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Miami-Dade County Urban Tree Canopy Assessment

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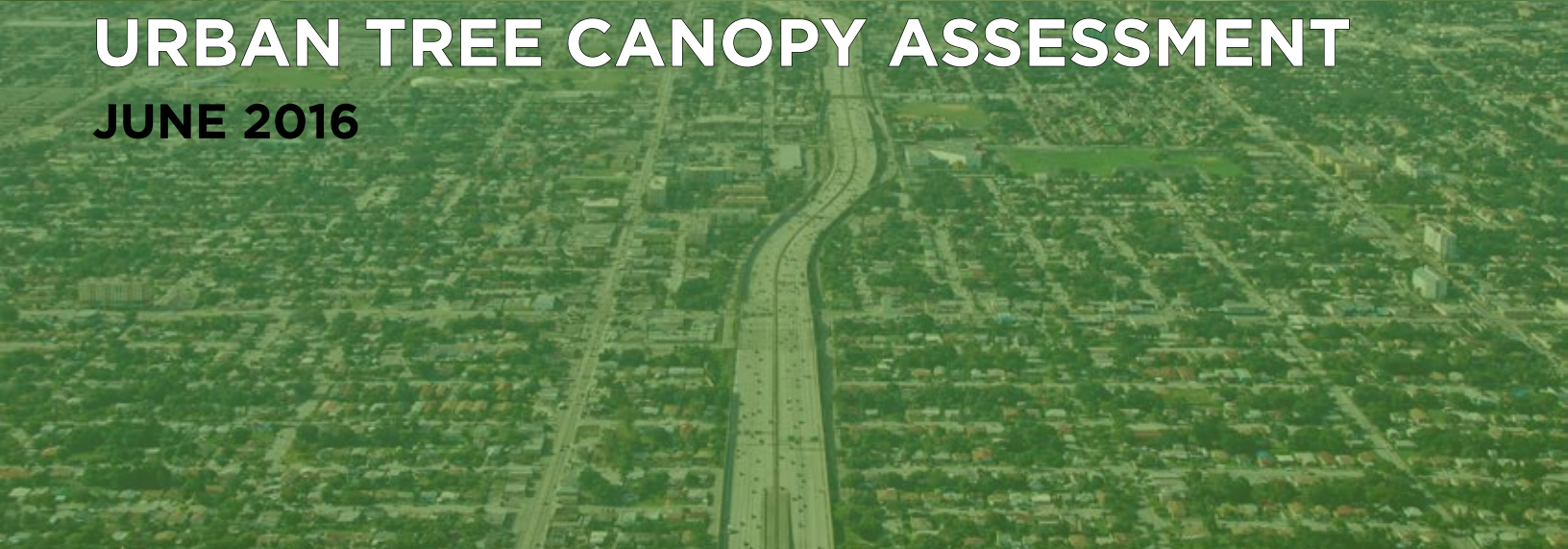
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MIAMI-DADE COUNTY

URBAN TREE CANOPY ASSESSMENT

JUNE 2016



AMERICAN FORESTS



ACKNOWLEDGMENTS

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This Miami-Dade assessment was created by 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.

Our Partners





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EXECUTIVE SUMMARY

This assessment focuses on the environmental and socioeconomic impacts from the urban tree canopy (UTC) within the Urban Development Boundary of Miami-Dade County, as defined by the Miami-Dade County MPO (Figure 1). The area (intracoastal water areas excluded) encompasses approximately 1150 km² (444 mi²). A combination of remote sensing and publicly available vector data was used to classify the following land cover classes: tree canopy/shrubs, grass, bare ground, wetland, water, building, street/railroad, other impervious surfaces, and cropland.

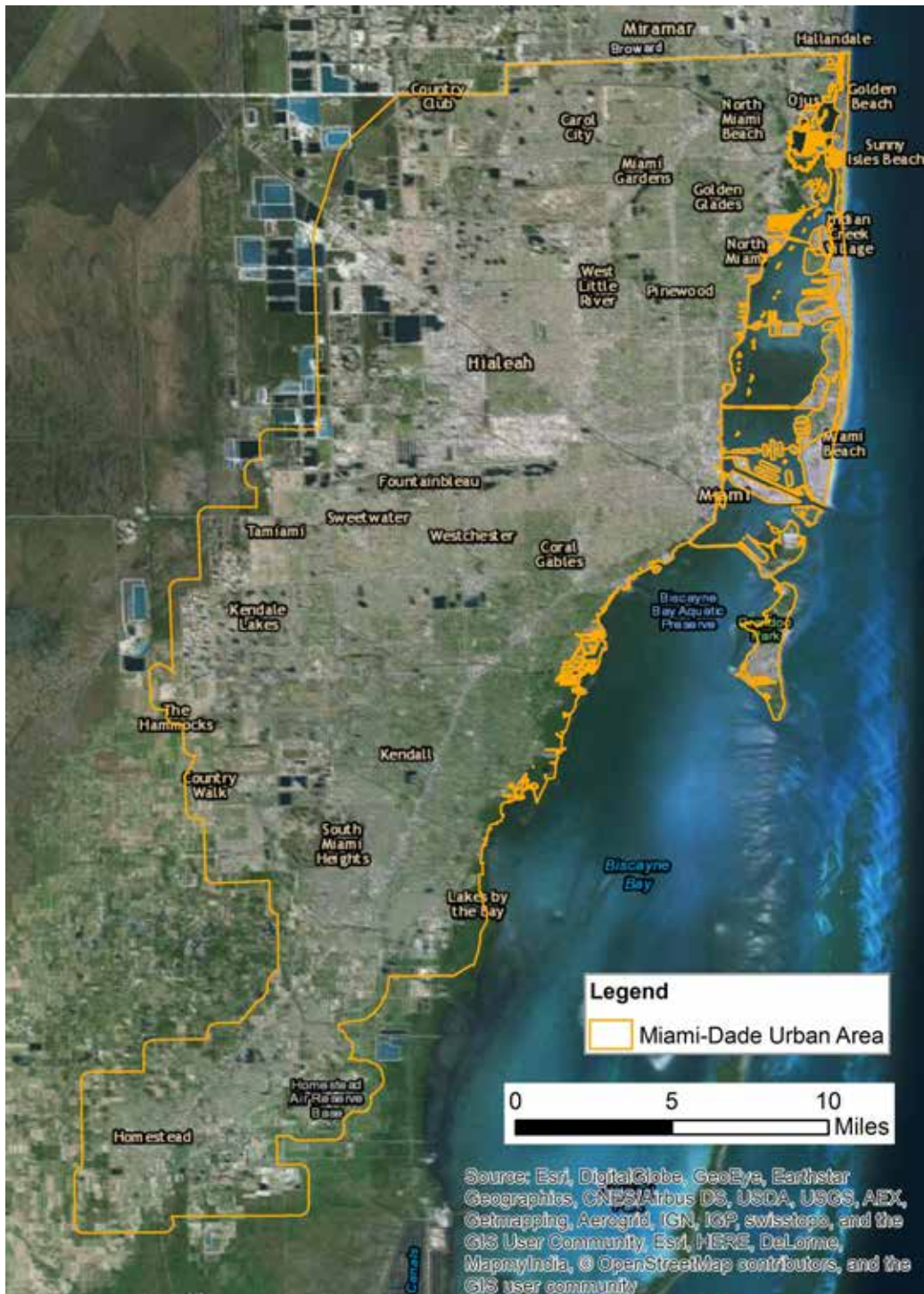
Primary Goals

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. To that end, the assessment estimates the area with current tree canopy (existing UTC), the area of potential tree canopy (possible UTC), and the area currently unsuitable for tree canopy, based on various other land cover categories. Assessments are made for the entire County as well as in census places, municipalities and commission districts to support strategic planning and implementation.

Results

- Overall tree canopy within the Miami-Dade Urban Development Boundary is 19.9%.
- A large portion of the project area offers the potential for additional urban tree canopy. These areas consist of pervious surfaces (grass, bare ground) and impervious surfaces (asphalt), with a slightly higher share falling into the pervious surface category.
- Residential housing (single family, duplex, multiple family and townhouses) represent 42% of the existing tree canopy and 33% of possible tree canopy on pervious surfaces in the study area.
- Tree canopy and water bodies are associated with lower surface temperatures. Therefore, planting trees in targeted areas can reduce heat islands.
- Tree canopy is positively correlated with median income, but negatively correlated with percentage of African American and Hispanic residents. Therefore, strategically planting trees in minority and lower income communities can support environmental equity.
- Higher tree canopy percentage is associated with lower overall hospitalization numbers and also with lower hospitalization numbers related to asthma. Since tree canopy is positively correlated with income, this association can at least be partially attributed to higher income and the healthier lifestyle associated with higher income.

Figure 1. Urban Area of Miami-Dade County

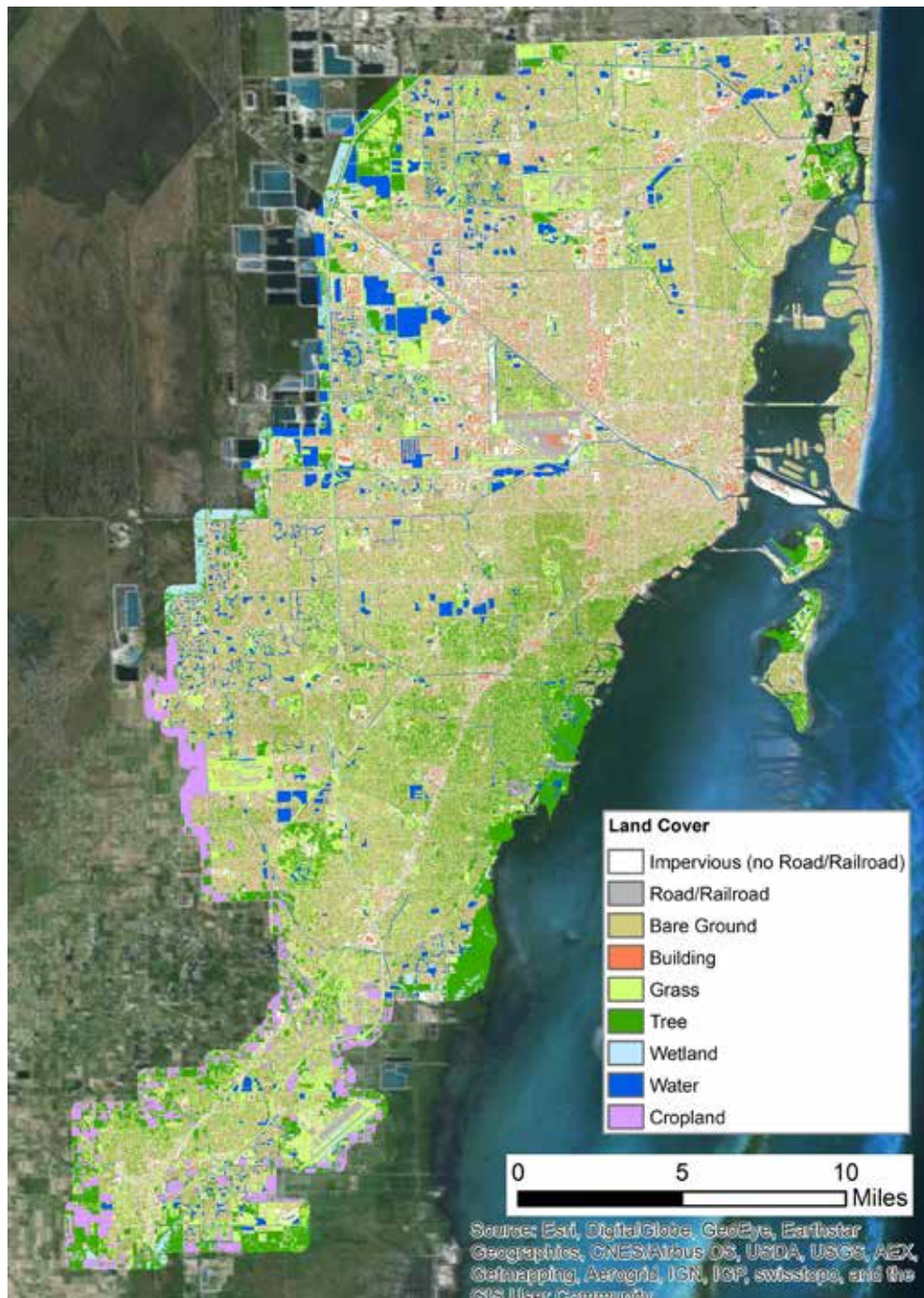


PROJECT AREA LAND COVER CLASSIFICATION

Land Cover Classification Map

Figure 2 shows the land cover classification map with its nine classes, where shrubs and trees are combined into one class. Cropland occurs primarily on the southwestern edges of the study area. Inland water bodies (lakes, ponds, canals, rivers) are also shown on the land cover classification map, whereas coastal water areas (bay, ocean) were excluded from the land cover generation process and the computation of land cover statistics.

Figure 2. Land cover classification map



Land Cover Statistics

The project area covers approximately 1,150 km² (444 mi²). Grass has the largest percent cover of 22.2 ± 1.4%, followed by impervious surface 20.1 ± 1.2%, and tree canopy (including shrubs) 19.9 ± 1.2% (Figure 3, Table 2). Total additional possible tree canopy, which includes grass, bare ground, and impervious surface (e.g., parking lots, but not buildings, streets, or railroads) make up 44.2% (Figure 3b, Table 2) and the remaining 35.9% of the study area include streets and railroads, buildings, wetlands, water bodies, and cropland 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 toward possible UTC areas since the wetland area was only 1.6 ± 0.4% of the entire mapped area. Within possible tree canopy areas, only pervious surfaces (grass, bare ground) cover 24.1%. Total area in km² and mi², percent cover and classification accuracies for each land cover class are provided in Table 1.

Figure 3. Percentage of land cover classes

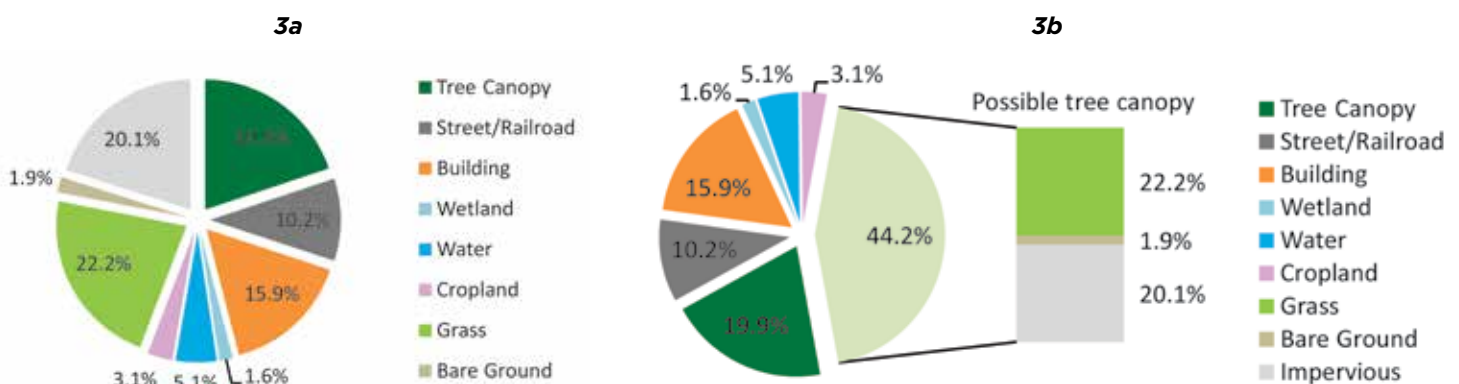


Table 1. Area, percent and user's accuracy of land cover classes and their standard error (SE) estimates (SE * ± 1.96 provides 95% confidence intervals). Area and percent cover are accuracy adjusted estimates.

