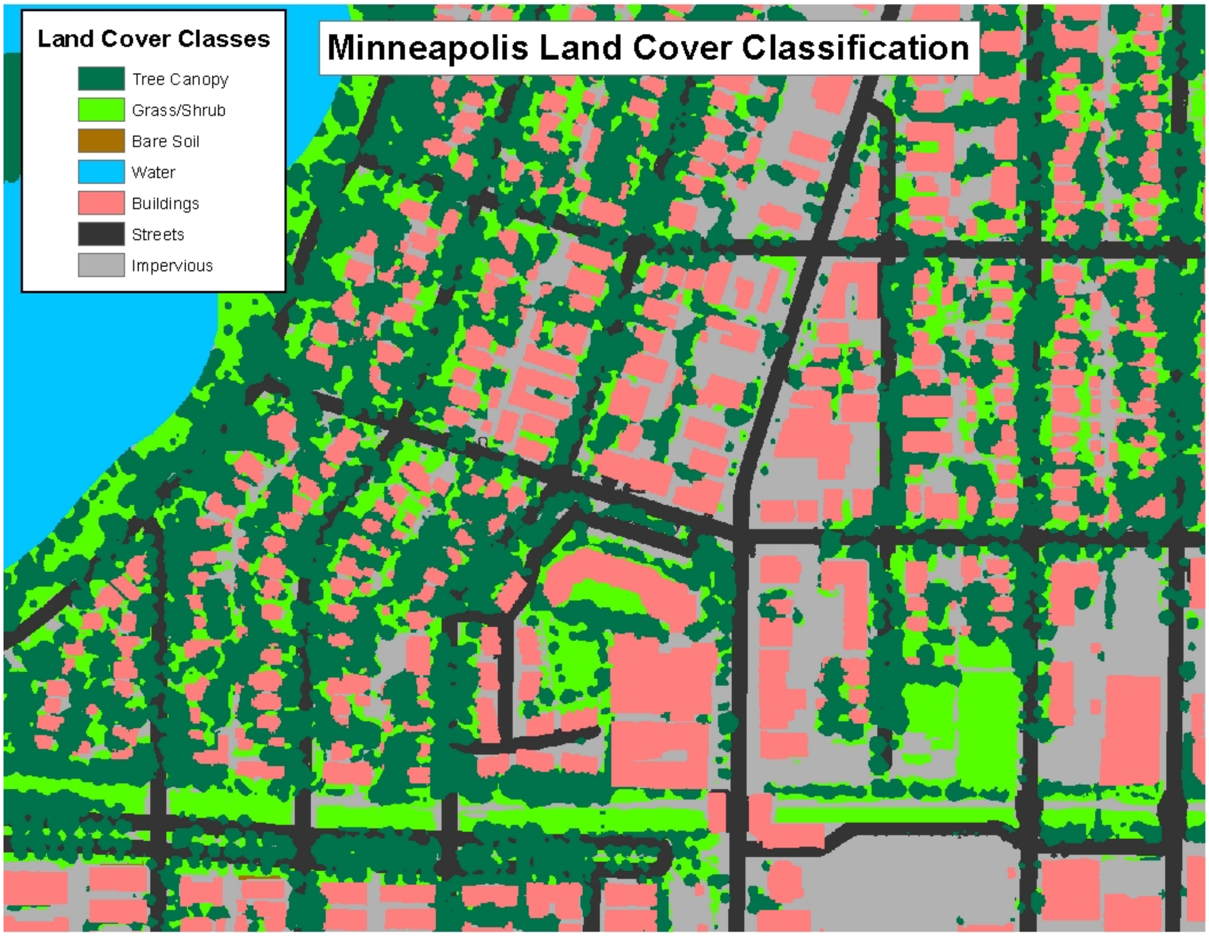

Figure 8. Detailed view of the classification of the area near the intersection of Lake Street and Hennepin Avenue.

Table 2. Tabulation of the percent area of each of the seven land cover classes.

Land Cover Class	Percent
1. Tree Canopy	31.5
2. Grass and Shrubs	19.7
3. Bare Soil	0.2
4. Water	6.2
5. Buildings	15.5
6. Streets	9.5
7. Other Impervious	17.3

A comparison of a high resolution aerial photograph to the image classification illustrating the high correlation between the classification and a reference image and providing a qualitative indication of the classification accuracy is shown in Figure 9.

Figure 9. Comparison of high resolution aerial photo (top) and image classification (bottom) of an example subset of the image near the intersection of W 36th Street and Calhoun Boulevard.

