Digital Classification and Mapping of Urban Tree Cover:

City of St. Paul

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, 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 canopy or cover is not routinely available, and 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 high resolution color orthoimagery that has been acquired is early spring, leaf-off imagery, so is not really suitable for mapping tree cover in St. Paul, Minnesota 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 St. Paul area. QuickBird has four spectral bands, blue, green, red and near infrared, with the near infrared being especially useful for mapping vegetation at 2.4 meter spatial resolution, plus a panchromatic band at 0.6 meter resolution. With "pan-sharpening" a 0.6 meter resolution image can be generated that is actually higher than the 1-meter USDA 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 St. Paul 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 cover the ground when viewed from above.

General Approach

QuickBird satellite imagery acquired on May 28, 2009 was used for the image classification. A small strip of about 100 meters on the far west edge of the city was missing from this image and was replaced with an image acquired on June 25, 2009. The images were clear and cloud-free. Natural color and false color (includes the near infrared band) images are shown in Figure 1.

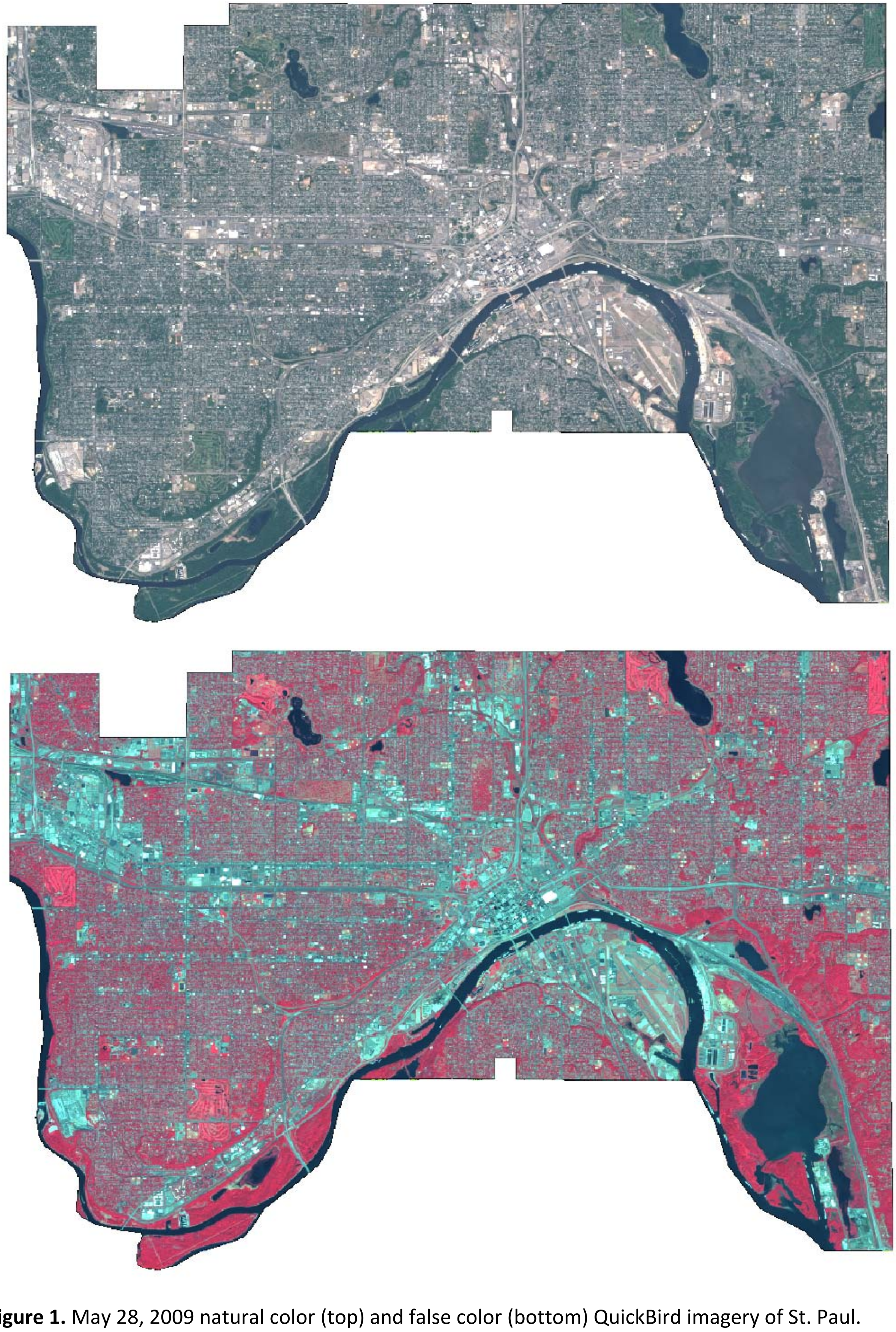

Figure 1. May 28, 2009 natural color (top) and false color (bottom) QuickBird imagery of St. Paul.

In addition, lidar (Light Detection and Ranging) data acquired on five separate days in June of 2007 was available from the US Army Corps of Engineers. This data consisted of first return information as well as bare earth; using the two, a normalized digital surface model (nDSM) was created which depicted height above bare earth across the city. The horizontal accuracy of this data was roughly 0.5 meters and stated to be "better than 1 meter." Its vertical accuracy determined from 33 control points was 0.087 meters. Unfortunately, we did not have full coverage of St. Paul as a strip approximately 1,500 meters wide was omitted on the eastern edge of the city.

Figure 2. June 2007 normalized digitial surface model (nDSM) lidar imagery of St. Paul. Note the missing data on the east side of the City.

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.