Class	Area (km ²)	Area (mi ²)	Percent cover	Accuracy
Tree Canopy	228.6 (± 13.7)	88.3 (± 5.3)	19.9 (± 1.2)	88.1 (± 4.2)
Street/Railroad	117.2 (± 4.4)	45.2 (± 1.7)	10.2 (± 0.4)	100.0 (± 0.0)
Building	183.1 (± 11.7)	70.7 (± 4.5)	15.9 (± 1.0)	93.2 (± 3.3)
Wetland	18.7 (± 4.2)	7.2 (± 1.6)	1.6 (± 0.4)	94.8 (± 2.9)
Water	58.6 (± 4.6)	22.6 (± 1.8)	5.1 (± 0.4)	96.7 (± 2.3)
Cropland	35.6 (± 0.9)	13.8 (± 0.3)	3.1 (± 0.1)	96.6 (± 2.4)
Grass	255.8 (± 15.6)	98.7 (± 6.0)	22.2 (± 1.4)	88.2 (± 4.2)
Bare Ground	21.4 (± 0.9)	8.3 (± 0.4)	1.9 (± 0.1)	89.4 (± 4.0)
Impervious	230.9 (± 13.5)	89.2 (± 5.2)	20.1 (± 1.2)	84.8 (± 4.7)
Total/Overall	1150.0	444.0	100.0	90.1 (± 1.7)

LAND COVER AND SURFACE TEMPERATURE

Surface Temperature Map

Figure 4 color-codes temperature in degrees Fahrenheit for the study area. Figure 5 provides a zoomed view of a region that covers residential neighborhoods, industrial complexes, and water bodies. The upper map (Figure 5a) depicts surface temperature as a raster layer whereas the lower map (Figure 5b) shows temperature contour lines with a background aerial photograph underneath. Visual inspection of both maps allows for the identification of temperature hot spots, which occur primarily in areas with large warehouses, commercial sites, and sparse tree canopy. Cool spots are found around water bodies, residential areas with high tree canopy density and larger patches of grassland. Areas covered by both buildings and tree canopy (e.g., residential areas) show mid-range temperatures.

Figure 4. Surface temperature map

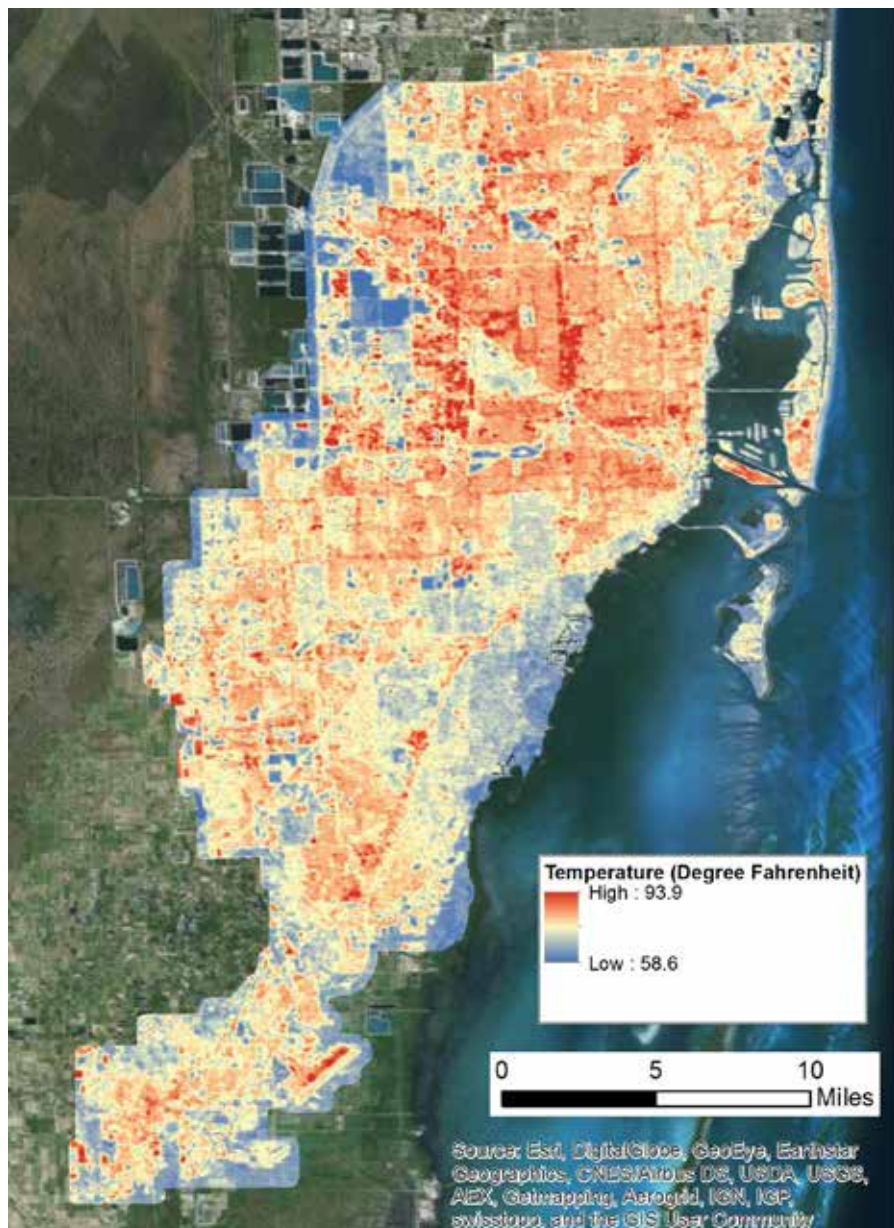
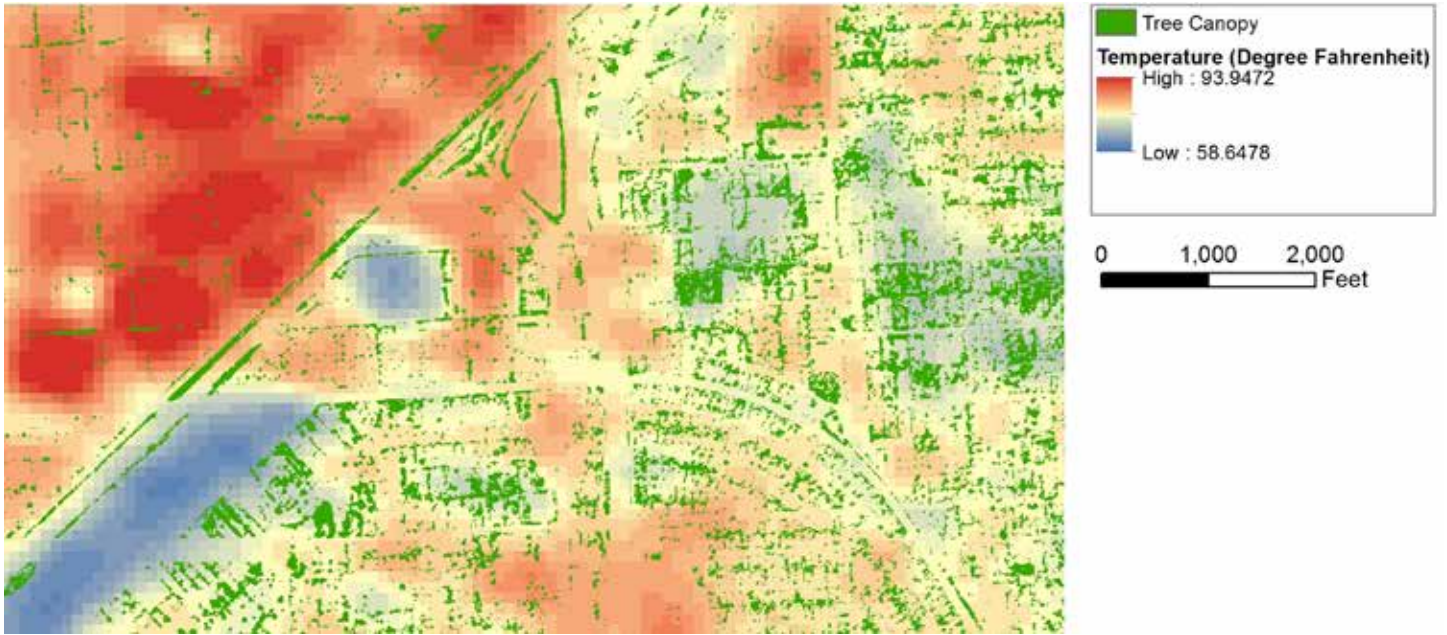


Figure 5. Zoomed surface temperature and contour map (in Degree Fahrenheit)

5a



5b



Correlations Between Surface Temperature and Land Cover Class

Figure 6 graphically visualizes the relationship between surface temperature and percent land cover of selected land cover types based on a random sample of 14,796 cells. Each scatterplot is overlaid with a linear regression line. The two land cover variables included in the upper figures (% tree canopy, % water) demonstrate that temperatures decrease as % tree canopy and % surface water increase. The lower left figure demonstrates no significant relationship between temperature and % bare ground (Figure 6c), whereas % impervious surface in Figure 6d demonstrates that the surface temperature rises as % impervious surface, such as concrete, increases.

Figure 6. Scatter plots relating surface temperature with selected land cover variables

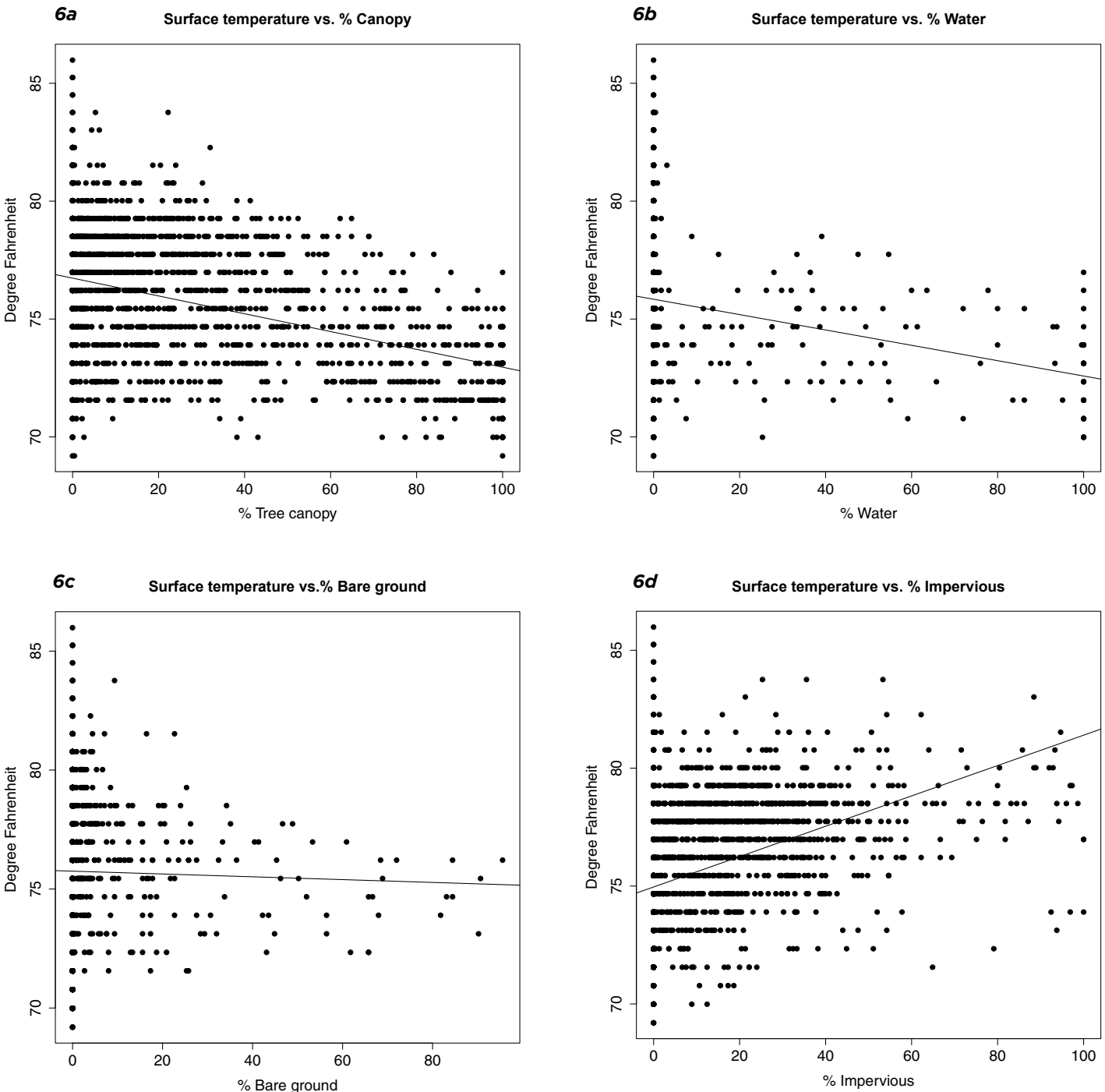
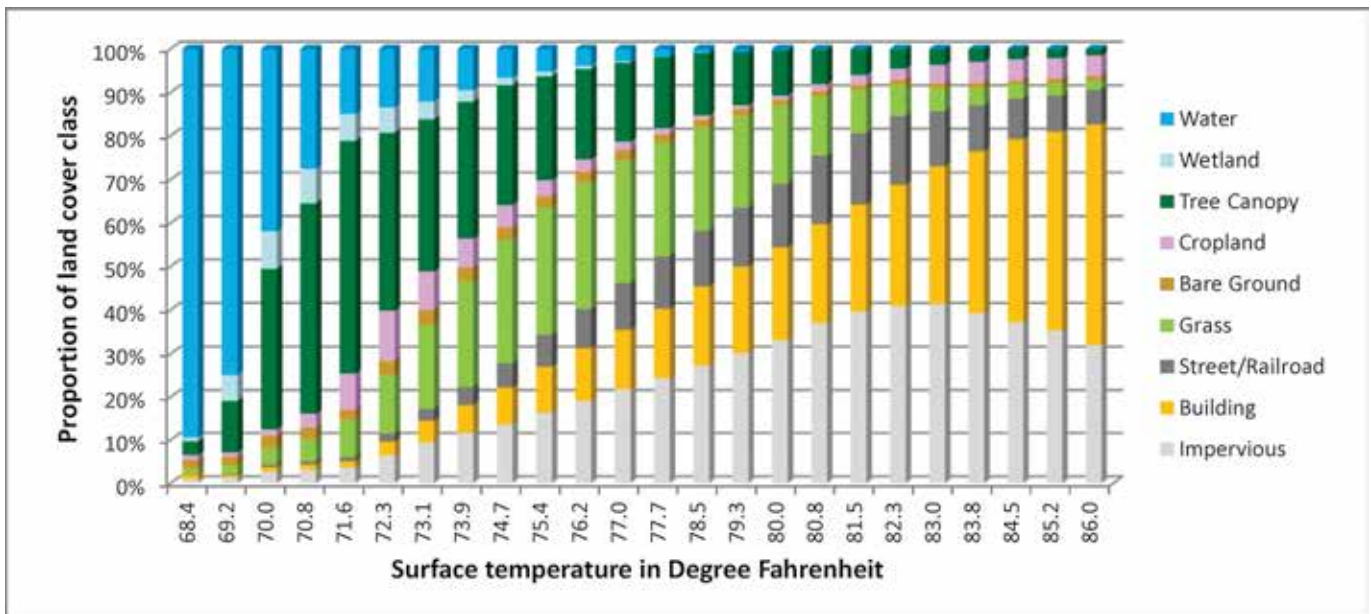


Figure 7 visualizes the relationship between land cover mix and surface temperature by plotting discrete temperature values against the proportion of land cover classes associated with that temperature. The diagram demonstrates the cooling effect of water bodies, wetland, tree canopy and crop, which occur primarily in the left half of the diagram associated with lower surface temperatures. A small portion of crop can also be found in higher temperature cells. This could be because of a temporary cover of nurseries with plastic foil or similar materials, leading to higher surface temperatures than crop. Bare ground is also largely found in the left half of the diagram, although not being significantly associated with cooler surface temperature. The proportion of grass is highest in the mid-temperature ranges. Areas with higher surface temperature demonstrate a higher share of streets/railroads, buildings, and impervious surfaces.

