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Change Analysis of Urban Tree Canopy in Miami-Dade County

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Abstract: This study mapped and analyzed urban tree canopy change between 2014 and 2019 within the Urban Development Boundary of Miami-Dade County, Florida. The goal was to identify local areas of tree canopy gain or loss over this 5-year period. The comparison is based on land cover maps delineated from WorldView-2 satellite data applying a random forest classification algorithm, in combination with publicly available vector data of infrastructure (roads, railroads) and land use maps (water, cropland). Existing urban tree canopy (EUTC) was computed for census block groups and municipalities to compare tree canopy cover loss or gain to support strategic planning of equitable urban reforestation. For the entire study area, the percentage of EUTC did not change significantly between 2014 (19.9 ± 1.2%) and 2019 (20.1 ± 1.5%). However, some municipalities experienced changes in EUTC by over 10%. Comparison of Landsat-8 Thermal Infrared satellite imagery between both periods identified land cover change patterns that were associated with an increase or decrease in surface temperature. A significantly negative relationship between percentage of African American population and tree canopy in 2014 turned statistically insignificant in 2019, whereas the negative relationship with percentage of Hispanic population further strengthened in 2019 compared to 2014.

Keywords: land cover; remote sensing; surface temperature; change detection

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1. Introduction

Urban land use accounts for about 4% of the total terrestrial land area on Earth; increasingly, these urban areas are expanding into surrounding forested and agricultural areas [1]. As these urban areas expand, it is important that development is undertaken in a sustainable manner. The United Nations introduced Sustainable Development Goals (SDGs) to provide an evidence-based framework for planning development on a global scale from 2015 through 2030 [2]. SDGs cover a broad spectrum of sustainability measures related to the economy, the environment, and society at large. With forested land and agricultural areas near urban areas increasingly being developed or under threat of development, it is critical that forests and treed areas within new and existing urban areas are supported, given the many positive ecosystem services that they provide [3]. These benefits of tree canopy in urban surroundings include improvements in neighborhood residents' health [4], the local economy [5], and neighborhood aesthetics [6] and in mitigating heat island effects [7]. Furthermore, the maintenance and improvement of tree canopy within urban areas satisfy SDG 11, "Make cities and human settlements inclusive, safe, resilient, and sustainable", (https://sdgs.un.org/goals/goal11) (accessed on 15 June 2022), in particular outcome target 11.7, "Provide universal access to safe, inclusive and accessible, green and public spaces", and SDG 13, "Take urgent action to combat climate change and its impacts", (https://sdgs.un.org/goals/goal13) (accessed on 15 June 2022) () through delivery of ecosystem services supporting human well-being, biodiversity, and carbon sequestration for climate change mitigation [8]. Urban forests can also contribute to SDG 10, "Reduce inequality within and among countries", (https://sdgs.un.org/goals/goal10) (accessed on 15 June 2022)) by providing shared spaces that facilitate mixing of community across ages, religions, cultures, and incomes [9]. The economic annual benefits of forests within nine megacities, including Beijing, Buenos Aires, and Los Angeles, were estimated to be nearly $1 billion due to reductions in air pollution, stormwater, building energy, and carbon emissions [10]. With increasing populations in urban areas, urban densification is a sustainable urban planning methodology implemented to counteract urban sprawl. However, densification can pose a threat to urban green space [11] as infill development without providing more public green space can lead to decreases in living quality in a neighborhood [12].

The term "urban forest" describes the woody vegetation on private and public land and other land uses within municipality boundaries, and includes street trees, forest fragments, urban parks, and trees on residential property [13] as well as other green spaces with trees, such as riparian corridors, rooftops, and nurseries [3]. A closely related concept is "urban tree canopy", which is the leafy, green overhead cover from trees that comes with benefits such as beauty, shade, wildlife habitat, energy conservation, stormwater mitigation, and public health [14]. Given the previously stated importance of urban forests, many urban municipalities are interested in monitoring, maintaining, and expanding the tree canopy area within their boundaries. Thus, numerous regions around the U.S. established tree planting initiatives, such as Million Trees NYC [15] or Million Trees LA [16]. Funding agencies are interested in the assessment of canopy growth as an outcome of such initiatives. For instance, a canopy cover initiative for coastal Los Angeles between 2014 and 2019 [17] revealed that although overall tree coverage did not change overall, localized changes could be observed at the parcel level. Furthermore, higher-income communities tended to have less canopy loss over time than others [18]. Another study found that despite high planting and growth rates through urban greening efforts in selected U.S. cities, urban tree canopy decreased over time [19], partially due to low life expectancy of street trees and high mortality rates of seedlings [20]. This is problematic given that street trees need to survive for several decades to attain carbon neutrality, based on carbon costs associated with nursery production, tree maintenance, and disposal [21]. A study that applied object-based image analysis (OBIA) on 0.5-m resolution lidar data and 1-m 3-band (RGB) aerial imagery for Oklahoma City between 2006 and 2013 identified a 2% loss of its urban tree canopy extent, which could be primarily attributed to population growth and urban development in the southern portion of the study area [22]. Land cover and land use maps produced from 30-m resolution Landsat-5 Thematic Mapper (TM) imagery showed tree loss between 2008 and 2010 in Worcester County, Massachusetts [23]. Approximately 2% of tree canopy was lost due to various causes, including expansion of low-density residential land use, tree removal for Asian long-horned beetle eradication, timber harvest, and ice storm damage. Meanwhile, renovation and redevelopment of single-family homes was estimated to cause a 1.2 percentage point annual decrease in tree/shrub cover in the 20 largest cities in the Los Angeles Basin due to emerging preferences for larger homes [24].

Some studies focus on the effect of extreme events, such as hurricanes, on urban forests. One study, for example, which relied on responses and measurements by homeowners, found urban forest loss between 13% for Hurricane Georges (1998) in Puerto Rico and 16% for Hurricane Charley (2004) in Florida, where palms survived significantly better than all other trees [25]. Another study found that peak gust speeds recorded during past hurricane events were negatively associated with canopy coverage across the 300 most populated municipalities in Florida [26].

Historical tree canopy/shrub coverage in Miami was 23.3% and 21.6% in 2003 and 2009, respectively [19], resulting in a drop of tree cover by 1.7%. This decrease closely matched a 1.1% average decline in absolute tree cover in 18 American urban cities between these years. Miami was also found to be lagging the 28.8% average urban tree canopy cover in 2009 of these 18 cities. A county organization called Neat Streets Miami set an ambitious goal for the Million Trees Miami initiative in the mid-2010s, namely to reach a 30% tree canopy coverage across Miami-Dade County [27]. Neat Streets Miami partnered with the Society of American Forests to conduct both a baseline study in 2014 [28] and a 5-year follow-up study in 2019 to determine change in tree canopy cover, resulting from the Million Trees Miami tree planting initiative and the impacts by Hurricane Irma in 2017. Progress toward the 30% canopy cover goal was to be measured via tree canopy loss and gain both countywide and at the community scale. The impact of Hurricane Irma in 2017, if significant, was expected to lead to a uniform reduction in canopy cover across the study area. Therefore, the main objective of this study is to analyze the change in Existing Urban Tree Canopy (EUTC) within the Urban Development Boundary (UDB) of Miami-Dade County between 2014 and 2019. Various other studies analyzed the association between the abundance of tree canopy and socioeconomic characteristics (e.g., household income, race) in urban environments [29] and explored the role of tree canopy on land surface temperature [30]. Despite these efforts, there is a need to analyze the effect of other land cover categories (besides tree canopy) on land surface temperature to better understand planning options and consequences for the reduction in heat islands in urban environments. Furthermore, the Miami-Dade area features distinct spatial clusters of Hispanic and African communities, which allows investigation of their association with EUTC in a single study site. In addition, there are only few longitudinal studies analyzing the relationship between changes in tree canopy and demographic characteristics [31]. Based on these research gaps, this study:

- Computes the EUTC change between 2014 and 2019 based on satellite data derived land cover maps for areal administrative units, including census places and municipalities, to assess the effect of both Hurricane Irma in 2017 and local tree planting initiatives on tree canopy;
- Highlights local areas of tree canopy gain or loss and discusses their causes;
- Statistically relates land cover change categories involving loss or gain in tree canopy to changes in surface temperature between 2014 and 2019, and;
- Compares the association between percent EUTC and socioeconomic characteristics between 2014 and 2019 at the scale of census block groups and municipalities.

2. Materials and Methods

2.1. Data Sources and Data Preparation

Land cover maps were generated from WorldView-2 (WV2) imagery. This section provides a description of data sources and methodology for the 2019 study, which was similar to the process in 2014. For further description of data sources and methods utilized to create the 2014 map, interested readers are referred to [28].

The land cover classification was based on spectral reflectance patterns of 8-band WV2 data with a 2-m spatial resolution that were acquired on 28 November 2019. A small sliver subset along the coast on the easternmost edge of the study area used WV2 imagery from 27 March 2020. Because most of the data were from 2019, this is the epoch for the land cover discussed hereafter. The satellite images were first orthorectified using the Rigorous Orthorectification extension in ENVI 5.5.2 (L3 Harris Geospatial Inc.), using the Global Multi-resolution Terrain Elevation Data (GMTED) 2010 dataset provided with the ENVI software. Following the orthorectification, the satellite data were radiometrically and atmospherically corrected in ENVI 5.5.2. using the Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) algorithm [32], selecting a Tropical atmospheric model with a Tropospheric aerosol model and a visibility of 100 km. To be able to use a single set of training points across the two data acquisition dates, brightness values in the eastern sliver were recomputed using linear regression models that were constructed using 407 points distributed across the overlapping areas and representing spectrally stable surface types, such as asphalt and concrete. The resulting images were merged into one raster mosaic covering the analysis area.