We also conducted quantitative assessments of the classification by comparing a stratified random sample of points from the classification to high resolution aerial photography. The results are presented in the form of a contingency table or error matrix; further details on interpretation of error matrices and the statistics derived from them are in Appendix 1.

Our previous work had shown that automated object based classification, while effective, can still result in obvious misclassifications. To reduce this impact, the classifications were compared to reference imagery and were edited manually where necessary. As an example, grass near freeways can become quite dry and take on the appearance of impervious cover. Larger objects with height such as trucks and buses on roads are often interpreted as a building. We assessed the accuracy after these corrections were made and the results are shown in Table 3. The overall accuracy was 91.9 percent.

Table 3. Classification accuracy following corrections.

Classification	Reference Data							*Total*	User's Accuracy (%)
	Tree Canopy	Grass/ Shrub	Bare Soil	Water	Buildings	Streets	Impervious		
Tree Canopy	**414**	23	0	0	2	2	2	*443*	93.4
Grass/Shrub	7	**246**	0	0	3	0	15	*271*	90.8
Bare Soil	0	0	**3**	0	0	0	1	*4*	75.0
Water	0	0	0	**95**	0	0	0	*95*	100.0
Buildings	1	3	0	0	**215**	**0**	3	*222*	96.8
Streets	3	5	0	1	**0**	**110**	10	*129*	85.3
Impervious	1	7	1	0	8	16	**216**	*249*	86.8
Total	*426*	*284*	*4*	*96*	*228*	*128*	*247*	*1413*	–
Producer's Accuracy (%)	97.2	86.6	75.0	99.0	94.3	85.9	87.4	–	**91.9**

Overall accuracy: 1299 / 1413 =91.9%
95 percent Confidence Interval: 90.5 – 93.4%
Kappa Statistic: 0.90

Discussion

The overall accuracy of 91.9 percent and user's and producer's accuracies of 93.5 and 97.2 percent for tree canopy meets the expected accuracy goals of the project. The primary errors are some confusion between trees and grass/shrub, between buildings and impervious, and streets and impervious. The single largest area of confusion was the 23 points out of 284 grass and shrub points that were erroneously classified as tree canopy.

Although the pixel size of the pan-sharpened QuickBird imagery is approximately 0.6 meters, the lower limit for size detection of individual objects is between 2 and 3 meters square. More specifically, to improve the spatial resolution of the multispectral imagery we used a pan-sharpening process which takes the spectral information from the 2.4-meter multispectral pixels and distributes it mathematically to the higher resolution 0.6-meter panchromatic pixels to create 0.6-meter multispectral pixels. While the pixel size is 0.6 meters, small or narrow objects (e.g., a sidewalk) may not be resolved in the imagery or classification.

Another limitation to the study was the temporal mismatch between the QuickBird and LiDAR imagery. The QuickBird image was acquired approximately two years after the LiDAR data and this resulted in several inconsistencies in the classification. An example is trees present in the LiDAR but subsequently removed prior to the QuickBird image acquisition. Where the tree had overhung a street, the classifier interpreted the existing height as an impervious object and classified it as a building. If it overhung grass, it was interpreted as a tree. Where found, these errors were manually corrected. More difficult to correct was the reverse situation where a new tree planting did not have matching LiDAR height information. Many of these were classified as grass/shrub areas.

As a final note, for this analysis, tree canopy was allowed to grow over any street and road layers and was not truncated by the latter. The exception to this is the parcel analyses. In the parcel analysis, only the percentage of the tree canopy that actually falls within the border of the parcel is included. Since parcels do not extend into the street, the canopy does not as well.

Summary and Recommendations

Multispectral QuickBird satellite imagery acquired on June 25, 2009 and LiDAR data acquired in June 2007 were classified into land cover classes of trees, grass and shrubs, buildings, roads, impervious, water, and bare soil using an object-based image analysis approach. The overall classification accuracy was 91.9 percent. Citywide, the amount of tree canopy cover was found to be 31.5 percent.

The most serious limitation of the classification was the temporal mismatch between the optical and LiDAR imagery which caused confusion between objects removed or added between the image acquisition dates. This limitation could be overcome by additional assessments with more recent, matched imagery. LiDAR data will be flown again in the spring 2011 and will be available for use sometime later in 2011. We suggest the City consider re-analyzing tree canopy when the new LiDAR data is available and using satellite imagery matching the LiDAR acquisition dates as closely as possible.