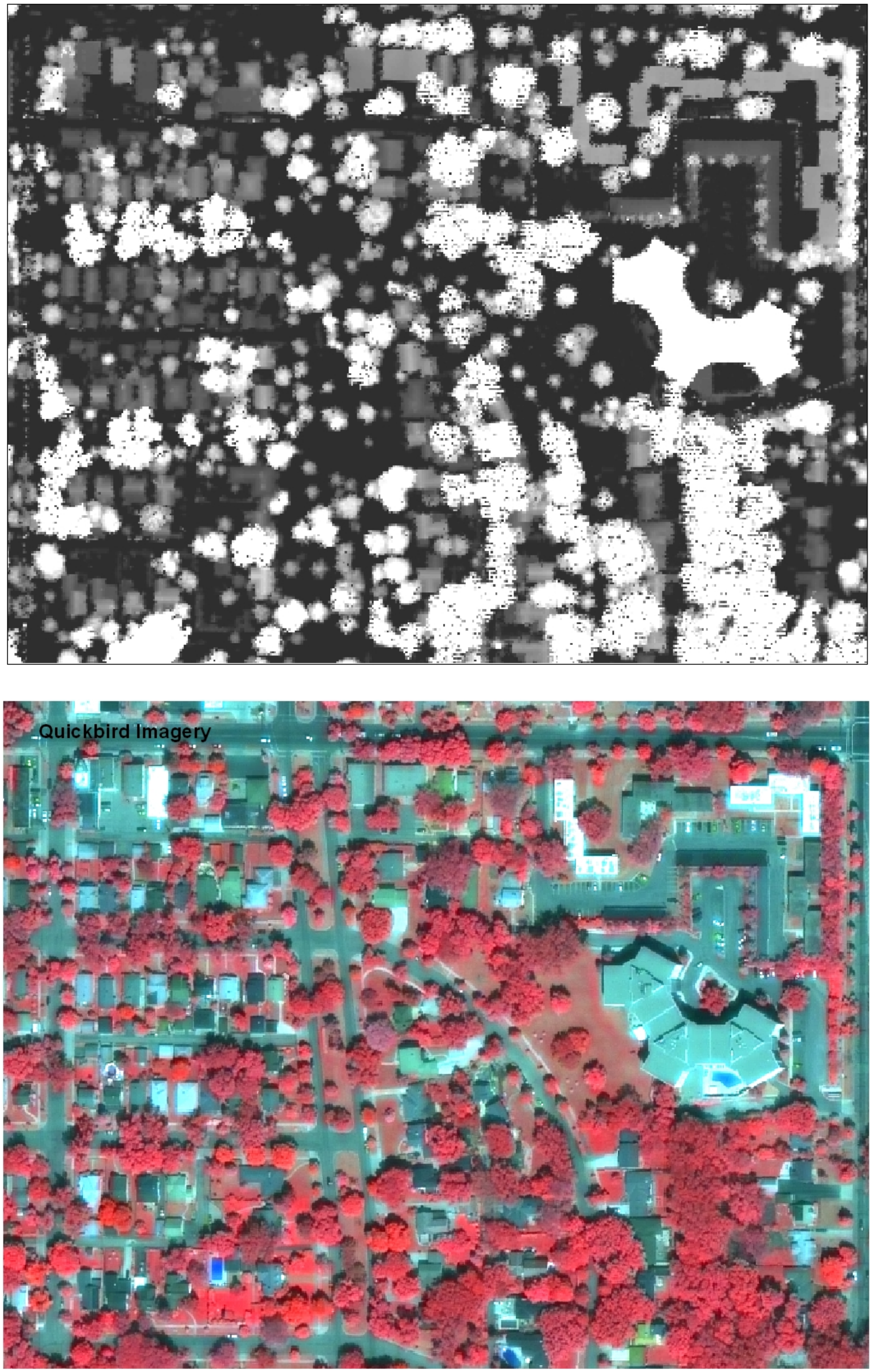

Figure 3. Enlargements of the lidar nDSM (top) and false color (bottom) QuickBird imagery.

The land cover classes include: tree canopy, grass and shrubs (including agricultural fields), buildings, impervious (streets, driveways and parking areas), water and bare soil.

The primary land classifications were produced using object based image analysis (OBIA) techniques available in eCognition Developer version 8.0. Ancillary software utilized in the project 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 St. Paul to help identify streets, buildings, roads and highways and water features.

The following principle steps were followed to implement the project:

- QuickBird Imagery was pan sharpened using subtractive resolution in ERDAS Imagine.
- QuickBird Imagery was georeferenced utilizing the available RPC files and a 30 meter DEM layer.
- Lidar data was 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% overlap for further processing. This step created 180 individual tiles.
- The street layer containing road information was buffered in ArcGIS by one meter to create a polygon shapefile for subsequent use in eCognition.
- Three rule sets were developed to process the following subsections of the city:
  - The small western section which included both June QuickBird and lidar data.
  - The 1,500 meter strip on the east side of the city which had May QuickBird imagery but no lidar data.
  - The remaining large section of the city which had May QuickBird and lidar data.
- Each of the 3 rule sets was created using a similar process:
  - Imagery was examined to locate a representative tile.
  - Supportive image layers were created such as Normalized Difference Vegetation Index. (NDVI) and Lee's Sigma Edge Extraction to aid classification efficacy.
  - Image objects were generated representing roads and water features from shapefiles and classified as such.
  - If lidar data were available 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.
- Each rule set was fine tuned and tested on additional random tiles throughout the city.
- Each of the final rule sets was used to classify all the tiles comprising its section of St. Paul using eCognition Server.
- Individual classified tiles were joined into a single mosaic using geometric seam lines in ERDAS Imagine Mosaic Pro.
- The three different sections of the city, represented by 402 individual tiles, were combined into a single classification file.

