AMERICAN FORESTS COMMUNITY RELEAF

MIAMI-DADE NORTHWEST CORRIDOR
URBAN TREE CANOPY ASSESSMENT

OCTOBER 2015

AMERICAN FORESTS

ACKNOWLEDGMENTS

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American Forests partnered to create this report with the Dr. Hartwig Henry Hochmair and Adam Benjamin in the Geomatics Program at the University of Florida, as well as Daniel Gann and Zhaohui Jennifer Fu of Florida International University's Geographic Information Systems and Remote Sensing Center.

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EXECUTIVE SUMMARY

This report was developed through American Forests Community ReLeaf program for the County of Miami-Dade for the Million Trees Miami initiative developed by Neat Streets Miami. The assessment, conducted in partnership with the University of Florida and Florida International University, focuses on the environmental and socioeconomic impacts from the urban tree canopy (UTC) among 147 square miles of the most dense, growing, and socioeconomically diverse urban core communities of northwestern Miami-Dade County. The primary goals of this assessment and report are to establish baseline data on the extent and function of the existing urban forest and to provide a resource to guide future community forest management and reforestation efforts. It will serve as the foundation for a forthcoming assessment of the entirety of Miami-Dade within its urban growth boundary.

This analysis estimated the area with current tree canopy (existing UTC), the area of potential tree canopy (possible UTC), and various other land cover categories. The analysis found that tree canopy covers 12.2% of the study area and impervious surfaces, including buildings, cover 55.3%, with 6.2% water. If all other vegetation and bare soil in the city were suitable for growing trees, the study area's maximum potential UTC tree canopy cover could reach 25.9%.

Tree canopy cover provides benefits to the entire community by removing pollutants and carbon from the air and reducing peak stormwater flows. The annual benefits the Miami-Dade study are received from its tree cover are estimated to be approximately $2,663,896 annually in pollution mitigation, plus a total of $35,145,546 worth of carbon dioxide stored in the trees themselves. Tree canopy in Miami removed about 73,000 tons of carbon and over 1 million pounds of other pollutants. This study also analyzed temperature and found that areas with heavy tree canopy had cooler temperatures than those with heavy concentrations of buildings, parking lots, and other gray infrastructure. The benefits provided by Miami-Dade's urban forest have the potential to increase over time as existing trees mature and new trees are planted.

In addition to the environmental benefits, the UTC assessment explored the relationship of tree canopy cover to social and economic factors, including population density, income, concentrations of African American individuals, and respiratory illlness. A correlation was found between high tree canopy and predominantly African American populations, as well as rates of respiratory illness and income. Each of these factors can be considered individually or in composite to develop targeted planting plans to improve conditions in under-treed cities and neighborhoods.

The assessment used two methods to establish those estimates. The first utilized the i-Tree canopy assessment tool provided by the USDA Forest Service. The second method used a combination of multi-spectral satellite data and airborne Light Detection and Ranging (LiDAR) datasets for detection and classification of land cover. Classification results were further analyzed in a Geographic Information System (GIS) to relate land cover distribution patterns (obtained from the second land cover classification method) to surface temperatures, land use patterns, socioeconomic factors, and health data.

I-TREE CANOPY ASSESSMENT

Software

The i-Tree Canopy online application provided by the USDA Forest Service was used to estimate tree and other land cover classes within the study area, based on 500 sample points (Figure 1). This tool randomly laid points onto Google basemap imagery. The user then classified what land cover class each point fell upon. The eight land cover classes used for this assessment were tree, road/railroad, bare ground, building, grass, impervious (excluding roads and buildings), water, and wetland. Tree and shrub were combined into one class to be consistent with the image-based land cover classification process explained below. The study area extended between Golden Glades in the North-East, Turnpike and Okeechobee Road in the North West, Sweetwater in the South-West, and Miami in the South-East.

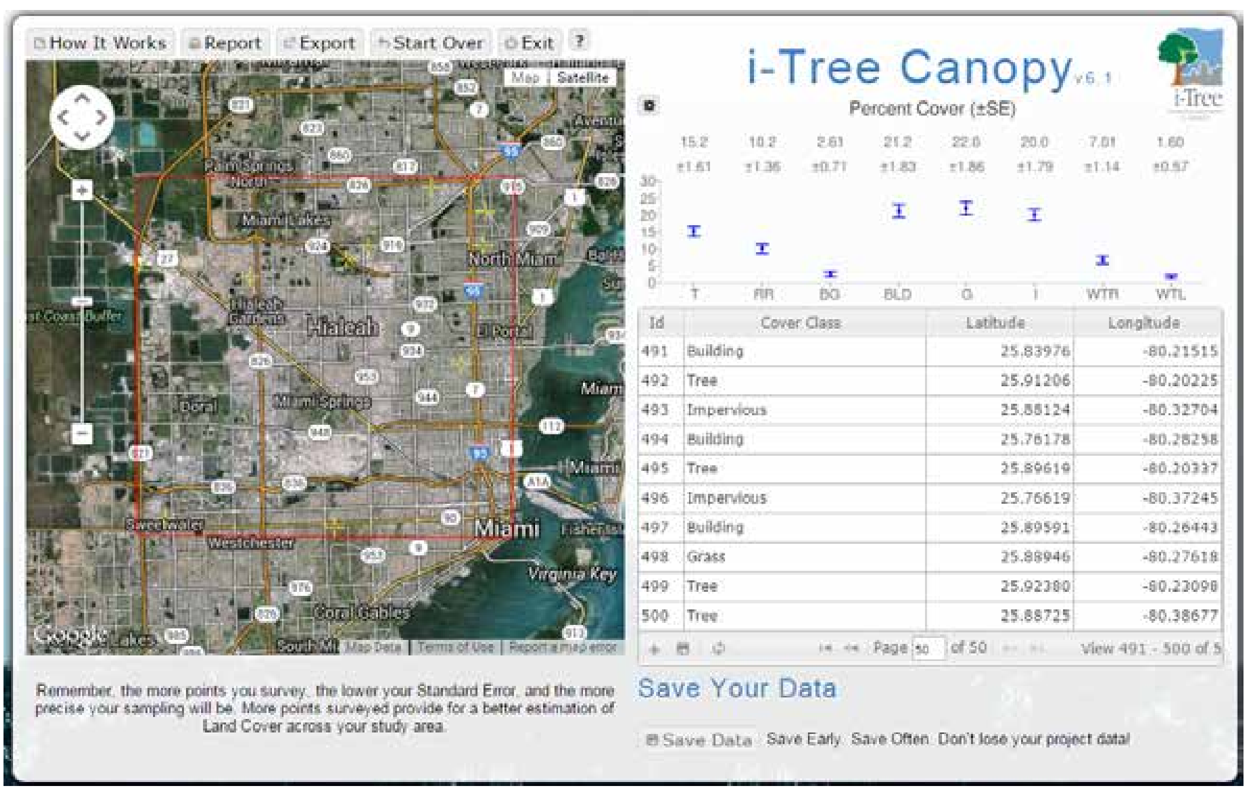
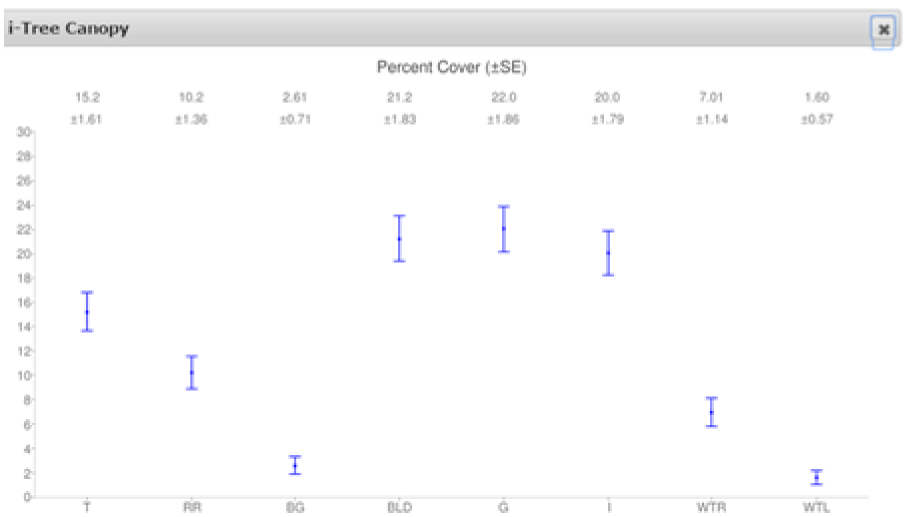


Figure 1. i-Tree Canopy software interface

Results

Figure 2 shows the statistical estimate of percent cover in each land cover class along with an estimate of the uncertainty of the estimate, expressed as standard error (SE). Grass (22.0%) has the largest percent cover, closely followed by building (21.1%), and impervious (20.0%). Considering the standard error of the estimate for each of the three classes, they can be considered to share the same percent cover. The lowest percent cover was found for wetland (1.6%) and bare ground (2.6%).Due to the uncertainty in the estimate of the percent cover, the latter two classes can also be considered equivalent. Figure 3 presents the results for the tree benefit estimates as computed by the software. The study area's tree canopy provides $2,663,896 in annual pollution mitigation services and over $35.1 million in total value for carbon dioxide stored in the trees themselves.