Finally, we present examples in Figures 16 and 17 of the potential of what is possible in further GIS analyses by the City. The examples summarize the percent tree cover by parcel and neighborhood, but could be by zoning district or other areas of interest to the City. The first in Figure 16 is the existing or current tree canopy and possible tree cover summarized by parcel. Possible tree canopy is defined as areas with grass, bare soil or impervious surface (e.g., parking lots) where it is theoretically possible to plant trees. Figure 17 depicts the existing and possible percent tree canopy for all neighborhoods of the City. The next step would be to define criteria for identifying preferred area for adding trees. The capability exists in the data for the City to create any definition that is desired and do its own GIS analysis of where trees might be planted. Many factors will determine when and where trees are planted and maintained, but an urban tree canopy assessment is an essential first step in determining where trees can be planted if the requisite social-political and financial capital exits.

Figure 16. Example of parcel level GIS analyses summarizing existing and possible percent tree cover near Lake of the Isles.

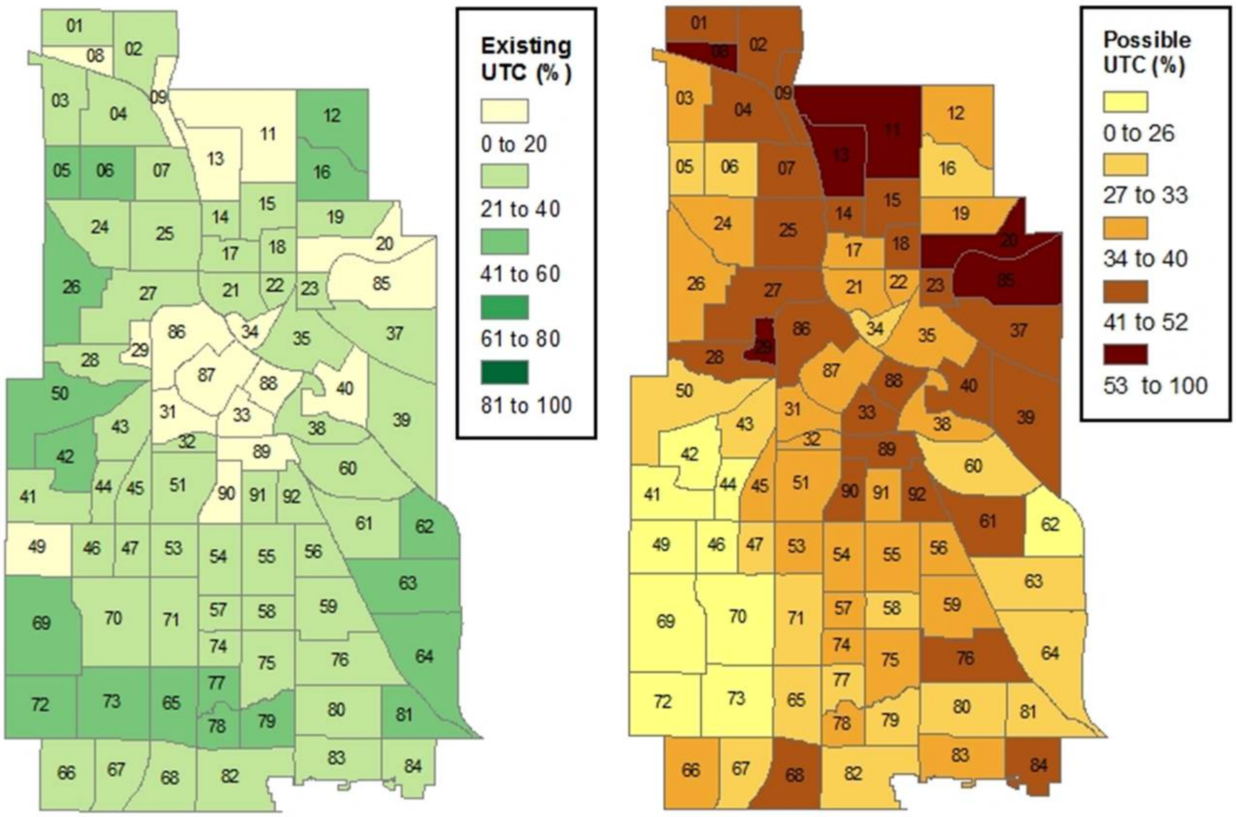

Figure 17. Example of further GIS analyses with summaries of percent existing and possible tree cover by neighborhood.

The classification maps and statistical data are available in a GIS database and a web-based mapping application for further analysis by the City.

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