As an additional data source, five vector data feature classes were downloaded from the Miami-Dade County Open Data Hub (https://gis-mdc.opendata.arcgis.com/) (accessed on 15 June 2022), updated, and incorporated into the map generation process after the initial land cover classification. Two feature classes needed substantial manual data handling prior to their integration in the land cover map. The first one was the Buildings feature class, which was found to be less complete and less up to date than buildings in OpenStreetMap (OSM). OSM previously incorporated two earlier versions of the Miami-Dade Building dataset through data imports in 2016 [33] and in 2018–2019 (https://wiki.openstreetmap.org/wiki/Miami-Dade_County_Address_Import) (accessed on 15 June 2022). Because OSM is an open, collaborative project, anyone can edit (e.g., add, delete, modify) map objects. Many changes to the originally imported buildings occurred since the previously mentioned data imports, which include, for example, the deletion of demolished buildings and the addition of new ones. These changes can render the OSM dataset more timely than government agency versions updating their datasets during regularly scheduled update cycles. To further ensure the quality and completeness of the Buildings feature class in this study, a dedicated mapping project was deployed on the OSM US Tasking Manager (TM), which is a web-based software tool to coordinate mapping efforts among multiple editors within a geographic area [33]. Using the TM, the study area was divided into 385 tiles so that Florida International University students and additional OSM community members could systematically review and update buildings within these tiles. This review included visual comparison of existing buildings with the most recent freely available satellite and aerial photography imagery layers from Bing Maps, Mapbox, and the United States Geological Survey. Building layer editing included the manual digitization of missing buildings from new housing developments and resolving geometry conflicts from overlapping building polygons. Overall, 17 mappers contributed 4797 new buildings, modified 1996, and deleted about 220 (e.g., due to overlap). As a result, the OSM building dataset closely resembled ground conditions as seen on the latest freely available imagery background layers. The second feature class, Edge of Pavement, was downloaded as a polyline feature class. The polylines were closed for all roads at the periphery of the study area and at all road intersections with overpasses to convert them to polygons.

To produce a surface temperature map, Landsat-8 Thermal Infrared Sensor (TIRS) 1 (Band 10) data with a 30-m resolution (original 100-m resolution), acquired on 16 January 2019, were converted to degree Celsius with a freely available Spatial Model [34] in ERDAS Imagine 2020, which follows equations provided in the literature [35].

2.2. Land Cover Classification

Corrected, multi-spectral reflectance values were used in the classification of eight land cover classes: asphalt, trucks/containers on asphalt, concrete (these three were combined into class "Impervious" in the final land cover map for areas not covered by polygon vector classes, such as roads); tree canopy/shrubs; grass; bare ground; wetland, and water. Land cover was classified with the random forest classification algorithm [36,37] of the caret R-package [38], based on 14,816 training points. The classifier was trained on spectral reflectance values of all eight WV2 spectral bands and classification accuracy was assessed with a bias adjusted calculation of the confusion matrix between predicted and actual land cover class [39]. Accuracy assessment samples were selected in a design-based post-classification stratified random sampling procedure and all samples were visually interpreted from aerial imagery. Inland water bodies (e.g., lakes, ponds, canals, rivers) made up the water class, whereas coastal water areas (e.g., bay, ocean) were excluded from the land cover mapping process. This is due to inland water bodies potentially changing over time (e.g., through construction, overgrowth, or drainage); coastal water areas are much less susceptible to such changes including gain and loss of tree canopy. A canopy height model (CHM) was created from two data sources. State of Florida Division of

Emergency Management (http://dpanther2.ad.fiu.edu/Lidar/lidarNew.php) (accessed on 15 June 2022) 2015 lidar data were used to create a digital surface model (DSM) with the lidar module in ENVI. Miami-Dade County Open Data Hub provided the digital elevation model (DEM) that was subtracted from the DSM to generate the CHM. The CHM was resampled to a 2-m resolution to align it with the WV2 satellite imagery.

The following five vector feature classes that were obtained from the Miami-Dade County Open Data Hub were overlaid on the satellite imagery-based land cover map to mask and reclassify known land uses:

- Buildings (polygons);
- Edge of pavement (polylines converted to polygons);
- Railroads (polylines buffered with a 3-m distance);
- Water bodies (polygons);
- Cropland (polygons).

Edge of pavement and railroad features were combined into a “Street/Railroad” class, and the CHM described above was used to reclassify wetland areas with a height of at least 50 cm as shrub or tree canopy. To remove spurious pixels, the final map was filtered with a 3×3 kernel using a majority decision rule with varying class-specific minimum mapping units (MMU) (Table 1).

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
Water	50	200
Wetland	50	200
Cropland	5	20
Grass	5	20
Bare ground	10	40
Impervious	50	200

2.3. Tree Canopy Gain and Loss

To determine tree canopy change, the land cover map from the 2014 baseline study was compared to the 2019 map on a pixel-by-pixel basis. This comparison allowed for identification of areas with tree loss (i.e., tree/shrub pixels in the 2014 map replaced by any other land cover class in 2019) and gain (i.e., any other land cover pixels in 2014 replaced by tree/shrub pixels in 2019). These changes were aggregated for administrative units to show EUTC change expressed in (a) changed EUTC proportion among all land cover classes or (b) total areal units (e.g., km^2) within each polygon. The administrative units that were assessed include 1446 census block groups and 79 census places.

2.4. Change in Land Cover, Socioeconomic Factors, and Surface Temperature

The bivariate correlations between % EUTC and annual household income, %African American, and %Hispanic population at the census block level were examined using socioeconomic data from the American Community Survey (ACS) for the years 2014 and 2019. The 2015–2019 5-year estimates at the block group level were downloaded from the US Census Bureau (https://www.census.gov/cgi-bin/geo/shapefiles/index.php) (accessed on 15 June 2022). The ACS data were spatially joined with census block group geometries, which were downloaded as TIGER/Line shapefiles. The same procedure was followed for the 2014 study, which used ACS 2010–2014 5-year estimates. For statistical analysis, the 1446 census block groups that had a complete set of socioeconomic variables both in the 2014 and 2019 ACS estimates were used. Census place geometries were downloaded in shapefile format from the US Census Bureau.

To establish surface temperature increase or decrease with specific land cover class changes, we simplified the classification scheme to capture significant change in land cover functionality through reclassifying 8 of the 9 original land cover categories into four aggregated classes (Table 2). A non-vegetated class (nonVeg) comprises the original street/railroad, building, impervious, and bare ground classes and a vegetated class (veg) includes the original grass and wetland classes. Meanwhile, a water (wtr) and a tree canopy (tree) class reflect the names of their original classes. Cropland was excluded in the reclassification process for two reasons. First, cropland areas contain built structures (e.g., glass houses, protective sheets), bare soil, grass, and other vegetation. Second, agricultural areas undergo frequent phenological cycles of bare soil, planting maturity, and harvest; therefore, cropland pixels cannot be unambiguously assigned to either the vegetated or non-vegetated aggregated class. This reclassification results in a total of 12 potential land cover transitions for a 2-m pixel between 2014 and 2019 (Table 2).

Table 2. Simplified set of land cover transitions between 2014 and 2019.

From→To	Non-Vegetated	Vegetated	Tree	Water
Non-vegetated	-	nonVeg→veg	nonVeg→tree	nonVeg→wtr
Vegetated	veg→nonVeg	-	veg→tree	veg→wtr
Tree	tree→nonVeg	tree→veg	-	tree→wtr
Water	wtr→nonVeg	wtr→veg	wtr→tree	-

The difference in surface temperature between land cover categories varies across annual seasons [40]. For example, in hot summer months, water bodies (e.g., lakes, rivers) are cooler relative to concrete surfaces than in winter months. To reduce this effect when assessing the relationship between land cover change and surface temperature change between 2014 and 2019, surface temperature maps for the different years were based on Landsat-8 Thermal Infrared satellite imagery that were acquired at approximately the same time of the year with similar ambient air temperature. The acquisition dates for the thermal infrared satellite imagery were 18 January 2014 and 16 January 2019, respectively. Because both images had some cloud coverage, only those areas which were cloud free in both images were used for the analysis. Specifically, the quality assessment (QA) masks that come with Landsat 8 Collection 2 (C2) Level 2 Science Products (L2SP) were used to identify cloud free areas.

To assess the mean temperatures for the aggregated land cover classes (i.e., vegetated, non-vegetated, tree, water) in 2014 and 2019, a sample of 30-m resolution pixels was used from Landsat-8 Band 10 TIRS 1 satellite imagery, which provided surface temperature and spatially overlapped with the 2-m pixel aggregated land cover map. To reduce the number of mixed pixels falling into a 30-m temperature pixel, only 30-m pixels covered with at least 90% of a single aggregated land cover class were used for this purpose.

The effect of land cover change between 2014 and 2019 on surface temperature was determined by measuring temperature change in 30-m thermal pixels where an observed land cover transition existed between the two analyzed periods. A single land cover transition type (compare Table 2) had to be >50% for the 30-m thermal pixels to be considered for the analysis. Within these pixels, the surface temperature change between January 2014 and January 2019 was determined. These pixels were subsequently binned into surface temperature change classes with intervals of 0.25 °C. Classes that contained at least thirty 30-m pixels were used to relate surface temperature change with the 12 land cover transition categories. To visualize the temperature change, the proportion of transition categories for each temperature class were plotted as bars in a stacked bar chart.

The role of tree canopy in surface temperature change was statistically assessed with a one-way ANOVA [41] to determine whether temperature change associated with the different transition categories were significantly different, followed by a Tukey post hoc test to determine if temperature changes between pairs of land cover transition types were significantly different. Data for the ANOVA test were limited to temperature change from 30-m thermal pixels that had at least half of their area covered by a single transition type (Table 2) and that included tree canopy in either its "From" or its "To" class.

3. Results

3.1. Land Cover Classification and Statistics

In 2019, grass has the largest percent cover of 24.8 ± 1.6%, followed by tree canopy including shrubs (20.1 ± 1.5%) and buildings (17.7 ± 0.7%) (Table 3). Corresponding percent cover numbers for the 2014 study were 22.2 ± 1.4% for grass, 19.9 ± 1.2% for tree canopy/shrubs, and 15.9 ± 1.0% for buildings. The differences are not significant between years when considering a 95% confidence interval. Figure 1 shows the 2019 land cover map with nine classes as a result of the land cover classification process described in Section 2.2. A similar map produced in the baseline study together with area and percent cover statistics can be found elsewhere [28]. The analysis of tree canopy and land cover change was based on a comparison of 2014 and 2019 land cover maps at the pixel level and for pre-defined areal units.