Figures 7. Proportion of land cover classes for different surface temperatures



ANALYSIS OF LAND USE PATTERNS

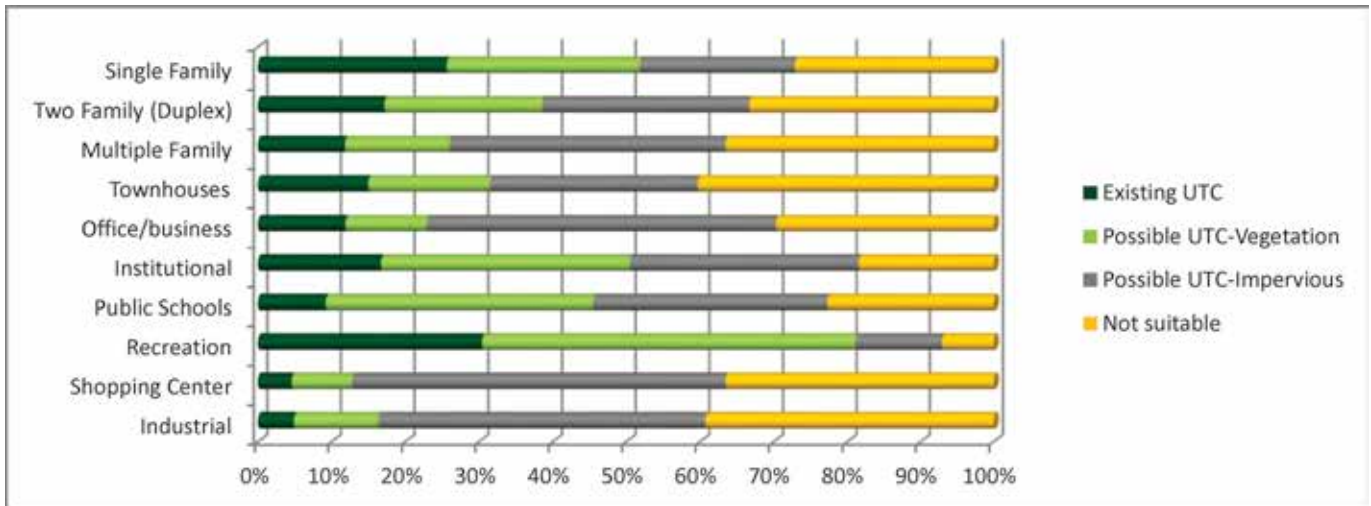
For further analysis, all land cover types were reclassified into different UTC types as follows:

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

UTC classes were summarized by land use category (Figure 8). For this purpose, selected land use categories from the Miami-Dade County general land use classification map were aggregated as follows:

- **Institutional:** Cemeteries; colleges and universities; governmental/public administration (other than military or penal); hospitals; nursing homes, houses of worship and religious; military facilities; penal and correctional; private schools including playgrounds; social services, fraternal, charitable; parking - public and private garages and lots;
- **Public Schools:** Public schools including playgrounds;
- **Recreation:** Golf courses, public and private, recreational vehicle parks/camps; municipal operated parks and county operated parks;
- **Multiple Family:** Multi-family with high-density and low-density; government-owned or government subsidized multi-family residential or elderly housing;
- **Single Family:** Mobile home parks and permanent mobile homes; single-family with high-density, low-density, medium-density;
- **Industrial:** Industrial extensive; industrial intensive, commercial condominium type of use, industrial intensive, heavy-light manufacturing, and warehousing-storage type of use; industrial intensive, office type of use;
- **Office / Business:** Office and/or business and other services (ground level) / residential (upper levels); office building, office/business/hotel/residential;

Figure 8. UTC metrics summarized by land use



This analysis found:

- **Existing UTC:** The highest percentage of existing urban tree canopy can be found in recreation areas (30.4%), followed by single-family land (25.6%).
- **Possible UTC – pervious:** The highest percentage of possible tree cover comprised of grass and bare ground is found in recreation areas (50.7%), followed by public schools (36.3%).
- **Possible UTC – impervious:** Possible tree cover replacing impervious surface is highest for shopping centers (50.7%), followed by office / business facilities (47.4%).
- **Not suitable:** Townhouse areas provide the largest percent of land cover not suitable for tree canopy (40.3%), followed by industrial sites (39.3%).

Additional UTC metrics, sorted by UTC type, are summarized for the 10 dominant land use types in Table 2. 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 8.

The large values of percent Land and percent UTC Type for existing UTC in the single-family home land-use category can be attributed to the large size of single family residential areas (~332km²/128mi²), together with a relatively high proportion of existing UTC areas within single family land use (26%). Single-family home areas provide also the largest total area of possible UTC on grass and bare ground (8%) and impervious surfaces (6%). Equations and examples for all three types of percentage values are provided below the table.

Table 2. Refined UTC metrics summarized by land use, shown for eight dominant land use categories

Land Use	Existing UTC			Possible UTC-Vegetation			Possible UTC-Impervious		
	% Land	% Category	%UTC Type	% Land	% Category	%UTC Type	% Land	% Category	%UTC Type
Single Family	7%*	26%**	37%***	8%	26%	28%	6%	21%	27%
Two Family (Duplex)	0%	17%	1%	0%	21%	1%	0%	28%	2%
Multiple Family	1%	12%	3%	1%	14%	3%	2%	38%	8%
Townhouses	0%	15%	1%	0%	17%	1%	0%	28%	2%
Office/ Business	0%	12%	1%	0%	11%	0%	0%	47%	2%
Institutional	1%	17%	3%	1%	34%	5%	1%	31%	6%
Public Schools	0%	9%	1%	0%	36%	2%	0%	32%	2%
Recreation	1%	30%	7%	2%	51%	8%	1%	12%	2%
Shopping Center	0%	5%	0%	0%	8%	0%	0%	51%	1%
Industrial	0%	5%	1%	1%	11%	2%	2%	44%	9%

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 single-family housing land use category.

% Category = (Area of UTC type for specified land use) / (Area of all land for specified land use)

(**) 26% of Single-family housing land is covered by tree canopy.

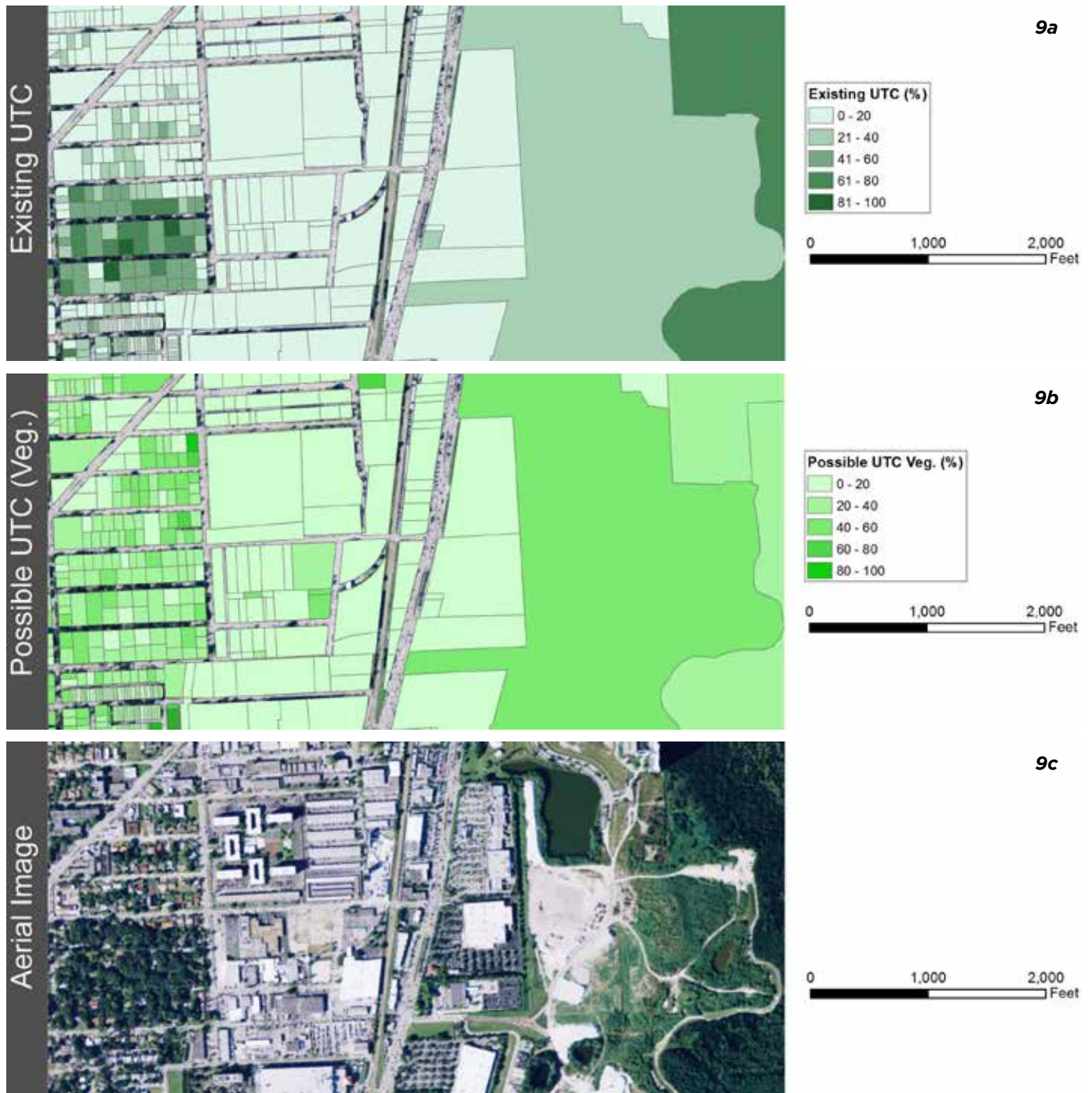
% UTC Type = (Area of UTC type for specified land use) / (Area of all land for specified UTC Type)

(***) 37% of all existing tree canopy lies in the Single-family housing land use.

ANALYSIS OF PARCELS

Based on the generated land cover map, the percentage of existing UTC (Figure 9a) and possible UTC on pervious land, including grass and bare soil (Figure 9b) can be computed for each property parcel. This breakdown provides more detailed information about existing tree canopy on each ownership unit. The upper map (Figure 9a) reveals a high density of existing tree canopies in selected residential areas (west) and mangrove forests (east), and a lower percentage of existing UTC for industrial and commercial sites (center region). Figure 9b reveals a high percentage of possible tree canopy on barren land to the east of the commercial area and also for most of the residential parcels to the west.

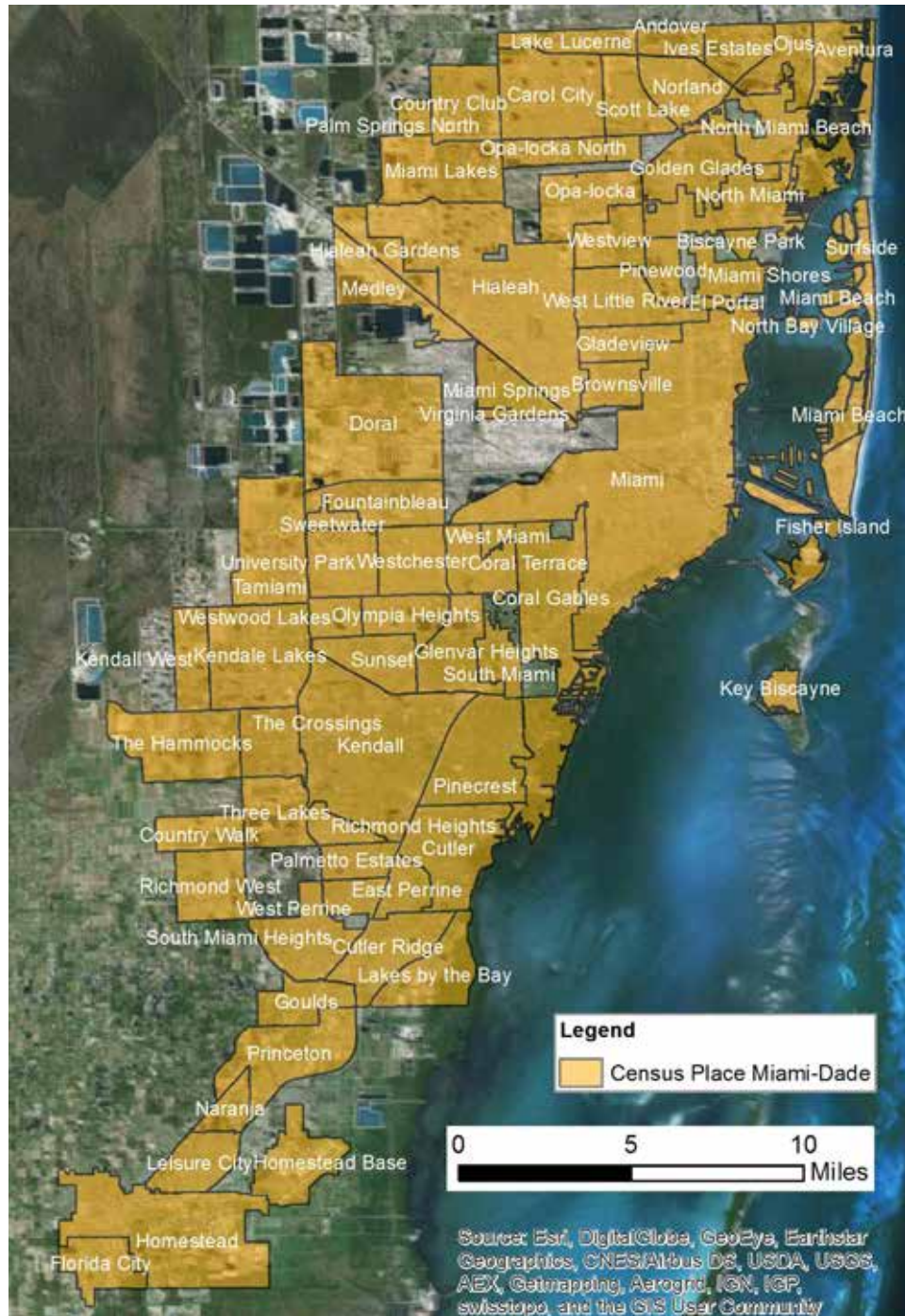
Figure 9. Distribution of existing and possible urban tree canopy in parcels



ANALYSIS OF CENSUS PLACES

Canopy patterns were analyzed for 79 census places falling into the study area. Some census places extend beyond the Urban Development Boundary and were therefore clipped to the Urban Development Boundary for the analysis (Figure 10).

Figure 10. Census places in the Miami-Dade Urban Area



UTC metrics by census place are summarized in Figure 11. The bars in the upper figure (Figure 11a) show percent UTC type by census place, sorted by percent existing UTC from largest to smallest. The red vertical line separates communities that meet the county’s 20% tree canopy goal from those that do not.

