# COMPARISON OF URBAN TREE CANOPY CLASSIFICATION WITH HIGH RESOLUTION SATELLITE IMAGERY AND THREE DIMENSIONAL DATA DERIVED FROM LIDAR AND STEROSCOPIC SENSORS

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*"Get going. Get up and walk if you have to, but finish the damned race."* -- *Ron Hill*

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# ABSTRACT

Matthew Lee Baller

## COMPARISON OF URBAN TREE CANOPY CLASSIFICATION WITH HIGH RESOLUTION SATELLITE IMAGERY AND THREE DIMENSIONAL DATA DERIVED FROM LIDAR AND STEREOSCOPIC SENSORS

Despite growing recognition as a significant natural resource, methods for accurately estimating urban tree canopy cover extent and change over time are not well-established. This study evaluates new methods and data sources for mapping urban tree canopy cover, assessing the potential for increased accuracy by integrating high-resolution satellite imagery and 3D imagery derived from LIDAR and stereoscopic sensors. The results of urban tree canopy classifications derived from imagery, 3D data, and vegetation index data are compared across multiple urban land use types in the City of Indianapolis, Indiana. Results indicate that incorporation of 3D data and vegetation index data with high resolution satellite imagery does not significantly improve overall classification accuracy. Overall classification accuracies range from 88.34% to 89.66%, with resulting overall Kappa statistics ranging from 75.08% to 78.03%, respectively. Statistically significant differences in accuracy occurred only when high resolution satellite imagery was not included in the classification treatment and only the vegetation index data or 3D data were evaluated. Overall classification accuracy for these treatment methods were 78.33% for both treatments, with resulting overall Kappa statistics of 51.36% and 52.59%.

Jeffery S. Wilson, Ph.D.

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# CHAPTER 1: INTRODUCTION

Urban forests are correlated with environmental quality and, through appropriate planning, can function to mitigate environmental impacts brought on by urban development (McPherson and Rowntree, 1991). Improved water quality, reduced rainfall runoff, and enhanced flood protection have been attributed to urban forests and green space (Nowak and Dwyer, 2000). Urban forests also affect air quality by reducing air temperatures, atmospheric pollutants, and energy use in buildings (Nowak, 2000). The significance of urban forests and green space goes beyond physical and biological environmental impacts. The social and economic environments of an urban area can also be positively influenced. These influences can range from enhanced aesthetics and property values to the creation of a strong connection between the public and the natural environment (Dwyer *et al.,* 2000).

Despite growing recognition as a significant natural resource, well-established methods for accurately estimating urban tree canopy cover extent and change over time are lacking. Previous remote sensing research has evaluated the utility of statistical classification approaches [e.g. maximum-likelihood, ISODATA, expert system approaches] applied to moderate spatial resolution satellite imagery, (e.g., 10 – 30m) for mapping urban landscapes. However, due to the spatially heterogeneous composition of urban areas, moderate spatial resolution data have proved less than adequate (Hodgson *et al.,* 2003). One of the primary problems is the presence of multiple land cover types within each pixel, commonly referred to as the mixed pixel problem (Lu and Weng, 2005). In order to address the mixed pixel problem, high spatial resolution data are needed. Historically, these data were primarily acquired by time consuming and expensive aerial survey, but high-resolution commercial satellite data have recently become available that offer potential for improved urban tree canopy mapping (Davis and Wang, 2002).

Even high spatial resolution satellite or aerial imagery may not be adequate for mapping urban tree canopy with traditional spectral classification approaches. High spatial resolution imagery captures greater variation in spectral response within a given land-cover class. Greater variation in spectral response within a given land-cover class can contribute to decreased classification accuracy (Lu and Weng, 2005). Shading, caused by topography, tall buildings, or trees, is also more prevalent in high resolution imagery which, in turn, presents problems in the selection of suitable image processing approaches over large areas (Asner and Warner, 2003). New forms of spatial data, such as light detection and ranging (LIDAR), provide potential for addressing urban tree canopy mapping problems inherent in image-based approaches by providing three dimensional information on urban landscapes that aid in separation of trees from other vegetated land cover types (Hodgson *et al.,* 2003).

The purpose of this study is to evaluate new methods and data sources for mapping urban tree canopy cover. We assess the potential for increased accuracy in urban tree canopy mapping by integrating high resolution imagery and 3D data derived from LIDAR and stereoscopic sensors. 3D data serves as an enhancement to the imagery by providing additional information on surface height to compliment spectral information captured by imaging sensors. The results of urban tree canopy classifications derived from imagery, 3D data, and vegetation index data are compared across multiple urban land use types in the City of Indianapolis, Indiana.

# CHAPTER 2: BACKGROUND

## Moderate Spatial Resolution Satellite Imagery

Considerable research has been focused on the accurate mapping of urban areas. Until recently, statistical pattern recognition algorithms applied to moderate resolution satellite imagery have been the primary approach utilized (Hodgson *et al.,* 2003). Lu and Weng (2005), for example, utilized a maximum likelihood algorithm to compare different image processing routines to identify suitable remote sensing variables for urban classification by incorporating spectral reflectance, texture, surface temperature, and data fusion techniques with 30m resolution Landsat ETM+ imagery. The best overall classification accuracy of 78% was achieved when textures from a higher resolution panchromatic image were incorporated with the 30m image data. Average producer's and user's accuracies for the urban forest class were 88% and 81% respectively.

Hale and Rock (2003) processed Landsat ETM+ imagery using band ratios, the Minnaert Correction, aspect partitioning, and combinations of these three treatments. Image combinations were classified using the minimum-distance decision rule. Resulting overall classification accuracies ranged from 59% to 63% and no treatment proved to be significantly more accurate than another. Average producer's accuracies for all forest classes ranged from 63% to 79% while average user's accuracies for all forest classes ranged from 53% to 61%.

Yuan *et al.* (2005) utilized a three-stage hybrid classification method for regional-scale multi-level land cover mapping using three Landsat TM/ETM+ images of the Twin Cities Metropolitan Area of Minnesota representing Spring, Summer, and Fall conditions, which were combined into a "stacked" 21-band image. Resulting images at each stage were classified into one of three levels of the Minnesota Land Cover Classification System (MLCCS), with each level increasing in specificity. The first stage involved an unsupervised classification and stratification, resulting in a MLCCS Level 1 classification. The second stage included supervised classification of forest types, rule-based clustering of non-forested vegetation, and estimation of percent impervious area using a regression model, resulting in a MLCCS Level 2 classification. The third stage combined the results from the first and second stages for final map generation. Post processing was performed to remove single, isolated pixels from the classification by merging the isolated pixel with the predominant surrounding class. Resulting images were classified into three levels of the MLCCS. Overall accuracies for Level-1 and Level-2 classes were 95% and 89%, respectively. Producer’s accuracy and user’s accuracy for the Level-2 coniferous forest class were 63% and 40%, respectively, while producer’s accuracy and user’s accuracy for the Level-2 deciduous forest class were 96% and 82%, respectively. Accuracies for Level-3 classification were not reported.

Regardless of classification accuracy, the inability of moderate resolution sensors to resolve finer-scale variation in tree canopy cover precludes their application to inform policy and management decisions within individual urban areas. Planners and urban foresters are often interested in canopy cover variation between individual neighborhoods, parks, or other districts that may be represented by only a few pixels in moderate resolution imagery. The research on moderate resolution imagery is informative, however, suggesting that incorporation of ancillary data may improve the delineation of urban tree canopy cover at finer scales.

## High Spatial Resolution Multi-Spectral Satellite Imagery

Previous research has explored the application of high resolution multispectral imagery for urban land cover mapping. Davis and Wang (2002), for example, examined the generation of urban land cover maps using pan-sharpened 1m IKONOS satellite imagery. A parallelepiped supervised classification algorithm was used to obtain urban land cover classifications unless there was a tie (overlap), which was resolved by the use of a maximum-likelihood decision rule. Each image was classified twice: once using a 3-band R/G/B combination and once using a 4-band R/G/B/NIR combination. The 4-band 11-bit 1m pan-sharpened image yielded the highest overall accuracy of 83%. No accuracy for the tree canopy class was given for the random sample sites, but the classification yielded a 99.8% accuracy for tree canopy class at each training site location.

Herold *et al.* (2003) evaluated how spectral resolution of high spatial resolution remote sensing data can influence accuracy in mapping of urban land cover. The study used Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data acquired at a spatial resolution of approximately 4m. The authors concluded that the optimal spectral setting for urban mapping was derived using the B-distance separability analysis, resulting in a subset of 14 bands. Performance of this spectral setting was evaluated and compared against common multi-spectral sensors, such as IKONOS, by assessing the accuracy for 26 urban land cover classes. The AVIRIS data yielded the highest overall classification accuracy (73.5%) in comparison with IKONOS data (61.8%) and Landsat TM data (68.9%). Herold *et al.* attributed the relatively low accuracy to spectral similarities of urban materials and the high degree of within-class variability. However, the "*green vegetation"* class, which is assumed to contain tree canopy, yielded a 95% producer's accuracy and an 80.5% user's accuracy. These results suggest that high spatial resolution imagery can be used to separate vegetation from other land cover types in urban landscapes.

Shackleford and Davis (2003) investigated the usefulness of high resolution IKONOS multispectral (MS) satellite imagery for classification of urban areas and the effects of applying a fuzzy logic methodology in order to improve classification accuracy. Imagery was first classified using a traditional maximum-likelihood decision rule, yielding accuracies between 79% and 87%. Several texture measures utilizing different pixel window sizes were investigated and added to the four bands of the IKONOS MS image data as an extra channel. Inclusion of texture measures yielded varied results. Entropy texture measures increased the average classification accuracy of the Grass and Tree classes by 10%, while decreasing the average classification accuracy of the Building and Road classes by 1.5%. Length-width contextual measures decreased average classification accuracy of Grass and Tree classes by 9%, while increasing the classification accuracy of the Building and Road layers by 5%. The incorporation of a hierarchical fuzzy classification scheme also proved to be effective, increasing discrimination between urban land cover classes with similar spectral signatures. Resulting overall classification accuracies of 8% to 11% higher than those using a traditional maximum-likelihood approach were reported.

Dell'Acqua *et al.* (2004) examined spectral and spatial analysis of high spatial resolution hyperspectral imagery to provide detailed land cover maps of urban areas. The aim of the research was to determine if the combination of spectral classifiers and local anomaly detectors could fully exploit the spectral and spatial datasets. Local anomaly detectors, based on joint spectral and spatial analysis of a small window surrounding each considered pixel, were chosen over global anomaly detectors, where the local analysis is linked to overall segmentation of the imagery. The research suggested global anomaly detectors provide higher classification accuracies, but are computationally expensive and therefore not cost effective. In the context of urban tree canopy mapping, the inclusion of local anomaly detectors had no effect on the Tree class, yielding an accuracy of 61% in both the original imagery and the enhanced imagery.

Thomas *et al.* (2003) compared three different classification approaches applied to 1m 4-band (R/G/B/NIR) imagery captured using the Airborne Data Acquisition and Registration (ADAR) 5500 platform. Imagery was collected over an urban setting. Approach 1, an unsupervised classification of all four ADAR bands, yielded an overall classification accuracy of 45% and an accuracy of 93% for the urban vegetation class, including tree canopy. Approach 2 used raster-based spatial modeling incorporating ancillary GIS layers and reflexive modeling derived from contextual pixel relationships based on the results of Approach 1. The raster-based spatial modeling approach yielded the highest overall classification accuracy at 79% and an urban vegetation class accuracy of 92%. Approach 3 dealt with developing a way of summarizing information from a contiguous cluster of homogeneous pixels that is lost when higher resolution imagery is used. Overall classification accuracy for Approach 3 was 70% while yielding an accuracy of 80% for the urban vegetation class.