- The resulting classification was used to create an accuracy assessment in ERDAS Imagine using 1,067 stratified random points.
- The classification mosaic was then manually examined and edited to eliminate errors.
- Error corrections were re-run in eCognition Server to incorporate 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.

An object-oriented 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 was used for the image classification. 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 of, for example, streets and water bodies, could also be incorporated into the decision rules.

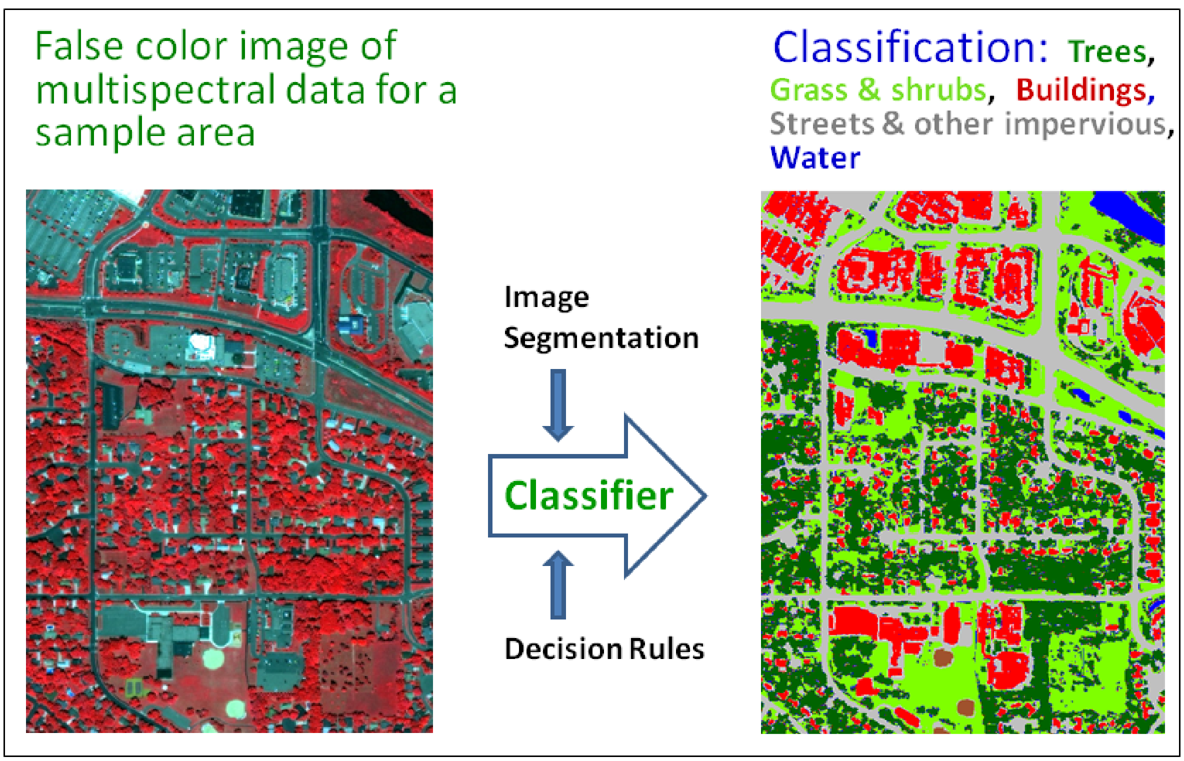

Figure 4. Major steps in the object-based image analysis approach to image classification.

The object-oriented 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, for example, a building are combined where the brightness, NDVI and color information are similar 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.

Post Processing Analysis

Accuracy assessment was performed on the results after the tiles were edited for corrections. The accuracy assessment was executed by generating stratified random points across the image and comparing the classified results to reference imagery (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 features in that class across the image. There were 1,067 points in the sample.