Figure 2. i-Tree Canopy software interface



Cover Class	Description	Abbr.	Points	% Cover
Tree	Tree/shrub	T	76	15.2 ±1.61
Road	Road/railroad	RR	51	10.2 ±1.36
Bare ground	Bare ground	BG	13	2.61 ±0.71
Building	Building	BLD	106	21.2 ±1.83
Grass	Grass	G	110	22.0 ±1.86
Impervious	Impervious	I	100	20.0 ±1.79
Water	Water	WTR	35	7.01 ±1.14
Wetland	Wetland	WTL	8	1.60 ±0.57

Figure 3. Tree Benefit Estimates

Tree Benefit Estimates

Abbr.	Benefit Description	Value	±SE	Amount	±SE
CO	Carbon Monoxide removed annually	$551.94	±58.29	6.51 T	±0.69
NO2	Nitrogen Dioxide removed annually	$950.23	±100.36	35.50 T	±3.75
O3	Ozone removed annually	$49,486.14	±5,226.33	353.55 T	±37.34
PM2.5	Particulate Matter less than 2.5 microns removed annually	$102,296.91	±10,803.78	17.18 T	±1.81
SO2	Sulfur Dioxide removed annually	$166.08	±17.54	22.37 T	±2.36
PM10*	Particulate Matter greater than 2.5 microns and less than 10 microns removed annually	$35,925.66	±3,794.18	118.43 T	±12.51
CO2seq	Carbon Dioxide sequestered annually in trees	$2,474,519.34	±261,338.84	71,988.58 T	±7,602.85
CO2stor	Carbon Dioxide stored in trees (Note: this benefit is not an annual rate)	$35,145,546.81	±3,711,790.19	1,815,056.27 T	±191,691.66

i-Tree Canopy Annual Tree Benefit Estimates based on these values in lbs/acre/yr and $/T/yr: CO 0.902 @ $85.08 | NO2 4.917 @ $26.86 | O3 48.968 @ $140.47 | PM2.5 2.379 @ $5,975.67 | SO2 3.098 @ $7.45 | PM10 16.403 @ $304.43 | CO2seq 9,970.817 @ $34.50 | CO2stor is a total biomass amount of 251,395.359 @ $19.43*
Note: Standard errors of removal amounts and benefits were calculated based on standard errors of sampled and classified points.

PROJECT AREA LAND COVER CLASSIFICATION

Land Cover Classification Map

Figure 4 shows the final land cover classification map with its eight classes across 147 square miles (382 km2). Grass and impervious have the largest percent cover (23.1% each), followed by buildings (19.7%) (Figure 5a). Existing tree canopy (including shrubs) covers 12.2% (46.10 km2). Possible tree canopy, which includes grass, bare ground, and impervious surfaces (e.g. parking lots, but not buildings, streets, or railroads) covers an additional 48.9% (185.24 km2) (Figure 5b).

The remaining 38.9% (147.30 km2) of the study area included streets and railroads, buildings, wetlands, and water bodies, which are generally unsuitable for UTC improvement. Even though wetland areas are suitable for native wetland tree species (e.g., pond apple trees, cypress trees), they were not counted towards possible UTC areas since detection accuracies were low. Further, the wetland area was only 0.5% of the entire mapped area. Total area and percent cover for each land cover class are summarized in Table 2.

Figure 4. Final land cover classification map

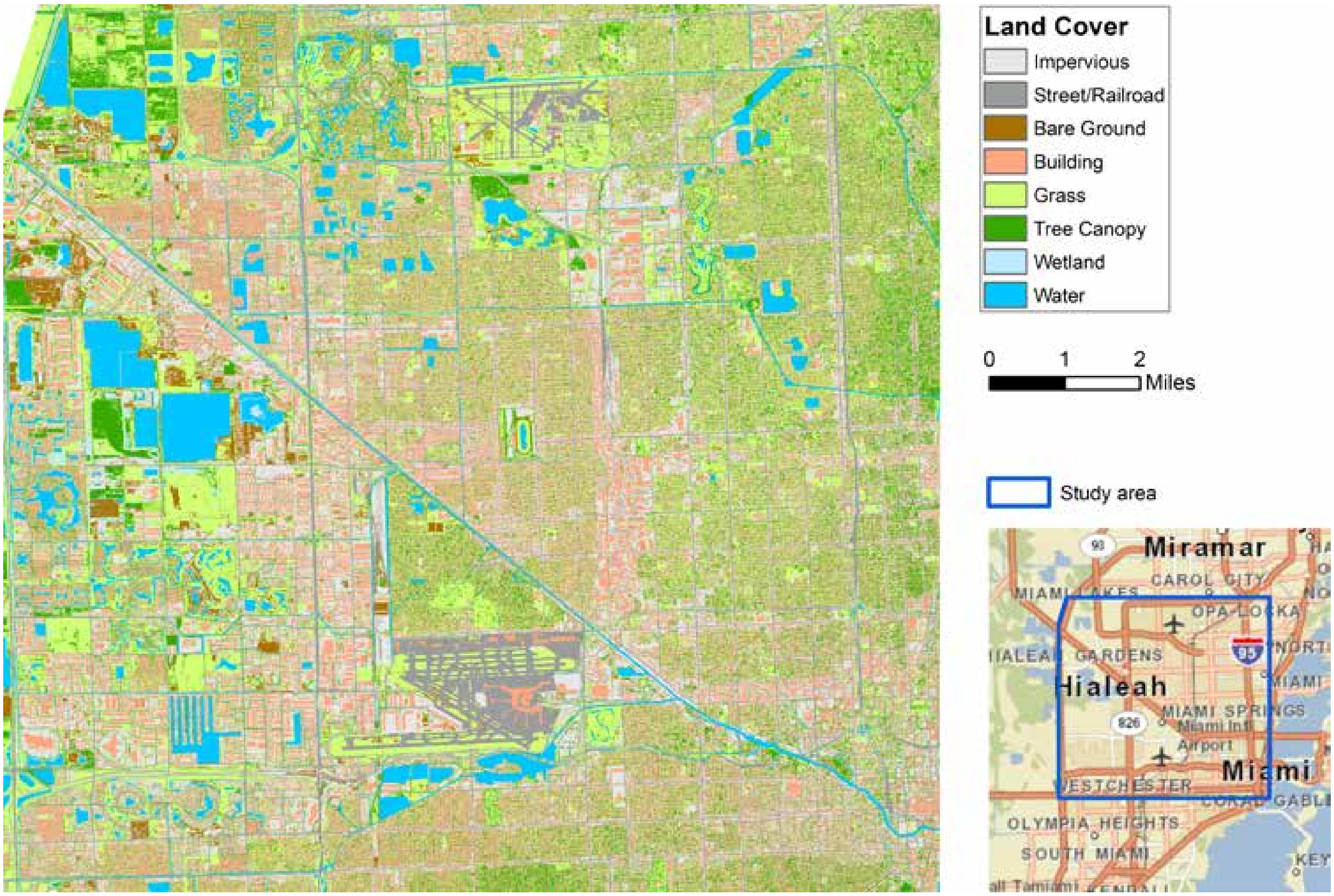


Table 1. Minimum mapping unit (MMU) for different land cover classes

Class	MMU (pixels)	MMU (m^2)
Tree Canopy	2	8
Street/Railroad	10	40
Building	2	8
Wetland	50	200
Water	50	200
Grass	5	20
Bare Ground	5	20
Impervious	10	40

Figure 5. Percentage of land cover classes.