Myeong *et al.* (2001) utilized high-spatial resolution digital aerial imagery to test effective methods for the development of land cover classifications in urban areas. An initial classification of the original imagery yielded an overall classification accuracy of 58%. This low classification accuracy was attributed to confusion between classes with similar spectral signatures. In order to improve the classification accuracy, texture and NDVI were incorporated with the original imagery. The incorporation of texture resulted in increased separability between tree canopy and grass in urban areas, while NDVI provided increased separability between vegetation classes and all other classes. The incorporation of these ancillary data improved overall accuracy to 81.75% and yielded an accuracy of 86.2% for the Tree/Shrub class.

High spatial resolution satellite or aerial imagery addresses the need for analysis of canopy cover variation between individual neighborhoods, parks, or other districts that may be represented by only a few pixels in moderate resolution imagery. However, these data sources may still not be entirely adequate for mapping urban tree canopy using a traditional spectral classification approach. High spatial resolution imagery captures greater variation in spectral response within a given land-cover class and increased occurrences of shading in high resolution imagery can present problems in the selection of suitable image classification techniques. The incorporation of ancillary data such as LIDAR may further improve the delineation of urban tree canopy cover at finer scales by providing three dimensional information on urban landscapes that aid in separation of trees from other vegetated land cover types.

**The Emerging Use of LIDAR**

Hodgson *et al.* (2003) mapped urban parcel imperviousness using high spatial resolution digitized color orthophotography and surface-cover height extracted from multiple-return LIDAR data. Triangulated irregular networks (TINs) were created for LIDAR datasets representing ground and surface cover. The three color channels from the aerial photography, combined with the surface-cover height model, were processed to derive land cover at both the pixel level and for homogeneous segments within the aerial photography. At the per-pixel classification level, a maximum-likelihood algorithm, the

ISODATA algorithm, and See5-generated rules were utilized. Segment-level classification was performed utilizing only See5-generated rules. These algorithms were applied to the natural color imagery and the surface-cover height data individually, and also to a combination of both layers. The results showed that the addition of the LIDAR-derived cover-height information improved modeled imperviousness results for all classification approaches. $R^2$ values increased by 2% to 25% depending on which approach was utilized and the standard error when using the combination of both the color imagery and the surface-cover height data was lower than when using any single data type.

The isolation of individual tree crowns and the relevant information extracted from tree structures can have significant implications in a variety of applications including urban tree canopy mapping. Chen *et al.* (2006) notes that intensive research has been done on isolating individual tree crowns using remotely sensed data, such as large-scale aerial photography and high spatial resolution satellite imagery. Recently, applications of LIDAR data to individual tree detection and canopy information extraction have been applied to direct measurement of geometric three-dimensional coordinates of tree canopies (Brandtberg *et al.*, 2003). Chen *et al.* (2006) and Koch *et al.* (2006) utilized canopy height models (CHM) in conjunction with additional algorithms to isolate individual tree crowns, yielding 63% and 64% overall accuracy, respectively. These canopy height models are similar to the surface height model approach of Hodgson *et al*. (2003), as they were calculated by subtracting the height value of the bare-earth digital elevation model (DEM) from the height value of the digital surface model (DSM).

Haala and Walter (1999) combined Digital Surface Models (DSM) resulting from airborne laser scanning (LIDAR) and color aerial imagery (NIR/R/G) for land cover classification in an urban environment. The study examined the difference between first response (first echo measurement) and last response (last echo measurement) data collected using a pulsed laser scanning system. Haala and Walter (1999) determined that the difference between first echo and last echo DSMs could be useful in the detection of urban tree canopy and building footprints. Geometric information derived from the DSMs was combined with multispectral information provided from high resolution color aerial imagery. Both types of information were integrated in a pixel-based classification, integrating height above terrain into the classification approach. Though the authors did not present quantitative results of their analysis, they were able to demonstrate that this approach considerably improved the classification of urban scenes.

# CHAPTER 3: METHODOLOGY

## Study Area

The study area is defined by an 800m buffer surrounding the Indianapolis Parks (Indy Parks) Urban Greenway Trail System in Center Township, Marion County, Indiana. The greenway corridor covers an area of approximately 27 km$^2$ (Fig. 1). Land use within the greenway corridor is diverse and spatially heterogeneous. This diversity provides an opportunity for comparison and evaluation of the classification methods developed in this research by land use class. Table 1 lists the area and percentage of major land use classes within the entire greenway corridor and within each individual greenway corridor in Center Township.

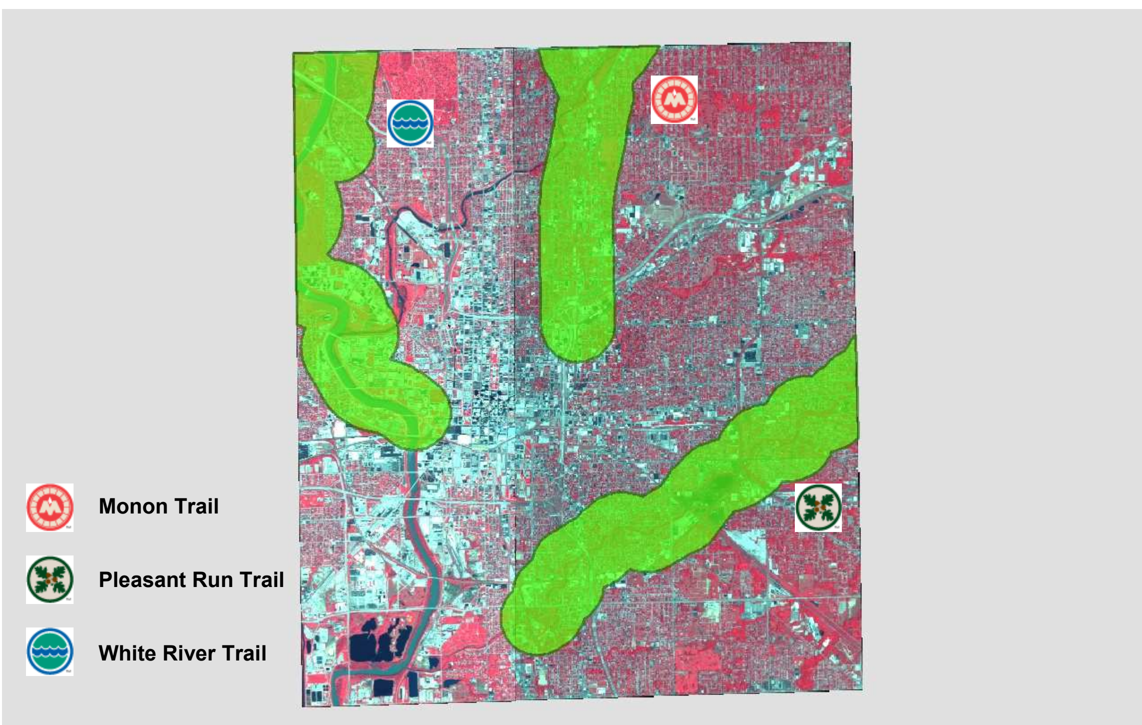


**Fig. 1. Half mile buffers surrounding Indy Parks Greenway Trails (green polygons) overlain on satellite imagery of Center Township, Indianapolis (DigitalGlobe QuickBird sensor); R=4, G=3, B=2.**

**Table 1. Land use statistics for Indy Parks Greenway Corridors within Center Township, Marion County, Indianapolis, IN. Land use dataset was compiled using 2004 zoning data and provided by the Indianapolis Mapping and Geographic Infrastructure System (IMAGIS).**

**Table 1a. Land Use Statistics - Entire Greenway Corridor**

| Land Use Class | Area ($km^2$) | Percent |
|---|---|---|
| Commercial/Central Business District | 3.13 | 11.38% |
| Industrial | 5.12 | 18.61% |
| Public Use | 4.48 | 16.28% |
| Residential | 12.26 | 44.57% |
| Special Use/University Quarter | 2.52 | 9.16% |
| **Totals** | **27.51** | **100.00%** |

**Table 1b. Land Use Statistics - Monon Trail Greenway Corridor**

| Land Use Class | Area ($km^2$) | Percent |
|---|---|---|
| Commercial/Central Business District | 0.73 | 9.76% |
| Industrial | 1.71 | 22.86% |
| Public Use | 0.91 | 12.17% |
| Residential | 3.74 | 50.00% |
| Special Use/University Quarter | 0.39 | 5.21% |
| **Totals** | **7.48** | **100.00%** |

**Table 1c. Land Use Statistics - Pleasant Run Trail Greenway Corridor**

| Land Use Class | Area ($km^2$) | Percent |
|---|---|---|
| Commercial/Central Business District | 1.06 | 10.01% |
| Industrial | 2.17 | 20.49% |
| Public Use | 1.12 | 10.58% |
| Residential | 5.97 | 56.37% |
| Special Use/University Quarter | 0.27 | 2.55% |
| **Totals** | **10.59** | **100.00%** |

**Table 1d. Land Use Statistics - White River Trail Greenway Corridor**

| Land Use Class | Area ($km^2$) | Percent |
|---|---|---|
| Commercial/Central Business District | 1.34 | 14.19% |
| Industrial | 1.24 | 13.14% |
| Public Use | 2.45 | 25.95% |
| Residential | 2.55 | 27.01% |
| Special Use/University Quarter | 1.86 | 19.70% |
| **Totals** | **9.44** | **100.00%** |

## Imagery

QuickBird satellite imagery was captured in two overpasses of the study area on April 25, 2005 and June 23, 2005. The QuickBird sensor collects four band multispectral imagery (RGB and NIR), with a spatial resolution of 2.4m at nadir. Spectral variation, especially predominant in vegetated areas because of seasonal differences, occurs between the two images. The April 25, 2005 imagery, containing the White River Trail greenway corridor, was collected under mostly clear conditions, with only trace amounts of precipitation recorded on the day of acquisition. However, 6.45cm of precipitation were recorded in the Indianapolis area in a 24-hour period from April 22-23. The June 23, 2005 imagery, containing the Pleasant Run Trail and Monon Trail greenway corridors, was collected under clear conditions with no precipitation events recorded in the week preceding data collection. Each image dataset was processed independently to control for variation in algorithm performance due to time of image acquisition.

## Elevation Data

Two sources of elevation data were used in the current study: 1) airborne LIDAR measurements and 2) surface height measurements generated from stereoscopic aerial imagery. LIDAR data were collected in March and April of 2003 for the City of Indianapolis using the Optech Airborne Laser Terrain Mapper (ALTM) 2033 sensor. Specifications provided by the data vendor indicate each LIDAR point has a final accuracy, or root mean square error, of 6-inch vertical and 1-foot horizontal. The LIDAR data were delivered in post-processed format consisting of two data layers: a digital surface model (DSM) including non-terrain features, and a “bald earth” digital elevation model (DEM). The LIDAR data were provided by the Indianapolis Mapping and Geographic Infrastructure System (IMAGIS) (http://www.indiana.edu/~gisdata/metadata/marion2003_lidar_metadata.html).

A digital surface model (DSM) was generated from data collected under leaf-off conditions from December 2004 to March 2005, by the State of Indiana using two Leica black and white Airborne Digital Sensors (ADS40). The DSM was generated by auto-correlation of stereoscopic aerial imagery using a processing system developed by ISTAR, resulting in a 1.5m spacing full surface model with “leaf-off” trees and buildings (http://www.in.gov/igic/projects/elevation.html). This dataset was obtained through Indiana University Spatial Data Services.