The largest percent of existing UTC exists in three communities relatively near the coast south of Miami:

- Lakes by the Bay (48.0%)
- Coral Gables (46.8%)
- Pinecrest (45.9%)

The smallest percent of existing UTC in a census place exists in:

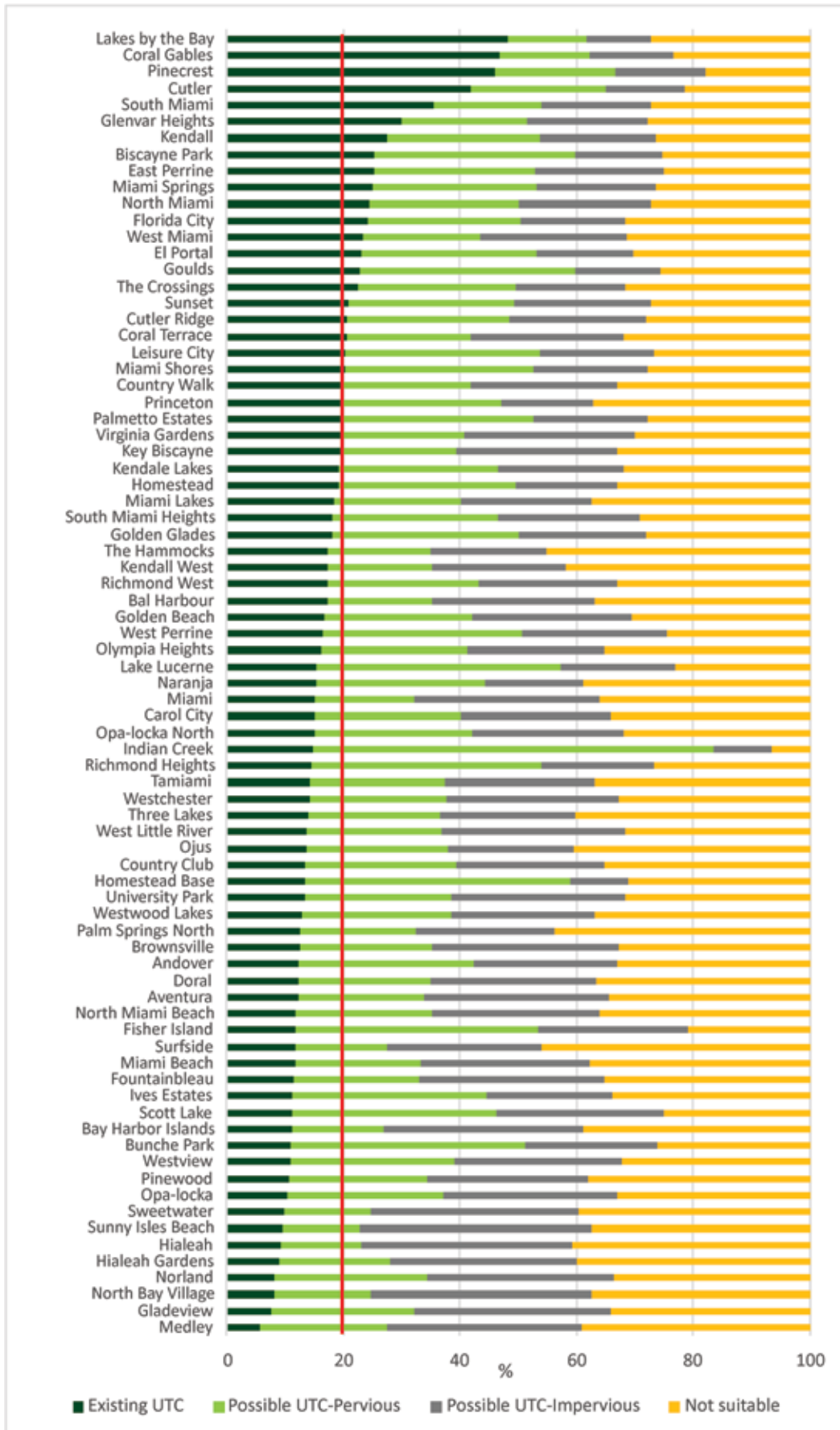
- Medley (5.5%), northwest of Miami
- Gladeview (7.5%), northwest of Miami
- North Bay Village (8.0%), a densely developed island that is less than one square mile in Biscayne Bay

Absolute area values for UTC metrics provide a more accurate picture about the impact of UTC initiatives on a census place area (Figure 11b). Using this measure, the largest coverage of existing UTC among the 79 analyzed census places exists in:

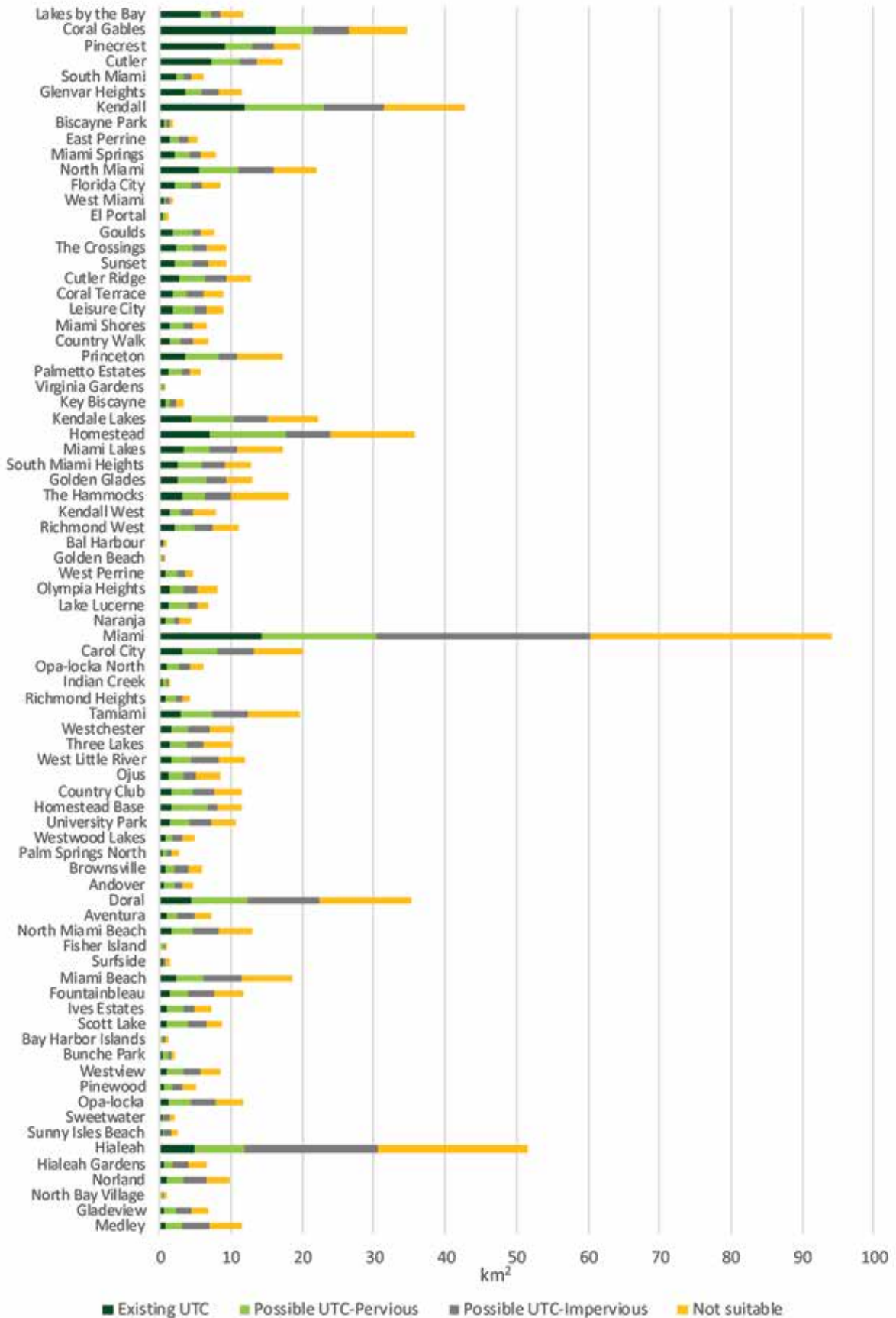
- Coral Gables (16.2 km²/6.3 mi²)
- Miami (14.2 km²/5.5 mi²), as the largest census place
- Kendall (11.7 km²/4.5 mi²), to the southwest of Miami

Figure 11. UTC metrics summarized by census places

11a



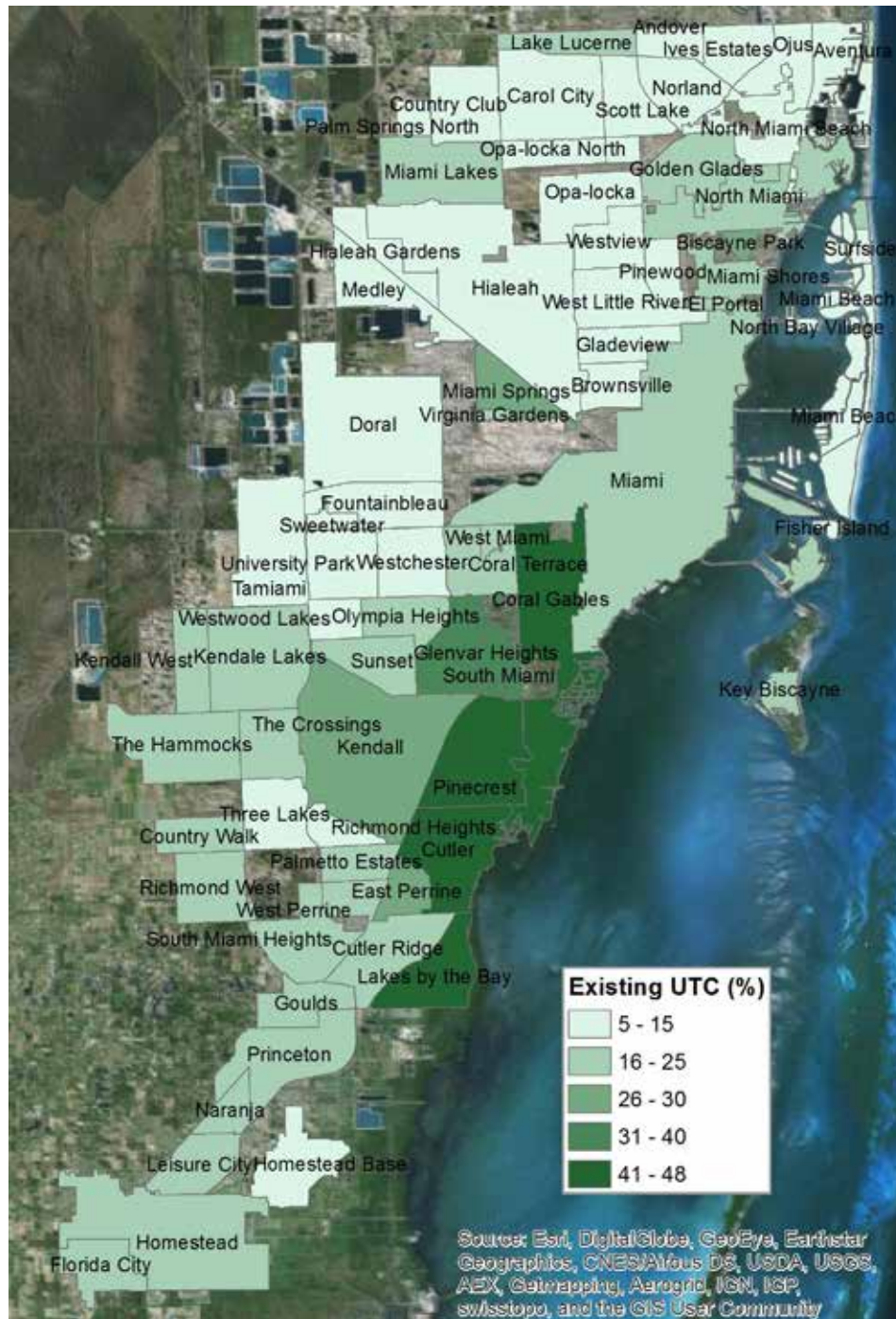
11b



Based on the same data for each census place, Figure 12 maps the percent of existing UTC (a), and of possible UTC on pervious surface (b). Figure 13 maps the percent of possible UTC on impervious surface (a), and of areas non-suitable for UTC (b).

Figure 12. Percent existing UTC (a) and possible UTC with pervious surface (b); summarized by census place