Table 3. Area, percent cover, 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	230.6 (±17.0)	89.0 (±6.6)	20.1 (±1.5)	85.1 (±4.4)
Street/Railroad	136.0 (±2.1)	52.5 (±0.8)	11.9 (±0.2)	98.5 (±1.5)
Building	202.6 (±8.5)	78.2 (±3.3)	17.7 (±0.7)	95.5 (±2.5)
Water	53.7 (±1.3)	20.7 (±0.5)	4.7 (±0.1)	97.0 (±2.1)
Wetland	5.2 (±3.3)	2.0 (±1.3)	0.5 (±0.3)	92.9 (±5.0)
Cropland	39.8 (±0.9)	15.4 (±0.4)	3.5 (±0.1)	98.5 (±1.5)
Grass	284.9 (±17.9)	110.0 (±6.9)	24.8 (±1.6)	80.6 (±4.9)
Bare ground	23.1 (±2.0)	8.9 (±0.8)	2.0 (±0.2)	67.2 (±5.8)
Impervious	170.9 (±10.3)	66.0 (±4.0)	14.9 (±0.9)	86.6 (±4.2)
Total	**1146.8**	**442.8**	**100.0%**	**Overall Accuracy = 87.4% (±1.5%)**

Using a stratified random sample (N = 564) with multinomial distribution sampling based on a 95% confidence, the bias-adjusted, design-based accuracy assessment of land cover classes estimated the overall accuracy of the map to be 87.4%, with a standard error of 1.5%. This corresponds to the 95% upper and lower confidence of the true accuracy to be between 85.9% and 91.3%. Areas in Table 3 are error-adjusted estimates with their standard errors and based on the accuracy assessment and the constructed error matrix, following the procedures described in [39].

Class-specific map accuracies ranged from 67.2 ± 5.8% for bare ground to 98.5 ± 1.5% for the streets/railroads and cropland classes (Table 3). Buildings were mapped with an accuracy of 95.5 ± 2.5%, grass with 80.6 ± 4.9%, trees/shrubs with 85.1 ± 4.4%, and impervious surfaces with 86.6 ± 4.2%.

Percentage values across rows in the confusion matrix (see Table A1) sum up to 100%. Main diagonal elements correspond to the probability (user accuracy) that a value predicted to be in a certain class belongs to that class. User accuracy is listed under "Accuracy" in Table 3. Off-diagonal elements provide information on misclassifications of predicted land cover classes. For example, the matrix shows that 16.4% of pixels classified as grass were actually tree/shrub, which led to the highest misclassification in the grass land cover class. Vice versa, the predicted tree/shrub class contained 11.9% of pixels that were actually grass and not tree/shrub. The corresponding confusion matrix for the land cover map generated for the 2014 baseline study can be found in Table A2.

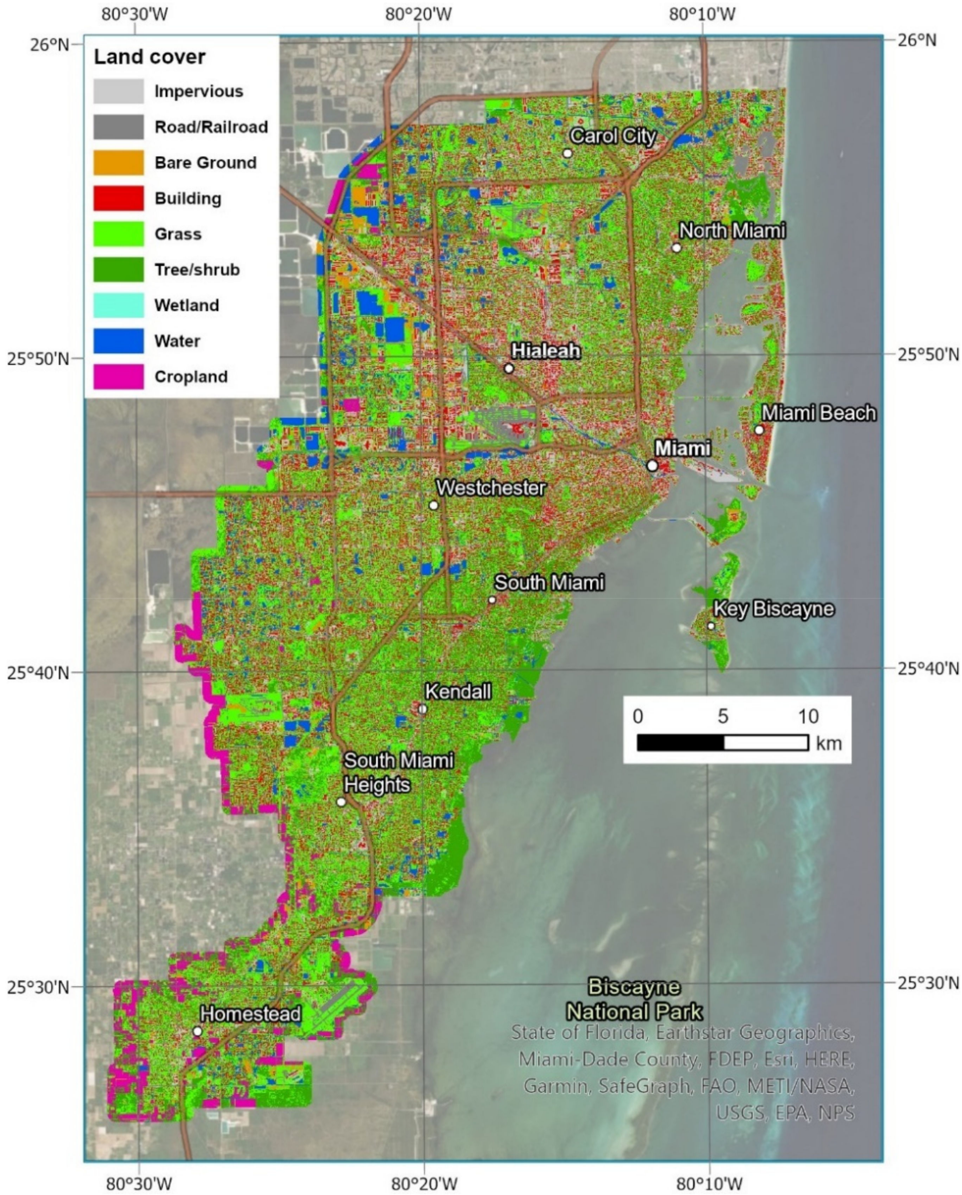


Figure 1. Generated 2019 land cover classification map within the UDB of Miami-Dade County (background map credits: State of Florida, Earthstar Geographics, Miami Dade County, FDEP, Esri, HERE, Garmin, SafeGraph, FAO, METI/NASA, USGS, EPA, NPS).

3.2. Change in Urban Tree Canopy

Tree cover within the study area did not significantly change in % EUTC between 2014 (19.9% ± 1.2%) and 2019 (20.1% ± 1.5%). Comparison of land cover between 2014 and 2019 for census places indicates that the ten census places with the highest percentage of EUTC loss (red bars) and gain (green bars), respectively, ranged between −6.8% for West Miami and +11.2% for Biscayne Park (Figure 2a). The ten census places with the largest absolute change of tree canopy loss and gain were observed for Kendall with a loss of −1.99 km^2 and a gain for North Miami with an increase of +1.55 km^2 (Figure 2b).

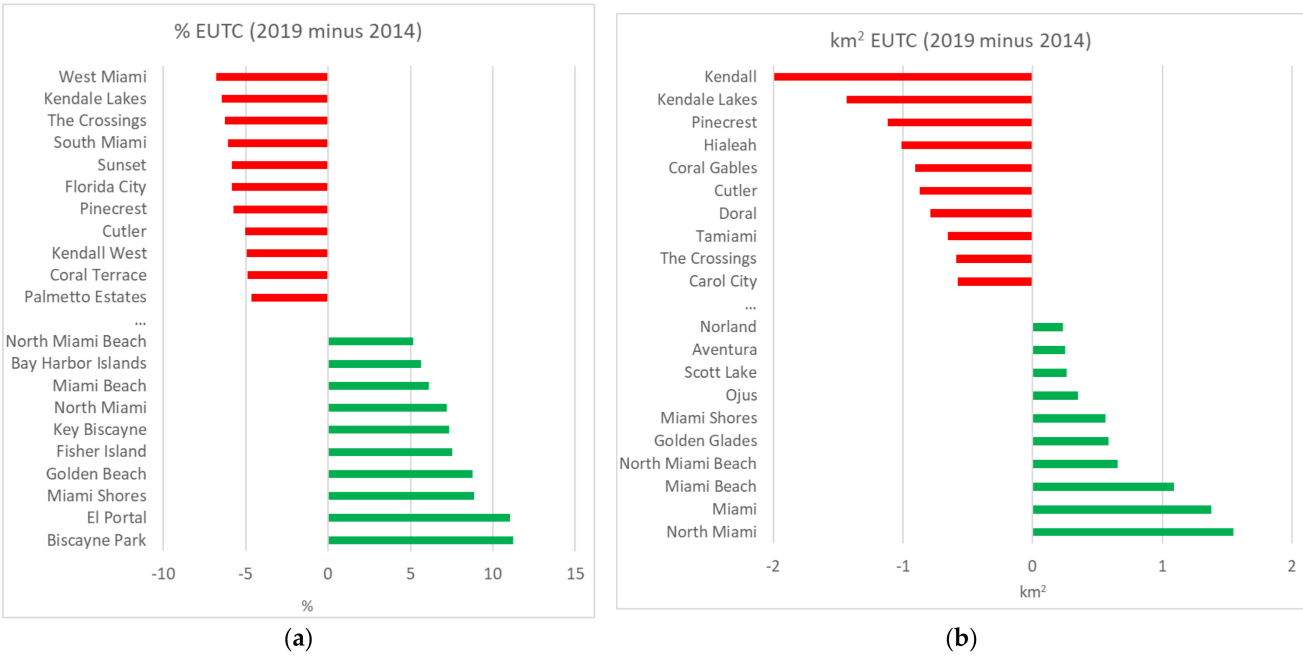


Figure 2. Change in tree canopy between 2014 and 2019 for selected census places within the UDB of Miami-Dade County: (**a**) Change in % EUTC; (**b**) Change in km^2 of EUTC.

The comparison in land cover further suggests that relative tree gain tends to take place in the northeast portion of the urban area including coastal areas, whereas new commercial and residential construction tends to reduce EUTC further inland (Figure 3).

At the local level, a pixel-based review of canopy gain and loss helps to correlate causes. An example of a census place that experiences a high gain in % EUTC is El Portal (see green pixels in Figure 4c). The high gain was a result of the removal of a mobile home park to the east, which was present in 2013 (see Figure 4a) but was taken out before 2020 (see Figure 4b). The empty area was replaced by tree canopy over the years (marked by "1"). This featured area contributed to the increase in the share of EUTC from 23.2% to 34.3% across El Portal during the examined period.

Large-scale construction activities lead to substantial loss in tree canopy, as shown for the northwestern portion of Hialeah (Figure 5). In this case, tree canopy has given way to construction sites (1), warehouses (2), residential developments (3, 4), and deforested wasteland (5). These changes contributed to a decline in EUTC from 12.7% (2014) to 7.4% (2019) for Hialeah.