Elevation datasets were re-sampled to a resolution of 2.4m, matching that of the QuickBird imagery. All data sources were re-projected to Universal Transverse Mercator, North American Datum 1983, Zone 16, with meters as units. For this study, the LIDAR data will be referred to as *DSM LIDAR* (Fig. 2) and the stereo-generated data will be referred to as *DSM Stereo* (Fig. 3).

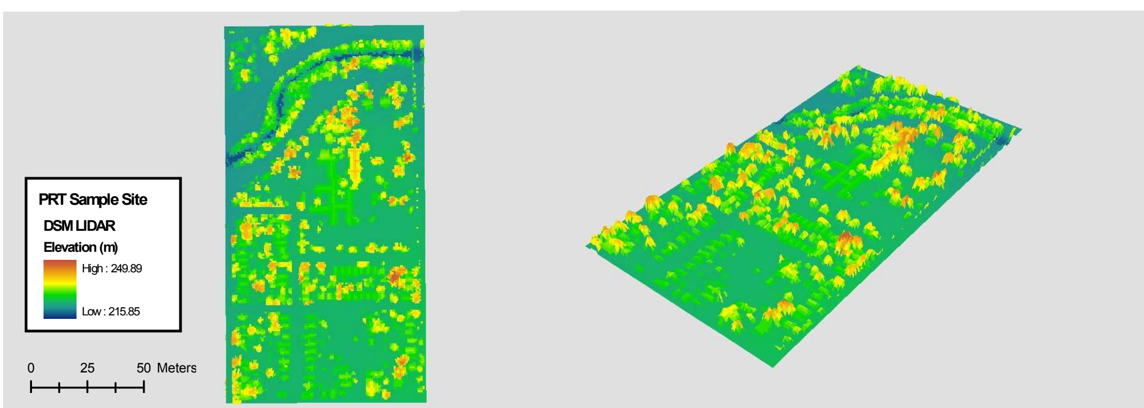


**Fig. 2. Subset of DSM LIDAR dataset along Pleasant Run Trail (PRT) at left. Three-dimensional rendering of the Pleasant Run sample site (right).**

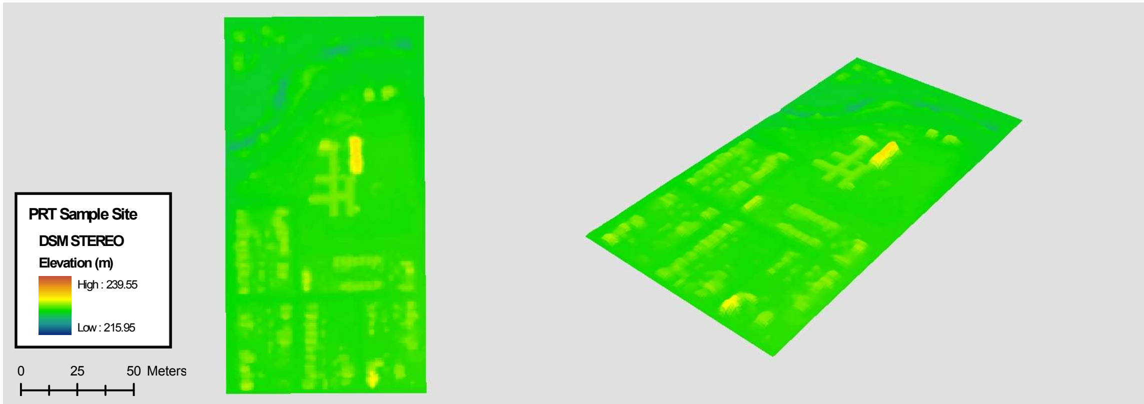


**Fig. 3. The image on the left represents the same site as Fig. 2. However, this subset represents DSM Stereo along the Pleasant Run Trail (PRT) within the Indy Parks Greenway Corridor. The image on the right represents a three-dimensional rendering of the Pleasant Run site.**

### Height Differential Layer

A *height differential layer* was created by subtracting DSM Stereo from DSM LIDAR. Both DSM datasets capture aboveground surface features such as buildings, but the stereo-generated data were collected during leaf-off conditions, resulting in little or no deciduous tree canopy detected by the airborne sensor. Conceptually, the difference between the two sources should remove building features in the resultant image, leaving only a representation of tree canopy elevation data (Fig. 4).

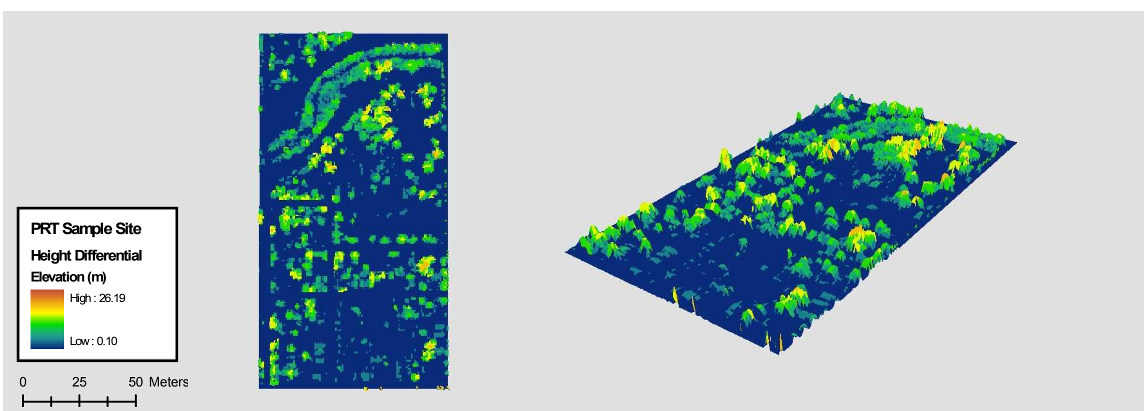


**Fig. 4. Two-dimensional and three-dimensional rendering of the *height differential layer* for the Pleasant Run Trail (PRT) sample site. The *height differential layer* was generated by subtracting DSM Stereo from DSM LIDAR.**

## Creation of Vegetation Indices

A normalized difference vegetation index (NDVI) was created for the study area from the QuickBird multispectral imagery. The NDVI was developed as a method for estimating vegetation characteristics from remotely sensed imagery and results in an index image with a possible range of -1 to +1 (Rouse *et al.,* 1974). The goal of vegetation indices is to reduce multiple bands to a single band that provides information on variables such as biomass or leaf-area index (LAI). NDVI values have been shown to correlate significantly with vegetation characteristics including percent ground cover (Jensen, 2005), biomass and LAI (Running *et al.,* 1994). NDVI is calculated as:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}$$

## Classification Treatments

Two classification treatments were evaluated to assess their performance in urban tree canopy delineation: an unsupervised classification using the ISODATA algorithm and a spatial modeling approach. Unsupervised classification was applied to the QuickBird imagery, height differential layer, and NDVI data individually and in combination as summarized in Table 2. A separate classification was performed on the height differential layer using a spatial model generated in ERDAS Imagine. Two classes, Tree and Other, were generated in all classification treatments.

Table 2. Representation of classification treatment applied to each individual image or image combination

| ***Image*** | ***Alias*** | ***ISODATA Algorithm*** | ***Spatial Model*** |
|---|---|---|---|
| QuickBird Satellite Image | Method 1 | X | |
| Satellite Image + Height Differential | Method 2 | X | |
| NDVI | Method 3 | X | |
| Satellite Image + NDVI | Method 4 | X | |
| Satellite Image + Height Differential + NDVI | Method 5 | X | |
| Reclassified Height Differential | Method 6 | | X |

*Traditional Spectral Classification:* Unsupervised per-pixel classification was performed using the ISODATA algorithm, separating the resultant image into twenty-five homogeneous clusters. The algorithm was limited to a maximum of fifty iterations with a convergence threshold of 0.980. The number of iterations required to meet the convergence threshold of 0.980 for the study area are summarized in Table 3. The resulting twenty-five clusters were assigned to either the Tree or Other information class based on visual interpretation of the satellite imagery and high resolution aerial photography.

**Table 3. Summary of iterations run by the ISODATA algorithm for each treatment method in each greenway corridor needed to meet the required convergance threshold of 0.980.**

| **Number of Iterations (Per Greenway Corridor)** | | | |
|---|---|---|---|
| **Treatment** | Monon | Pleasant Run | White River |
| Method 1 | 16 | 16 | 16 |
| Method 2 | 18 | 18 | 19 |
| Method 3 | 40 | 40 | 40 |
| Method 4 | 16 | 16 | 16 |
| Method 5 | 18 | 18 | 18 |

*Spatial Modeling:* Spatial modeling was utilized to divide the height differential image into two separate classes, Tree or Other, for comparison with the results of the ISODATA classification treatments. The following is an example of the logic used for the spatial model:

*FOR EACH [pixel in the map]*

*IF [pixel is ≥ 3m]*

*THEN [pixel is classified as Tree (1)]*

*IF [pixel is < 3m]*

*THEN [pixel is classified as Other (0)]*

Elevation data is the only data source being analyzed by the spatial modeling process. Therefore, the most practical way to model tree canopy was to set a standard height for defining a pixel as tree canopy. Conceptually, this should work because buildings and other structures have been removed by the subtraction of DSM Stereo from DSM LIDAR. The current National Land Cover Data standard for defining the Forested Upland land cover class is a canopy height of 6m. Due to the urban setting of the Indianapolis area, it was decided that a height of 3m would be an appropriate conservative estimate.

**Reference Data**

Reference data were created from visual interpretation of digital orthophotography collected in the winter of 2005 as part of a project by the State of Indiana. The spatial resolution for the area including Marion County and the City of Indianapolis was 0.15m. A traditional random sampling approach was used to determine the location of each reference sample site. The number of reference sites was determined by using the formula associated with the binomial probability theory (Fitzpatrick-Lins, 1981):

$$N = \frac{Z^2(p)(q)}{E^2}$$

Where:

*p* = expected accuracy of entire map

*q* = 100 – *p*

*E* = allowable error

*Z* = 2 from the standard normal deviate of 1.96 for the 95% two-sided confidence interval

This study used the U.S. Geological Survey (USGS) accuracy specification of 85% (Anderson *et al., 1976)* with an allowable error of 5%, resulting in the generation of 203 reference sites within each greenway corridor (609 total) to be compared with the results of each classification. Table 4 summarizes the distribution of the resulting randomly generated reference data points by land use class.