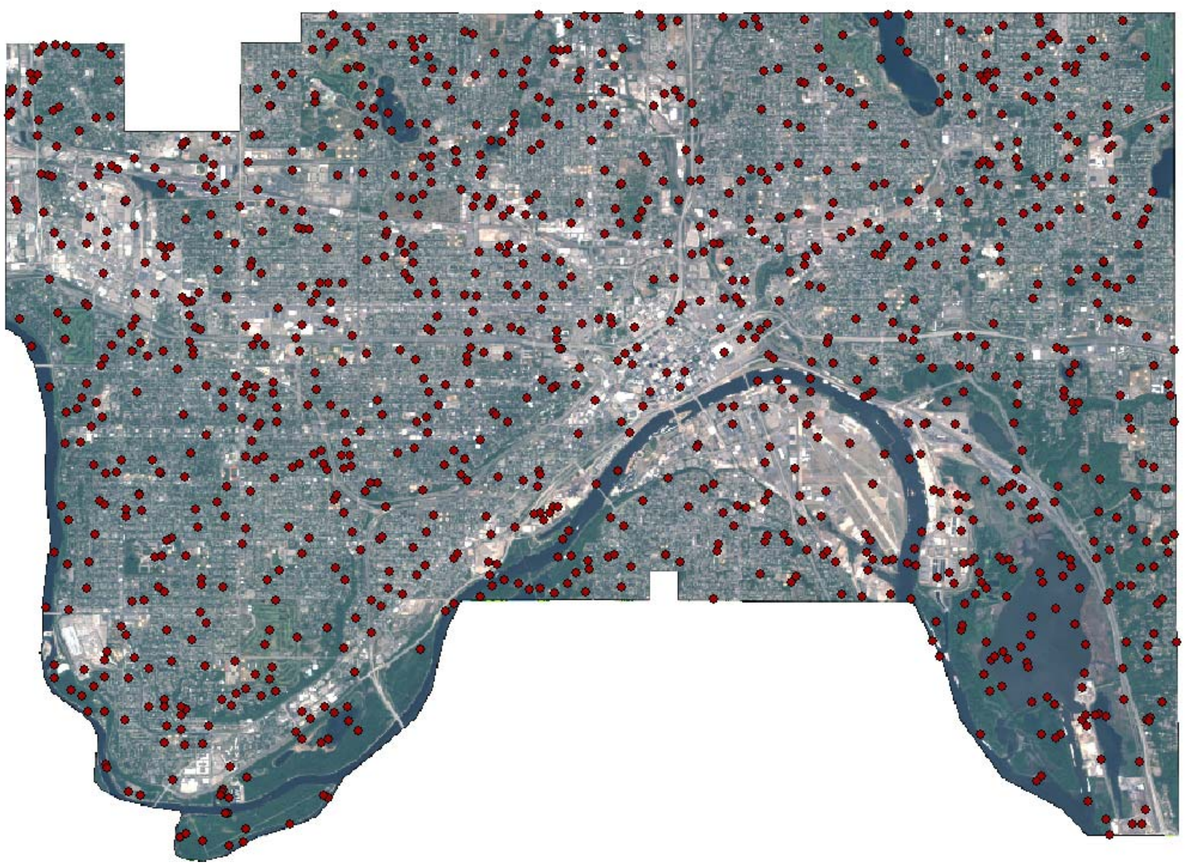

Figure 4. Locations of 1,067 sample points used for the final accuracy assessment.

In Figure 4 the assessment points are depicted with labels large enough to be visible on the map, but in reality these points are geometric points that ERDAS randomly puts on the image. Below 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 is tree canopy, grass or a building roof. 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.

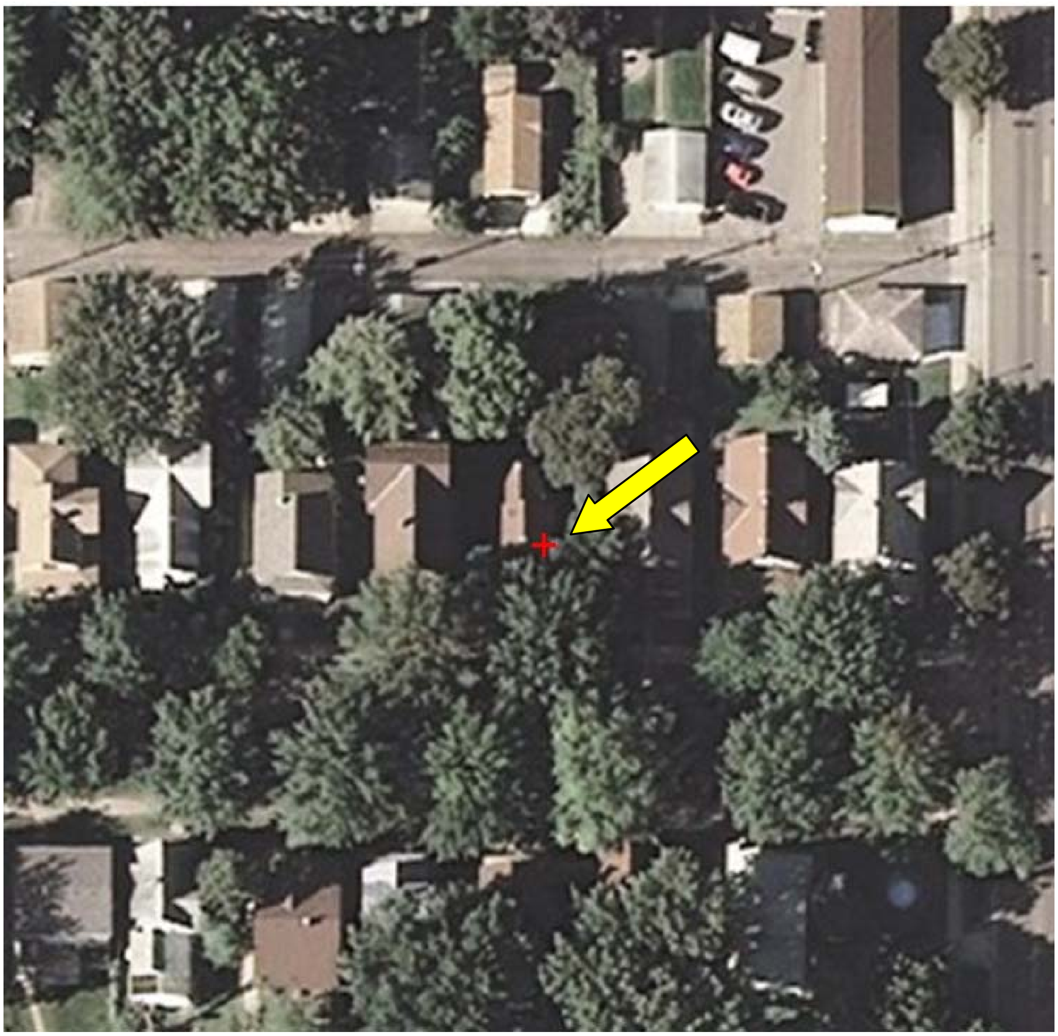

Figure 5. Example of a randomly selected sample point for accuracy determination.

Results

The final classification raster image is depicted in Figures 6 and 7. The results in Table 1 show that 32.5 percent of the area of the City is tree canopy.