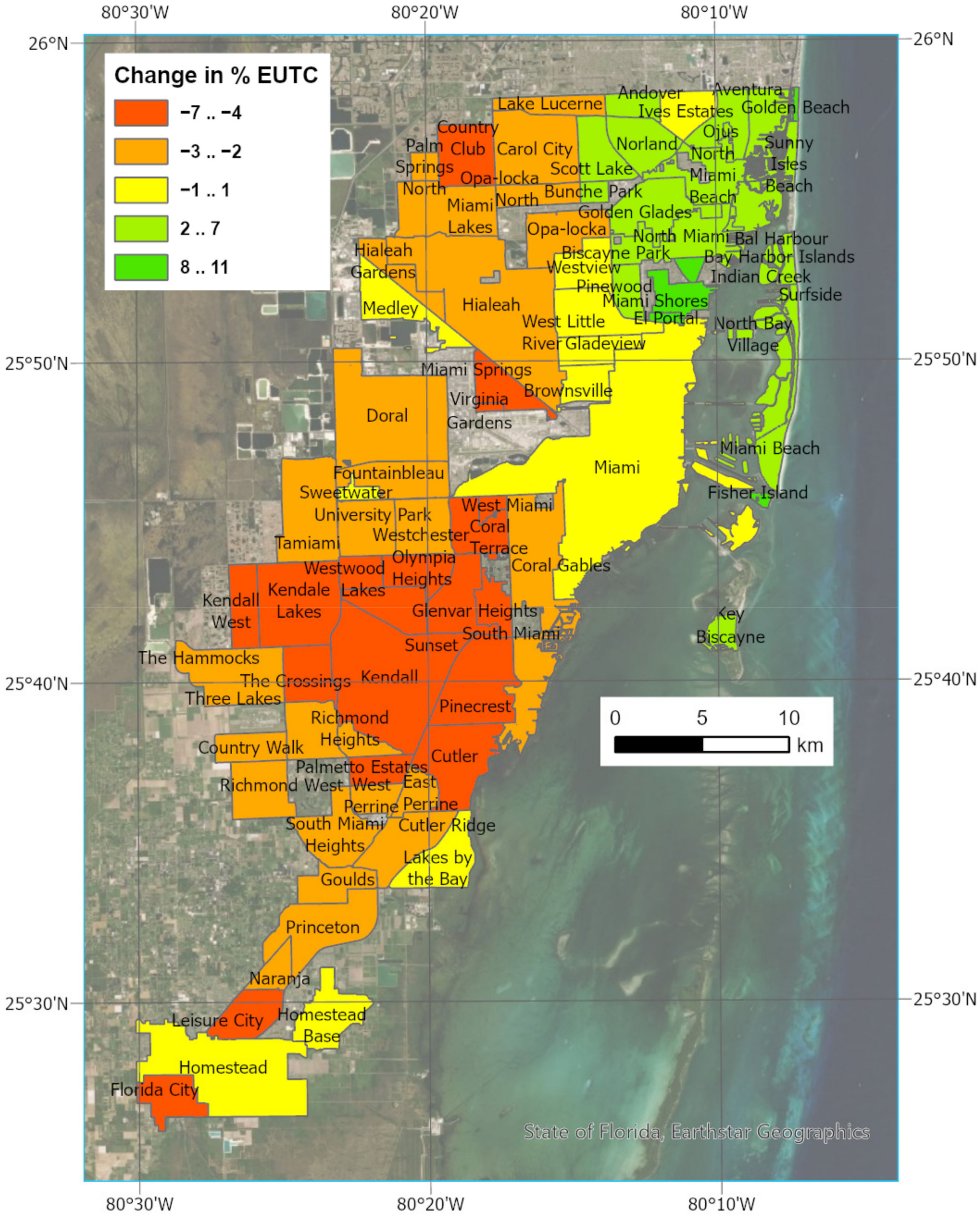


Figure 3. Change in % EUTC for census places within the UDB of Miami-Dade County (background map credits: State of Florida, Earthstar Geographics).

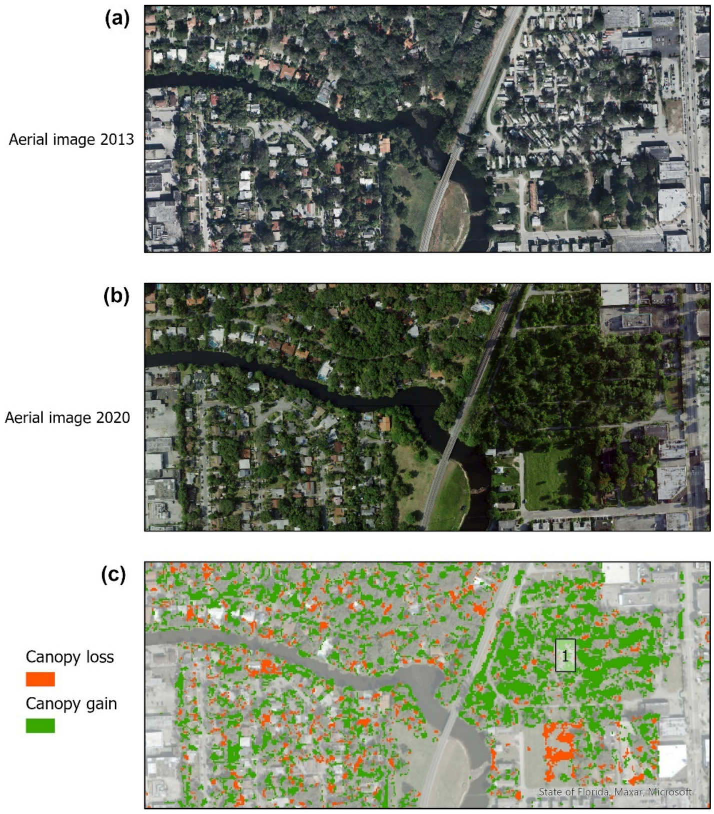


Figure 4. Tree canopy gain in El Portal through reforestation of a former mobile home park area: (**a**) Mobile home park present (2013); (**b**) Mobile home park removed (2020); (**c**) Tree canopy gain in reforested area (background map credits: State of Florida, Maxar, Microsoft).

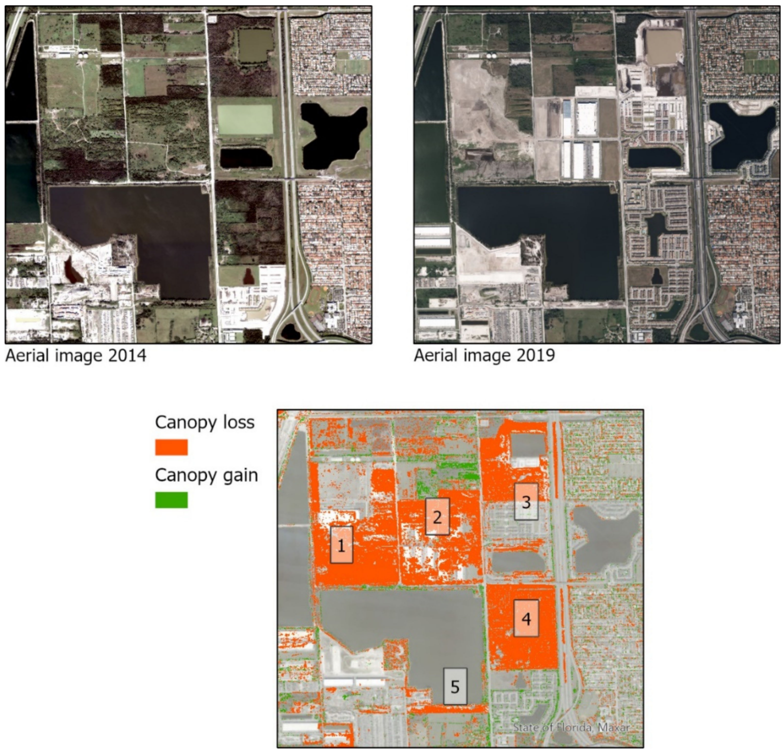


Figure 5. Area of tree canopy loss in Hialeah (municipality and census place) through commercial and residential construction activities (background map credits: State of Florida, Maxar).

3.3. Association between Change in Land Cover and Surface Temperature

Mean surface temperature (in °C) of the four aggregated land cover categories for both the 2014 and 2019 maps was lowest for tree cover, followed by water, vegetated, and non-vegetated surfaces (Table 4). Mean temperature between both acquisition dates was most similar for tree canopy (within 0.1 °C) and differed most for vegetated areas (within 0.5 °C).

Table 4. Mean surface temperatures and their standard deviations (in degree Celsius) for aggregated land cover classes.

Land Cover	18 January 2014	16 January 2019
Tree	13.2 ± 0.4	13.3 ± 0.4
Water	13.5 ± 0.4	13.7 ± 0.3
Vegetated	14.0 ± 0.5	14.5 ± 0.5
Non-vegetated	14.6 ± 0.5	14.8 ± 0.4

The observed change in surface temperature between 18 January 2014 and 16 January 2019 ranged between −2.7 °C to +3.3 °C for all thermal pixels. This range reduces to −1.5 °C through 2.3 °C for temperature change classes with at least thirty 30-m pixels that satisfy the 50% coverage threshold of a single land use transition class. This temperature range was subsequently used for the stacked bar chart in Figure 6.