**Table 4. Summary of Reference Data Distribution by Land Use Class Designation**

| Land Use Class | All Trails Sample Points | All Trails Percent | Monon Sample Points | Monon Percent | Pleasant Run Sample Points | Pleasant Run Percent | White River Sample Points | White River Percent |
|---|---|---|---|---|---|---|---|---|
| Commercial | 68 | 11.17% | 19 | 9.36% | 16 | 7.88% | 33 | 16.26% |
| Industrial | 103 | 16.91% | 37 | 18.23% | 41 | 20.20% | 25 | 12.32% |
| Public Use | 104 | 17.08% | 30 | 14.78% | 22 | 10.84% | 52 | 25.62% |
| Residential | 280 | 45.98% | 107 | 52.71% | 119 | 58.62% | 54 | 26.60% |
| Special Use | 54 | 8.87% | 10 | 4.93% | 5 | 2.46% | 39 | 19.21% |
| **Totals** | **609** | 100.00% | **203** | 100.00% | **203** | 100.00% | **203** | 100.00% |

## Statistical Analysis

Accuracy associated with classification maps is commonly presented through several statistics, including user's accuracy, producer's accuracy, overall accuracy, and the Kappa statistic. These estimates help determine the success of the classification. Following the methods of Burt and Barber (1996), the Kappa statistics resulting from each classification treatment at each site were compared using a two-sample, two-sided difference-of-proportions test to determine if there was significant statistical difference between classification results. The following hypotheses at the 0.05 significance level were considered:

$H_0$: $|\pi_1 - \pi_2| \leq D_0$ $H_A$: $|\pi_1 - \pi_2| > D_0$ $D_0 = 0$

Where:

$\pi_1$ = Population proportion 1

$\pi_2$ = Population proportion 2

$D_0$ = Difference of proportions

For this study, the Kappa statistic served as the population proportion statistic, with the reference data sample population serving as *n.* The reference data sample population and the resulting Kappa statistics were used to calculate an observed *z* statistic, using the following equation:

$$Z = \frac{P_1 - P_2 - D_0}{\hat{\sigma}_{P_1 - P_2}} = \frac{P_1 - P_2 - D_0}{\sqrt{\frac{P_1(1-P_1)}{n_1} + \frac{P_2(1-P_2)}{n_2}}}$$

Where:

$P_1$ = Sample population proportion 1

$P_2$ = Sample population proportion 2

$D_0$ = Difference of proportions

$\hat{\hat{\sigma}}_{P_1 - P_2}$ = Standard deviation estimate of $D_0$

The *z* statistic was used to determine if the comparisons of difference in Kappa statistics were statistically significant.

# CHAPTER 4: RESULTS

Each classification result was compared to the reference data in order to assess the accuracy of the six different treatment methods. The results were compared at three different levels: the entire study area, each individual greenway corridor and by land use type. Table 5 summarizes the resulting classification accuracies.

**Entire Study Area**

When comparing results of each treatment method over the entire study area, the best overall accuracy was achieved by Method 4, a combination of QuickBird satellite imagery and NDVI. The overall accuracy was 89.66%, with a Kappa statistic of 0.7803, or 78.03%. Method 3, NDVI only, resulted in the poorest overall accuracy of 78.33% and an overall Kappa statistic of 51.36%. Method 6, the reclassified height-differential layer, also yielded an overall accuracy of 78.33%, but yielded a higher overall Kappa statistic. Complete accuracy assessments of the entire study area for each treatment method are presented in Appendix A.

**Individual Greenway Corridor**

As previously stated, satellite imagery for the study area was captured in two separate overpasses, allowing for a comparison of results by individual greenway corridor and date of capture. Results produced using imagery captured on June 23, 2005, included both the Pleasant Run Trail and Monon Trail greenway corridors, and yielded similar best overall accuracies (92.61% and 91.63%, respectively) and Kappa statistics (82.43% and 84.51%), respectively. Results produced using imagery captured on April 25, 2005, containing the White River Trail greenway corridor yielded a best overall accuracy of

91.13% and Kappa statistic of 80.61%. Resulting accuracies and Kappa statistics for each classification treatment per individual greenway corridor are presented below.

*Monon Trail*

Method 5, a combination of all image sources, produced the best overall accuracy for the Monon Trail greenway corridor. The overall accuracy was 91.63%, with an overall Kappa statistic of 82.43%. Method 6, the reclassified height-differential layer, produced the lowest overall accuracy and Kappa statistic at 72.91% and 39.09%, respectively. Complete accuracy assessments for each treatment method result within the Monon Trail greenway corridor are presented in Appendix B under Table B-1.

*Pleasant Run Trail*

Method 2, a combination of QuickBird satellite imagery and the height-differential layer, produced the best overall accuracy for the Pleasant Run Trail greenway corridor. The overall accuracy was 92.61%, with an overall Kappa statistic of 84.51%. Method 3, consisting of only NDVI values, produced the lowest overall accuracy and Kappa statistic, 77.34% and 48.95%, respectively. Method 6, the reclassified height differential layer, also produced an overall classification accuracy of 77.34%, but produced an overall Kappa statistic of 51.13%. Accuracy assessments for the treatment methods within the Pleasant Run Trail greenway corridor are presented in Appendix B under Table B-2.

*White River Trail*

Methods 1, 2, 4, and 5 all produced identical overall classification accuracies and Kappa statistics. The overall accuracy for these methods was 91.13% with an overall Kappa statistic of 80.61%. Method 3 produced the lowest overall accuracy at 73.89%% with an overall kappa statistic of 38.45%. It should be noted that Method 6 generated results with the highest amount of success in comparison with the performance of Method 6 in the other greenway corridors, yielding an overall accuracy of 84.73% and an overall Kappa statistic of 66.35%. Accuracy assessments for the treatment methods within the White River Trail greenway corridor are presented in Appendix B under Table B-3.

**Land Use Class**

*Commercial/Central Business District*

Method 4 produced the best overall accuracy of 95.59% and overall Kappa statistic of 85.34% for areas zoned as Commercial/Central Business District. Method 6 produced the lowest overall classification accuracy at 86.76%, with an overall Kappa statistic of 56.03%. Areas zoned for commercial land use generally had the highest overall accuracy, regardless of classification methods, in comparison to areas zoned for other land use classes. Complete accuracy assessments for each treatment method result within commercial land use zones are presented in Appendix C under Table C-1.

*Industrial*

When comparing results of each treatment method within areas zoned for industrial use, Method 2 produced the best overall accuracy. The overall classification accuracy was 93.20% and the overall Kappa statistic was 84.04%. Of note, Method 6 produced the lowest overall classification accuracy at 76.70%, but did not produce the lowest overall Kappa statistic (43.07%). Method 3 produced a higher overall classification accuracy of 78.64% than Method 6, but produced the lowest overall Kappa statistic at 42.22%. Complete accuracy assessments for each treatment method result within industrial land use zones are presented in Appendix C under Table C-2.

*Public Parks*

Method 1, QuickBird satellite imagery only, produced the best overall classification accuracy results for each treatment method within areas zoned for public parks. The overall classification accuracy was 89.42% with an overall Kappa statistic of 78.62%. Method 3 produced the lowest overall accuracy at 75.96% and the lowest overall Kappa statistic 49.30%. Complete accuracy assessments for each treatment method result within public park land use zones are presented in Appendix C under Table C-3.

*Residential*

Method 4 produced the best overall classification accuracy when comparing results for each treatment method within areas zoned for residential use. Overall classification accuracy was 87.86% with an overall Kappa statistic of 75.26%. Method 6 produced the lowest overall accuracy and overall Kappa statistic, 75.00% and 48.36%, respectively. Areas zoned for residential land use generated produced the lowest overall accuracy, regardless of classification method, in comparison to areas zoned for other land use classes. Complete accuracy assessments for each treatment method result within residential land use zones are presented in Appendix C under Table C-4.

*Special Use/University Quarter*

Methods 1, 2, and 5 each generated the highest overall accuracies (92.59%) and overall Kappa statistics (83.86%) when comparing results for each treatment method within areas zoned for university and special use. Method 3 produced the lowest overall accuracy of 70.37% and overall Kappa statistic of 30.43%. Method 4 produced an overall accuracy of 90.74% and an overall Kappa statistic of 79.64%. Method 6 produced an overall accuracy of 81.48% and an overall Kappa statistic of 58.90%.

Complete accuracy assessments for each treatment method result within special land use zones are presented in Appendix C under Table C-5.

**Table 5. Accuracy Assessment Comparison of Different Treatment Methods**

| | **Method 1** | | **Method 2** | | **Method 3** | |
|---|---|---|---|---|---|---|
| | **QuickBird Only** | | **QuickBird + Height Differential** | | **NDVI** | |
| | OCA | OKS | OCA | OKS | OCA | OKS |
| ***Entire Study Area*** | 88.34% | 0.7508 | 89.00% | 0.7645 | 78.33% | 0.5136 |
| ***Per Greenway Corridor*** | | | | | | |
| Monon Trail | 83.74% | 0.6456 | 83.25% | 0.6341 | 83.74% | 0.6441 |
| Pleasant Run Trail | 90.15% | 0.7939 | 92.61% | 0.8451 | 77.34% | 0.4895 |
| White River Trail | 91.13% | 0.8061 | 91.13% | 0.8061 | 73.89% | 0.3845 |
| ***Per Land Use Type*** | | | | | | |
| Commercial/Central Business District | 94.12% | 0.7988 | 92.65% | 0.7409 | 91.18% | 0.6792 |
| Industrial | 91.26% | 0.7915 | 93.20% | 0.8404 | 78.64% | 0.4222 |
| Public Park | 89.42% | 0.7862 | 88.46% | 0.7662 | 75.96% | 0.4930 |
| Residential | 84.29% | 0.6774 | 85.71% | 0.7064 | 77.86% | 0.5379 |
| Special Use/University Quarter | 92.59% | 0.8386 | 92.59% | 0.8386 | 70.37% | 0.3043 |
| | | | | | | |
| | **Method 4** | | **Method 5** | | **Method 6** | |
| | **NDVI + QuickBird** | | **All Sources** | | **Height Differential Reclass** | |
| | OCA | OKS | OCA | OKS | OCA | OKS |
| ***Entire Study Area*** | 89.66% | 0.7803 | 89.49% | 0.7767 | 78.33% | 0.5259 |
| ***Per Greenway Corridor*** | | | | | | |
| Monon Trail | 87.68% | 0.7372 | 91.63% | 0.8243 | 72.91% | 0.3909 |
| Pleasant Run Trail | 90.15% | 0.7939 | 85.71% | 0.6960 | 77.34% | 0.5113 |
| White River Trail | 91.13% | 0.8061 | 91.13% | 0.8061 | 84.73% | 0.6635 |
| ***Per Land Use Type*** | | | | | | |
| Commercial/Central Business District | 95.59% | 0.8534 | 95.59% | 0.8534 | 86.76% | 0.5603 |
| Industrial | 92.23% | 0.8162 | 91.26% | 0.7948 | 76.70% | 0.4307 |
| Public Park | 86.54% | 0.7258 | 88.46% | 0.7662 | 81.73% | 0.6125 |
| Residential | 87.86% | 0.7526 | 86.79% | 0.7299 | 75.00% | 0.4836 |
| Special Use/University Quarter | 90.74% | 0.7964 | 92.59% | 0.8386 | 81.48% | 0.5890 |

**Note:** OCA - Overall Classification Accuracy; OKS - Overall Kappa Statistic

**Statistical Significance Analysis**

Kappa statistics resulting from each classification treatment for the entire study area were compared using a two-sample, two-sided difference-of-proportions test to determine if there was significant statistical difference between classification results. Results indicate that there was no statistically significant difference between Methods 1, 2, 4, and 5. However, there was a significant difference between each of these methods and Methods 3 and 6. A cross tabulation of the results is summarized in Table 6. Complete results for the difference-of-proportions statistical tests for each classification method are presented in Appendix D under Table D-1.

**Table 6. Statistically Significant Difference of Kappa Values Between Treatment Methods**

| Method | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1 | -- | No | Yes | No | No | Yes |
| 2 | No | -- | Yes | No | No | Yes |
| 3 | Yes | Yes | -- | Yes | Yes | No |
| 4 | No | No | Yes | -- | No | Yes |
| 5 | No | No | Yes | No | -- | Yes |
| 6 | Yes | Yes | No | Yes | Yes | -- |

Using the classification treatment producing the highest overall classification accuracy (Method 4), the same test was run to compare kappa statistics by land use class. Table 7 contains a summarization of the results. Complete results for the difference-of-proportions statistical tests per land use class are presented in Appendix D under Table D-2.