12a



12b

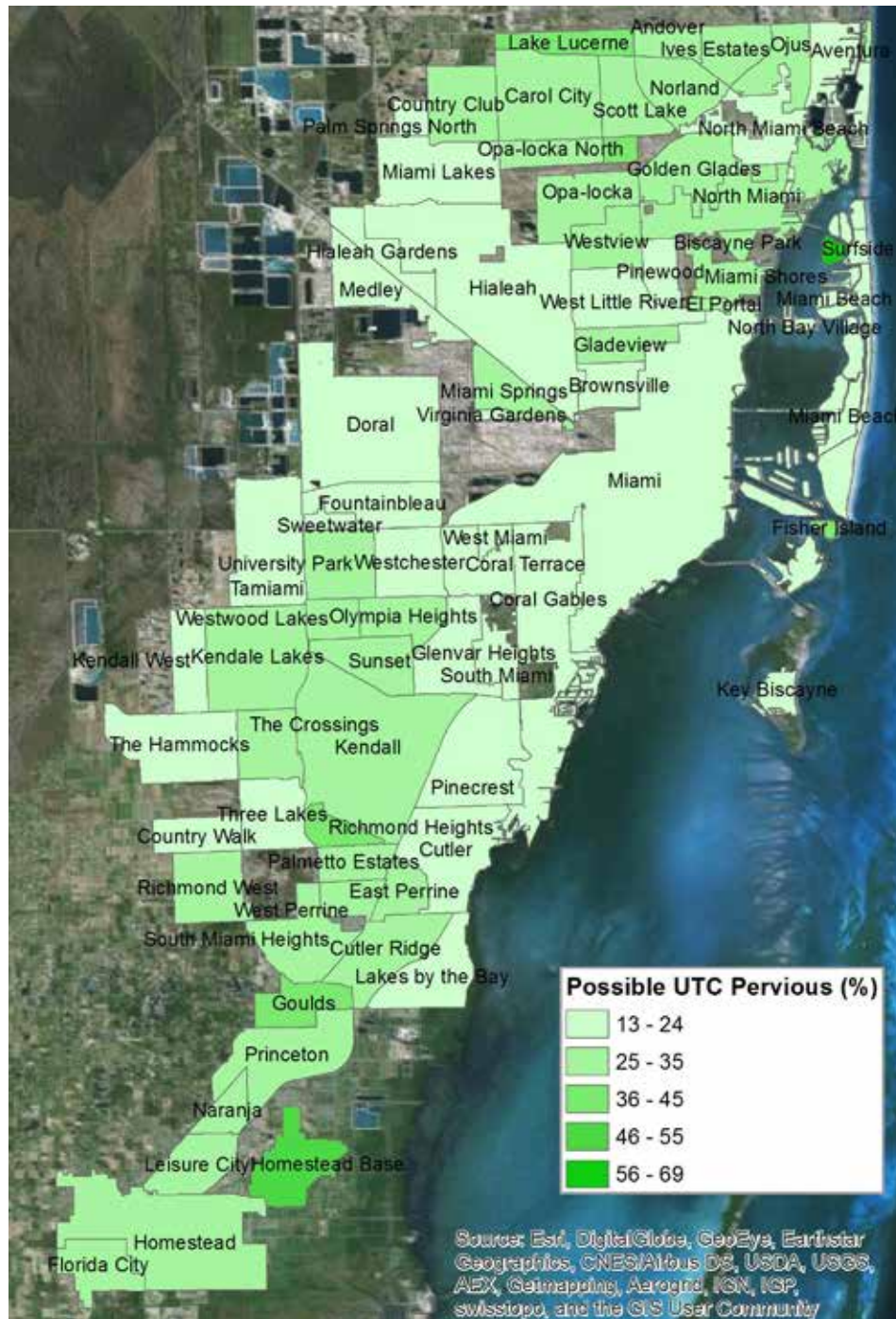
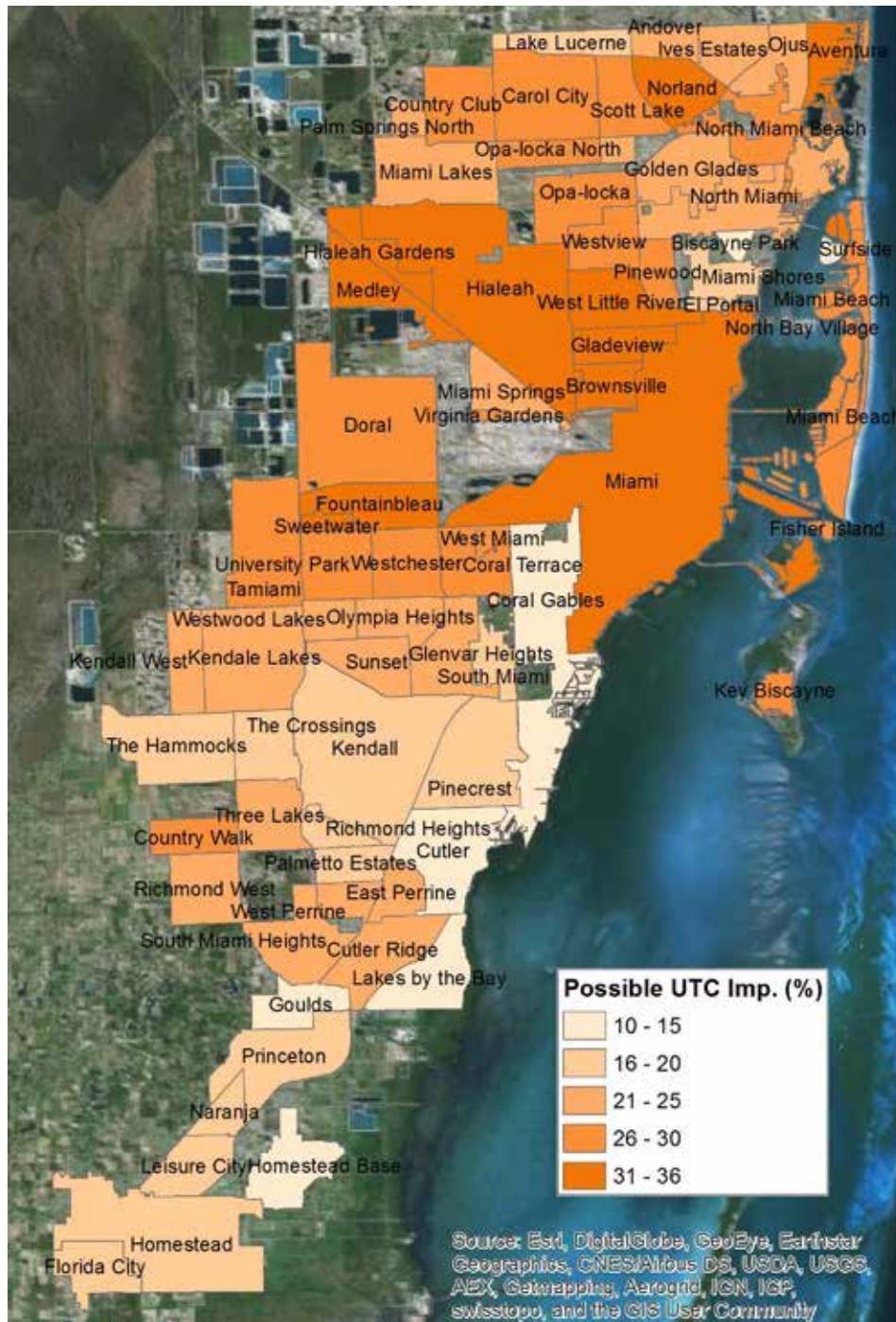


Figure 13. Percent possible UTC on impervious surface (a) and percent not suitable for UTC (b); summarized by census place

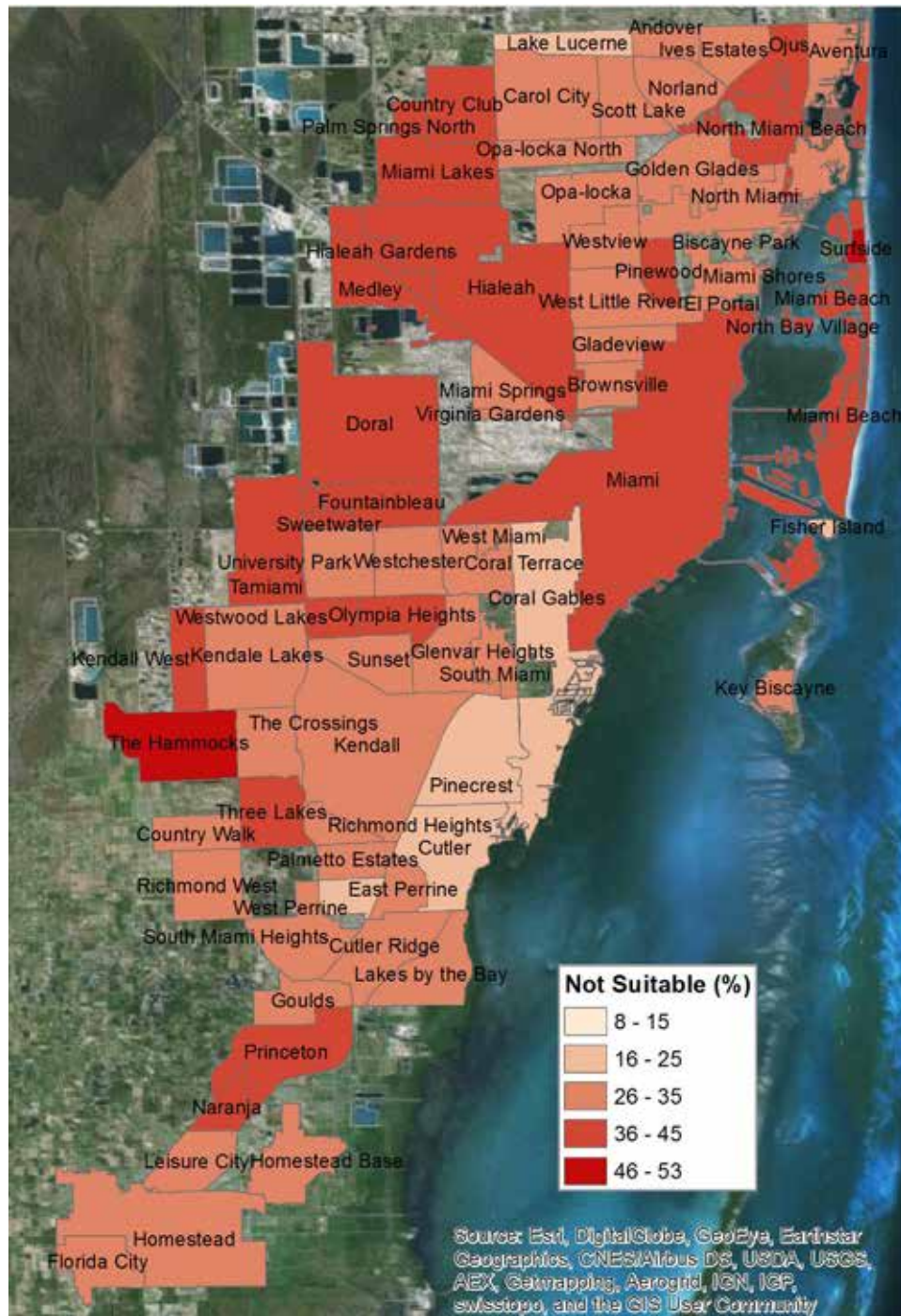
13a



The census places with the largest percent of possible UTC on pervious surface (grass, bare soil) were found in:

- Indian Creek (68.6%), an island near North Beach in Biscayne Bay, due to a large area covered by a golf course (Figure 14).

13b



- Homestead Base (45.4%) in the south of Miami-Dade County. This is largely due to the grass surrounding the runway area.
- Lake Lucerne (41.9%) to the north, where large portions of a landfill are covered with grass.

Figure 14. Indian Creek: The census place with the largest percent of possible UTC on pervious surfaces



Using absolute area values for UTC metrics, the largest possible UTC on pervious surface exists in:

- Miami (16.0 km²/6.2 mi²), toward the central east of the County
- Kendall (11.2 km²/4.3 mi²), further south in the County
- Homestead (10.8 km²/4.2 mi²), near the southern edge of the County

The largest percent of possible UTC on impervious surface (parking lots, concrete structures, but not roads, railroads, or buildings) was found for:

- Sunny Isles Beach (39.7%) along the coast north of Miami
- North Bay Village (36.2%, Figure 15), an island in Biscayne Bay
- Hialeah (36.1%), northwest of Miami

Using absolute area values for UTC metrics, the largest possible UTC on impervious surface exists in:

- Miami (30.0 km²/11.6 mi²)
- Hialeah (18.6 km²/7.2 mi²)
- Doral (10.0 km²/3.9 mi²) toward the western edge of the County

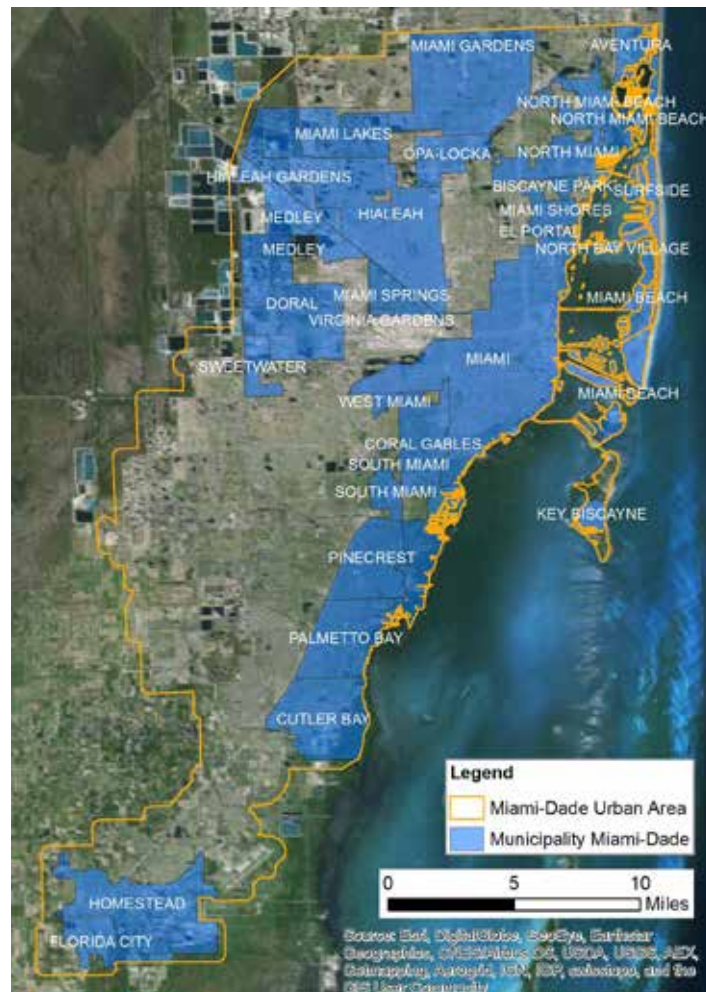
Figure 15. North Bay Village: A census place with a large percent of possible UTC on impervious surfaces



ANALYSIS OF MUNICIPALITIES

Canopy patterns were also analyzed for 34 municipalities falling into the study area (ocean and bay water removed). For the municipality analysis, polygons were clipped to the Urban Development Boundary (Figure 16).

Figure 16. Municipalities in the Miami-Dade Urban Area



UTC metrics by municipality are summarized in Figure 17. The bars in the upper figure (Figure 17a) show percent UTC type by municipality, sorted by percent existing UTC from largest to smallest. The red vertical line separates municipalities that meet the County's 20% tree canopy goal from those that do not.

The municipalities with the largest percent of existing UTC are:

- Coral Gables (46.7%)
- Pinecrest (46.0%)
- Palmetto Bay (38.2%)

The municipalities with the smallest percent of existing UTC are:

- Medley (5.5%)
- North Bay Village (7.7%)
- Sunny Isles Beach (9.6%)

Absolute area values for UTC metrics provide a more accurate picture about the impact of UTC initiatives on a municipality (Figure 17b). Using this measure, the largest coverage of existing UTC is found in:

- Coral Gables (16.3 km²/6.3 mi²)
- Miami (14.3 km²/5.5 mi²)
- Cutler Bay (9.8 km²/3.8 mi²)