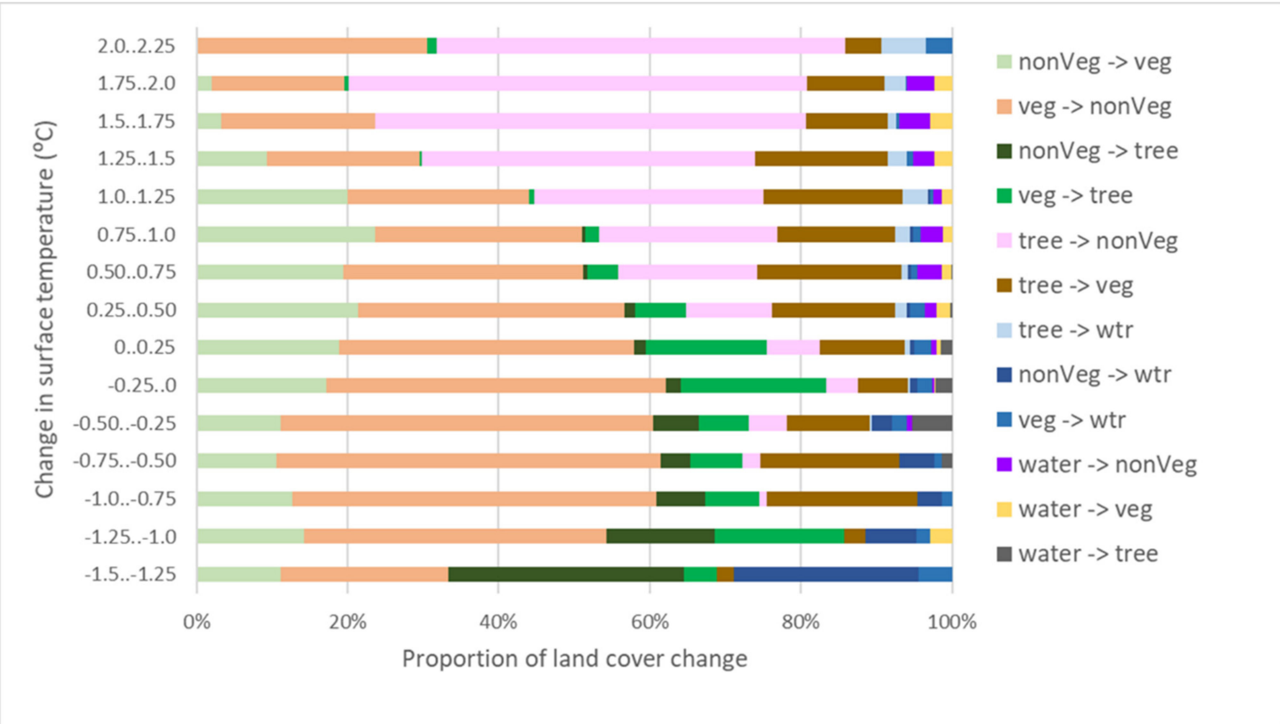


Figure 6. Proportion of land cover transition categories for surface temperature change classes between 2014 and 2019.

The bottom part of the chart shows land cover transition patterns that tend to be associated with a surface temperature decrease, whereas the upper portion reflects the opposite. Some patterns emerge from the chart. Pronounced surface temperature increases are associated with a transition from tree canopy to non-vegetated land cover (pink). As opposed to this, a transition from non-vegetated (dark green) and vegetated (medium green) surfaces to tree canopy as well as a land cover change from non-vegetated to water surfaces (dark blue) is mainly found in the lower temperature change classes. This suggests that (a) sealing existing water and wetland areas with impervious surfaces (e.g., concrete slabs, buildings) and (b) replacing tree canopy with impervious surfaces should be avoided to prevent the formation of local heat islands. The role of transition between non-vegetated and vegetated surfaces is less clear from the chart; however, a change from non-vegetated (e.g., bare soil) to vegetated surfaces (e.g., grass) (light green) is rarely found within high temperature increase classes.

The following example demonstrates at the local level the relationship between land cover transition category and change in surface temperature for an area in Hialeah, which underwent construction between 2014 and 2019 (Figure 7). The two aerial images in Figure 7a,b show the situation before and after land use transition. Figure 7c maps land use transition categories, whereas Figure 7d shows the temperature change for the area over the same period. Several types of land cover transitions can be observed that experienced high temperature increases. For example, tree canopy was replaced with non-vegetated land for industrial development (e.g., buildings, parking lots) in the western half of the plot (1) and for residential development to the east (2). Trees were also replaced by grass areas (vegetated land) near industrial development in the center north (3). Replacement of vegetated land with impervious surfaces, in this case with buildings along the lake, can also be observed (4).

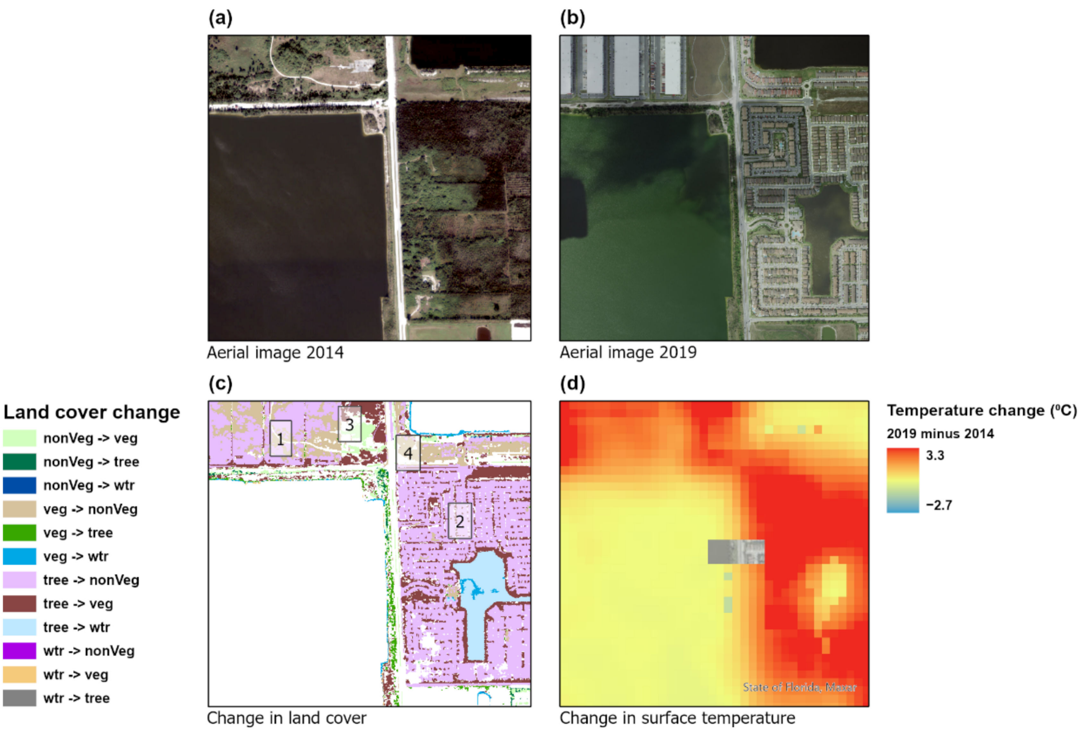


Figure 7. Land cover transition and surface temperature change for a development in Hialeah: (**a**) Forested areas present in 2014; (**b**) Commercial and residential development (2019) replacing most forested areas; (**c**) Land cover transition map; (**d**) Change in surface temperature between 2014 and 2019 (background map credits: State of Florida, Maxar).

Replacement of tree canopy with other land cover types between 2014 and 2019 is associated with a higher increase in surface temperature than the reverse transition (Table 5). The largest difference of 1.0 °C can be observed for transitions that involve tree canopy and non-vegetated surfaces (upper two rows).

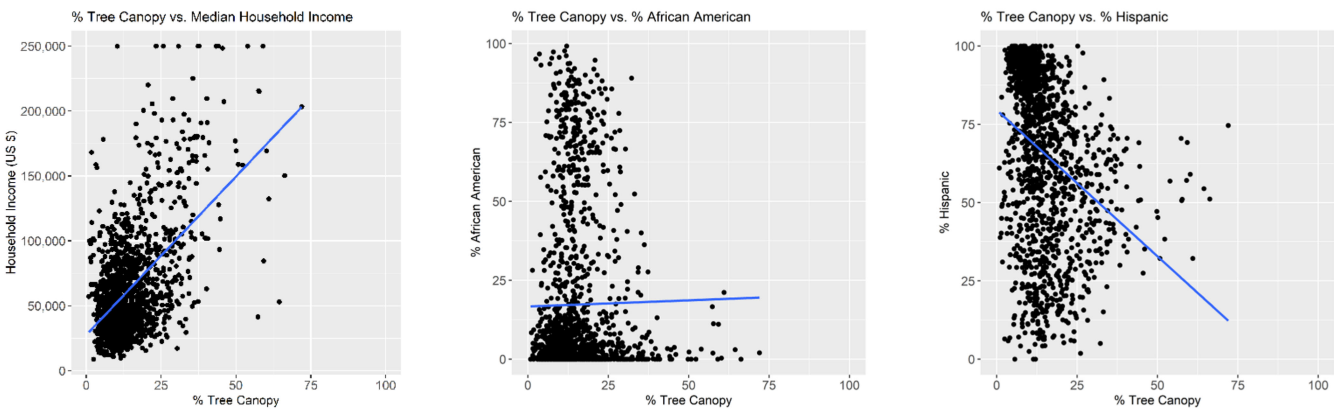
Table 5. Change in mean surface temperature (in °C) for transition between tree and other land cover classes and the differences between mean changes for reverse transition classes. Values with ± indicate standard deviations of differences.

Transition	Mean Temperature Change	Difference between Reverse Transitions
tree -> nonVeg	0.9 ± 0.6	1.0 ± 0.8
nonVeg -> tree	−0.1 ± 0.6	
tree -> veg	0.5 ± 0.6	0.4 ± 0.6
veg -> tree	0.1 ± 0.3	
tree -> wtr	0.8 ± 0.5	0.8 ± 0.6
wtr -> tree	0.0 ± 0.2	

A one-way ANOVA between the six land-cover transition types listed in Table 5 and surface temperature change between 2014 and 2019 shows that there was a statistically significant difference in surface temperature change between at least two land cover transition types. Thus, the null hypothesis of an equal mean value of surface temperature change across all transition types (F(5, 10989) = 867.8, $p < 0.0001$) can be rejected. Tukey's HSD test for multiple comparisons found that the mean value of surface temperature change was significantly different between all transition types ($p < 0.0001$) except for the mean difference between wtr -> tree-and nonVeg -> tree transitions ($p = 0.63$). These results, in connection with mean temperature changes listed in Table 5, point toward the strong relative cooling effect of increased tree canopy relative to tree removal.

3.4. Change in Tree Canopy and Socioeconomic Variables

Evaluating % EUTC against annual household income, %African American population, and %Hispanic population shows a positive association for household income and a negative association with %Hispanic; meanwhile, the regression line for %African American shows virtually no slope and hence no correlation (Figure 8). The latter changed compared to 2014 [28] where a weak negative correlation with %African American could be observed (Table 6). In addition, compared to 2014 the negative correlation between % EUTC and % Hispanic strengthened from r = −0.11 ($p < 0.001$) to r = −0.31 ($p < 0.001$) in 2019, whereas the role of household income remained virtually unchanged compared to 2014.