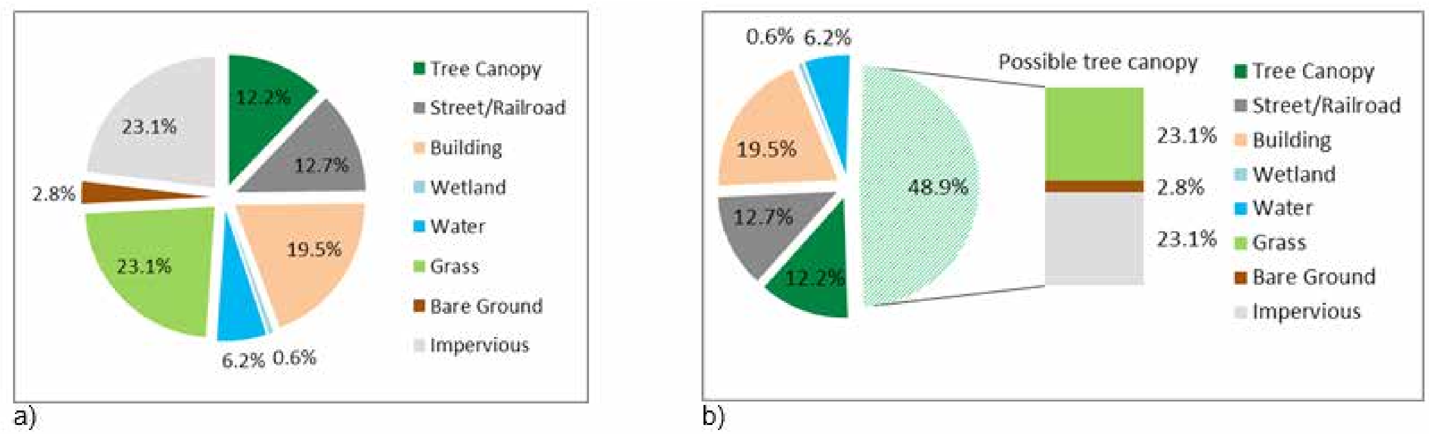


Table 2. Area and percent cover of land cover classes

Class	Area (km^2)	Percent cover
Tree Canopy	46.10	12.2%
Street/Railroad	47.91	12.7%
Building	73.93	19.5%
Wetland	2.08	0.6%
Water	23.37	6.2%
Grass	87.40	23.1%
Bare Ground	10.51	2.8%
Impervious	87.33	23.1%
Total	**382.80**	**100.00%**