Figure 17. UTC metrics summarized by municipality

17a

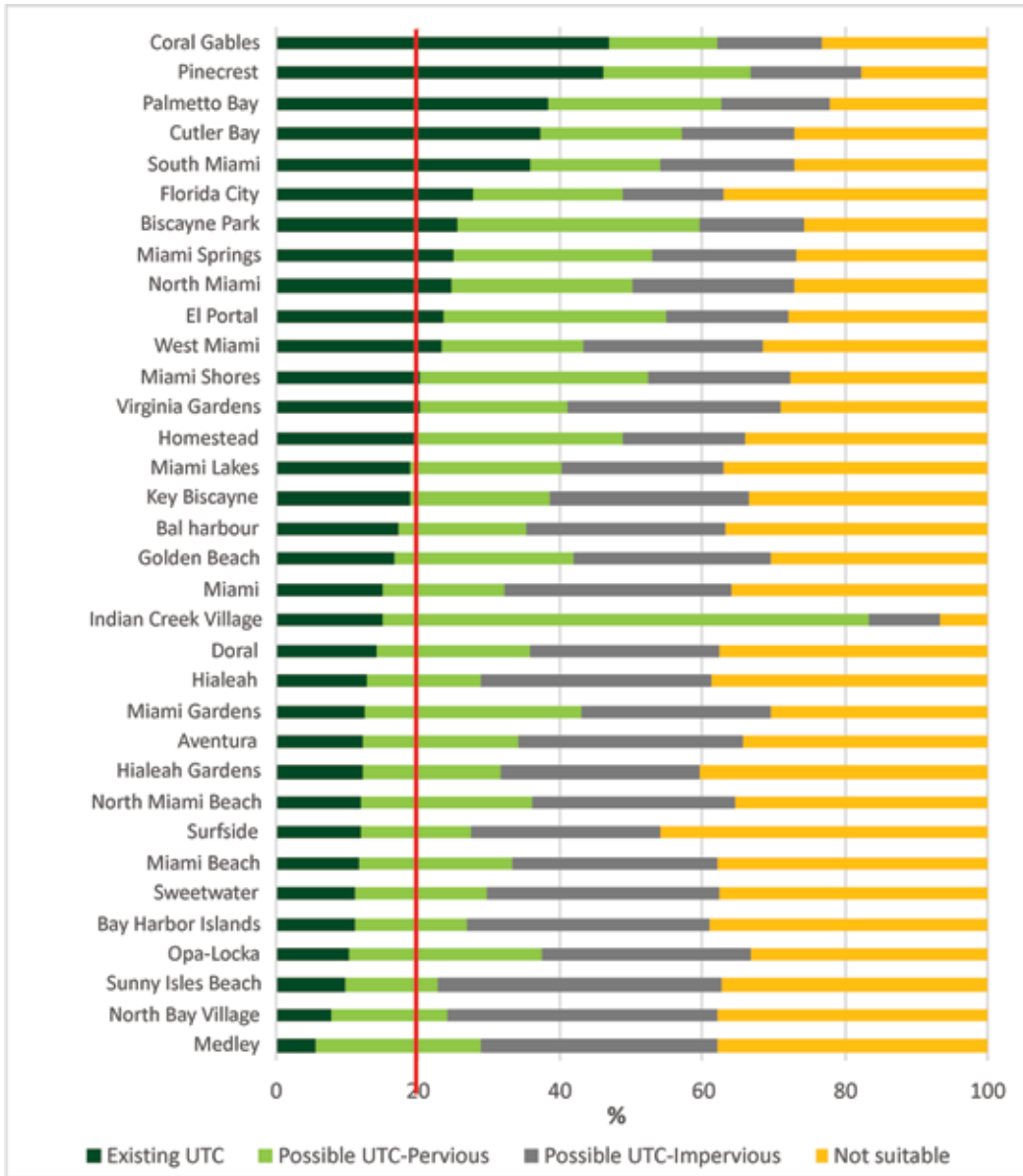
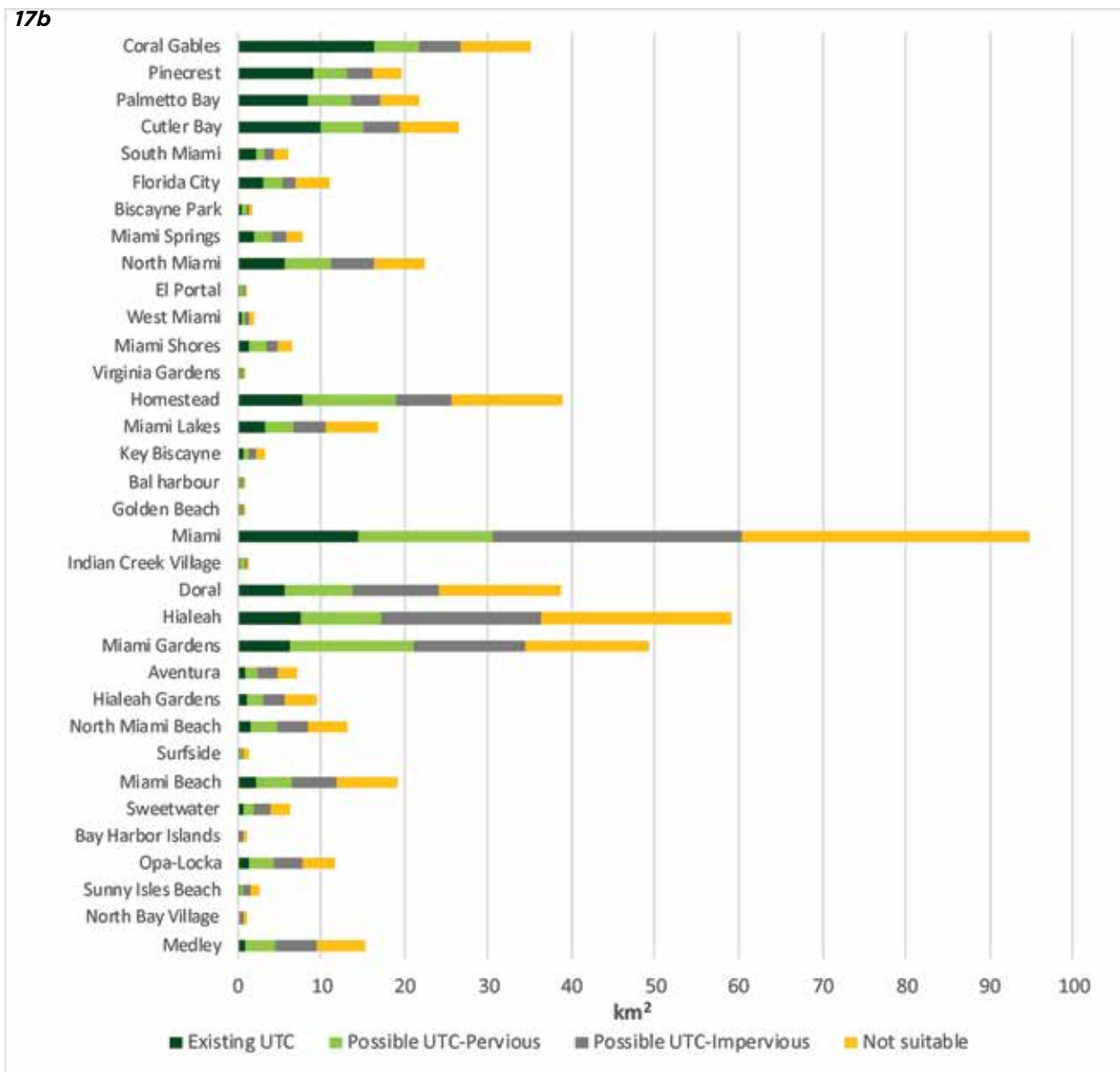


Figure 17. UTC metrics summarized by municipality



The largest percent of possible UTC on pervious surface (grass, bare soil) is found for:

- Indian Creek Village (68.6%)
- Biscayne Park (34.2%)
- Miami Shores (32.3%)

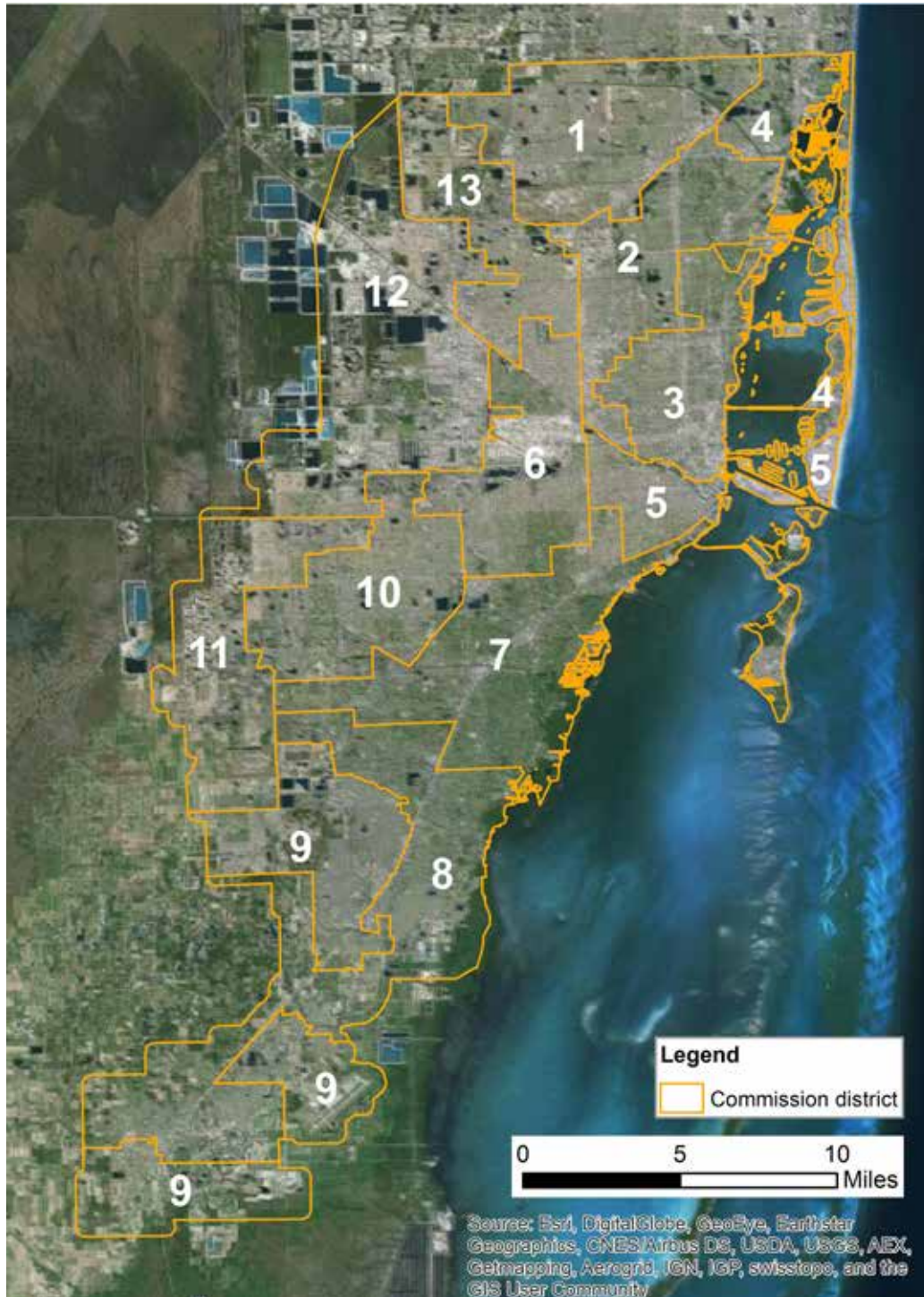
When measuring absolute acreage, the largest area of possible UTC on pervious surface exists in:

- Miami (16.2 km²/6.2 mi²)
- Miami Gardens (14.9 km²/5.8 mi²)
- Homestead (11.2 km²/4.3 mi²)

ANALYSIS OF COMMISSION DISTRICTS

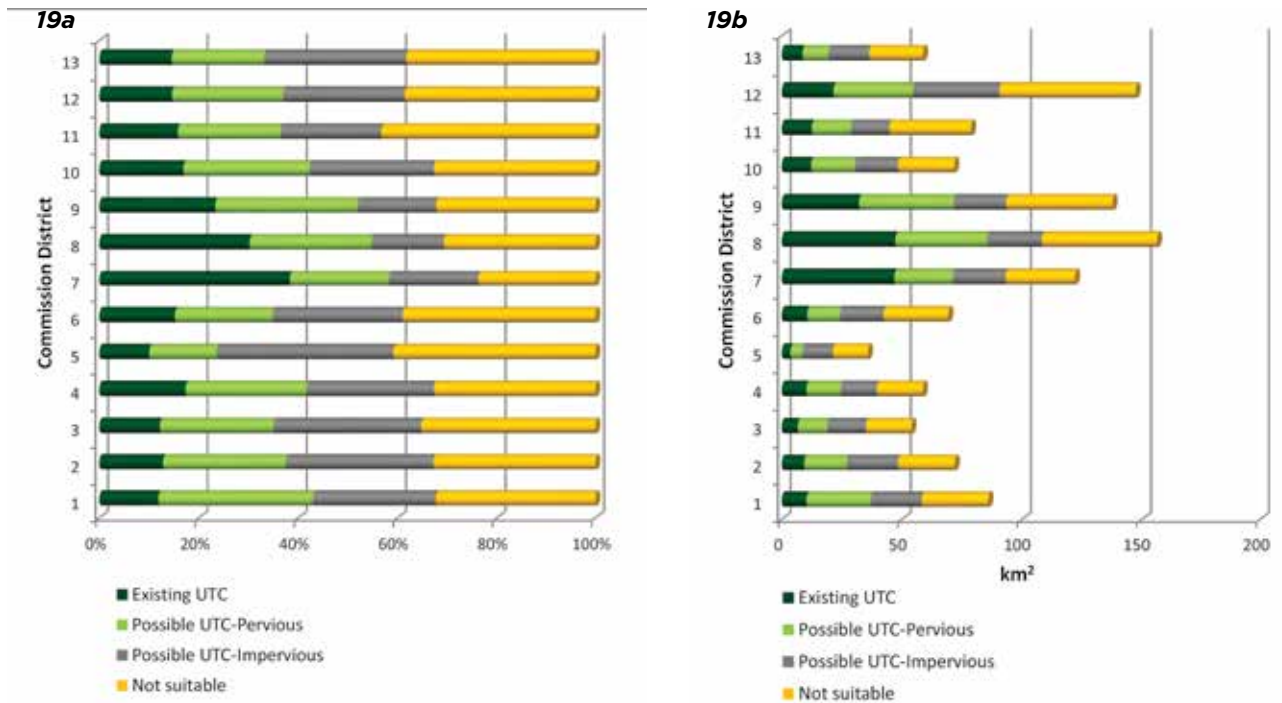
Canopy patterns were analyzed for the Urban Area portions of 13 commission districts in Miami-Dade County (Figure 18).

Figure 18. Commission districts clipped to Miami-Dade Urban Areas



UTC metrics by commission district are summarized in Figure 19. The bars in the left figure (Figure 19a) show percent UTC type by commission district, and the right figure shows the corresponding areas expressed in km² (Figure 19b). Since the analysis covers only areas within the Urban Development Boundary and many commission districts extend beyond the Urban Development Boundary, the areas denoted by bars in Figure 19b do not reflect the total area of some of the commission districts.

Figure 19. UTC metrics summarized by commission district



Based on these numbers, Figure 20 maps for each commission district:

- The percent of existing UTC
- The percent of possible UTC on pervious surface
- The percent of possible UTC on impervious surface
- The percent of areas non-suitable for UTC

Due to canopy frequently found in residential neighborhood yards, as well as mangrove forests along the coastline to the east, the highest percentage of existing UTC is found in:

- District 7 (38.3%)
- District 8 (30.2%)

Smallest percentage of land cover not suitable for tree canopy:

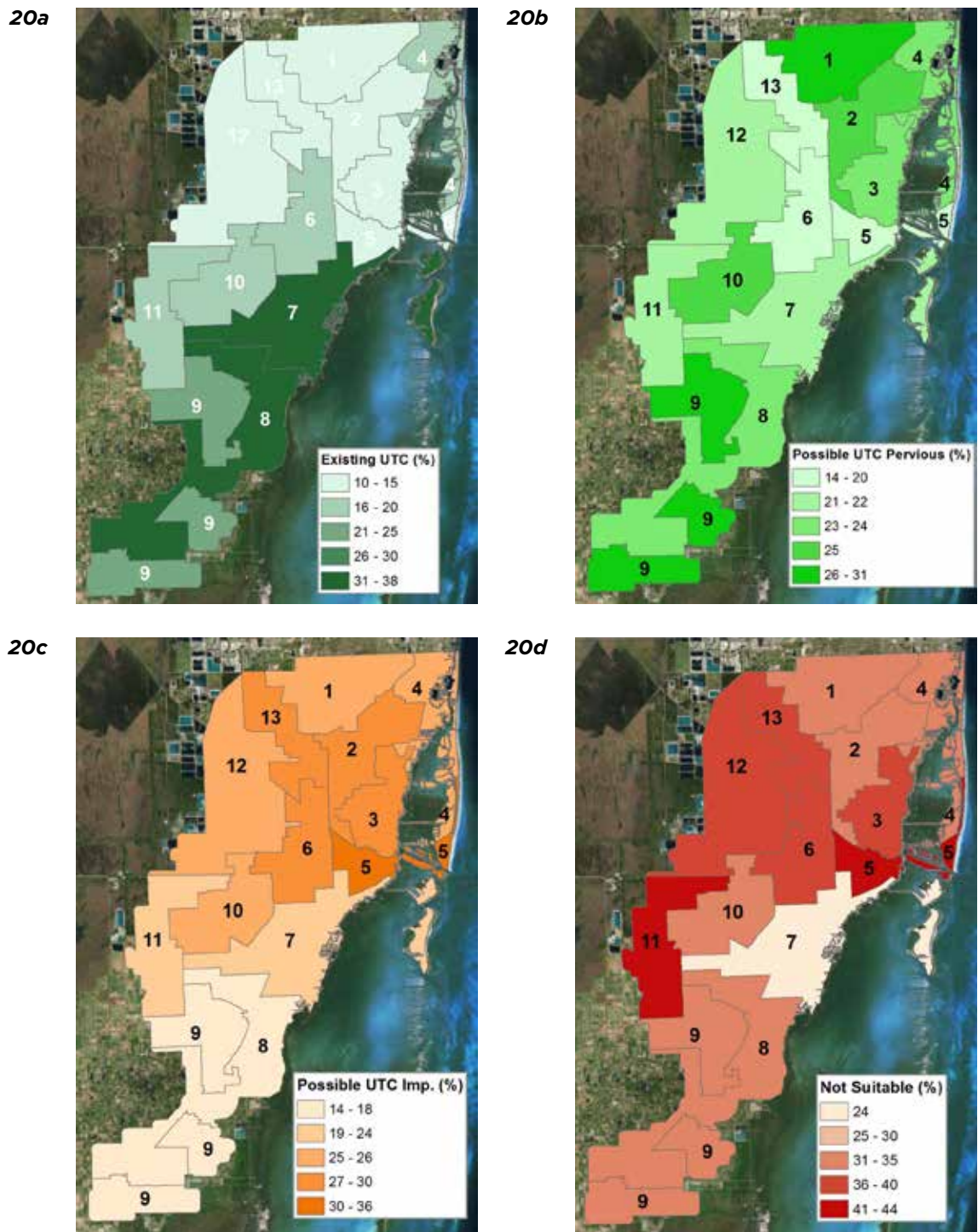
- District 7 (23.7%)
- District 8 (30.7%)

Highest area of existing tree canopy in absolute measures:

- District 7 (46.8 km²)
- District 8 (47.2 km²)

The highest percent of possible tree canopy on pervious surfaces is found in District 1 (31.3%), which is located in the central north of the county and contains Miami Opa Locka Executive Airport, multiple golf courses and large parks.