(**a**) (**b**) (**c**)

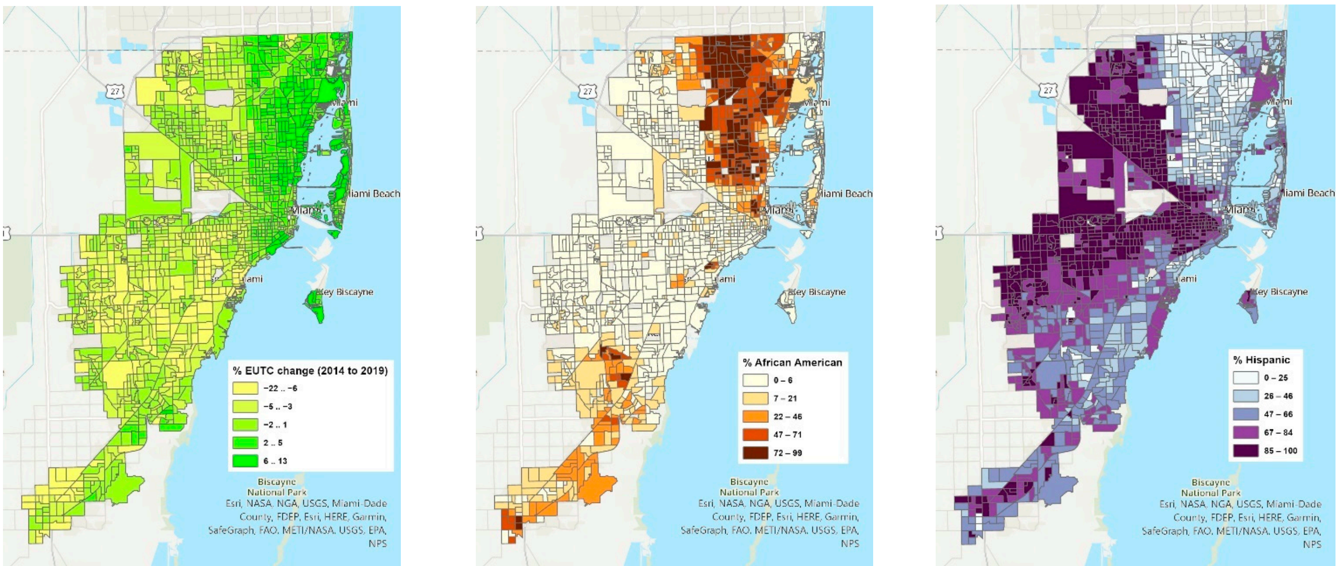
Figure 8. Scatter plots for 2019 socioeconomic data at the census block group level: (**a**) % EUTC vs. Annual Household Income, (**b**) % EUTC vs. % African American population, and (**c**) % EUTC vs. % Hispanic population.

Table 6. Bivariate correlations between % EUTC and socioeconomic variables.

Year	Household Income	% African American	% Hispanic
2014	**0.541** **	**−0.157** *	**−0.111** **
2019	**0.543** **	0.014	**−0.313** **

**: Significant at 0.1%; *: Significant at 5%.

These correlation changes can also be visually discerned in the thematic maps. Figure 9a shows the change in % EUTC for block groups between 2014 and 2019. A more pronounced tree canopy gain can be observed primarily in the northeast portion of the study area, which also features a high percentage of African Americans (Figure 9b). Hence, in the latest analysis, access to urban tree canopy by predominantly African American communities has improved. Contrary, census block groups with a high percentage of Hispanic population (Figure 9c) corresponded to areas of reduced EUTC, which includes the central and western portions of the study area.



(**a**) (**b**) (**c**)

Figure 9. Tree canopy relative to race and ethnicity data at the block group level within the UDB of Miami-Dade County: (**a**) Change of % EUTC between 2014 and 2019, (**b**) % African American population in 2019, (**c**) % Hispanic population in 2019 (background map credits: Miami-Dade County, FDEP, Esri, HERE, Garmin, SafeGraph, FAO, METI/NASA, USGS, EPA, NPS).

4. Discussion

The detected % EUTC in 2014 and 2019 is in line with a previous study which showed that the % EUTC in Miami was 23.3.% in 2003 and 21.9% in 2009 [19]. The specific boundary used in that referenced study was not provided, so a one-to-one correspondence to the UDB used herein cannot be obtained; however, the % EUTC from earlier years provides evidence that tree canopy conditions in the study area as a whole are in a relatively steady state in the early 21st century in southeastern Florida. This finding further highlights the importance of targeted municipal and census block level tree canopy analyses to identify areas that could benefit most from planning decisions on tree planting locations.

A primary motivation for funding this study was to understand the near-term impacts of Hurricane Irma in 2017 on the overall EUTC within the UDB of Miami-Dade County. Given the non-insignificant difference in EUTC across the county between 2014 and 2019, the subsequent conclusion is that Hurricane Irma had minimal near-term impact on EUTC. The findings herein are supported by tree-level analyses that highlight wind speed as the most likely determinant in permanent tree failure [42]. Given that Hurricane Irma was downgraded from a Category 3 to Category 1 hurricane and did not make landfall in Miami-Dade County, impacts from wind speed were greatly reduced relative to the perceived potential. Hurricane Irma caused an estimated $50 billion dollars in damages [43] with most derived from flooding impacts [44]. The logical conclusion is that either (a) most of the landscape debris collected post storm was tree limbs and non-permanent tree damage and/or (b) tree planting initiatives of not yet fully mature trees helped mitigate some of the loss in tree canopy. These factors combined enabled the tree canopy across Miami-Dade County to remain largely unaffected two years after Hurricane Irma.

Although impacts from Hurricane Irma were negligible, the relatively short revisit time between countywide evaluations of EUTC between 2014 and 2019 did provide an opportunity to analyze localized transitions in land cover and their relationship to both surface temperature changes and socioeconomic variables to changes in EUTC. Relating to the prior, a comparison of surface temperature between 18 January 2014 and 16 January 2019 (i.e., the acquisition dates of Landsat-8 Thermal Infrared satellite imagery) revealed a moderate surface temperature increase for all four considered aggregated land cover categories (vegetated, non-vegetated, tree, and water), ranging between 0.1 °C for tree canopy and 0.5 °C for vegetated areas (Table 4). Besides this general trend, analysis of land cover transition showed that the replacement of tree canopy with other land cover categories led to a significantly higher increase in surface temperature than the reverse transition (Table 5). This points toward the relative cooling that tree canopy provides compared to other land cover. The observed effect on change in surface temperature based on reverse land cover transitions (up to 1.0 °C) is moderate, which can be ascribed to the overall cool temperatures in January in the Miami-Dade study area for all land cover types. However, it can be expected that tree and water surfaces will provide more pronounced relative cooling effects during warmer months of the year. This claim is supported by earlier studies which showed that land cover has stronger effects on surface temperatures during the summer [40], which underlines the high capacity of tree canopy and water surfaces during summer to mitigate excessive heat.

Relating to socioeconomic variables, another study [31], which used the United States Geological Survey (USGS) National Land Cover Database (NLCD) resource over Atlanta, GA, found that the relationship between minority concentration and tree canopy changed over time when testing the environmental inequity hypothesis for the years 2000 and 2013. Such a change could be observed in our study when a significant negative relationship between percentage of African American population and tree canopy in 2014 turned statistically insignificant in 2019. In addition, similar to our results, low income was consistently associated with greater environmental inequality in the Atlanta study [31]. This suggests that race (or the change in the percentage of the sub-population of a certain race) alone is not a reliable predictor of tree canopy (or its change) and that poverty rate needs to be considered in combination with race and ethnicity. Along the same line, negative correlations were observed between race and % EUTC in bivariate models for various U.S. cities, whereas they were not observed with multivariate regressions that include additional variables on income, education, and housing age [29].

Our results showed that percent EUTC increased in predominantly African American communities but decreased in areas with a high percentage of Hispanic population. Several possible factors may contribute to the corresponding observed pattern of EUTC change (Figure 9a). First, Miami-Dade County distributed funds to municipalities to plant trees as part of the Million Trees Miami initiative. There is no clear statistical relationship between new trees planted per km^2 in 2016 (the first year these data became available) through 2019 and % EUTC change between 2014 and 2019. Interestingly, some larger municipalities with a high percentage of African American population (e.g., North Miami Beach, North Miami) received above-average funding in terms of trees per km^2 (M = 13.8, SD = ±23.8) (Figure 10); meanwhile, relatively smaller municipalities with predominantly a Hispanic population (e.g., Sweetwater, Virginia Gardens, West Miami) had an above average number of trees per km^2 planted based on funding of that initiative during 2016 and 2019. Areas not covered by polygons within the UDB of Miami-Dade County in Figure 10 denote undesignated areas outside any municipality for which no funding information is available.

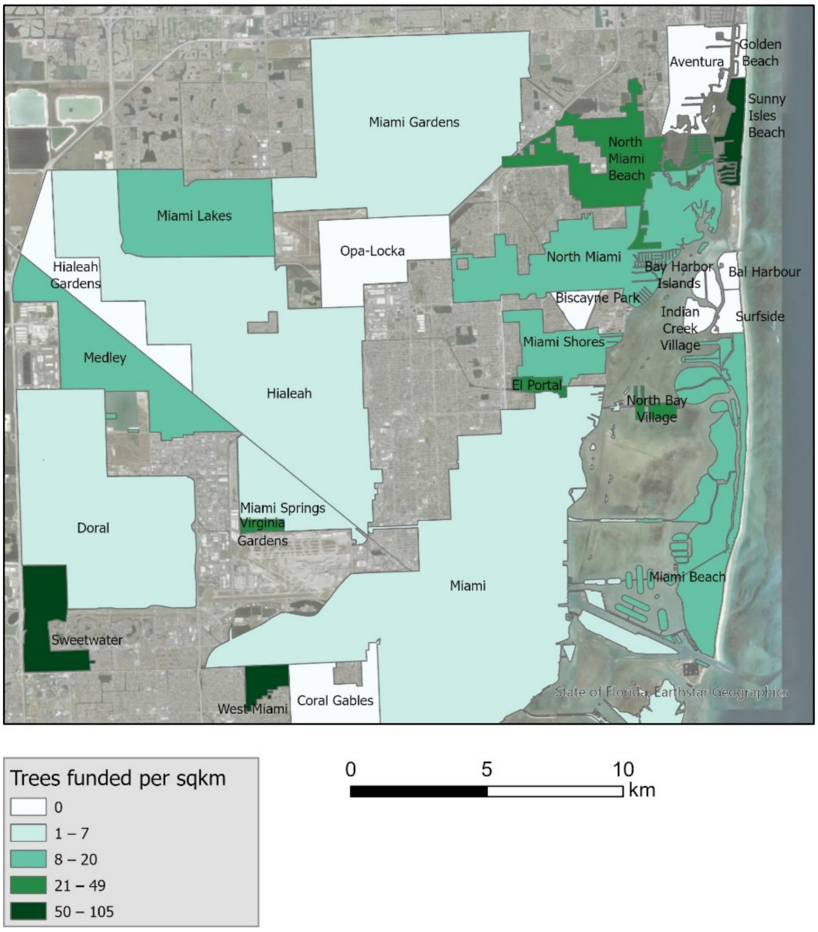


Figure 10. New trees planted per km^2 in selected municipalities of Miami-Dade County between 2016 and 2019 based on funding from the Million Trees Miami initiative (background map credits: State of Florida, Earthstar Geographics).