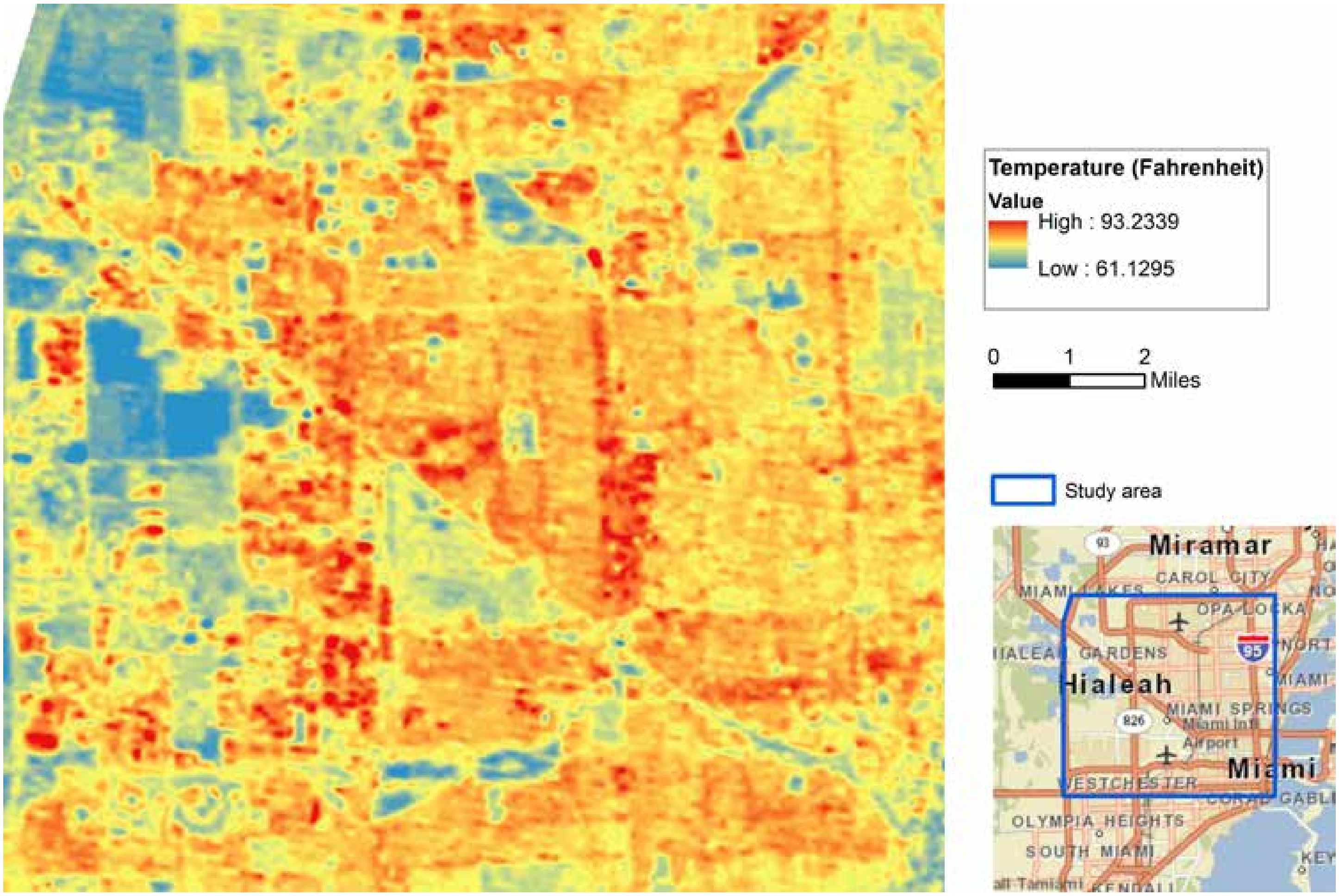
LAND COVER AND SURFACE TEMPERATURE

Land Cover Classification Map

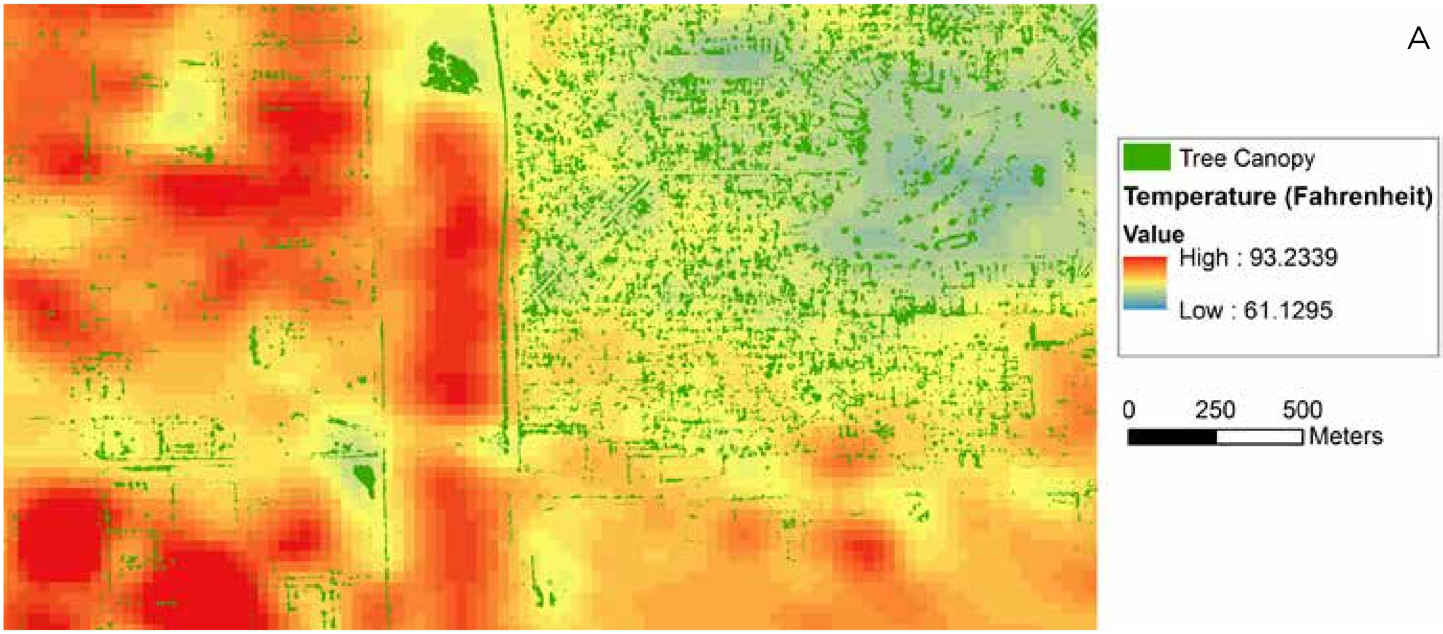
A land surface temperature map was derived from the Landsat Enhanced Thematic Mapper (ETM) thermal band acquired on November 10, 2011. This layer is recorded at a 120m spatial resolution and resampled at 30m using the cubic convolution resampling method.

Figure 6 color codes temperature (in degrees Celsius) overlaid with existing tree canopy (shown in green) for the study area. Figure 7 provides a zoomed view of a region that covers residential neighborhoods, industrial complexes, and water bodies. The upper map (Figure 7a) depicts surface temperature. The lower map (Figure 7b) shows temperature contour lines with a background aerial photograph underneath. Visual inspection of both maps allows for the identification of hot spots, which occur primarily in areas with sparse tree canopy and large buildings surrounded by parking lots. Cool spots are found in areas around water bodies and with higher tree canopy density and grass land (e.g., golf courses, parks). Areas covered by both buildings and tree canopy (e.g. residential areas) show mid-range temperatures.

Figure 6. Surface temperature map



Figures 7a and 7b. Zoomed surface temperature and contour map



Correlations Between Surface Temperature and Land Cover Class

To assess the statistical association (Pearson's r) between surface temperature and land-cover class, the proportion of land-cover class for each 30m x 30m temperature cell was computed, using 413,504 cells (Table 3). To avoid outliers, only temperature values which were observed on at least 1 km2 of the study area were considered. Results show that all arithmetic signs of statistical association are as expected, except for Wetland, which shows a small positive correlation with temperature. An increased proportion of buildings in a cell is associated with an increased surface temperature, whereas a higher proportion of grass, water, or tree canopy in a cell is associated with a lower surface temperature.

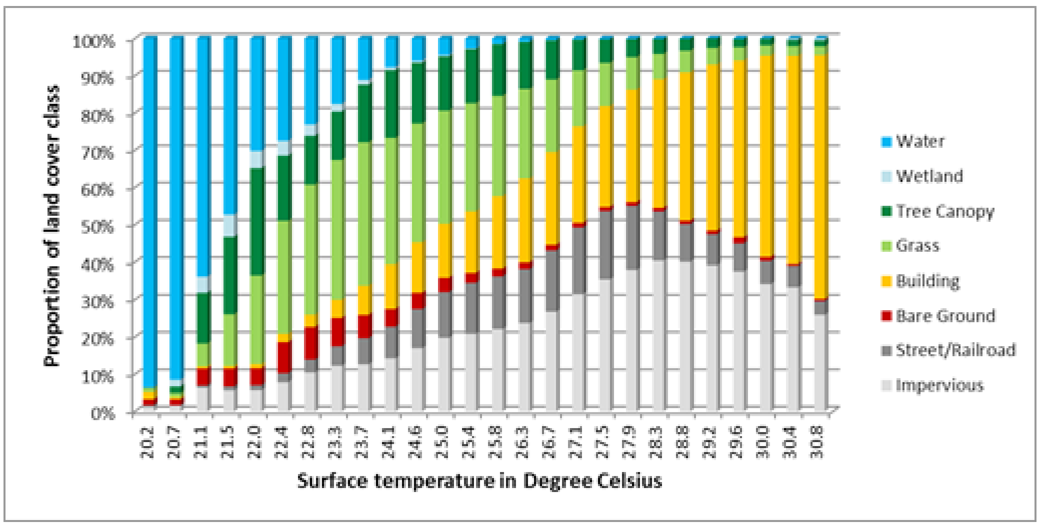
Table 3. Bivariate correlations between percent land cover and surface temperature (Degree Celsius)

	% Tree Canopy	% Street/RR	% Building	% Wetland	% Water	% Grass	% Bare Ground	% Impervious
r	**-0.033**	**0.021**	**0.047**	**0.013**	**-0.047**	**-0.054**	0.001	**0.052**
p	0.000	0.000	0.000	0.000	0.000	0.000	0.377	0.000

Bold indicates correlation significant at $p<0.05$

A more comprehensive picture of the relationship between land cover mix and surface temperature can be obtained by plotting discrete temperature values against the proportion of land cover classes associated with that temperature (Figure 8). The diagram demonstrates the cooling effect of water bodies, tree canopy and grass cover, where water appears to have the strongest effect. Areas with higher surface temperature have a higher share of impervious surfaces and buildings.

Figure 8. Portion of land cover classes for different surface temperatures



ANALYSIS OF LAND USE PATTERNS

For further analysis, all land cover types were reclassified into different UTC types as follows:

- Existing UTC: Trees/shrubs
- Possible UTC – vegetation: Grass, bare ground
- Possible UTC – impervious: Impervious surface (e.g. asphalt) excluding streets/railroads and buildings
- Not suitable: Streets/railroads, buildings, wetland, water

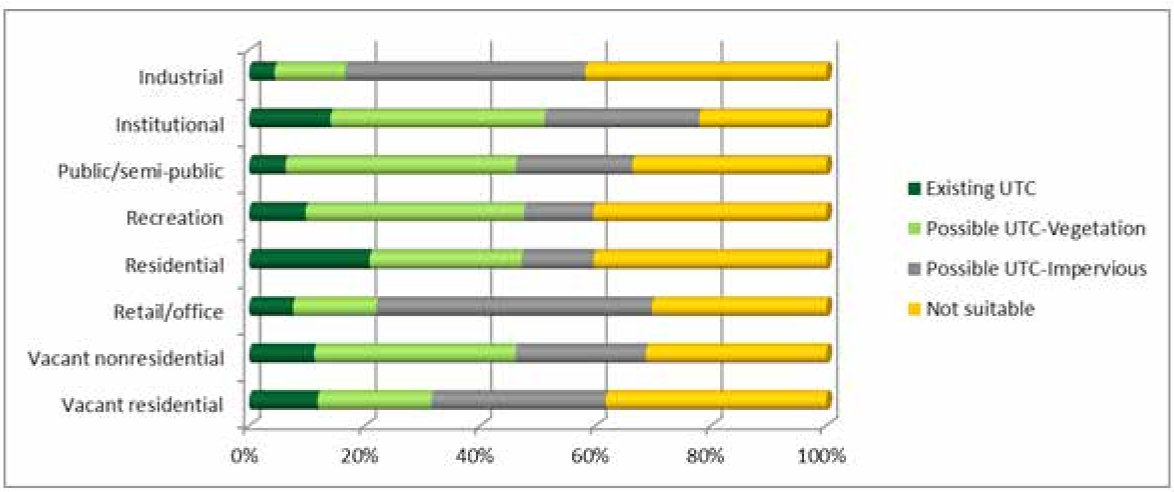
UTC classes were summarized by land use category (Figure 9) based on selected land use categories from the FDOT 2014 general land use classification map.