**Table 7. Statistically Significant Difference of Kappa Statistic per Land Use Class (Treatment Method 4)**

| Land Use Class | Com | Ind | Pub Use | Res | Sp Use |
|---|---|---|---|---|---|
| Commercial/CBD | -- | No | Yes | Yes | Yes |
| Industrial | No | -- | Yes | Yes | No |
| Public Use | Yes | Yes | -- | No | Yes |
| Residential | Yes | Yes | No | -- | Yes |
| Special Use/Uni Qtr | Yes | No | Yes | No | -- |

# CHAPTER 5: DISCUSSION

This study evaluated the relative contribution of 3D data from LIDAR and airborne stereoscopic imagery in combination with high resolution multispectral imagery as a new method for mapping urban tree canopy cover. Based on prior research, it was expected that the addition of 3D data would generate significantly higher overall classification accuracy compared to the use of high resolution satellite imagery alone (Hodgson *et al.,* 2003). For the entire study area, the differences in overall accuracy between classification methods were relatively small in range (78.33 to 89.66 percent). In particular, when 3D data was utilized in combination with Quickbird satellite imagery (Methods 2 and 5), overall classification accuracy only increased between 0.66% and 1.15%. Statistically significant differences in the accuracy occurred only when Quickbird satellite imagery was not included in the classification treatment (Methods 3 and 6).

Image-based methods (Methods 1, 2, 4, and 5) produced overall classification accuracies ranging from 88.34% to 89.66%, exceeding the expected 85% USGS accuracy standard. High classification accuracies could be attributed to the small number of land cover classes used in this study. Using only two (2) classes, Tree or Other, allows for an equal percent chance of success (50%) or failure (50%) in terms of classification accuracy, as opposed to five (5) classes, which yields a lower percent chance of success (20%) and a higher percent chance of failure (80%). Previous studies have demonstrated that, all else equal, more detailed land cover classification with a higher number of land cover classes produces lower overall classification accuracies (Lu and Weng, 2005).

Satellite imagery was captured in two separate overpasses of the study area, allowing for an examination of variation in classification results by date of capture. Despite similarities in classification accuracies between dates, results within the White River Trail greenway corridor (April 2005 imagery) were more consistent between classification treatments than classification results within both the Monon and Pleasant Run greenway corridors (June 2005 imagery). Examination of NDVI values provides insight into the differences in accuracy consistency between classification treatments within the study area. NDVI values for tree canopy derived from imagery captured in April 2005 were consistently lower than NDVI values for tree canopy derived from imagery captured in June 2005. Date of capture played a significant role in the difference. Forest inventory data collected in 2003 indicated that deciduous species constitute approximately 90% of forested areas in Marion County, Indiana (Woodall *et al.*, 2006). Due to the high percentage of deciduous species in the study area, tree canopy examined from imagery captured in April 2005 consisted of more sparsely populated leaf layers, resulting in lower NDVI values and a higher discrepancy between tree canopy and other vegetation (Fig. 5). Tree canopy present in imagery captured in June 2005 consisted of a multiple leaf layer canopy resulting in higher NDVI values (Fig. 6), due to a phenomenon referred to as *leaf additive reflectance*, in which multiple leaf layers in a healthy, mature canopy can result in greater near infrared reflectance (Jensen, 2005). NDVI values for tree canopy and other vegetation were more similar in the June 2005 imagery, indicating the possibility for spectral confusion between tree canopy and herbaceous plants.

Overlap in NDVI values between trees and herbaceous plants were especially prominent in residential areas in the June 2005 imagery. Due to differing lawn care practices (i.e. heavily fertilized lawns with appropriate levels of sunlight and shade versus non-fertilized lawns in poor soils and direct sunlight with little or no shade), environmental stressors, and the leafing out of deciduous tree canopy within the period of April to June, these factors could explain the inconsistencies in overall classification accuracy success rate for June 2005 imagery in comparison with overall classification accuracy success rate for April 2005 imagery.

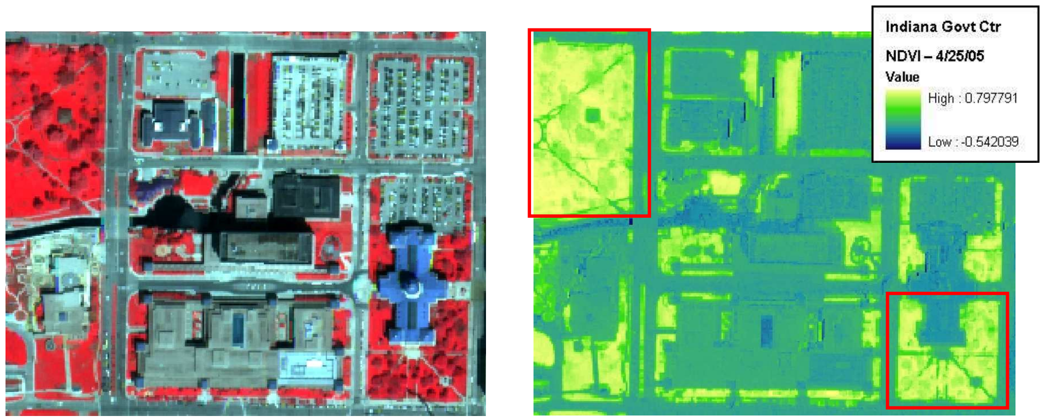


**Fig. 5. Left – Quickbird satellite imagery of the Indiana State Capital and Government Center, captured on April 25, 2005. Right – NDVI of same image. Areas of interest in the red boxes display the clear distinction between tree canopy and other vegetation in the April imagery.**

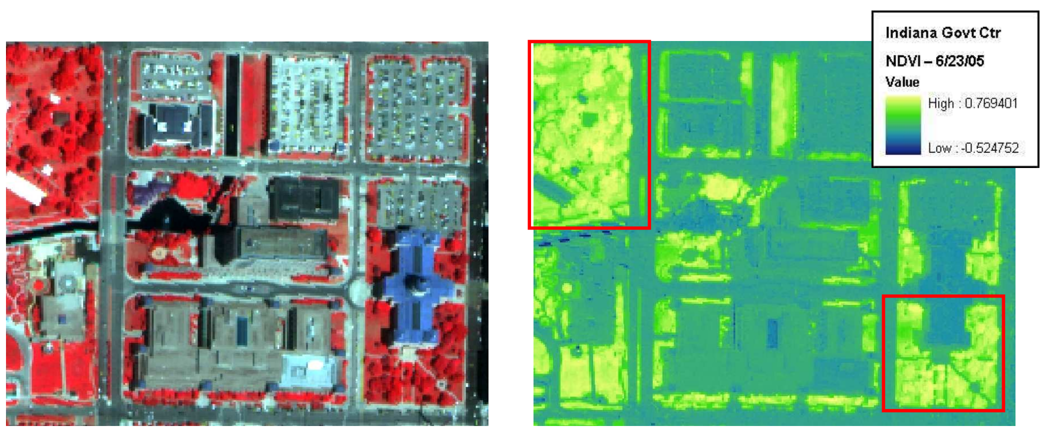


**Fig. 6. Left – Quickbird satellite imagery of the Indiana State Capital and Government Center, captured on June 23, 2005. Right – NDVI of same image. Areas of interest in the red boxes display a noticeably reduced distinction between tree canopy and other vegetation.**

Comparison of NDVI values for tree canopy and other vegetation by date of capture helped to explain the most glaring misclassification of tree canopy within the study area. An examination of two golf courses, South Grove Golf Course within the White River Corridor (imagery date of capture: April 25, 2005), and Douglass Golf Course within the

Monon Trail Corridor (imagery date of capture: June 23, 2005), reveals further how date of capture can affect infrared reflectance of tree canopy and other vegetation, therefore having an effect on classification results (Figs. 7 and 8). April NDVI values within the South Grove Golf Course site for turfgrass ranged approximately from 0.70 to 0.78, whereas NDVI values for tree canopy ranged approximately from 0.50 to 0.65. Conversely, June NDVI values within the Douglass Golf Course site for turfgrass ranged approximately from 0.65 to 0.73, whereas NDVI values for tree canopy ranged approximately from 0.64 to 0.75. The inconsistency of these NDVI values indicates how the phenological difference between grass and tree can affect classification results when multi-temporal imagery is used. Examination of the distribution of these values reveals why confusion between tree canopy and turfgrass occurred in five of the six classification treatment methods at the Douglass Golf Course site within the Monon Trail greenway corridor. The only treatment method to correctly classify the Douglass site was Method 6, the reclassified height differential layer, which relies solely on elevation data.

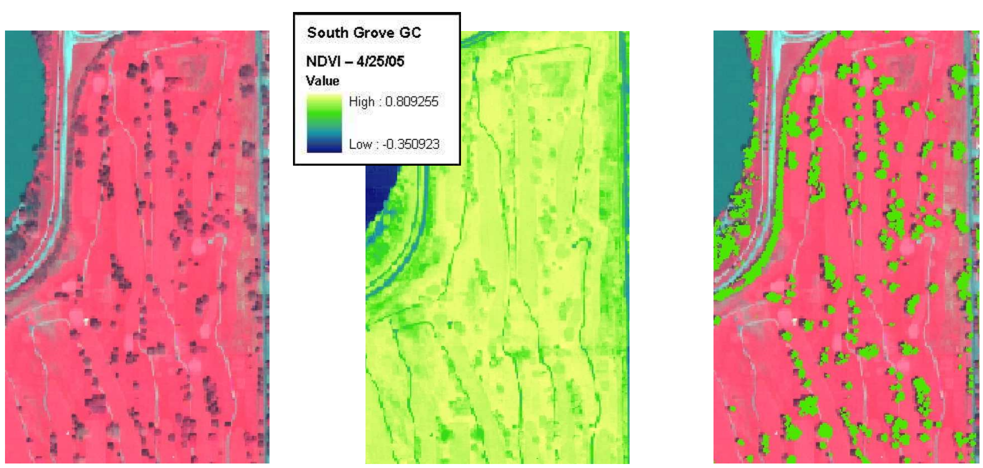


**Fig. 7.** ***Left*** **– Quickbird Satellite Imagery, South Grove Golf Course, April 2005.** ***Center*** **– NDVI image of South Grove GC.** ***Right*** **– Resultant classification of tree canopy (Treatment Method 5).**

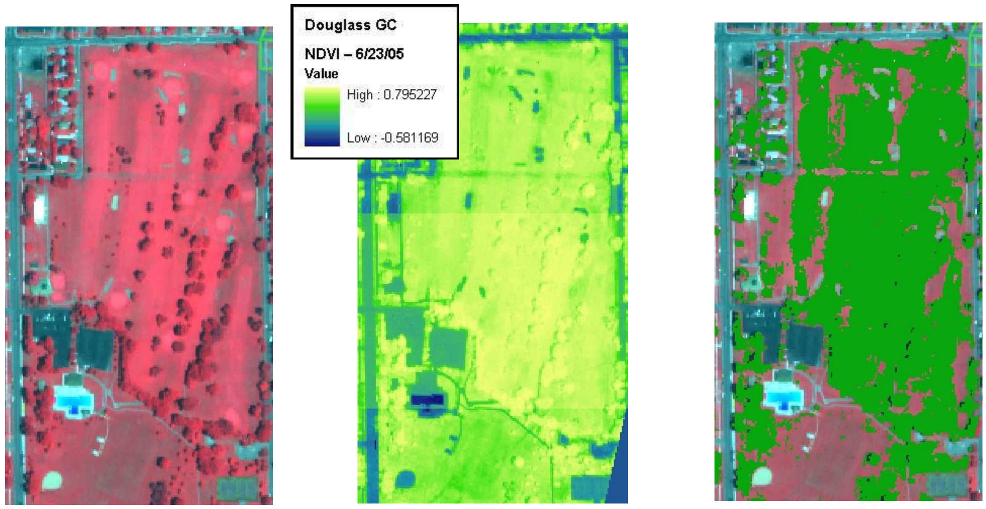


**Fig. 8.** ***Left*** **– Quickbird Satellite Imagery, Douglass Golf Course, June 2005.** ***Center*** **– NDVI image of Douglass GC.** ***Right*** **– Resultant classification of tree canopy (Treatment Method 2).**

A possible explanation for the consistent results within the White River Trail greenway corridor could be the percentage breakdown of land use classes within the corridor. Forty seven percent of the land use in the White River Trail greenway corridor was composed of land use classes that had significantly higher classification accuracies (Appendix D, Table D-2), and the lowest percentage (27%) of areas zoned as residential, the land use class that consistently yielded the lowest overall accuracy. The Monon Trail and Pleasant Run Trail greenway corridors contain only 33% and 31% of land use classes with significantly higher classification accuracies, respectively, while consisting of substantially higher percentages of areas zoned as residential (53% and 59%, respectively). Areas zoned for residential land use are important because the residential land use class consistently yielded the lowest classification accuracies of the five (5) land use classes used in this study. Residential areas tend to have more spatially heterogeneous land cover and when coupled with the inherent variation in reflectance values within individual features in high resolution imagery, classification success within these areas can prove difficult to achieve (Hodgson *et al.*, 2003). Within both the Monon Trail and Pleasant Run Trail greenway corridors, changes in overall classification accuracy were directly correlated to overall classification accuracy within areas zoned for residential land use.