Second, various natural habitat areas to the north and northeast with a large percentage of African American population revealed a densely growing tree canopy over the years. See Figure 11 for an example in Miami Gardens. Third, new industrial and residential developments are more often located in the western and northwestern parts of the county due to the availability of larger tracts of land compared to closer to the coast. When these predominantly Hispanic population areas are developed, there is often a drop in % EUTC in these areas when forest is present. Although not performed in this study, a spatially high-resolution change analysis of longitudinal data (e.g., using Granger causality tests) could be used in future work. This would determine which variables (e.g., distribution of funding for tree planting, change in demographic variables) could be useful in forecasting tree canopy change and refining the exploratory observations previously described.

A limitation of this study is the lack of tree species identification, including a distinction between palm trees and other woody perennials. This distinction may be relevant for determining the need to replace a removed tree in the case of planned construction or hurricane damage. Although eight spectral band WV2 imagery limits such endeavors, the use of hyperspectral imagery, especially when combined with lidar-derived structural metrics, facilitates a distinction between numerous tree species [45]. Therefore, future work explores if such (airborne) data could become available for the Miami-Dade study area. The difference in collection dates between WorldView-2 imagery acquisition (2019/2020) and lidar data collection (2015) for this Miami-Dade County study limited the fusion of these two data sources for distinguishing between trees and shrubs. For future iterations of tree canopy assessment within the UDB, lidar datasets that are released more quickly after data collection would be welcome in the research community. Another future improvement for the surface temperature component of this study would be an investigation of not only tree canopy presence but also tree canopy characteristics. One study found that impacts on surface temperature in Seattle and Baltimore had varying responses based on categories of tree canopy cover ratio and infrastructure development nearby [46].

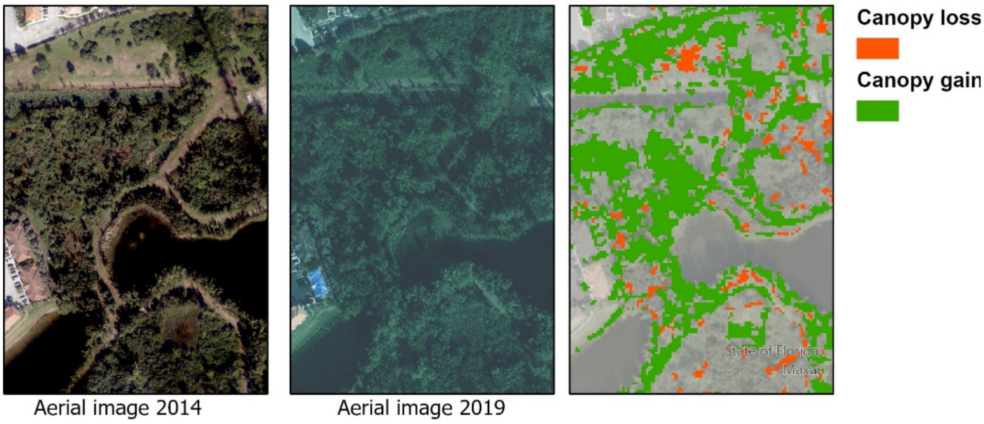


Figure 11. Canopy densification in a Miami Gardens natural area (background map credits: State of Florida, Maxar).

Before delving into the census block group and municipal level analyses, it is important to acknowledge that tree loss/gain at these levels have unknown uncertainties. This is because the land cover classification accuracy assessment was made only for the entire UDB study area and not for each individual sub-area. Given this limitation, the community level assessments can still provide valuable information to planners hoping to improve urban tree canopy across Miami-Dade County.

To improve tree planting strategies, closer examination is needed into the relationship between EUTC and the race/ethnicity of constituents in each community. This includes an investigation of the factors that led to an increase in tree canopy in predominantly African American neighborhoods. For instance, the high amount of green vegetation in similar neighborhoods in Baltimore was found to be potentially reflective of the increased number of vacant lots in those neighborhoods, which resulted in part from decades of deliberate underinvestment and discrimination [47,48]. Furthermore, studies have shown that low levels of homeownership, low incomes, substandard housing quality, and higher initial levels of pollution are all inequities that predominant Hispanic and African American communities face relative to predominantly White neighborhoods [49]. With lower levels of homeownership and potentially less residual income to spend on parcel beautification, it is incumbent on planning entities to utilize public funds to improve tree canopy in these areas. This is especially true when disadvantaged communities are reliant on public spaces for urban forest ecosystem services due to housing density or reduced income [50]. Public efforts to retain canopy cover in low-income and minority neighborhoods are important, because these population groups are more likely than others to remove trees due to the lack of resources to maintain trees [51]. One potential pitfall of improving access to tree canopy and urban green spaces in disadvantaged communities is fear of gentrification changing the existing social structure and forcing some community members to be relocated due to rising rents and property values [52]. Thus, any tree planning initiatives that are implemented should avoid being pure top-down measures but instead incorporate more community-centric planning to assuage fears and ensure community buy-in for improved tree canopy, with the ecosystem services that it provides.

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Appendix A

Table A1. Confusion matrix (2019). Values are percent (%) of samples classified (rows) and referenced (columns).

	Reference								
	Bare Ground	**Building**	**Cropland**	**Grass**	**Impervious**	**Street/Railroad**	**Tree**	**Wetland**	**Water**
Bare Ground	67.16	1.49	2.99	5.97	19.40	1.49	1.49	0.00	0.00
Building	0.00	95.52	0.00	2.99	1.49	0.00	0.00	0.00	0.00
Cropland	0.00	0.00	98.51	0.00	0.00	0.00	0.00	0.00	1.49
Grass	0.00	0.00	0.00	80.60	2.99	0.00	16.42	0.00	0.00
Impervious	0.00	8.96	0.00	2.99	86.57	0.00	1.49	0.00	0.00
Street/Railroad	0.00	0.00	0.00	0.00	0.00	98.51	1.49	0.00	0.00
Tree	0.00	1.49	0.00	11.94	0.00	0.00	85.07	1.49	0.00
Wetland	3.57	0.00	0.00	0.00	0.00	0.00	0.00	92.86	3.57
Water	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.99	97.01

Table A2. Confusion matrix (2014). Values are percent (%) of samples classified (rows) and referenced (columns).

	Reference								
	Bare Ground	**Building**	**Cropland**	**Grass**	**Impervious**	**Street/Railroad**	**Tree**	**Wetland**	**Water**
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	0.00	0.00	0.00	8.47	3.39	0.00	88.14	0.00	0.00
Wetland	0.00	0.00	0.00	0.00	1.69	0.00	1.69	96.61	0.00
Water	0.00	0.00	0.00	3.39	1.69	0.00	0.00	0.00	94.92

References

1. Seto, K.C.; Fragkias, M.; Güneralp, B.; Reilly, M.K. A Meta-Analysis of Global Urban Land Expansion. *PLoS ONE* **2011**, *6*, e23777. [CrossRef] [PubMed]
2. United Nations. Transforming Our World: The 2030 Agenda for Sustainable Development. Available online: https://www.un.org/ohrlls/sites/www.un.org.ohrlls/files/2030_agenda_for_sustainable_development_web.pdf (accessed on 6 April 2022).
3. Endreny, T.A. Strategically growing the urban forest will improve our world. *Nat. Commun.* **2018**, *9*, 1160. [CrossRef] [PubMed]
4. Ulmer, J.M.; Wolf, K.L.; Backman, D.R.; Tretheway, R.L.; Blain, C.J.A.; O'Neil-Dunne, J.P.M.; Frank, L.D. Multiple health benefits of urban tree canopy: The mounting evidence for a green prescription. *Health Place* **2016**, *42*, 54–62. [CrossRef] [PubMed]