Figure 20. Maps for UTC metrics summarized by commission district (showing portions falling within the Urban Development Boundary)



ANALYSIS OF SOCIOECONOMIC VARIABLES

Tree canopy increases quality of life in neighborhoods (e.g., by providing shade for outdoor activities, fresh air, and cooling the surface). Therefore, it is of interest for urban planners to know if tree canopy is equally distributed among certain population groups.

In this regard, maps — for 1,525 populated census block groups within the study area — in Figure 21 visualize the:

- a. Percent of existing tree canopy
- b. Median annual household income in US \$

Figure 22 visualizes, per Census Block Group, the:

- a. Percent African American population
- b. Percent Hispanic population

Figure 21. Percent Urban Tree Canopy (a) and Median annual household income (b) at the Census Block Group level

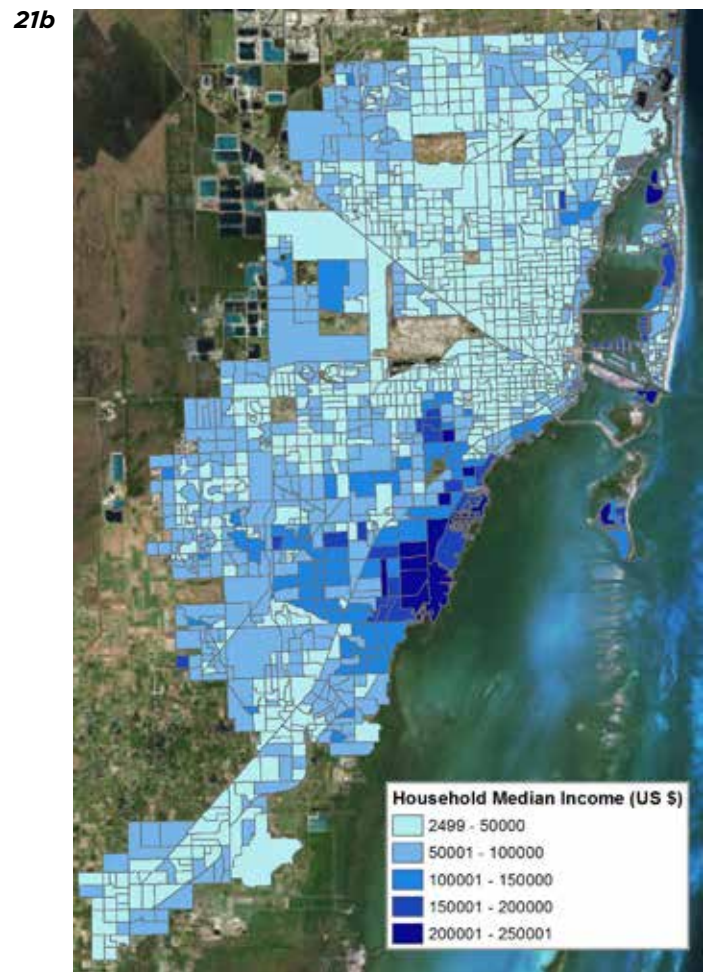
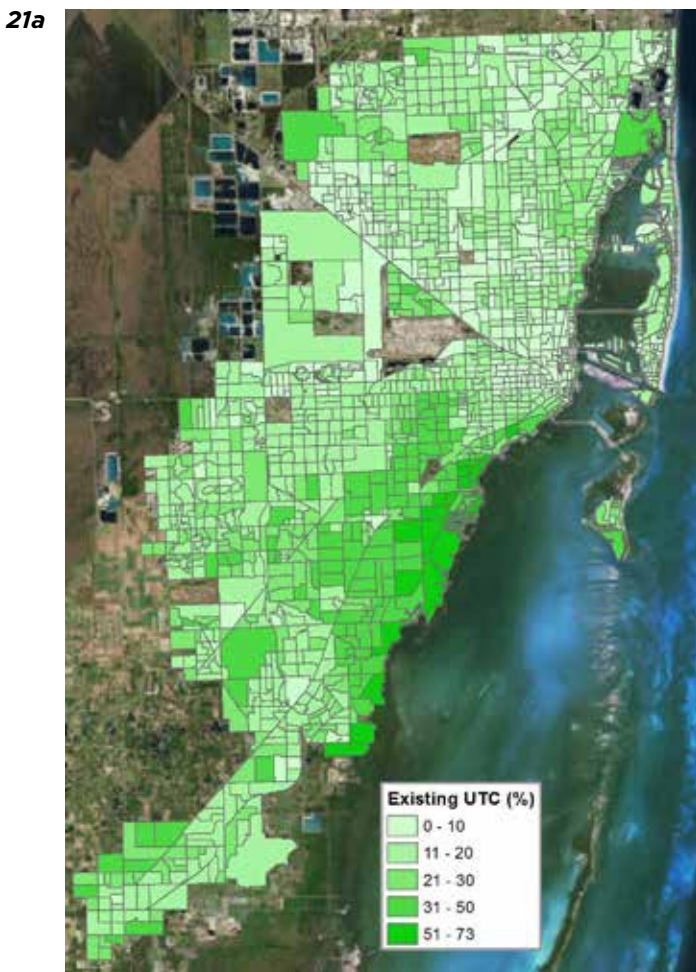
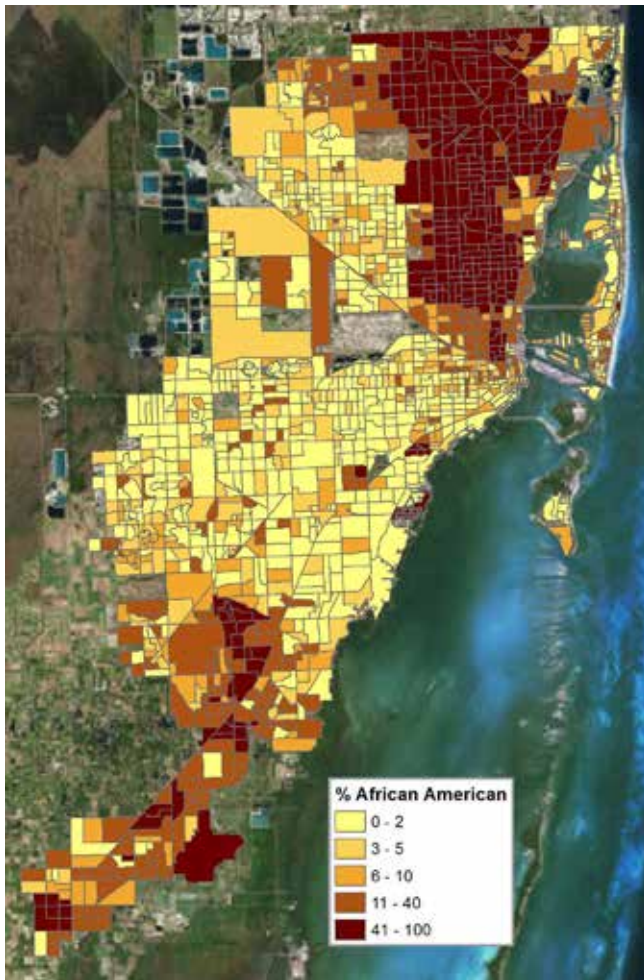
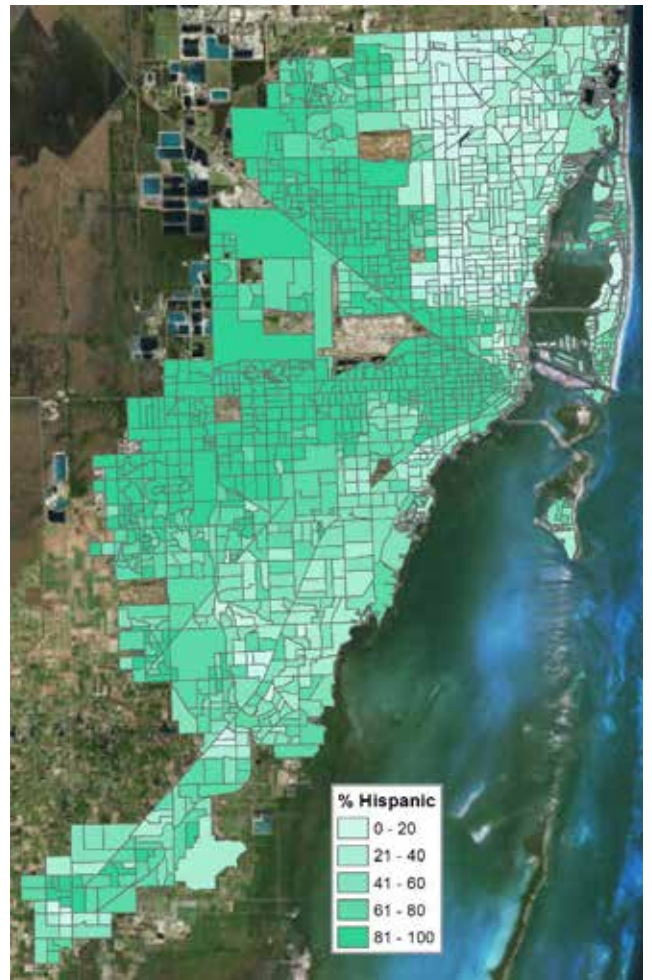


Figure 22. Percent African American (a) and percent Hispanic (b) at the Census Block Group level

22a

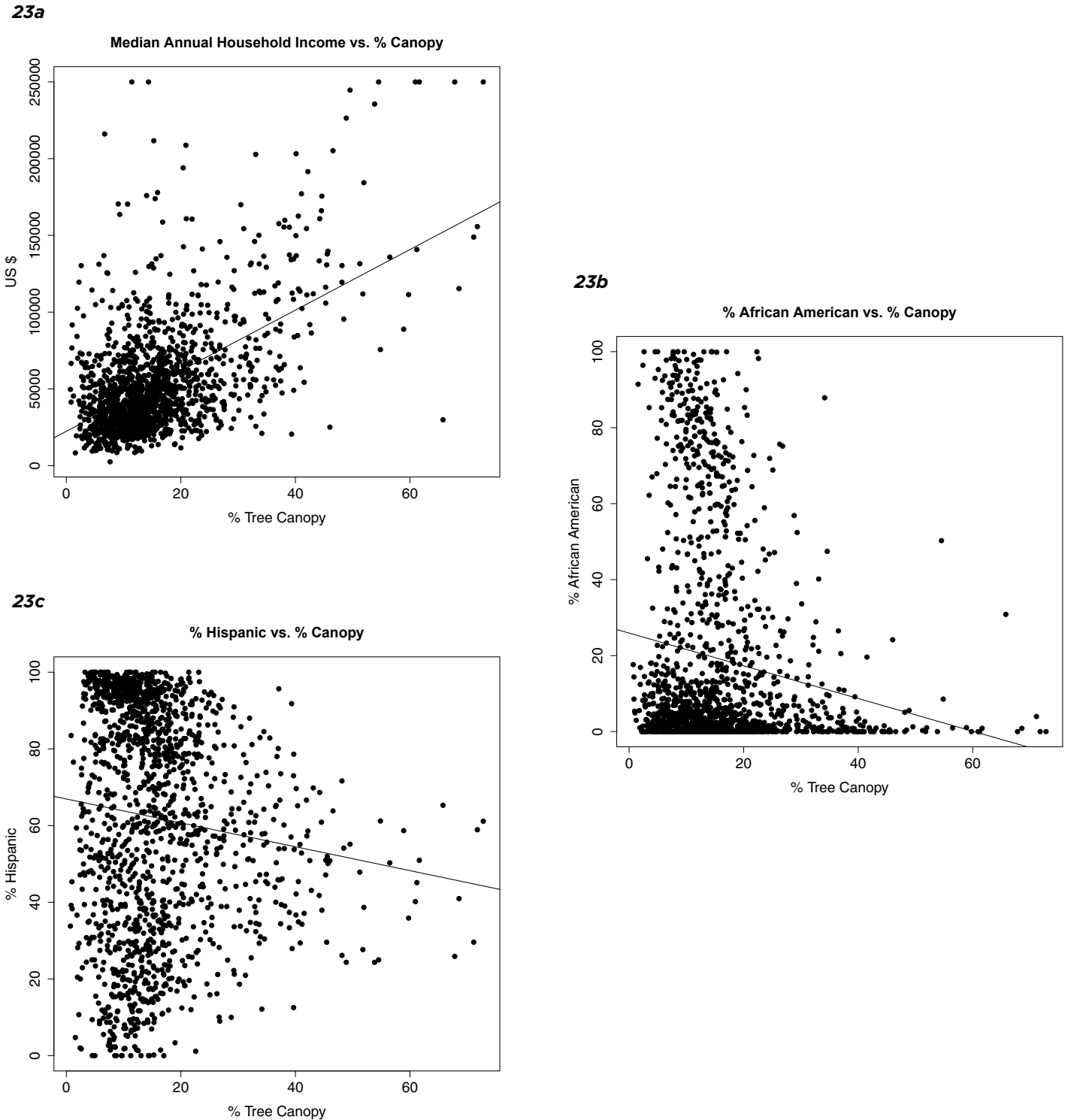


22b



A scatter plot for all three demographic variables compared to % UTC is provided in Figure 23 with a linear regression line.