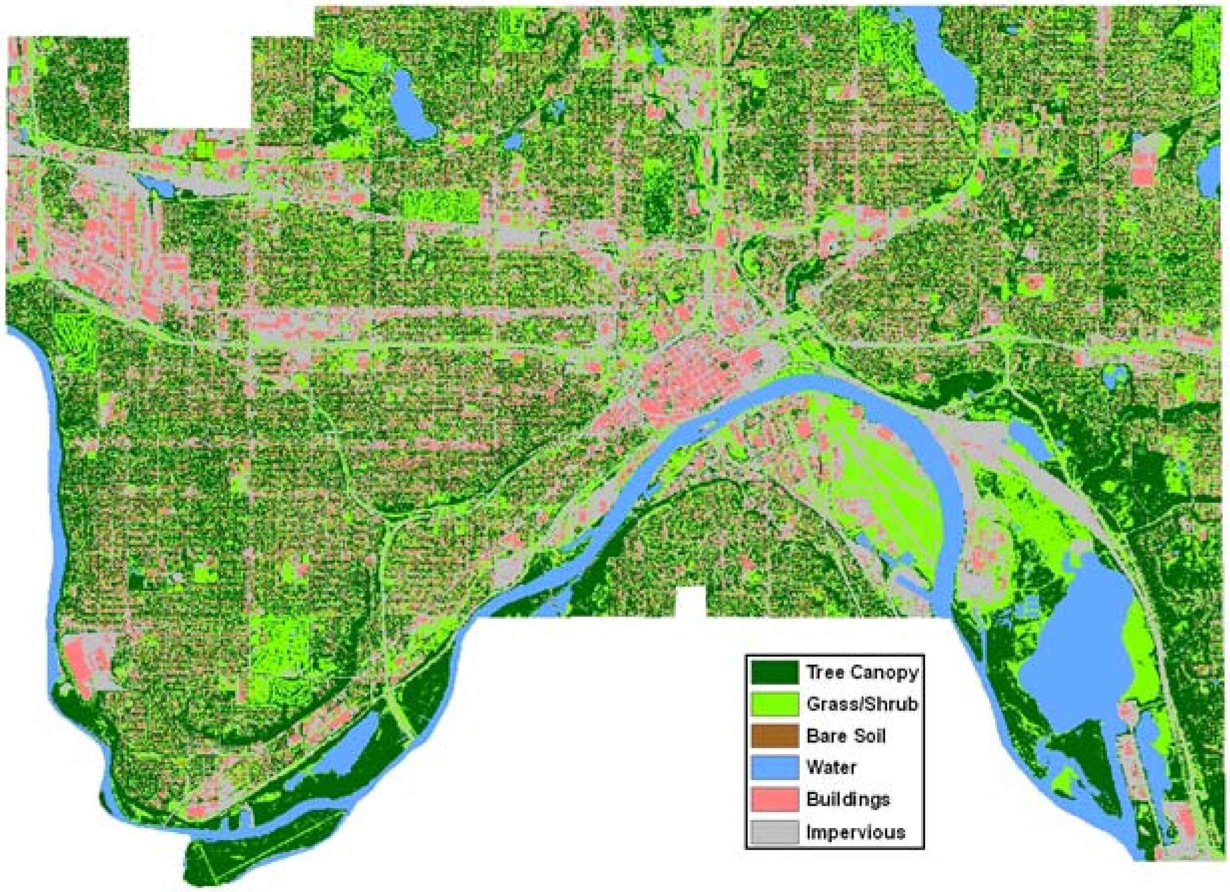

Figure 6. Land cover classification of St. Paul.

Table 1. Tabulation of the percent area of each of the six land cover classes.

Class	Percent
Tree Canopy	32.5
Grass/Shrub	22.6
Impervious	23.9
Buildings	13.7
Water	7.1
Bare Soil	0.2
Total	100.0