5. Sander, H.; Polasky, S.; Haight, R.G. The value of urban tree cover: A hedonic property price model in Ramsey and Dakota Counties, Minnesota, USA. *Ecol. Econ.* **2010**, *69*, 1646–1656. [CrossRef]
6. Locke, D.H.; Roman, L.A.; Murphy-Dunning, C. Why Opt-in to a Planting Program? Long-term Residents Value Street Tree Aesthetics. *Arboric. Urban For.* **2015**, *41*, 324–333. [CrossRef]
7. Tan, Z.; Lau, K.K.-L.; Ng, E. Urban tree design approaches for mitigating daytime urban heat island effects in a high-density urban environment. *Energy Build.* **2016**, *114*, 265–274. [CrossRef]
8. Baumgartner, R.J. Sustainable Development Goals and the Forest Sector—A Complex Relationship. *Forests* **2019**, *10*, 152. [CrossRef]
9. Salbitano, F.; Borelli, S.; Conigliaro, M.; Chen, Y. *Guidelines on Urban and Peri-Urban Forestry: FAO Forestry Paper No. 178*; Food and Agriculture Organization of the United Nations: Rome, Italy, 2016.
10. Endreny, T.; Santagata, R.; Perna, A.; De Stefano, C.; Rallo, R.F.; Ulgiatib, S. Implementing and managing urban forests: A much needed conservation strategy to increase ecosystem services and urban wellbeing. *Ecol. Model.* **2017**, *360*, 328–335. [CrossRef]
11. Haaland, C.; van den Bosch, C.K. Challenges and strategies for urban green-space planning in cities undergoing densification: A review. *Urban For. Urban Green.* **2015**, *14*, 760–771. [CrossRef]
12. Sivam, A.; Karuppannan, S.; Mobbs, M. How "open" are open spaces: Evaluating transformation of open space at residential level in Adelaide—A case study. *Local Environ.* **2012**, *17*, 815–836. [CrossRef]
13. McGee, J.A.; Day, S.D.; Wynne, R.H.; White, M.B. Using Geospatial Tools to Assess the Urban Tree Canopy: Decision Support for Local Governments. *J. For.* **2012**, *110*, 275–286. [CrossRef]
14. Forest Service. *Urban Tree Canopy Assessment: A Community's Path to Understanding and Managing the Urban Forest. FS–1121*; U.S. Department of Agriculture: Washington, DC, USA, 2019; p. 16.
15. Campbell, L.K. Constructing New York City's urban forest. The politics and governance of the MillionTreesNYC campaign. In *Urban Forests, Trees and Greenspace. A Policy Perspective*; Sandberg, L.A., Bardekjian, A., Butt, S., Eds.; Routledge: New York, NY, USA, 2014; pp. 242–260.
16. McPherson, E.G.; Simpson, J.R.; Xiao, Q.; Wu, C. Million trees Los Angeles canopy cover and benefit assessment. *Landsc. Urban Plan.* **2011**, *99*, 40–50. [CrossRef]
17. Locke, D.H.; Romolini, M.; Galvin, M.; O'Neil-Dunne, J.P.M.; Strauss, E.G. Tree Canopy Change in Coastal Los Angeles, 2009–2014. *Cities Environ. (CATE)* **2017**, *10*, 3.
18. Chuang, W.-C.; Boone, C.G.; Locke, D.H.; Grove, J.M.; Whitmer, A.; Buckley, G.; Zhang, S. Tree canopy change and neighborhood stability: A comparative analysis of Washington, D.C. and Baltimore, MD. *Urban For. Urban Green.* **2017**, *27*, 363–372. [CrossRef]
19. Nowak, D.J.; Greenfield, E.J. Tree and impervious cover change in U.S. cities. *Urban For. Urban Green.* **2012**, *11*, 21–30. [CrossRef]
20. Roman, L.A.; Scatena, F.N. Street tree survival rates: Meta-analysis of previous studies and application to a field survey in Philadelphia, PA, USA. *Urban For. Urban Green.* **2011**, *10*, 269–274. [CrossRef]
21. Petri, A.C.; Koeser, A.K.; Lovell, S.T.; Ingram, D. How Green Are Trees? *—Using Life Cycle Assessment Methods to Assess Net Environmental Benefits. J. Environ. Hortic.* **2016**, *34*, 101–110.
22. Ellis, E.A.; Mathews, A.J. Object-based delineation of urban tree canopy: Assessing change in Oklahoma City, 2006–2013. *Comput. Environ. Urban Syst.* **2019**, *73*, 85–94. [CrossRef]
23. Hostetler, A.E.; Rogan, J.; Martin, D.; DeLauer, V.; O'Neil-Dunne, J. Characterizing tree canopy loss using multi-source GIS data in Central Massachusetts, USA. *Remote Sens. Lett.* **2013**, *4*, 1137–1146. [CrossRef]
24. Lee, S.J.; Longcore, T.; Rich, C.; Wilson, J.P. Increased home size and hardscape decreases urban forest cover in Los Angeles County's single-family residential neighborhoods. *Urban For. Urban Green.* **2017**, *24*, 222–235. [CrossRef]
25. Duryea, M.L.; Kampf, E.; Littell, R.C.; Rodríguez-Pedraza, C.D. Hurricanes and the Urban Forest: II. Effects on Tropical and Subtropical Tree Species. *Arboric. Urban For.* **2007**, *33*, 98–112. [CrossRef]
26. Salisbury, A.B.; Koeser, A.K.; Hauer, R.J.; Hilbert, D.R.; Abd-Elrahman, A.H.; Andreu, M.G.; Britt, K.; Landry, S.M.; Lusk, M.G.; Miesbauer, J.W.; et al. The Legacy of Hurricanes, Historic Land Cover, and Municipal Ordinances on Urban Tree Canopy in Florida (United States). *Front. For. Glob. Change* **2022**, *5*, 742157. [CrossRef]
27. Miami-Dade County. Million Trees Miami. Available online: https://www.miamidade.gov/global/recreation/milliontrees/home.page (accessed on 6 June 2022).
28. Hochmair, H.H.; Gann, D.; Benjamin, A.; Fu, Z.J. *Miami-Dade County Urban Tree Canopy Assessment*; Funded by American Forests and Miami-Dade County; FIU GIS Center: Miami, FL, USA, 2016; p. 42.
29. Schwarz, K.; Fragkias, M.; Boone, C.G.; Zhou, W.; McHale, M.; Grove, J.M.; O'Neil-Dunne, J.; McFadden, J.P.; Buckley, G.L.; Childers, D.; et al. Trees Grow on Money: Urban Tree Canopy Cover and Environmental Justice. *PLoS ONE* **2015**, *10*, e0122051. [CrossRef] [PubMed]
30. Elmes, A.; Rogan, J.; Williams, C.; Ratick, S.; Nowak, D.; Martin, D. Effects of urban tree canopy loss on land surface temperature magnitude and timing. *ISPRS J. Photogramm. Remote Sens.* **2017**, *128*, 338–353. [CrossRef]
31. Koo, B.W.; Boyd, N.; Botchwey, N.; Guhathakurta, S. Environmental Equity and Spatiotemporal Patterns of Urban Tree Canopy in Atlanta. *J. Plan. Educ. Res.* **2019**. in print. [CrossRef]
32. Matthew, M.W.; Adler-Golden, S.M.; Berk, A.; Richtsmeier, S.C.; Levine, R.Y.; Bernstein, L.S.; Acharya, P.K.; Anderson, G.P.; Felde, G.W.; Hoke, M.P.; et al. Status of Atmospheric Correction Using a MODTRAN4-based Algorithm. In Proceedings of the

Algorithms for Multispectral, Hyperspectral, and Ultraspectral Imagery VI, Orlando, FL, USA, 24–26 April 2000; Volume 4049, pp. 199–207.

33. Juhász, L.; Hochmair, H.H. OSM Data Import as an Outreach Tool to Trigger Community Growth? A Case Study in Miami. *ISPRS Int. J. Geo-Inf.* **2018**, *7*, 113. [CrossRef]
34. Hexagon. Converting Landsat 8 Thermal Band 10 to Temperature Values. Available online: https://supportsi.hexagon.com/s/article/Converting-Landsat-8-Thermal-Band-10-to-Temperature-values?language=en_US (accessed on 14 May 2022).
35. USGS. Using the USGS Landsat Level-1 Data Product. Available online: https://www.usgs.gov/landsat-missions/using-usgs-landsat-level-1-data-product (accessed on 6 June 2022).
36. Liaw, A.; Wiener, M. Classification and Regression by randomForest. *R News* **2002**, *2*, 18–22.
37. Svetnik, V.; Liaw, A.; Tong, C.; Culberson, J.C.; Sheridan, R.P.; Feuston, B.P. Random Forest: A Classification and Regression Tool for Compound Classification and QSAR Modeling. *J. Chem. Inf. Comput. Sci.* **2003**, *43*, 1947–1958. [CrossRef]
38. Kuhn, M.; Wing, J.; Weston, S.; Williams, A.; Keefer, C.; Engelhardt, A.; Cooper, T.; Mayer, Z.; Kenkel, B.; Benesty, M.; et al. Caret: Classification and Regression Training. R Package Version 6.0-88. Available online: https://cran.r-project.org/web/packages/caret/index.html (accessed on 6 June 2022).
39. Olofsson, P.; Foody, G.M.; Stehman, S.V.; Woodcock, C.E. Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sens. Environ.* **2013**, *129*, 122–131. [CrossRef]
40. Zhou, W.; Qian, Y.; Li, X.; Li, W.; Han, L. Relationships between land cover and the surface urban heat island: Seasonal variability and effects of spatial and thematic resolution of land cover data on predicting land surface temperatures. *Landsc. Ecol.* **2014**, *29*, 153–167. [CrossRef]
41. Ross, A.; Willson, V.L. *Basic and Advanced Statistical Tests*; SensePublishers: Rotterdam, The Netherlands, 2017.
42. Landry, S.M.; Koeser, A.K.; Kanec, B.; Hilbert, D.R.; McLean, D.C.; Andreu, M.; Staudhammer, C.L. Urban forest response to Hurricane Irma: The role of landscape characteristics and sociodemographic context. *Urban For. Urban Green.* **2021**, *61*, 127093. [CrossRef]
43. Lee, J. The economic aftermath of Hurricanes Harvey and Irma: The role of federal aid. *Int. J. Disaster Risk Reduct.* **2021**, *61*, 102301. [CrossRef]
44. Miller, A.J.; Arias, M.E.; Alvarez, S. Built environment and agricultural value at risk from Hurricane Irma flooding in Florida (USA). *Nat. Hazards* **2021**, *109*, 1327–1348. [CrossRef]
45. Alonzo, M.; Bookhagen, B.; Roberts, D.A. Urban tree species mapping using hyperspectral and lidar data fusion. *Remote Sens. Environ.* **2014**, *148*, 70–83. [CrossRef]
46. Jung, M.C.; Dyson, K.; Alberti, M. Urban Landscape Heterogeneity Influences the Relationship between Tree Canopy and Land Surface Temperature. *Urban For. Urban Green.* **2021**, *57*, 126930. [CrossRef]
47. Boone, C.G.; Buckley, G.L.; Grove, J.M.; Sister, C. Parks and People: An Environmental Justice Inquiry in Baltimore, Marylan. *Ann. Assoc. Am. Geogr.* **2009**, *99*, 767–787. [CrossRef]
48. Troy, A.R.; Grove, M.; O'Neil-Dunne, J.P.M.; Pickett, S.T.A.; Cadenasso, M.L. Predicting Opportunities for Greening and Patterns of Vegetation on Private Urban Lands. *Environ. Manag.* **2007**, *40*, 394–412. [CrossRef]
49. Flocks, J.; Escobedo, F.; Wade, J.; Varela, S.; Wald, C. Environmental Justice Implications of Urban Tree Cover in Miami-Dade County, Florida. *Environ. Justice* **2011**, *4*, 125–134. [CrossRef]
50. Lin, B.; Meyers, J.; Barnett, G. Understanding the potential loss and inequities of green space distribution with urban densification. *Urban For. Urban Green.* **2015**, *14*, 952–958. [CrossRef]
51. Heynen, N.; Perkins, H.A.; Roy, P. The Political Ecology of Uneven Urban Green Space: The Impact of Political Economy on Race and Ethnicity in Producing Environmental Inequality in Milwaukee. *Urban Aff. Rev.* **2006**, *42*, 3–25. [CrossRef]
52. Keeler, B.L.; Hamel, P.; McPhearson, T.; Hamann, M.H.; Donahue, M.L.; Meza Prado, K.A.; Arkema, K.K.; Bratman, G.N.; Brauman, K.A.; Finlay, J.C.; et al. Social-ecological and technological factors moderate the value of urban nature. *Nat. Sustain.* **2019**, *2*, 29–38. [CrossRef]