Figure 23. Percent UTC vs. Median Annual Household Income (a), percent African American (b), and percent Hispanic (c) at the Census Block Group level



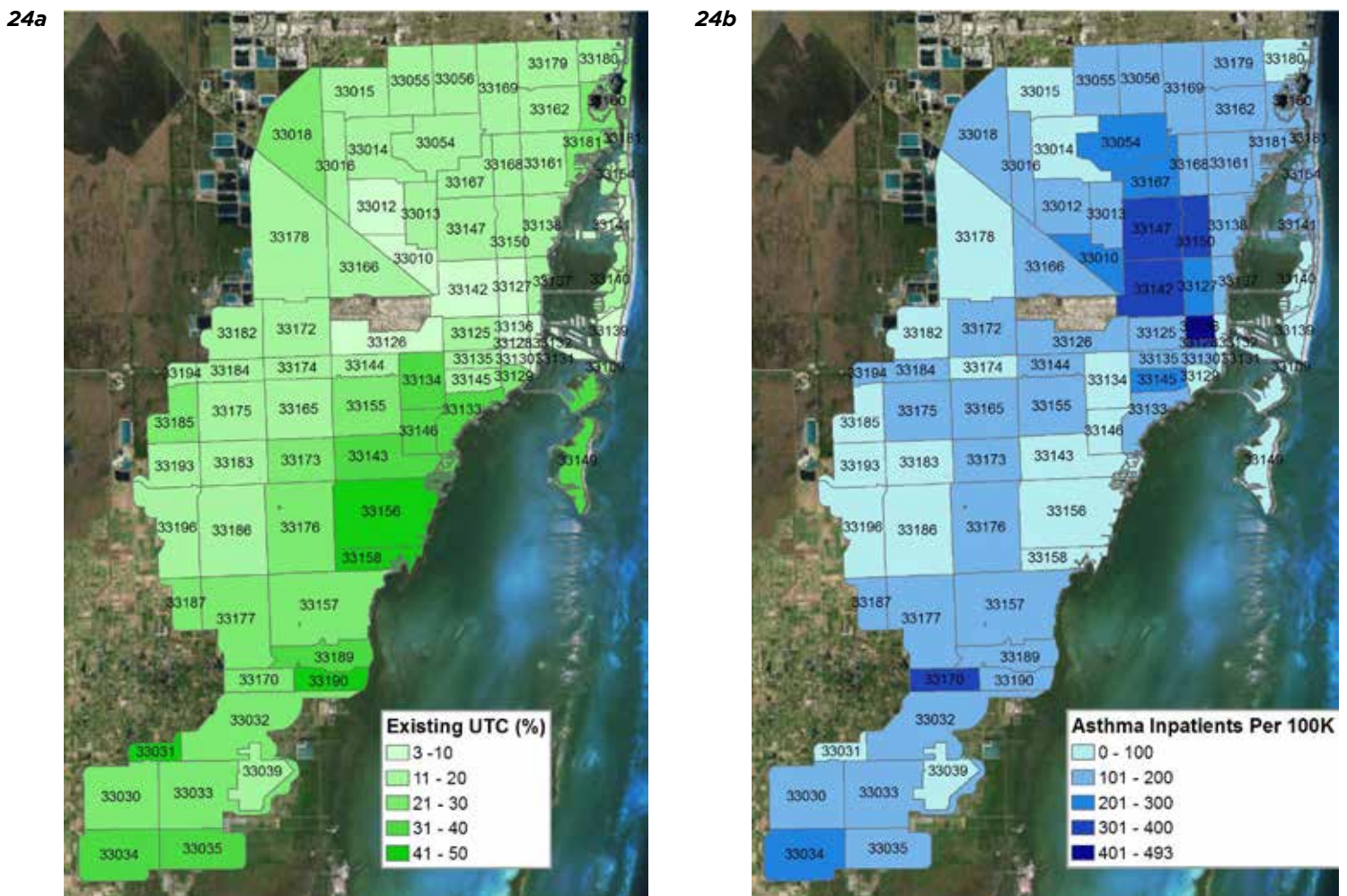
It must be noted that correlation does not imply any direct causal relationship between demographic variables and canopy density (e.g., that the Hispanic population avoids areas with high canopy density). However, it is possible that property in high-income areas has more available land area for planting trees. In turn, these owners may have more financial means to plant trees than homeowners in poorer neighborhoods.

ANALYSIS OF HEALTH DATA

This section assesses the relationship between asthma related hospitalization rates and the density of existing urban tree canopy. Figure 24 shows for the zip code areas:

- a. Percent of existing tree canopy
- b. Asthma inpatient rate per 100,000 residents

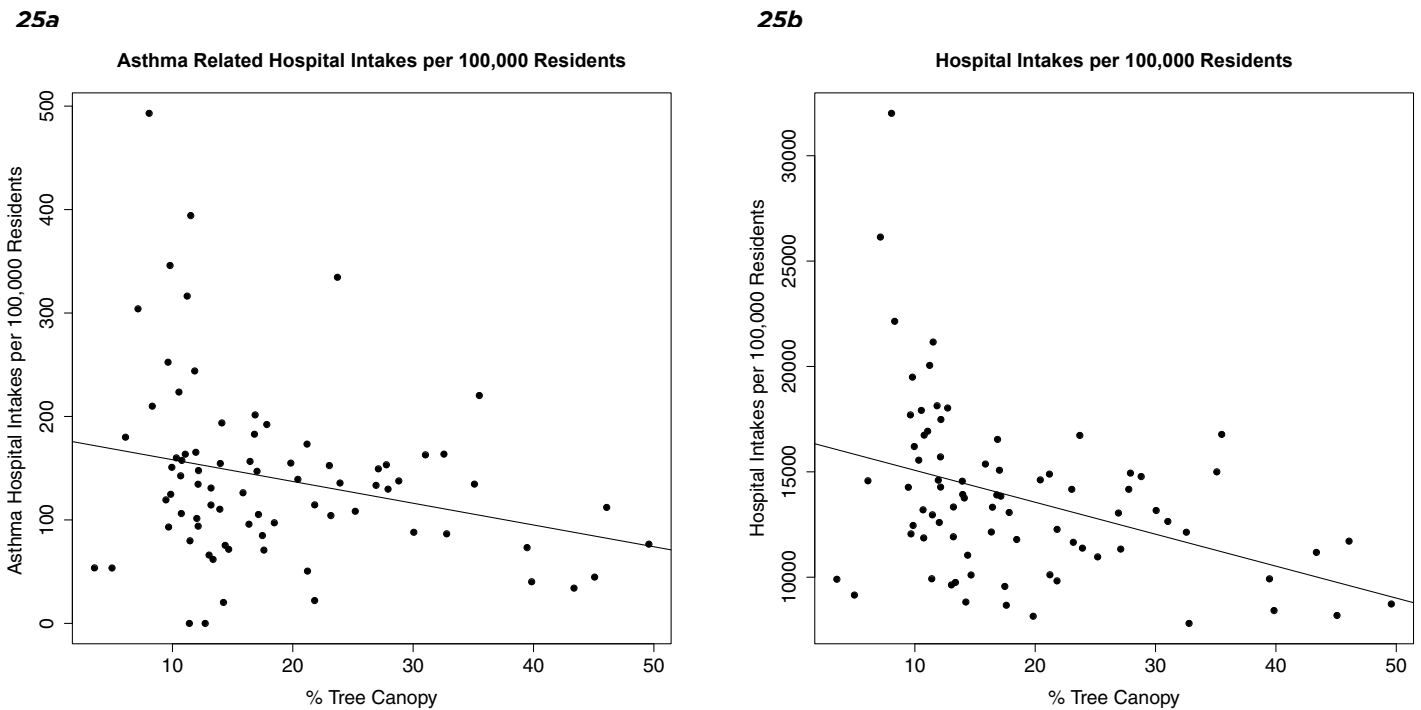
Figure 24. Percent Urban Tree Canopy (a) and Asthma inpatient rate per 100,000 residents (b) at the zip code level



Correlation analysis showed that areas with a higher percent UTC have smaller asthma related hospital rates per resident and also smaller overall hospital rates per resident. This could possibly be due to better health care, a healthier lifestyle, or better disease prevention mechanisms in higher income zip codes, which also tend to have higher tree canopy.

The scatter plot for these two examined health related variables vs. percent UTC is provided in Figure 25 with a linear regression line. Figures 25a and 25b visualize the lower hospital intake rates for areas with higher percent UTC for asthma related hospitalization events and all hospitalization events.

Figure 25. Asthma (a) and overall (b) inpatient rate per 100,000 residents



SUMMARY AND CONCLUSIONS

- For a project area located in the Urban Development Boundary of Miami-Dade County that excluded coastal water, ocean waters, and bay waters, a combination of remote sensing 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, other impervious surfaces, and cropland.
- Overall tree canopy is 19.9%.
- A large portion of the project area offers the potential for additional urban tree canopy. These areas consist of pervious surfaces (grass, bare ground) and impervious surfaces (asphalt), with a slightly higher share falling into the pervious surface category.
- Residential housing (single family, duplex, multiple family and townhouses) represent 42% of the existing tree canopy and 33% of possible tree canopy on pervious surfaces in the study area.
- Tree canopy and water bodies are associated with lower surface temperatures. Therefore, 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.
- Census place and commission district analysis utilizing metrics of existing and possible UTC can be used to help target tree canopy improvement and preservation activities.
- Tree canopy is positively correlated with median income, but negatively correlated with percentage of African American and Hispanic residents. Therefore, strategically planting trees in minority and lower income communities can support environmental equity.
- Higher tree canopy percentage is associated with lower overall hospitalization numbers and also with lower hospitalization numbers related to asthma. Since tree canopy is positively correlated with income, this association can at least be partially attributed to higher income and the healthier lifestyle associated with higher income.

METHODOLOGY NOTES

Overall Assessment Method

The study uses multi-spectral (eight band spectral resolution, 2m spatial resolution) satellite imagery together with selected vector feature layers for analysis and classification of land cover data. Based on the generated land cover classification map, a Geographic Information System (GIS) was used to estimate the existing and possible UTC for predefined areal units (municipalities, census places, census block groups, property parcels, zip codes) and by land use type.

The aggregated estimates are available as GIS polygon feature layers in an ESRI geodatabase that can be subsequently integrated with other GIS or mapping applications. Percent of existing UTC was related to socioeconomic and health variables at various spatial aggregation levels, and satellite imagery (Landsat ETM) was used to generate a surface heat map and to relate surface temperatures to the mix of land cover categories.

The land cover analysis was completed using remotely sensed imagery. 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.

Land Cover Classification Method

A land cover classification map was generated using a WorldView-2 (eight band spectral resolution, 2m spatial resolution) data acquired between 2011 and 2014 for different parts of the study area. Atmospherically corrected multi-spectral reflectance values were used in the classification of nine land cover classes.

The initial land-cover detection was based on a random forest classification algorithm (Liaw & Wiener, 2002; Svetnik et al., 2003) in the caret R-package (Kuhn & Team, 2014), which used the WorldView 2 spectral information. Next, various vector data layers, provided by Miami-Dade County, were updated and 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 5m radius)
- Edge of pavement (polylines converted to polygons)
- Railroads (polylines buffered with a 3m distance)
- Water bodies (polygons)
- Agricultural areas (polygons)

In order to remove spurious pixels, the final map was smoothed with a 4-edge kernel using a nearest neighbor replacement method with varying minimum mapping units (MMU) for the different classes (Table 3).

Table 3. 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
Cropland	50	200

Class-specific map accuracies ranged from 88.1 ± 4.2% for tree canopy to 100% for the street and railroad class (Table 1). Buildings were mapped with an adjusted accuracy of 93.2 ± 3.3%, grass at 88.2 ± 4.2%, bare ground at 89.4 ± 4.0%, and impervious at 84.8 ± 4.7% (Table 2). In Table 4, grass was predominantly misclassified as trees and shrub and vice versa at 8.5%, bare ground as impervious (5.1%), and impervious as buildings (8.5%).

A design-based accuracy assessment of land cover class stratified random samples (N = 531; multinomial distribution sampling based on a 95% confidence) estimated the bias adjusted overall accuracy of the map to be 90.1%, with a standard error of 1.7% which means that the 95% upper and lower confidence of the true accuracy is estimated to be between 86.7% and 93.5%.

Table 4. Confusion matrix. Values are percent of samples classified (rows) and referenced (columns)

	Reference								
	Bare Ground	Building	Cropland	Grass	Impervious	Street/Railroad	Tree Canopy	Water	Wetland
Bare Ground	89.83	1.69	0.00	3.39	5.08	0.00	0.00	0.00	0.00
Building	0.00	93.22	0.00	5.08	0.00	0.00	1.69	0.00	0.00
Cropland	0.00	0.00	96.61	0.00	3.39	0.00	0.00	0.00	0.00
Grass	0.00	1.69	0.00	88.14	0.00	0.00	8.47	0.00	1.69
Impervious	0.00	8.47	0.00	3.39	84.75	1.69	0.00	1.69	0.00
Street/Railroad	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00
Tree Canopy	0.00	0.00	0.00	8.47	3.39	0.00	88.14	0.00	0.00
Water	0.00	0.00	0.00	0.00	1.69	0.00	1.69	96.61	0.00
Wetland	0.00	0.00	0.00	3.39	1.69	0.00	0.00	0.00	94.92

Land Cover and Surface Area Method

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.

To assess the statistical association (Pearson’s *r*) between surface temperature and land-cover class, the proportion of land-cover class for each considered 30m x 30m temperature cell was computed, using a sample of 14,796 temperature cells (Table 5). To avoid temperature outliers, only temperature values which were observed in at least 1 km²/0.39 mi² of the study area were considered. Results show that an increased proportion of impervious surface, buildings, and roads is associated with an increased surface temperature, reflected by correlations larger than 0.34. A weak positive correlation can also be observed between percentage of grass and surface temperature, which is unexpected, and this relationship may be a spurious effect of many grass areas next to buildings. Tree canopy shows the strongest negative correlation with surface temperature, e.g. the highest cooling effect, followed by water, wetland, and crop. Bare ground did not significantly affect surface temperature.

Table 5. Bivariate correlations between percent land cover and surface temperature (Degree Fahrenheit)

	% Impervious	% Street/ Railroad	% Bare Ground	% Building	% Grass	% Tree	%Wetland	% Water	% Cropland
<i>r</i>	0.410	0.346	-0.018	0.359	0.169	-0.432	-0.151	-0.171	-0.116
<i>p</i>	0.000	0.000	0.402	0.000	0.000	0.000	0.000	0.000	0.000

Bold indicates correlation significant at $p < 0.001$

Analysis of Land Use Patterns Method

Percentage values for this analysis are derived from biased estimates, which are based on pixel counts from the land cover classification procedure, and no corrections from the classification accuracy assessment are applied.

Analysis of Socioeconomic Variables Method

A bivariate correlation (Pearson *r*) was determined between percent existing UTC and Median Annual Household Income, percent African American population, and percent Hispanic population at the Census Block Group level (Table 6). A moderate significant positive correlation was found between Median Annual Household Income and percent UTC ($r=0.547$, $p=0.000$). A weak significant negative correlation was found between percent UTC and percent African American population ($r=-0.151$, $p=0.000$), and between percent UTC and percent Hispanic population ($r=-0.107$, $p=0.000$).

Table 6. Bivariate correlations between percent land cover and socio-economic variables

	Median Annual Household Income	% African American	% Hispanic
r	0.547	-0.151	-0.107
p	0.000	0.000	0.000

Bold indicates correlation significant at $p < 0.001$

Socio-economic data were obtained from the America Community Survey (ACS) 2010-2014 5-year estimate.

Analysis of Health Data Method

Health data was obtained from the Agency for Health Care Administration (AHCA). The data file contains hospital inpatient records for 2014, including the patient's residential zip code and Principal Diagnosis (ICD-9-CM) Code. Data was analyzed for 78 populated zip codes falling into the study area. The variable analyzed is the number of asthma inpatient cases (X.493 ICD-9-CM code range) in a zip code per 100,000 residents in that zip code.

A Pearson's r correlation between percent UTC and asthma related intakes per 100,000 zip code residents was weakly negative and significant ($r = -0.253$, $p = 0.025$). This is in-line with the second correlation analysis, which shows that all hospital intakes per 100,000 zip residents were also negatively and significantly associated with areas of higher percent UTC (Table 7).

Table 7. Bivariate correlations between percent urban tree canopy and hospitalization rates for zip codes

	Asthma-related intakes per 100K residents	All hospital intakes per 100K residents
r	-0.253*	-0.387**
p	0.025	0.000

* indicates correlation significant at $p < 0.05$

** indicates correlation significant at $p < 0.001$

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