A more detailed explanation for some of the used land use categories is provided as follows:

- Public/semi-public: public schools, public hospitals, utilities, other land use governed by county, state, or federal
- Recreation: golf courses, forests, parks, other recreational areas
- Institutional: boarding homes; churches; private schools or hospitals; homes for aged; orphanages; mortuaries, cemeteries; clubs, loges, union halls; sanitariums, convalescent; cultural organizations; military; colleges

The highest percentage of existing UTC can be found in residential land (20.8%). The highest percentage of possible tree cover comprised of grass and bare ground is found in public/semi-public areas (39.9%), followed by recreational areas (37.9%) and institutional areas (37.1%). Possible tree cover replacing impervious surfaces is highest for the class retail/office (47.9%). The overall possible UTC (combined vegetation and impervious) is highest for the class retail/office (62.3%); however, most of these are impervious areas such as parking lots. Industrial areas provide the largest percent of land cover not suitable for tree canopy (41.8%), followed by residential and recreation (both 40.3%).

Figure 9. UTC metrics summarized by land use



Additional urban tree canopy (UTC) metrics, sorted by UTC type, are summarized for the eight dominant land use types in Table 4. For each land use category, UTC metrics were computed as a percentage of the total study area (% Land), as a percentage of the land area by land use category (% Category), and as a percentage of the area for the UTC type relative to the total study area (% UTC Type).

Values in the % Category columns correspond to proportions of bars in Figure 9 above.

The large values of percent Land and percent UTC type for existing UTC in the residential land use category can be attributed to the large size of residential areas (~97km2), together with a relatively high proportion of existing UTC areas within residential areas (21%). Residential areas also provide the largest total area of possible UTC on grass and bare ground (9%) and impervious surfaces (4%). Significant potential for UTC on grass and bare ground can also be found in public/semi-public areas (5%). Equations and examples for all three types of percentage values are provided below the table.

Figure 9. UTC metrics summarized by land use

	Existing UTC			Possible UTC-Vegetation			Possible UTC-Impervious		
Land use	*% Land*	*% Category*	*% UTC Type*	*% Land*	*% Category*	*% UTC Type*	*% Land*	*% Category*	*% UTC Type*
Industrial	1%	4%	5%	2%	12%	6%	5%	42%	25%
Institutional	0%	14%	4%	1%	37%	5%	1%	27%	4%
Public/semi-public	1%	6%	7%	5%	40%	22%	3%	20%	12%
Recreation	0%	10%	3%	1%	38%	5%	0%	12%	2%
Residential	7% (*)	21% (**)	62% (***)	9%	26%	37%	4%	12%	20%
Retail/office	1%	8%	7%	2%	14%	7%	5%	48%	24%
Vacant nonresidential	1%	11%	8%	3%	35%	11%	2%	23%	8%
Vacant residential	1%	12%	8%	2%	20%	6%	2%	30%	11%

Notes:
% Land = (Area of UTC type for specified land use) / (Area of all land)
(*) 7% of the land in the study area has tree canopy and falls into the "Residential" land use category.

% Category = (Area of UTC type for specified land use) / (Area of all land for specified land use)
(**) 21% of residential land is covered by tree canopy.

% UTC Type = (Area of UTC type for specified land use) / (Area of all land for specified UTC Type)
(***) 62% of all existing tree canopy lies in the residential land use.

ANALYSIS OF PARCELS

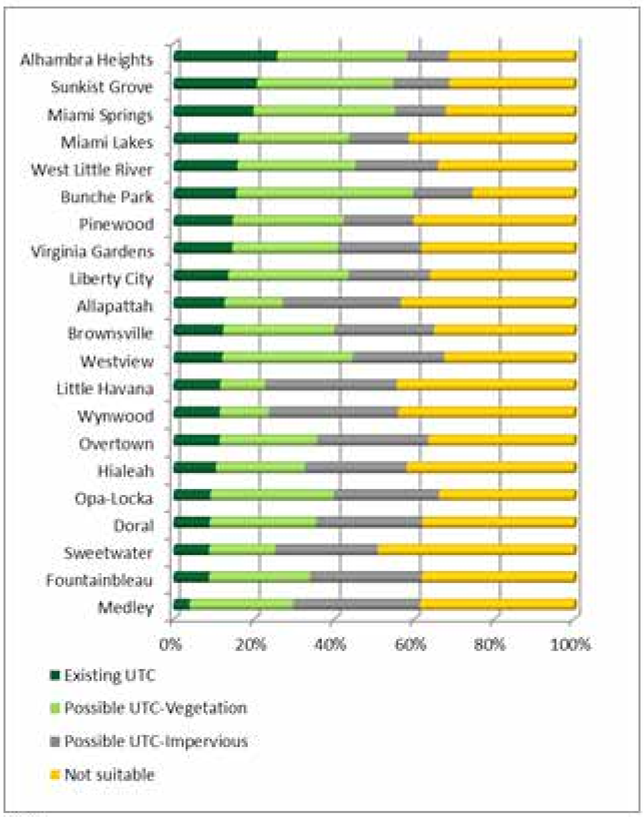
Based on the generated land cover map, the percentage of existing and possible UTC for each parcel can be computed. A zoomed view into a subregion is shown in Figure 10. This provides more detailed information about existing tree canopy on each ownership unit. The upper map (Figure 10a) suggests that the density of existing tree canopies is generally higher for residential areas (small, regular parcel layout). Likewise, the lower map (Figure 10b) suggests that the possible UTC percentage is higher for industrial and publicly administered locations (larger parcels).

Figures 10a and 10b. Distribution of existing and possible urban tree canopy in parcels.

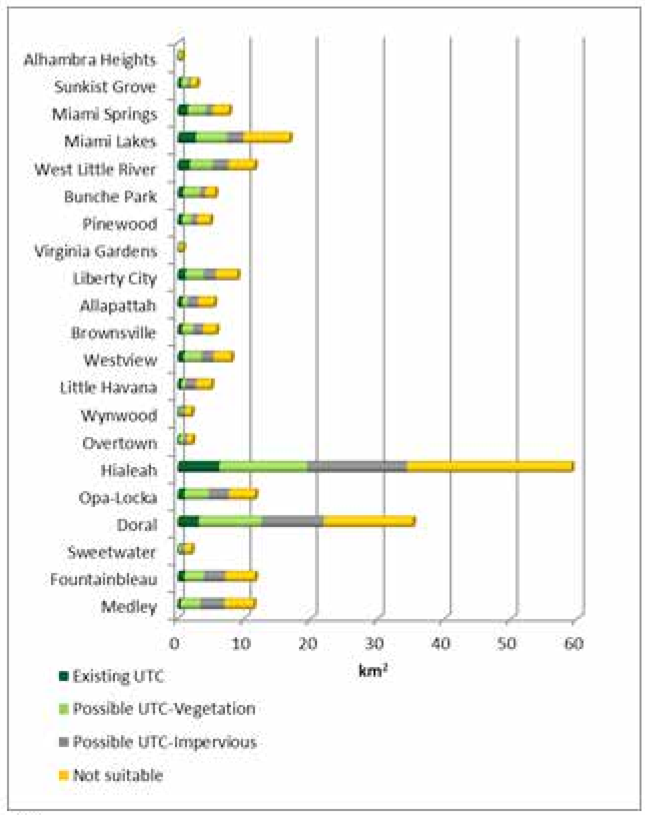
ANALYSIS OF NEIGHBORHOODS

Canopy patterns were analyzed for 21 neighborhoods falling completely into the study area. The areas analyzed include neighborhoods as defined by the Miami-Dade MPO, municipalities, and census places. UTC metrics by neighborhood are summarized in Figure 11. The bars in the left figure (Figure 11a) show percent UTC type by neighborhood, sorted by percent existing UTC. Alhambra Heights has the largest percent existing UTC (26.0%), and Medley the smallest (4.1%). Absolute area values for UTC metrics provide a more accurate picture about the impact of UTC initiatives on an area (Figure 11b). Under this aspect, due to their large spatial extent, Hialeah and Doral already have the largest coverage of existing UTC with 6.3 km2 and 3.2 km2, respectively. These two neighborhoods provide also the largest possible UTC areas on pervious land (grass and bare ground), with 13.2 km2 and 9.4 km2, respectively.