Prior research suggested that the addition of 3D data would generate significantly higher overall classification accuracy than the use of high resolution satellite imagery alone (Hodgson *et al.,* 2003). Based on the results of this study, the addition of 3D data produced no statistically significant improvement in overall classification accuracy. An examination of the elevation data and height differential layer generated from these data and how it was utilized in the classification process could offer an explanation as to why it did not significantly improve accuracy. In this study, 3D data was used as a image layer in conjunction with high resolution satellite imagery for classification of urban tree canopy. The ISODATA algorithm identifies or defines clusters based on statistics of each cluster, making it very likely that 3D data or height information will not be given much weight in defining a cluster because trees in an urban setting are often not statistically significant compared to non-tree features. This may explain why the inclusion of 3D data did not present significant improvement over classification treatments with no 3D data. From a data quality standpoint, the elevation datasets used in this study were collected using different sensors with different specifications, producing different accuracies and undergoing different quality control measures. In the future, it would be best to ensure that these datasets are collected using the same sensor and quality control measures, if possible. Finally, evergreen trees in both datasets will be negated in the height differential layer, reducing accuracy if using the height differential layer solely to model tree canopy cover.

The parameters for classification in this study allowed for a higher chance for success than in previous studies. However, improvements to the process can be made. The incorporation of spatial enhancements such as texture information could possibly increase overall classification accuracy and though the increase in accuracy may not be that significant overall, the incorporation of these data may serve to inhibit the variation in classification accuracies of urban tree canopy between land use classes. The incorporation of vegetation species data in the study area allows for further refinement of vegetation classification, possibly accounting for more distinct and significant differences (high or low) in classification accuracy between datasets. Moving away from the unsupervised ISODATA algorithm as an image classifier to a hierarchical rules-based expert classifier could also improve performance. However, the use of an expert classification system is more labor intensive and is more time consuming than the ISODATA algorithm. The question becomes whether or not an improvement in accuracy from 90 percent to approximately 93 to 95 percent is worth the time and effort spent to attain it.

# CHAPTER 6: CONCLUSIONS

The growing recognition of the urban forest as a natural resource underscores the need for a well-established method of accurately estimating urban tree canopy cover extent and change over time. The purpose of this study was to evaluate new methods and data sources for mapping urban tree canopy cover in the City of Indianapolis, Indiana. Assessed was the potential for increased accuracy in urban tree canopy mapping by integrating high resolution imagery and 3D data derived from LIDAR and stereoscopic sensors. The research presented in this paper represents an important first step in utilizing high resolution satellite imagery and digital surface models to accurately classify urban tree canopy.

Statistical analysis of the results indicated that no significant increase in classification accuracy occurred when elevation data were incorporated with satellite imagery, either singularly or in conjunction with a Normalize Difference Vegetation Index. Image-based methods (Methods 1, 2, 4, and 5) produced overall classification accuracies ranging from 88.34% to 89.66% and overall Kappa statistics ranging from 75.08% to 78.03%. Results of the spatial model applied to the height differential layer yielded an accuracy of 78.33%, significantly lower than the accuracies of the other treatment methods in this study. However, results for the height differential layer produced an overall accuracy for tree canopy similar or higher than results in previous studies using moderate spatial resolution.

Comparison of classification accuracies in this study with previous urban classification mapping studies (Thomas *et al.,* 2003) indicates that urban tree canopy may be easier to accurately classify than other urban land cover classes such as impervious surface. Despite high classification accuracies resulting in this study, further improvements can be made. The incorporation of textures derived from high resolution satellite imagery (Lu and Weng, 2005) and exploring the use of an expert classification system (Hodgson *et al.,* 2003) could help reduce inconsistencies in results, especially within residential areas, thus increasing overall classification accuracy.

# Appendix A

**Table A-1. Accuracy Assessments of Different Treatment Methods for the Entire Greenway Corridor Study Area**

**Method 1:** QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **189** | 15 | 204 | 92.65% | Overall Accuracy | 88.34% |
| Other | 56 | **349** | 405 | 86.17% | Kappa Statistic | 0.7508 |
| Totals | 245 | 364 | 609 | | | |
| Producer's Accuracy | 77.14% | 95.88% | **538** | | | |

**Method 2:** QuickBird + LIDAR

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **190** | 12 | 202 | 94.06% | Overall Accuracy | 89.00% |
| Other | 55 | **352** | 424 | 86.49% | Kappa Statistic | 0.7645 |
| Totals | 245 | 364 | 609 | | | |
| Producer's Accuracy | 77.55% | 96.70% | **542** | | | |

**Method 3:** NDVI

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **124** | 11 | 128 | 91.85% | Overall Accuracy | 78.33% |
| Other | 121 | **353** | 481 | 74.47% | Kappa Statistic | 0.5136 |
| Totals | 245 | 364 | 609 | | | |
| Producer's Accuracy | 50.61% | 96.98% | **477** | | | |

**Method 4:** NDVI + QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **198** | 16 | 214 | 92.52% | Overall Accuracy | 89.66% |
| Other | 47 | **348** | 395 | 88.10% | Kappa Statistic | 0.7803 |
| Totals | 245 | 364 | 609 | | | |
| Producer's Accuracy | 80.82% | 95.60% | **546** | | | |

**Method 5:** All Image Sources

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **197** | 16 | 213 | 92.49% | Overall Accuracy | 89.49% |
| Other | 48 | **348** | 396 | 87.88% | Kappa Statistic | 0.7767 |
| Totals | 245 | 364 | 609 | | | |
| Producer's Accuracy | 80.41% | 95.60% | **545** | | | |

**Method 6:** Height Differential Layer

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **142** | 29 | 171 | 83.04% | Overall Accuracy | 78.33% |
| Other | 103 | **335** | 438 | 76.48% | Kappa Statistic | 0.5259 |
| Totals | 245 | 364 | 609 | | | |
| Producer's Accuracy | 57.96% | 92.03% | **477** | | | |

# Appendix B

**Table B-1. Accuracy Assessments of Different Treatment Methods for the Monon Trail Greenway Corridor**

**Method 1:** QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **54** | 6 | 60 | 90.00% | Overall Accuracy | 83.74% |
| Other | 27 | **116** | 143 | 81.12% | Kappa Statistic | 0.6456 |
| Totals | 81 | 122 | 203 | | | |
| Producer's Accuracy | 66.67% | 95.08% | **170** | | | |

**Method 2:** QuickBird + LIDAR

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **53** | 6 | 59 | 89.83% | Overall Accuracy | 83.25% |
| Other | 28 | **116** | 144 | 80.56% | Kappa Statistic | 0.6341 |
| Totals | 81 | 122 | 203 | | | |
| Producer's Accuracy | 65.43% | 95.08% | **169** | | | |

**Method 3:** NDVI

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **53** | 5 | 58 | 91.38% | Overall Accuracy | 83.74% |
| Other | 28 | **117** | 145 | 80.69% | Kappa Statistic | 0.6441 |
| Totals | 81 | 122 | 203 | | | |
| Producer's Accuracy | 65.43% | 95.90% | **170** | | | |

**Method 4:** NDVI + QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **63** | 7 | 70 | 90.00% | Overall Accuracy | 87.68% |
| Other | 18 | **115** | 133 | 86.47% | Kappa Statistic | 0.7372 |
| Totals | 81 | 122 | 203 | | | |
| Producer's Accuracy | 77.78% | 94.26% | **178** | | | |

**Method 5:** All Image Sources

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **71** | 7 | 78 | 91.03% | Overall Accuracy | 91.63% |
| Other | 10 | **115** | 125 | 92.00% | Kappa Statistic | 0.8243 |
| Totals | 81 | 122 | 203 | | | |
| Producer's Accuracy | 87.65% | 94.26% | **186** | | | |

**Method 6:** Height Differential Layer

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **36** | 10 | 46 | 78.26% | Overall Accuracy | 72.91% |
| Other | 45 | **112** | 157 | 71.34% | Kappa Statistic | 0.3909 |
| Totals | 81 | 122 | 203 | | | |
| Producer's Accuracy | 44.44% | 91.80% | **148** | | | |

**Table B-2. Accuracy Assessments of Different Treatment Methods for the Pleasant Run Trail Greenway Corridor**

**Method 1:** QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **70** | 7 | 77 | 90.91% | Overall Accuracy | 90.15% |
| Other | 13 | **113** | 126 | 89.68% | Kappa Statistic | 0.7939 |
| Totals | 83 | 120 | 203 | | | |
| Producer's Accuracy | 84.34% | 94.17% | **183** | | | |

**Method 2:** QuickBird + LIDAR

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **72** | 4 | 76 | 94.74% | Overall Accuracy | 92.61% |
| Other | 11 | **116** | 127 | 91.34% | Kappa Statistic | 0.8451 |
| Totals | 83 | 120 | 203 | | | |
| Producer's Accuracy | 86.75% | 96.67% | **188** | | | |

**Method 3:** NDVI

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **38** | 1 | 39 | 97.44% | Overall Accuracy | 77.34% |
| Other | 45 | **119** | 164 | 72.56% | Kappa Statistic | 0.4895 |
| Totals | 83 | 120 | 203 | | | |
| Producer's Accuracy | 45.78% | 99.17% | **157** | | | |

**Method 4:** NDVI + QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **70** | 7 | 77 | 90.91% | Overall Accuracy | 90.15% |
| Other | 13 | **113** | 126 | 89.68% | Kappa Statistic | 0.7939 |
| Totals | 83 | 120 | 203 | | | |
| Producer's Accuracy | 84.34% | 94.17% | **183** | | | |

**Method 5:** All Image Sources

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **61** | 7 | 68 | 89.71% | Overall Accuracy | 85.71% |
| Other | 22 | **113** | 135 | 83.70% | Kappa Statistic | 0.6960 |
| Totals | 83 | 120 | 203 | | | |
| Producer's Accuracy | 73.49% | 94.17% | **174** | | | |

**Method 6:** Height Differential Layer

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **49** | 12 | 61 | 80.33% | Overall Accuracy | 77.34% |
| Other | 34 | **108** | 142 | 76.06% | Kappa Statistic | 0.5113 |
| Totals | 83 | 120 | 203 | | | |
| Producer's Accuracy | 59.04% | 90.00% | **157** | | | |