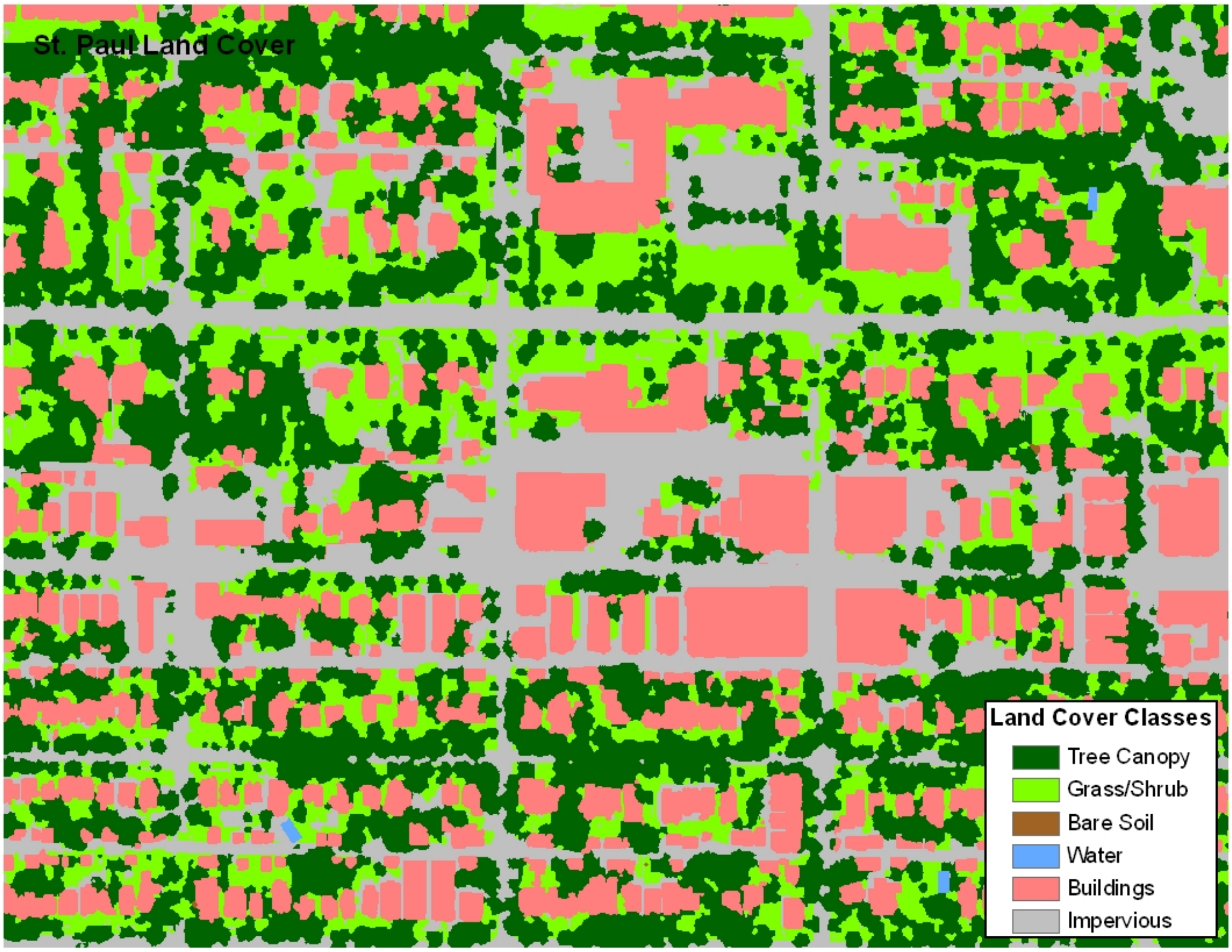

Figure 7. Detailed view of the classification of the area near the intersection of Victoria Street and Grand Avenue.

A comparison of a high resolution aerial photograph to the image classification illustrating the high correspondence between the two provides a qualitative indication of the classification accuracy is shown in Figure 8.

Figure 8. Comparison of high resolution aerial photo (top) and image classification (bottom) of an example subset of the image southwest of the intersection of Lexington Parkway and Randolph Avenue.

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 in Table 2; 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 image classification, while effective, can still result in obvious misclassifications. To reduce this impact, the classifications were compared to reference imagery and were edited manually (i.e., corrected) 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 for these errors were made and the results are shown in Table 2. The overall accuracy following the editing and corrections was 90.3 percent (Table 2).

Table 2. Classification accuracy following corrections.

Classification	**Reference Data**						***Total***	**User's Accuracy (%)**
	Tree Canopy	Grass & Shrub	Bare Soil	Water	Buildings	Impervious		
Tree Canopy	**312**	21	0	0	2	7	*342*	91.2
Grass & Shrub	15	**207**	0	0	5	17	*244*	84.8
Bare Soil	0	1	**0**	0	0	1	*2*	0
Water	1	0	0	**75**	1	1	*78*	96.1
Buildings	2	3	0	0	**129**	9	*143*	90.2
Impervious	4	8	1	1	4	**240**	*258*	93.0
Total	*334*	*240*	*1*	*76*	*141*	*275*	*1067*	–
Producer's Acc. (%)	93.4	86.3	0	98.7	91.5	87.3	–	**90.3**

Overall accuracy: 963 / 1067 =90.3% 95% Confidence Interval: 88.5 , 92 Kappa Statistic: 0.87

Discussion

The overall accuracy of 90.3 percent and user's and producer's accuracies of 93.4 and 91.2 percent for tree cover meets the expected accuracy goals of the project. The primary errors are some confusion between trees and grass/shrub, between buildings and impervious, and grass and impervious. The single largest area of confusion was the 17 impervious points which were erroneously classified as grass and shrub. Many of these occurred at the boundary of tree canopy and roadway where pixel "bleed" may have contributed to the errors.

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 our imagery we used a pan-sharpening process which takes QuickBird 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. Although creating very good multispectral imagery, it is not quite the same if the original multispectral data was 0.6 meter resolution. The is some “bleeding” of the spectral information which made it difficult to isolate narrow areas of impervious cover such as sidewalks and also caused the “fuzzy” boundaries noted in the above paragraph.

Another limitation to the study was the temporal mismatch between the QuickBird and lidar imagery. The QuickBird image was acquired approximately one year after the lidar data and this resulted in several inconsistencies in the classification. An example would be trees present in the lidar but subsequently removed prior to the QuickBird acquisition. Where the tree had overhung a street, the software 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 does 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 street layers and was not truncated at the edge of the street. The exception to this would be the parcel analyses that follow. In these cases, 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 May 28 and June 25, 2009 was classified into land cover classes of tree canopy, grass and shrubs, buildings, impervious, water, and bare soil utilizing lidar flown in June of 2007. The overall classification accuracy was 90.3 percent. Citywide, the amount of tree canopy cover was found to be 32.5 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 of the entire Twin Cities Metropolitan Area will be flown in the spring 2011 and will be available for use sometime later in 2011. We would recommend the City of St. Paul consider re-analyzing tree canopy when this lidar is available and re-acquire satellite imagery to match the lidar acquisition dates as closely as possible.

Finally, we present examples in Figures 9 and 10 illustrating the potential of what is possible in a GIS analysis. Figure 9 summarizes the percent tree canopy by parcel and neighborhood, but it could be by ward, zoning district or other areas of interest to the City. Another analysis, shown in Figure 10, is possible tree canopy -- defined as the sum of the existing tree canopy, and grass and shrub and bare soil where trees might be planted. 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 further GIS analysis.