Figures 11a and 11b. UTC metrics summarized by neighborhood



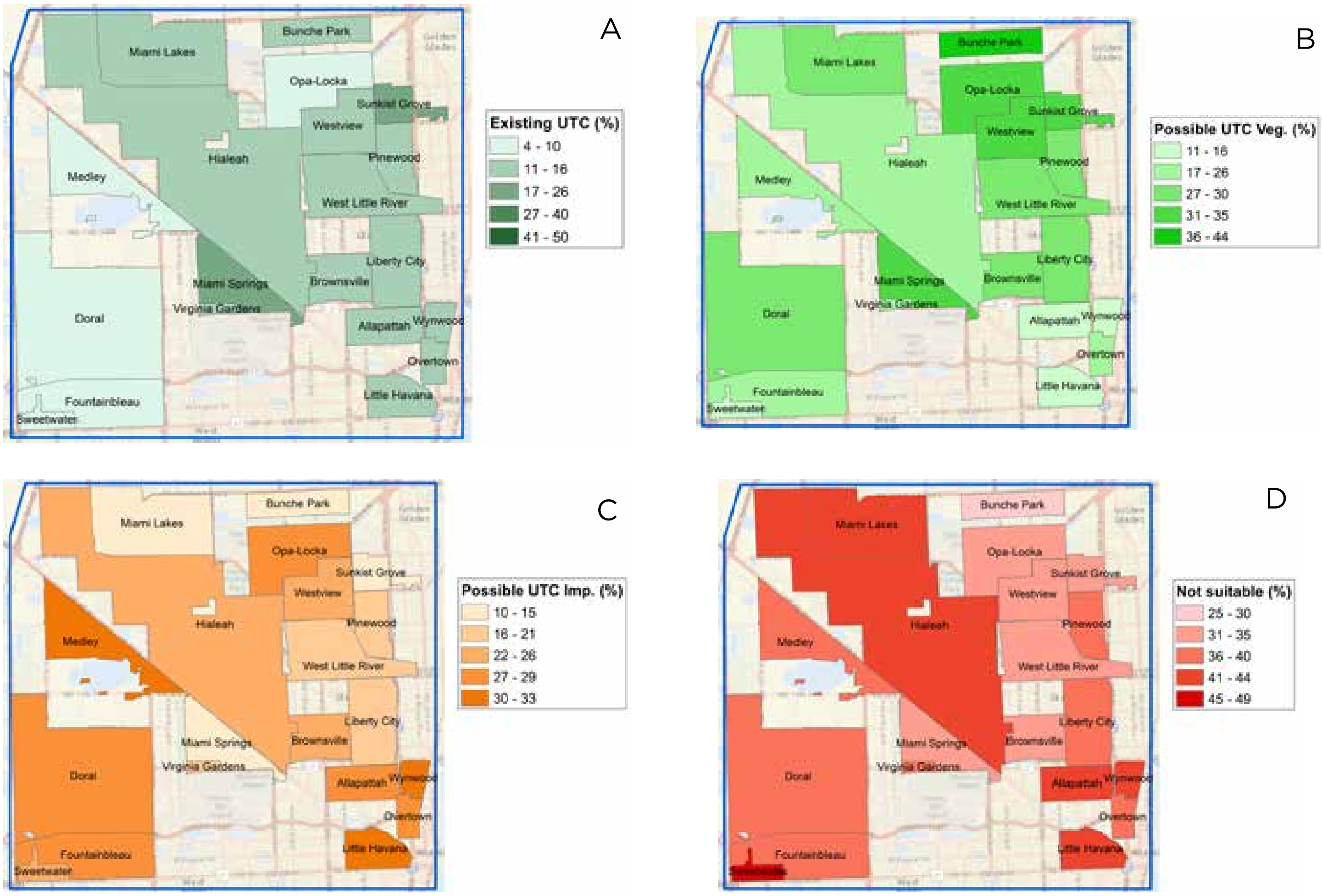
(a)



(b)

Based on the same data for each neighborhood, Figure 12 maps the percent of existing UTC (a), of possible UTC on pervious surfaces (b), of possible UTC on impervious surfaces (c), and of areas non suitable for UTC (d). Neighborhoods near Miami-downtown tend to have few land resources with pervious surfaces that could host additional UTC. Their percent value of area not suitable for UTC is also among the highest. Similarly, Hialeah and Doral, provide a relatively low percent cover with grass and bare soil for possible UTC, but a higher percent of possible UTC on impervious surfaces, such as asphalt, caused by large industrial zones.

Figures 12a, 12b, 12c and 12d. Maps for UTC metrics summarized by neighborhood



TREE CANOPY AND SOCIOECONOMIC VARIABLES

Tree canopy increases quality of life in neighborhoods (e.g., by providing shade for outdoor activities, fresh air, cooling the surface). Thus, it is of interest to see if tree canopy is equally distributed among certain population groups. Maps in Figure 13 visualize for 169 populated census tracts within the study area the percent of existing tree canopy (a), population size (b), mean annual household income in US $ (c), percent Hispanic population (d), and percent African American population (e). Socio-economic data were obtained from the America Community Survey (ACS) 2008-2012 5-year estimate. A bivariate correction (Pearson r) was determined between percent of UTC and population, household income, and various ethnicities. A significant negative correlation was found between UTC and percent Hispanic (r=-0.444, p=0.000), and a significant positive correlation was found between UTC and percent African American (r=0.387, p=0.000).

It must be noted that these correlation does not imply any direct causal relationship between ethnicity and canopy density (e.g. that the Hispanic population avoids areas with high canopy density). These correlation values may also change or become insignificant if other aerial units (instead of census tracts) were used. A scatter plot is provided in Figure 14 for percent Hispanic (a) and percent African American (b).