**Table B-3. Accuracy Assessments of Different Treatment Methods for the White River Trail Greenway Corridor**

**Method 1:** QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **62** | 2 | 64 | 96.88% | Overall Accuracy | 91.13% |
| Other | 16 | **123** | 139 | 88.49% | Kappa Statistic | 0.8061 |
| Totals | 78 | 125 | 203 | | | |
| Producer's Accuracy | 79.49% | 98.40% | **185** | | | |

**Method 2:** QuickBird + LIDAR

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **62** | 2 | 64 | 96.88% | Overall Accuracy | 91.13% |
| Other | 16 | **123** | 139 | 88.49% | Kappa Statistic | 0.8061 |
| Totals | 78 | 125 | 203 | | | |
| Producer's Accuracy | 79.49% | 98.40% | **185** | | | |

**Method 3:** NDVI

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **30** | 5 | 35 | 85.71% | Overall Accuracy | 73.89% |
| Other | 48 | **120** | 168 | 71.43% | Kappa Statistic | 0.3845 |
| Totals | 78 | 125 | 203 | | | |
| Producer's Accuracy | 38.46% | 96.00% | **150** | | | |

**Method 4:** NDVI + QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **62** | 2 | 64 | 96.88% | Overall Accuracy | 91.13% |
| Other | 16 | **123** | 139 | 88.49% | Kappa Statistic | 0.8061 |
| Totals | 78 | 125 | 203 | | | |
| Producer's Accuracy | 79.49% | 98.40% | **185** | | | |

**Method 5:** All Image Sources

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **62** | 2 | 64 | 96.88% | Overall Accuracy | 91.13% |
| Other | 16 | **123** | 139 | 88.49% | Kappa Statistic | 0.8061 |
| Totals | 78 | 125 | 203 | | | |
| Producer's Accuracy | 79.49% | 98.40% | **185** | | | |

**Method 6:** Height Differential Layer

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **54** | 7 | 61 | 88.52% | Overall Accuracy | 84.73% |
| Other | 24 | **118** | 142 | 83.10% | Kappa Statistic | 0.6635 |
| Totals | 78 | 125 | 203 | | | |
| Producer's Accuracy | 69.23% | 94.40% | **172** | | | |

# Appendix C

**Table C-1. Accuracy Assessments of Different Treatment Methods by Commercial Land Use**

**Method 1:** QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **10** | 0 | 10 | 100.00% | Overall Accuracy | 94.12% |
| Other | 4 | **54** | 58 | 93.10% | Kappa Statistic | 0.7988 |
| Totals | 14 | 54 | 68 | | | |
| Producer's Accuracy | 71.43% | 100.00% | **64** | | | |

**Method 2:** QuickBird + LIDAR

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **9** | 0 | 9 | 100.00% | Overall Accuracy | 92.65% |
| Other | 5 | **54** | 59 | 91.53% | Kappa Statistic | 0.7409 |
| Totals | 14 | 54 | 68 | | | |
| Producer's Accuracy | 64.29% | 100.00% | **63** | | | |

**Method 3:** NDVI

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **8** | 0 | 8 | 100.00% | Overall Accuracy | 91.18% |
| Other | 6 | **54** | 60 | 90.00% | Kappa Statistic | 0.6792 |
| Totals | 14 | 54 | 68 | | | |
| Producer's Accuracy | 57.14 | 100.00% | **62** | | | |

**Method 4:** NDVI + QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **11** | 0 | 11 | 100.00% | Overall Accuracy | 95.59% |
| Other | 3 | **54** | 57 | 94.74% | Kappa Statistic | 0.8534 |
| Totals | 14 | 54 | 68 | | | |
| Producer's Accuracy | 78.57% | 100.00% | **65** | | | |

**Method 5:** All Image Sources

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **11** | 0 | 11 | 100.00% | Overall Accuracy | 95.59% |
| Other | 3 | **54** | 57 | 94.74% | Kappa Statistic | 0.8534 |
| Totals | 14 | 54 | 68 | | | |
| Producer's Accuracy | 78.57% | 100.00% | **65** | | | |

**Method 6:** Height Differential Layer

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **8** | 3 | 11 | 72.73% | Overall Accuracy | 86.76% |
| Other | 6 | **51** | 57 | 89.47% | Kappa Statistic | 0.5603 |
| Totals | 14 | 54 | 68 | | | |
| Producer's Accuracy | 57.14% | 94.44% | **59** | | | |

**Table C-2. Accuracy Assessments of Different Treatment Methods by Industrial Land Use**

**Method 1:** QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **26** | 1 | 27 | 96.30% | Overall Accuracy | 91.26% |
| Other | 8 | **68** | 76 | 89.47% | Kappa Statistic | 0.7915 |
| Totals | 34 | 69 | 103 | | | |
| Producer's Accuracy | 76.47% | 98.55% | **94** | | | |

**Method 2:** QuickBird + LIDAR

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **28** | 1 | 29 | 96.55% | Overall Accuracy | 93.20% |
| Other | 6 | **68** | 74 | 91.89% | Kappa Statistic | 0.8404 |
| Totals | 34 | 69 | 103 | | | |
| Producer's Accuracy | 82.35% | 98.55% | **96** | | | |

**Method 3:** NDVI

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **12** | 0 | 12 | 100.00% | Overall Accuracy | 78.64% |
| Other | 22 | **69** | 91 | 75.82% | Kappa Statistic | 0.4222 |
| Totals | 34 | 69 | 103 | | | |
| Producer's Accuracy | 35.29% | 100.00% | **81** | | | |

**Method 4:** NDVI + QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **27** | 1 | 28 | 96.43% | Overall Accuracy | 92.23% |
| Other | 7 | **68** | 75 | 90.67% | Kappa Statistic | 0.8612 |
| Totals | 34 | 69 | 103 | | | |
| Producer's Accuracy | 79.41% | 98.55% | **95** | | | |

**Method 5:** All Image Sources

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **27** | 2 | 29 | 93.10% | Overall Accuracy | 91.26% |
| Other | 7 | **67** | 74 | 90.54% | Kappa Statistic | 0.7948 |
| Totals | 34 | 69 | 103 | | | |
| Producer's Accuracy | 79.41% | 97.10% | **94** | | | |

**Method 6:** Height Differential Layer

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **17** | 7 | 24 | 70.83% | Overall Accuracy | 76.70% |
| Other | 17 | **62** | 79 | 78.48% | Kappa Statistic | 0.4307 |
| Totals | 34 | 69 | 103 | | | |
| Producer's Accuracy | 50.00% | 89.86% | **79** | | | |

**Table C-3. Accuracy Assessments of Different Treatment Methods by Public Park Land Use**

**Method 1:** QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **41** | 7 | 48 | 85.42% | Overall Accuracy | 89.42% |
| Other | 4 | **52** | 56 | 92.86% | Kappa Statistic | 0.7862 |
| Totals | 45 | 59 | 104 | | | |
| Producer's Accuracy | 91.11% | 88.14% | **93** | | | |

**Method 2:** QuickBird + LIDAR

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **40** | 7 | 47 | 85.11% | Overall Accuracy | 88.46% |
| Other | 5 | **52** | 57 | 91.23% | Kappa Statistic | 0.7662 |
| Totals | 45 | 59 | 104 | | | |
| Producer's Accuracy | 88.89% | 88.14% | **92** | | | |

**Method 3:** NDVI

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **26** | 6 | 32 | 81.25% | Overall Accuracy | 75.96% |
| Other | 19 | **53** | 72 | 73.61% | Kappa Statistic | 0.4930 |
| Totals | 45 | 59 | 104 | | | |
| Producer's Accuracy | 57.78% | 89.83% | **79** | | | |

**Method 4:** NDVI + QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **38** | 7 | 45 | 84.44% | Overall Accuracy | 86.54% |
| Other | 7 | **52** | 59 | 88.14% | Kappa Statistic | 0.7258 |
| Totals | 45 | 59 | 104 | | | |
| Producer's Accuracy | 84.44% | 88.14% | **90** | | | |

**Method 5:** All Image Sources

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **40** | 7 | 47 | 85.11% | Overall Accuracy | 88.46% |
| Other | 5 | **52** | 57 | 91.23% | Kappa Statistic | 0.7662 |
| Totals | 45 | 59 | 104 | | | |
| Producer's Accuracy | 88.89% | 88.14% | **92** | | | |

**Method 6:** Height Differential Layer

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **28** | 2 | 30 | 93.33% | Overall Accuracy | 81.73% |
| Other | 17 | **57** | 74 | 77.03% | Kappa Statistic | 0.6125 |
| Totals | 45 | 59 | 104 | | | |
| Producer's Accuracy | 62.22% | 96.61% | **85** | | | |

**Table C-4. Accuracy Assessments of Different Treatment Methods by Residential Land Use**

**Method 1:** QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **91** | 7 | 98 | 92.86% | Overall Accuracy | 84.29% |
| Other | 37 | **145** | 182 | 79.67% | Kappa Statistic | 0.6774 |
| Totals | 128 | 152 | 280 | | | |
| Producer's Accuracy | 71.09% | 95.39% | **236** | | | |

**Method 2:** QuickBird + LIDAR

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **92** | 4 | 96 | 95.83% | Overall Accuracy | 85.71% |
| Other | 36 | **148** | 184 | 80.43% | Kappa Statistic | 0.7064 |
| Totals | 128 | 152 | 280 | | | |
| Producer's Accuracy | 71.88% | 97.37% | **240** | | | |

**Method 3:** NDVI

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **69** | 3 | 72 | 95.83% | Overall Accuracy | 77.86% |
| Other | 59 | **149** | 208 | 71.63% | Kappa Statistic | 0.5379 |
| Totals | 128 | 152 | 280 | | | |
| Producer's Accuracy | 53.91% | 98.03% | **218** | | | |

**Method 4:** NDVI + QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **102** | 8 | 110 | 92.73% | Overall Accuracy | 87.86% |
| Other | 26 | **144** | 170 | 84.71% | Kappa Statistic | 0.7526 |
| Totals | 128 | 152 | 280 | | | |
| Producer's Accuracy | 77.34% | 94.08% | **246** | | | |

**Method 5:** All Image Sources

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **98** | 7 | 105 | 93.33% | Overall Accuracy | 86.79% |
| Other | 30 | **145** | 175 | 82.86% | Kappa Statistic | 0.7299 |
| Totals | 128 | 152 | 280 | | | |
| Producer's Accuracy | 76.56% | 95.39% | **243** | | | |

**Method 6:** Height Differential Layer

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **73** | 15 | 88 | 82.95% | Overall Accuracy | 75.00% |
| Other | 55 | **137** | 192 | 71.35% | Kappa Statistic | 0.4836 |
| Totals | 128 | 152 | 280 | | | |
| Producer's Accuracy | 57.03% | 90.13% | **210** | | | |

**Table C-5. Accuracy Assessments of Different Treatment Methods Special Land Use/University Quarter**

**Method 1:** QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **17** | 0 | 17 | 100.00% | Overall Accuracy | 92.59% |
| Other | 4 | **33** | 37 | 89.19% | Kappa Statistic | 0.8386 |
| Totals | 21 | 33 | 54 | | | |
| Producer's Accuracy | 80.95% | 100.00% | **50** | | | |

**Method 2:** QuickBird + LIDAR

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **17** | 0 | 17 | 100.00% | Overall Accuracy | 92.59% |
| Other | 4 | **33** | 37 | 89.19% | Kappa Statistic | 0.8386 |
| Totals | 21 | 33 | 54 | | | |
| Producer's Accuracy | 80.95% | 100.00% | **50** | | | |