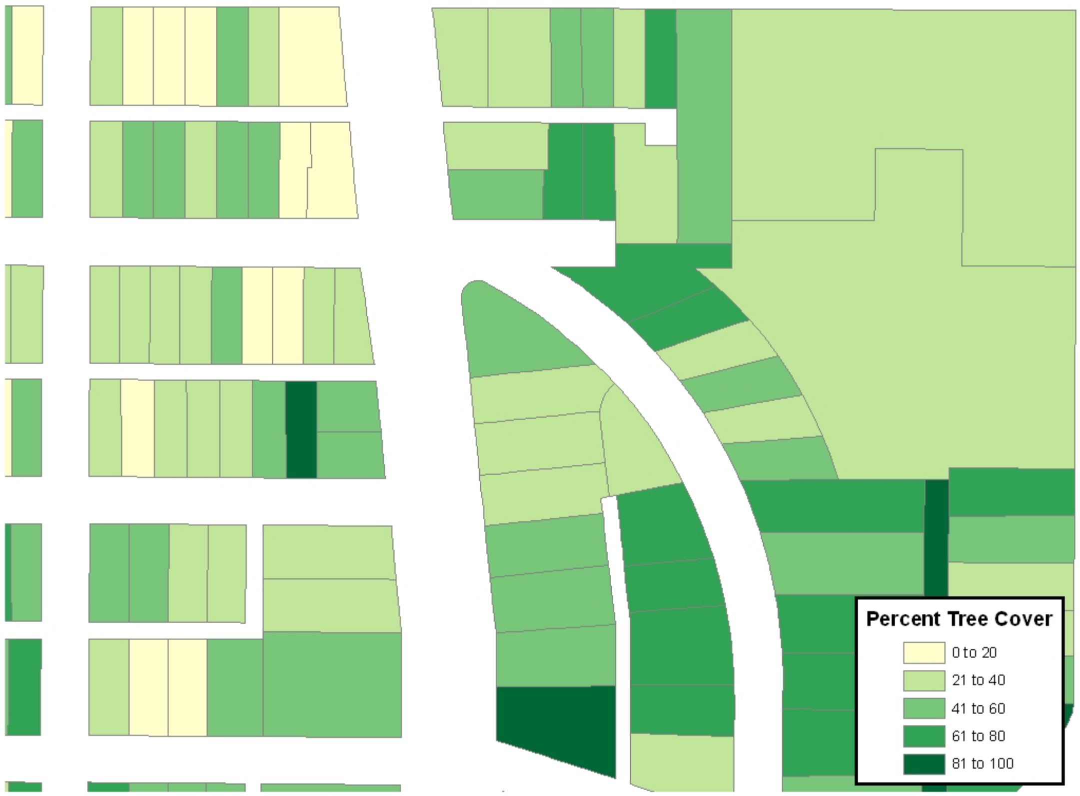

Figure 9. Example of GIS analysis summarizing existing percent tree cover by parcel.

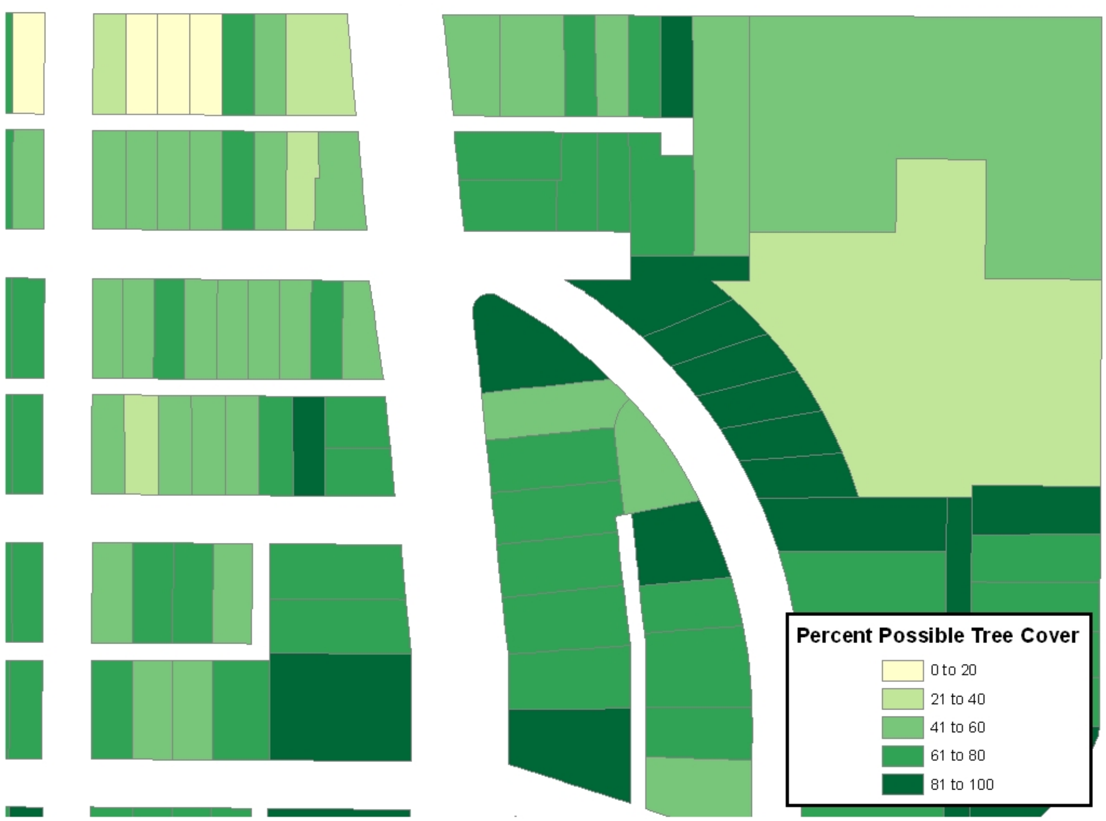

Figure 10. Percent possible tree canopy by parcel.