Figures 13a, 13b, 13c, 13d, and 13e. UTC and demographics for census tracts

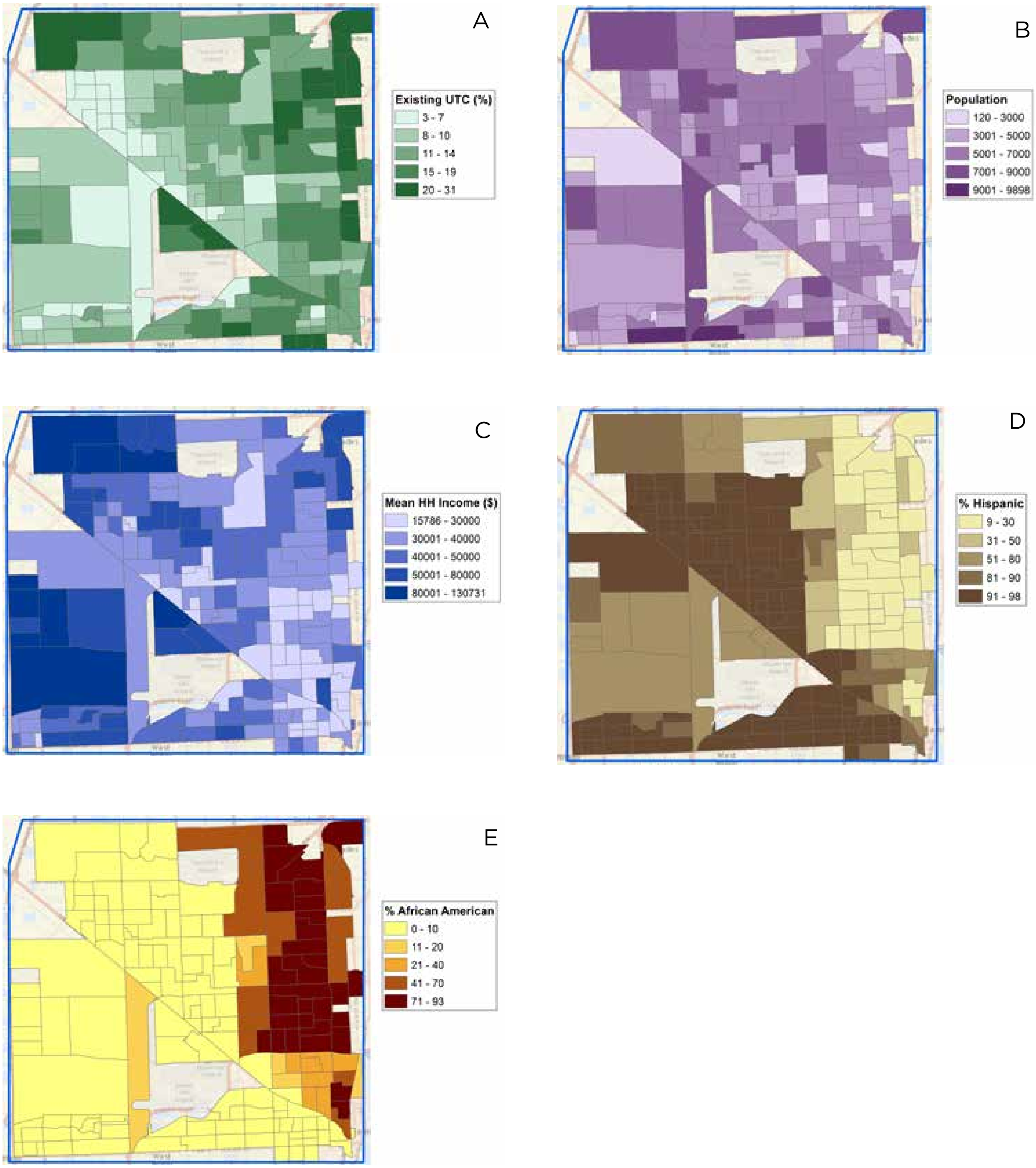
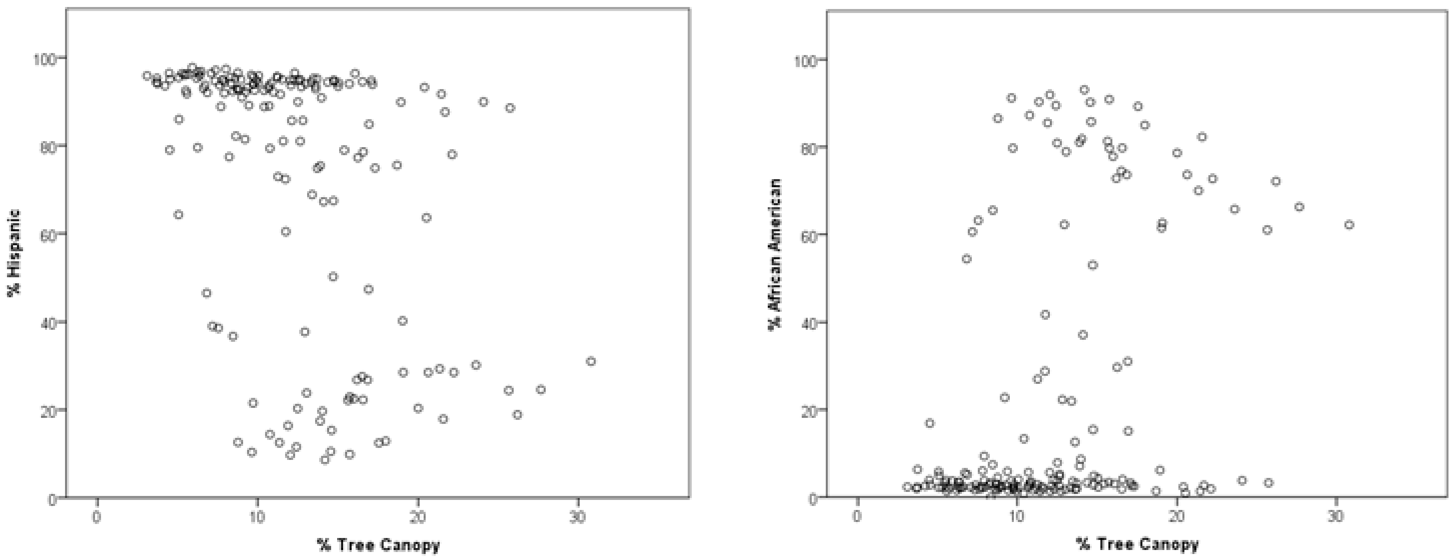


Figure 14. Percent of Hispanic/African American population and percent Tree Canopy in census tracts of the study



(a) (b)

ANALYSIS OF HEALTH DATA

This section reviews the potential relationship between respiratory illness variables and density of existing urban tree canopy. Health data were obtained from the Agency for Health Care Administration (AHCA). It contains Miami-Dade hospitalization rates of residents in zip codes for years 2010-2012. Data was analyzed for 19 zip codes falling into the study area. All respiratory illness reported may not be directly related to air quality issues.

Figure 15 shows for the selected zip code areas percent urban tree canopy (a), age-adjusted hospitalization rate due to adult asthma (b), age-adjusted ER rate due to adult asthma (c), and age-adjusted ER rate due to pediatric asthma (d).Visual inspection suggests that a higher density of urban tree canopy is associated with an increased rate of respiratory health incidents. There is also a statistical trend ($p<0.10$) in this direction (Table 5). However, this may be a spurious relationship, meaning that the tree canopy and asthma health variable have no causal connection. Instead, this association could be caused by an unknown confounding factor (e.g., smoking behavior, household income, education, people's health awareness).

Figures 15a, 15b, 15c and 15d. Mapping urban tree canopy and hospitalization rates due to asthma at the zip code level