**Method 3:** NDVI

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **7** | 2 | 9 | 77.78% | Overall Accuracy | 70.37% |
| Other | 14 | **31** | 45 | 68.89% | Kappa Statistic | 0.3043 |
| Totals | 21 | 33 | 54 | | | |
| Producer's Accuracy | 33.33% | 93.94% | **38** | | | |

**Method 4:** NDVI + QuickBird

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **16** | 0 | 16 | 100.00% | Overall Accuracy | 90.74 |
| Other | 5 | **33** | 38 | 86.84% | Kappa Statistic | 0.7964 |
| Totals | 21 | 33 | 54 | | | |
| Producer's Accuracy | 76.19% | 100.00% | **49** | | | |

**Method 5:** All Image Sources

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **17** | 0 | 17 | 100.00% | Overall Accuracy | 92.59% |
| Other | 4 | **33** | 37 | 89.19% | Kappa Statistic | 0.8386 |
| Totals | 21 | 33 | 54 | | | |
| Producer's Accuracy | 80.95% | 100.00% | **50** | | | |

**Method 6:** Height Differential Layer

| | Tree | Other | Totals | User's Accuracy | | |
|---|---|---|---|---|---|---|
| Tree | **13** | 2 | 15 | 86.67% | Overall Accuracy | 81.48% |
| Other | 8 | **31** | 39 | 79.49% | Kappa Statistic | 0.5890 |
| Totals | 21 | 33 | 54 | | | |
| Producer's Accuracy | 61.90% | 93.94% | **44** | | | |

# Appendix D

**Table D-1. Complete Results for Difference-of-Proportions Statistical Test**

**Method 1:** **Kappa Value: 0.7508**
***QuickBird Only***

| Method of Comparison | Kappa Value | $P_1 - P_2 - D_0$ | $\hat{\sigma}_{P_1-P_2}$ | Z Value | P Value (2-Sided) | Reject $H_0$? |
|---|---|---|---|---|---|---|
| QuickBird + HTDF | 0.7645 | 0.0137 | 0.02455 | 0.5580 | 0.5768 | No |
| NDVI | 0.5136 | 0.2372 | 0.02678 | 8.8557 | <0.0001 | Yes |
| NDVI + QuickBird | 0.7803 | 0.0295 | 0.02426 | 1.2158 | 0.2241 | No |
| All Sources | 0.7767 | 0.0259 | 0.02433 | 1.0645 | 0.2871 | No |
| HTDF Reclass | 0.5259 | 0.2249 | 0.02677 | 8.4012 | <0.0001 | Yes |

**Method 2:** **Kappa Value: 0.7645**
***QuickBird + Height Differential***

| Method of Comparison | Kappa Value | $P_1 - P_2 - D_0$ | $\hat{\sigma}_{P_1-P_2}$ | Z Value | P Value (2-Sided) | Reject $H_0$? |
|---|---|---|---|---|---|---|
| QuickBird | 0.7508 | 0.0137 | 0.02455 | 0.5580 | 0.5768 | No |
| NDVI | 0.5136 | 0.2509 | 0.02657 | 9.4438 | <0.0001 | Yes |
| NDVI + QuickBird | 0.7803 | 0.0158 | 0.02402 | 0.6577 | 0.5107 | No |
| All Sources | 0.7767 | 0.0122 | 0.02409 | 0.5064 | 0.6126 | No |
| HTDF Reclass | 0.5259 | 0.2386 | 0.02655 | 8.9859 | <0.0001 | Yes |

**Method 3:** **Kappa Value: 0.5136**
***NDVI***

| Method of Comparison | Kappa Value | $P_1 - P_2 - D_0$ | $\hat{\sigma}_{P_1-P_2}$ | Z Value | P Value (2-Sided) | Reject $H_0$? |
|---|---|---|---|---|---|---|
| QuickBird | 0.7508 | 0.2372 | 0.02678 | 8.8557 | <0.0001 | Yes |
| QuickBird + HTDF | 0.7645 | 0.2509 | 0.02657 | 9.4438 | <0.0001 | Yes |
| NDVI + QuickBird | 0.7803 | 0.2667 | 0.02630 | 10.1406 | <0.0001 | Yes |
| All Sources | 0.7767 | 0.2631 | 0.02636 | 9.9800 | <0.0001 | Yes |
| HTDF Reclass | 0.5259 | 0.0123 | 0.02863 | 0.4296 | 0.6675 | No |

**Method 4:** **Kappa Value: 0.7803**
***NDVI + QuickBird***

| Kappa Value: | Kappa Value | $P_1 - P_2 - D_0$ | $\hat{\sigma}_{P_1-P_2}$ | Z Value | P Value (2-Sided) | Reject $H_0$? |
|---|---|---|---|---|---|---|
| QuickBird | 0.7508 | 0.0295 | 0.02426 | 1.2158 | 0.2241 | No |
| QuickBird + HTDF | 0.7645 | 0.0158 | 0.02402 | 0.6577 | 0.5107 | No |
| NDVI | 0.5136 | 0.2667 | 0.02630 | 10.1406 | <0.0001 | Yes |
| All Sources | 0.7767 | 0.0036 | 0.02380 | 0.1513 | 0.8797 | No |
| HTDF Reclass | 0.5259 | 0.2544 | 0.02629 | 9.6785 | <0.0001 | No |

**Method 5:** **Kappa Value: 0.7767**
***All Image Sources***

| Method of Comparison | Kappa Value | $P_1 - P_2 - D_0$ | $\hat{\sigma}_{P_1-P_2}$ | Z Value | P Value (2-Sided) | Reject $H_0$? |
|---|---|---|---|---|---|---|
| QuickBird | 0.7508 | 0.0259 | 0.02433 | 1.0645 | 0.2871 | No |
| QuickBird + HTDF | 0.7645 | 0.0122 | 0.02409 | 0.5064 | 0.6126 | No |
| NDVI | 0.5136 | 0.2631 | 0.02636 | 9.9800 | <0.0001 | Yes |
| NDVI + QuickBird | 0.7803 | 0.0036 | 0.02380 | 0.1513 | 0.8797 | No |
| HTDF Reclass | 0.5259 | 0.2508 | 0.02635 | 9.5189 | <0.0001 | Yes |

**Method 6:** **Kappa Value: 0.5259**
***Height Differential Reclassification***

| Method of Comparison | Kappa Value | $P_1 - P_2 - D_0$ | $\hat{\sigma}_{P_1-P_2}$ | Z Value | P Value (2-Sided) | Reject $H_0$? |
|---|---|---|---|---|---|---|
| QuickBird | 0.7508 | 0.2249 | 0.02677 | 8.4012 | <0.0001 | Yes |
| QuickBird + HTDF | 0.7645 | 0.2386 | 0.02655 | 8.9859 | <0.0001 | Yes |
| NDVI | 0.5136 | 0.0123 | 0.02863 | 0.4296 | 0.6675 | No |
| NDVI + QuickBird | 0.7803 | 0.2544 | 0.02629 | 9.6785 | <0.0001 | Yes |
| All Sources | 0.7767 | 0.2508 | 0.02635 | 9.5189 | <0.0001 | Yes |

Table D-2. Results for Difference-of-Proportions Test per Land Use Class (Treatment Method 4)

**Commercial:** **0.8534**

| Land Use Class | Kappa Value | $P_1 - P_2 - D_0$ | $\hat{\sigma}_{P_1 - P_2}$ | Z Value | P Value (2-Sided) | Reject $H_0$? |
|---|---|---|---|---|---|---|
| Commercial/CBD | 0.8534 | 0.0000 | 0.02027 | 0.0000 | -- | -- |
| Industrial | 0.8162 | 0.0372 | 0.02125 | 1.7502 | 0.0801 | No |
| Public Use | 0.7258 | 0.1276 | 0.02307 | 5.5310 | <0.0001 | Yes |
| Residential | 0.7526 | 0.1008 | 0.02261 | 4.4584 | <0.0001 | Yes |
| Special Use/Uni Qtr | 0.7964 | 0.0570 | 0.02172 | 2.6245 | 0.0087 | Yes |

**Industrial:** **0.8162**

| Land Use Class | Kappa Value | $P_1 - P_2 - D_0$ | $\hat{\sigma}_{P_1 - P_2}$ | Z Value | P Value (2-Sided) | Reject $H_0$? |
|---|---|---|---|---|---|---|
| Commercial/CBD | 0.8534 | 0.0372 | 0.02027 | 1.8352 | 0.0665 | No |
| Industrial | 0.8162 | 0.0000 | 0.02125 | 0.0000 | -- | -- |
| Public Use | 0.7258 | 0.0904 | 0.02307 | 3.9185 | <0.0001 | Yes |
| Residential | 0.7526 | 0.0636 | 0.02261 | 2.8130 | 0.0049 | Yes |
| Special Use/Uni Qtr | 0.7964 | 0.0198 | 0.02172 | 0.9117 | 0.3619 | No |

**Public Use:** **0.7258**

| Land Use Class | Kappa Value | $P_1 - P_2 - D_0$ | $\hat{\sigma}_{P_1 - P_2}$ | Z Value | P Value (2-Sided) | Reject $H_0$? |
|---|---|---|---|---|---|---|
| Commercial/CBD | 0.8534 | 0.1276 | 0.02027 | 6.2951 | <0.0001 | Yes |
| Industrial | 0.8162 | 0.0904 | 0.02125 | 4.2532 | <0.0001 | Yes |
| Public Use | 0.7258 | 0.0000 | 0.02307 | 0.0000 | -- | -- |
| Residential | 0.7526 | 0.0268 | 0.02261 | 1.1854 | 0.2359 | No |
| Special Use/Uni Qtr | 0.7964 | 0.0706 | 0.02172 | 3.2507 | 0.0012 | Yes |

**Residential:** **0.7526**

| Land Use Class | Kappa Value | $P_1 - P_2 - D_0$ | $\hat{\sigma}_{P_1 - P_2}$ | Z Value | P Value (2-Sided) | Reject $H_0$? |
|---|---|---|---|---|---|---|
| Commercial/CBD | 0.8534 | 0.1008 | 0.02027 | 4.9729 | <0.0001 | Yes |
| Industrial | 0.8162 | 0.0636 | 0.02125 | 2.9923 | 0.0028 | Yes |
| Public Use | 0.7258 | 0.0268 | 0.02307 | 1.1617 | 0.2454 | No |
| Residential | 0.7526 | 0.0000 | 0.02261 | 0.0000 | -- | -- |
| Special Use/Uni Qtr | 0.7964 | 0.0438 | 0.02172 | 2.0167 | 0.0437 | Yes |

**Special Use:** **0.7964**

| Land Use Class | Kappa Value | $P_1 - P_2 - D_0$ | $\hat{\sigma}_{P_1 - P_2}$ | Z Value | P Value (2-Sided) | Reject $H_0$? |
|---|---|---|---|---|---|---|
| Commercial/CBD | 0.8534 | 0.0570 | 0.02027 | 2.8121 | 0.0049 | Yes |
| Industrial | 0.8162 | 0.0198 | 0.02125 | 0.9316 | 0.3515 | No |
| Public Use | 0.7258 | 0.0706 | 0.02307 | 3.0603 | 0.0022 | Yes |
| Residential | 0.7526 | 0.0438 | 0.02261 | 1.9373 | 0.0527 | No |
| Special Use/Uni Qtr | 0.7964 | 0.0000 | 0.02172 | 0.0000 | -- | -- |

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# CURRICULUM VITAE

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## Education

Indiana University-Purdue University Indianapolis, Geographic Information Science
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## Professional Experience

| | |
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## Publications

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