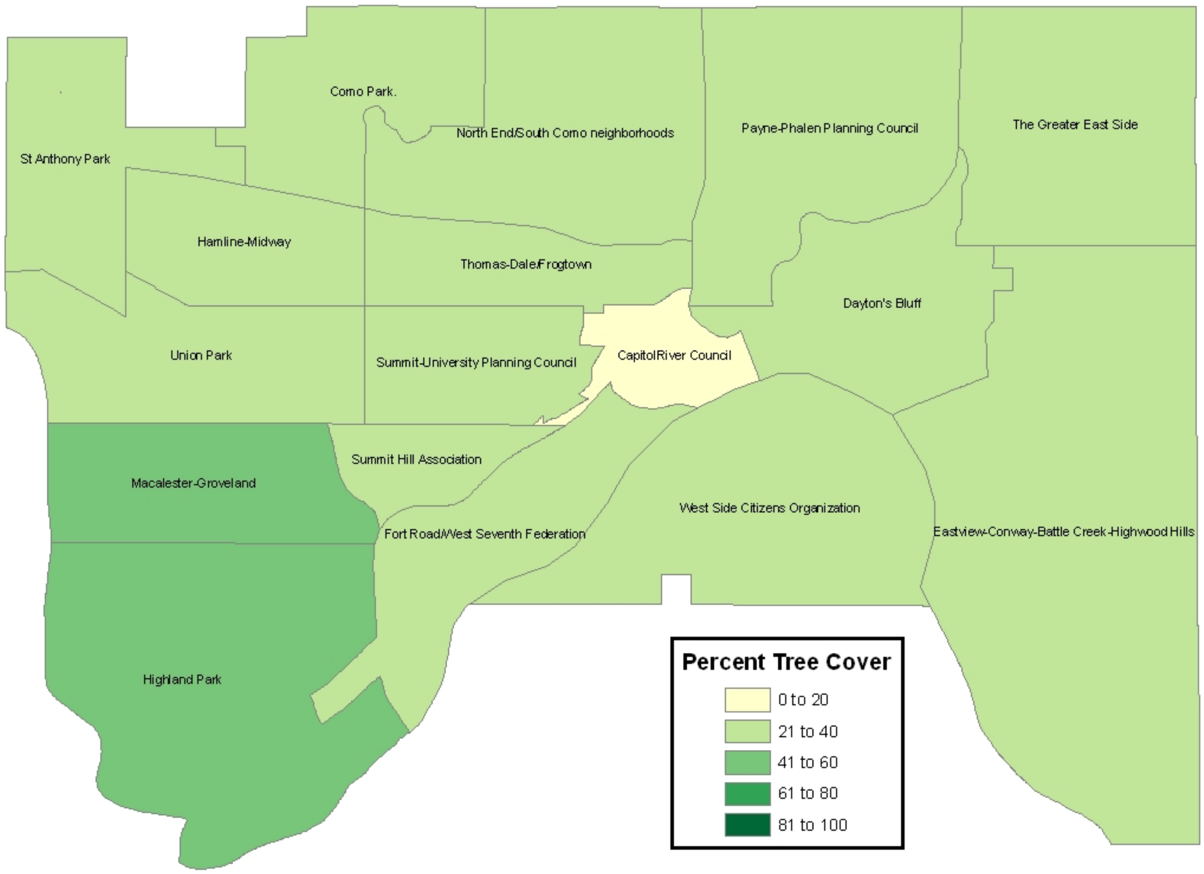

Figure 10. Example of further GIS analysis and summary of percent tree cover by neighborhood.

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Acknowledgements

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Appendix 1: Description of Accuracy Assessment Measures

Accuracy assessment provides information on reliability and useful of classification needed to support decision making and management using maps and data derived from remote sensing data. Quantitative, objective assessment of the classification accuracy, defined as the agreement between a standard or reference map or data (assumed to be correct) is a critical part of any serious remote sensing project (Congalton, 1991; Foody, 2002). The standard method of communicating the results is in a contingency or error matrix comparing the classification results to reference data for a random sample of points. The error matrix is the starting point for a series of descriptive and statistical techniques to evaluate accuracy.

Row totals equal the number of pixels in the reference data classes and the column totals equal the number of pixels assigned to each class. The diagonal show agreement between reference data and the classification (i.e., correct classification); points in off-diagonal cells are incorrect classifications. Overall accuracy is the number of correctly classified points divided by the total number of points in the sample. Columns include the errors of commission and rows include the errors of omission. Commission errors occur when a pixel or object was incorrectly called a class something it wasn't); errors of omission are when we did not classify something that it should have been classified as. Often the commission and omission errors are presented as user's accuracy and producer's accuracy. User's accuracy is based on the commission errors and is the probability that a pixel or object on the map actually represents that class on ground. Producer's accuracy is based on the omission errors and is the probability of a reference site being correctly classified.

The Kappa statistic is a discrete multivariate technique to interpret the results of a contingency matrix. The Kappa statistic incorporates the off diagonal observations of the rows and columns as well as the diagonal to give a more robust assessment of accuracy than the overall accuracy. The Kappa statistic is computed as the summation of the diagonal multiplied by the summation of each row multiplied by the summation of each column divided by the summation of each row multiplied by the summation of each column. It is a more conservative estimate of accuracy that measures the proportional (or percentage) improvement by the classifier over a purely random assignment to classes; in other words it removes the contribution of chance agreement to the accuracy.

Possible causes of classification errors include: spectral-radiometric similarity of classes leads to confusion between them, alignment or registration errors, and incorrect reference, including due differences in the time of acquisition of imagery and reference data.