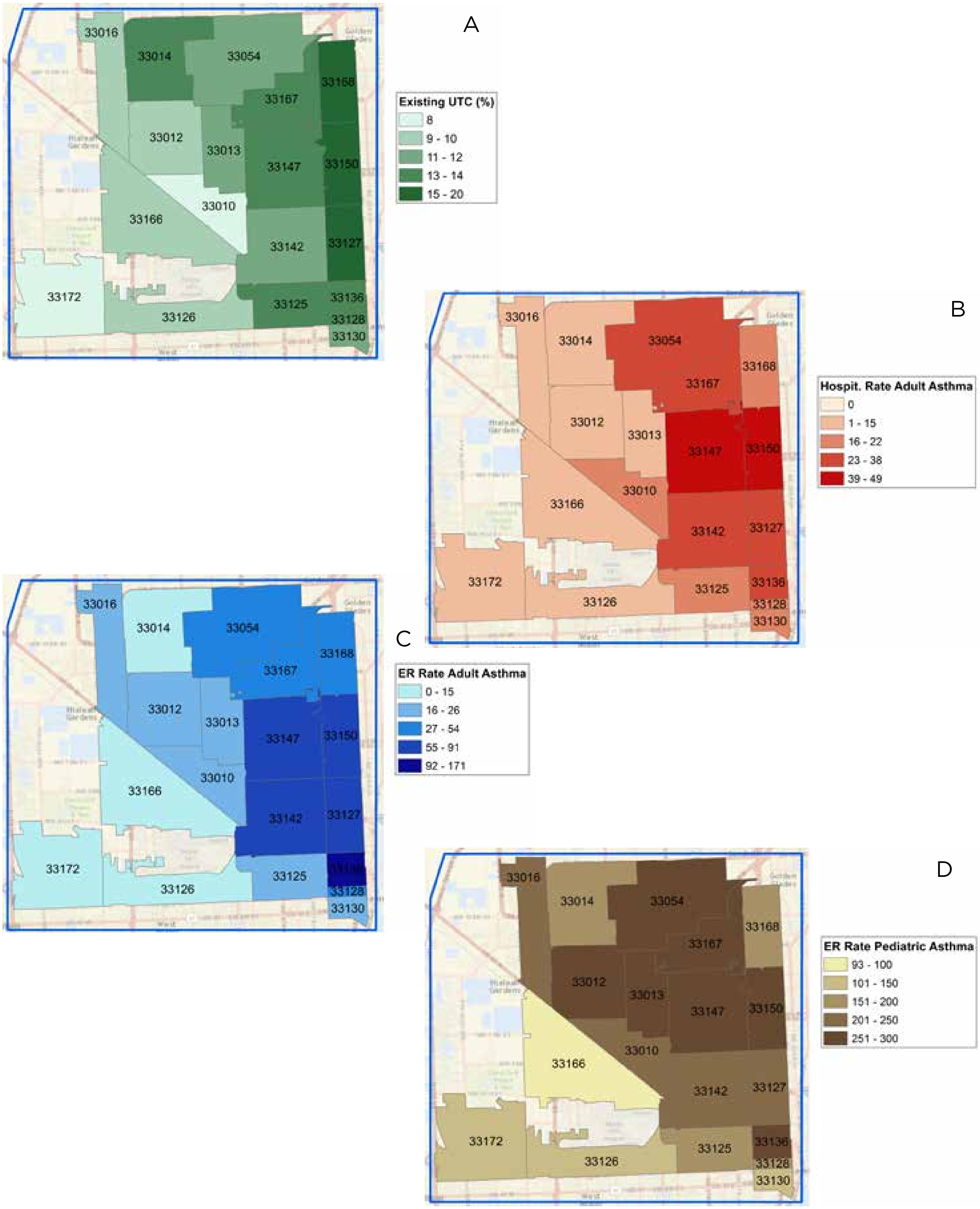


Table 5. Bivariate correlations between percent urban tree canopy and rates of respiratory health events for zip codes (N=19)

	Hospitalization rate adult asthma	ER rate adult asthma	ER rate pediatric asthma
r	0.455	0.399	0.235
p	0.050	0.091	0.333

SUMMARY AND CONCLUSIONS

- For a project area located in Miami-Dade County, a combination of remote sensing, LiDAR, and publicly available vector data was used in classification of the following land cover classes: tree canopy/shrubs, grass, bare ground, wetland, water, building, street/railroad, and other impervious surfaces.
- Overall tree canopy in the study area was found to be 12.2%.
- A large portion of the project area offers the potential for additional urban tree canopy. These areas consist of approximately equal parts pervious surfaces (grass, bare ground) and impervious surfaces (asphalt).
- Residential housing (vacant and non-vacant) represent 70% of the existing tree canopy in the study area.
- Tree canopy, grass, and water bodies are associated with lower surface temperatures. Therefore, adding grass and planting trees in targeted areas can avoid heat islands.
- The parcel layer could be used as first guidance in detecting patterns of higher or lower density of trees. However, accuracy estimates do not support parcel level use. Therefore, parcels should be subsequently investigated on the ground or through aerial photography to more accurately determine existing and potential tree canopy for planning purposes.
- Neighborhood analysis utilizing metrics of existing and possible UTC can be used to help target tree canopy improvement and preservation activities.
- Tree canopy percentages appear to have no overall significant influence on respiratory illness rates. A possible explanation is that expected positive health effects of tree canopy are masked by other influences in the analyzed zones.
- The land cover analysis was performed completely using remotely sensed imagery and LiDAR data. It does not study the specific species of trees that are present in the project area. In order to catalog the species that compose the urban tree canopy, ground surveys or higher spatial and spectral (hyper-spectral) remotely sensed data sets would be required.

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CLASSIFICATION METHODOLOGY

Classification Accuracy Assessment

A design-based accuracy assessment of land-cover class stratified random samples (N = 528; multinomial distribution sampling) estimated the overall accuracy of the map to be 91%, with a bias adjusted accuracy of 95% (adjusted for class distribution). The standard error of the adjusted accuracy was 2.19%, which means that the actual map accuracy is between 92.8% and 97.2%.

Class-specific accuracies ranged from 66.1 ±11.5% for wetlands to 100 ±0% for the road and rail class (Table 6). Trees were detected with an adjusted accuracy of 92.4 ±6.4% (Table 7). Wetland areas were overestimated by 19.6% (a difference of total mapped area of 0.1%, Table 7). Confusion errors were highest between wetland and water classes (27% commission error from wetlands to water and only a 1.5% commission error for water into wetland, Table 6). The reasons for these misclassifications are mainly a result of mixed pixels along shorelines of canals and lakes, shallow water areas with benthic vegetation, or sediment / algae rich water-columns. Another class that displays a systematic misclassification error is grass misclassified mainly as trees. This happened mostly along the edges of buildings where the LiDAR data over-estimated object heights (7.6% of grass samples were classified as trees,Table 6).

Table 6. Design-based confusion matrix. Values are percent of samples classified (rows) and referenced (columns)

	Bare Ground	Buildings	Grass	Impervious	Road & Rail	Trees	Water	Wetland
Bare Ground	87.9%	1.5%	1.5%	9.1%	0.0%	0.0%	0.0%	0.0%
Buildings	0.0%	93.9%	0.0%	6.1%	0.0%	0.0%	0.0%	0.0%
Grass	1.5%	0.0%	95.5%	3.0%	0.0%	0.0%	0.0%	0.0%
Impervious	4.5%	0.0%	0.0%	95.5%	0.0%	0.0%	0.0%	0.0%
Road & Rail	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%
Trees	0.0%	0.0%	7.6%	0.0%	0.0%	92.4%	0.0%	0.0%
Water	0.0%	0.0%	1.5%	0.0%	0.0%	1.5%	95.5%	1.5%
Wetland	3.0%	0.0%	3.0%	0.0%	0.0%	0.0%	27.3%	66.7%

Table 7. Land-cover class distribution (in percent and hectares) and estimated detection accuracies. Reported are map and bias-adjusted estimates and their associated standard errors (SE).

Land-Cover Class	Area %	Adj. %	Adj. % SE	Acc. (Biased)	Acc. Adj.	Acc. Adj. SE	ha	ha (Adj.)	ha SE
BareGround	2.8%	3.8%	0.7%	87.9%	88.0%	± 7.9%	1,055	1,470	± 267
Buildings	19.5%	18.4%	0.6%	93.9%	94.0%	± 5.8%	7,475	7,036	± 222
Grass	23.0%	23.1%	0.7%	95.5%	95.4%	± 5.1%	8,818	8,831	± 278
ImpNoRR	23.0%	24.1%	1.0%	95.5%	95.4%	± 5.1%	8,809	9,226	± 371
RoadRail	12.6%	12.6%	0.0%	100.0%	100.0%	± 0%	4,839	4,839	± 0
Trees	12.3%	11.5%	0.4%	92.4%	92.4%	± 6.4%	4,703	4,383	± 158
Water	6.2%	6.1%	0.2%	95.5%	95.6%	± 4.9%	2,370	2,320	± 62
Wetland	0.6%	0.5%	0.1%	66.7%	66.1%	± 11.5%	211	176	± 38

Land Cover Classification Methodology

A land cover classification map was generated using a combination of WorldView-2 (eight band spectral resolution, 2m spatial resolution) data acquired between 2011 and 2014 and 2008 LiDAR data. The raw LiDAR point cloud data was processed to derive a 2m Digital Surface Model (DSM), corresponding to the first object detected by the LiDAR sensor including the tops of vegetation, buildings, and vehicles, and a 2m bare ground Digital Elevation Model (DEM). The DSM and DEM were co-registered with WorldView-2 imagery. Object heights were derived by subtracting the DEM surface from the DSM surface. The resulting height surface together with atmospherically corrected multi-spectral reflectance values were used in the classification of eight land cover classes.

The initial land-cover detection was based a on a random forest classification algorithm (Liaw & Wiener, 2002; Svetnik et al., 2003) in the caret R-package (Kuhn & Team, 2014), which used the WV2 spectral information and LiDAR-derived object heights. Next, various vector data layers, provided by Miami-Dade County, were incorporated into the map generation process for quality enhancement after the initial classification. The vector layers included:

- Large buildings (polygons)
- Small buildings (points buffered with a 3m radius)
- Edge of pavement (polylines converted to polygons)
- Railroads (polylines buffered with a 3m distance)
- Water bodies (polygons)

LiDAR-derived 2m DSM pixels tend to underestimate the elevation of mixed pixels at the fringes of trees, which would result in an underestimation of tree canopy cover. Therefore, shrubs and trees were combined into one class. In order to remove spurious pixels, the final map (Figure 4) was smoothed with a 4-edge kernel using a nearest neighbor replacement method with varying minimum mapping units (MMU) for the different classes (Table 1).